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Biased forecasts or biased earnings? The role of reported earnings in explaining apparent bias and over/underreaction in analysts' earnings forecasts ☆

Jeffery Abarbanell[a], Reuven Lehavy[b,*]

[a] Kenan-Flagler Business School, University of North Carolina at Chapel Hill, Chapel Hill, NC 27599-3490, USA
[b] University of Michigan Business School, 701 Tappan Street, Ann Arbor, MI 48109-1234, USA

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Abstract

The extensive literature that investigates whether analysts' earnings forecasts are biased and/or inefficient has produced conflicting evidence and no definitive answers to either question. This paper shows how two relatively small but statistically influential asymmetries in the tail and the middle of distributions of analysts' forecast errors can exaggerate or obscure evidence consistent with analyst bias and inefficiency, leading to inconsistent inferences. We identify an empirical link between firms' recognition of unexpected accruals and the presence of the two asymmetries in distributions of forecast errors that suggests that firm reporting choices play an important role in determining analysts' forecast errors.

JEL classification: G10; G14; M41

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*Corresponding author. Tel.: +1-734-763-1508; fax: +1-734-936-0282.
E-mail address: rlehavy@umich.edu (R. Lehavy).

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1. Introduction

Four decades of research have produced an array of empirical evidence and a set of behavioral and incentive-based theories that address two fundamental questions: Are analysts' forecasts biased? And Do analysts underreact or overreact to information in prior realizations of economic variables? This empirical literature has long offered conflicting conclusions and is not converging to a definitive answer to either question. On the one hand, theories that predict optimism in forecasts are consistent with the persistent statistical finding in the literature of cross-sectional negative (i.e., bad news) mean forecast errors as well as negative intercepts from regressions of forecasts on reported earnings. On the other hand, such theories are inconsistent both with the finding that median forecast errors are most often zero and with the fact that the percentage of apparently pessimistic errors is greater than the percentage of apparently optimistic errors in the cross-section. A similar inconsistency is found in the literature on analyst over/underreaction to prior realizations of economic variables, including prior stock returns, prior earnings changes, and prior analyst forecast errors. Here, again, empirical evidence supports conflicting conclusions that analysts overreact to prior news, underreact to prior news, and both underreact and overreact as a function of the sign of prior economic news. Further reflecting the lack of consensus in the literature, a handful of studies fail to reject unbiasedness and efficiency in analyst forecasts after "correcting" methodological flaws or assuming nonstandard analyst loss functions.[1]

The accumulation of often inconsistent results concerning analyst rationality and incentives makes it difficult for researchers, practitioners, and policy makers to understand what this literature tells us. This motivates us to reexamine the body of evidence with the goal of identifying the extent to which particular theories for apparent errors in analysts' forecasts are supported by the data. Such an exercise is both appropriate and necessary at this juncture as it can, among other things, lead to modified theories that will be tested using the new and unique hypotheses they generate.

We extend our analysis beyond a synthesis and summary of the findings in the literature by identifying the role of two relatively small asymmetries in the cross-sectional distributions of analysts' forecast errors in generating conflicting statistical evidence. We note that the majority of conclusions concerning analyst-forecast rationality in the literature are directly or indirectly drawn from analyses of these distributions. The first asymmetry is a larger number and a greater magnitude of observations that fall in the extreme negative relative to the extreme positive tail of the forecast error distributions (hereafter, the *tail asymmetry*). The second asymmetry is a higher incidence of small positive relative to small negative forecast errors in cross-sectional distributions (hereafter, *the middle asymmetry*). The individual and combined impact of these asymmetries on statistical tests leads to three important observations. First, differences in the manner in which researchers

[1] A representative selection of evidence and theory relevant to both the bias and over/underreaction literatures is discussed in the body of the paper.

implicitly or explicitly weight observations that fall into these asymmetries contribute to inconsistent conclusions concerning analyst bias and inefficiency. Second, a variety of econometric techniques and data adjustments fail to eliminate inconsistencies in inferences across different statistical indicators and conditioning variables. Such techniques include using indicator variables or data partitions in parametric tests, applying nonparametric methods, and performing data truncations and transformations. Third, econometric approaches that choose loss functions that yield consistent inferences—essentially by attenuating the statistical impact of observations that comprise the asymmetries—will not provide definitive answers to the question of whether analysts' forecasts are biased and inefficient. This is because at this stage in the literature too little is known about analysts' actual loss functions, and such methods thus leave unresolved the question of why the asymmetries in forecast error distributions are present.

We present statistical evidence that demonstrates how the two asymmetries in forecast error distributions can indicate analyst optimism, pessimism, or unbiasedness. We also show how observations that comprise the asymmetries can contribute to, as well as obscure, a finding of apparent analyst inefficiency with respect to prior news variables, including prior returns, prior earnings changes, and prior forecast errors. For example, our empirical evidence explains why prior research that relies on parametric statistics always finds evidence of optimistic bias as well as apparent analyst underreaction to prior bad news for all alternative variables chosen to represent prior news. It also explains why evidence of apparent misreaction to good news is *not* robust across parametric statistics or across prior news variables, and why the degree of misreaction to prior bad news is always greater than the degree of misreaction to prior good news, regardless of the statistical approach adopted or the prior information variable examined.

Finally, while our analysis does not lead to an immediately obvious solution to problems of inferences in the literature, it does reveal a link between the reported earnings typically employed to benchmark forecasts and the presence of the two asymmetries in distributions of forecast errors. Specifically, we find that extreme negative unexpected accruals included in reported earnings go hand in hand with observations in the cross-section that generate the tail asymmetry. We also find that the middle asymmetry in distributions of forecast error is eliminated when the reported earnings component of the earnings surprise is stripped of unexpected accruals. This evidence suggests benefits to refining extant cognitive- and incentive-based theories of analyst forecast bias and inefficiency so that they can account for an endogenous relation between forecast errors and manipulation of earnings reports by firms. The evidence also highlights the importance of future research into the question of whether reported earnings are, in fact, the correct benchmark for assessing analyst bias and inefficiency. This is because common motivations for manipulating earnings can give rise to the appearance of analyst forecast errors of exactly the type that comprise the two asymmetries if unbiased and efficient forecasts are benchmarked against manipulated earnings. Thus, it is possible that some evidence previously deemed to reflect the impact of analysts' incentives and cognitive tendencies on forecasts is, after all, attributable to the fact that analysts do not have the motivation or ability to completely anticipate earnings management by firms in their forecasts.

This paper's emphasis is on fleshing out salient characteristics of forecast error distributions with an eye toward ultimately explaining how they arise. The analysis highlights the importance of new research that explains the actual properties of forecast error data and cautions against the application of econometric fixes that either fit the data to specific empirical models or fit specific empirical models to the data without strong a priori grounds for doing so. Our findings also represent a step toward understanding what analysts really aim for when they forecast, which is useful for developing more appropriate null hypotheses in tests of analysts' forecast rationality, and sounder statistical test specifications, as well as the identification of first-order effects that may require control when testing hypotheses that predict analyst forecast errors.

In the next section we describe our data and present evidence of the sensitivity of statistical inferences concerning analyst optimism and pessimism to relatively small numbers of observations that comprise the tail and middle asymmetries. Section 3 extends the analysis to demonstrate the impact of the two forecast error asymmetries on inferences concerning analyst over/underreaction conditional on prior realizations of stock returns and earnings changes, as well as on serial correlation in consecutive-quarter forecast errors. Section 4 presents evidence of a link between biases in reported earnings and the two asymmetries and discusses possible explanations for this link as well as the implications for interpreting evidence from the literature and for the conduct of future research. A summary and conclusions are provided in Section 5.

2. Properties of typical distributions of analysts' forecast errors and inferences concerning analysts' optimism, pessimism, and unbiasedness

2.1. Data

The empirical evidence in this paper is drawn from a large database of consensus quarterly earnings forecasts provided by Zacks Investment Research. The Zacks earnings forecast database contains approximately 180,000 consensus quarterly forecasts for the period 1985–1998. For each firm quarter we calculate forecast errors as the actual earnings per share (as reported in Zacks) minus the consensus earnings forecast outstanding prior to announcement of quarterly earnings, scaled by the stock price at the beginning of the quarter and multiplied by 100. Our results are insensitive to alternative definitions of forecasts such as the last available forecast or average of the last three forecasts issued prior to quarter-end. Inspection of the data revealed a handful of observations that upon further review indicated data errors. These observations had no impact on the basic features of cross-sectional distributions of errors that we describe, but they were nevertheless removed before carrying out the statistical tests reported in this paper. Empirical results obtained after removing these observations were virtually identical to those obtained when the distributions of quarterly forecast errors were winsorized at the 1st and 99th percentiles, a common practice for mitigating the possible effects of data errors followed in the literature. (To enhance comparability with the majority of studies cited below, all test results reported in the paper are based on the winsorized data.)

Lack of available price data reduced the sample size to 123,822 quarterly forecast errors. The data requirements for estimating quarterly accruals further reduced the sample on which our tabled results are based to 33,548 observations.[2] For the sake of brevity we present only results for this reduced sample. We stress, however, that the middle and tail symmetries we document below are present in the full sample of forecast errors and that the proportion of observations that comprise these asymmetries is roughly the same as that for the reduced sample. Moreover, the descriptive evidence and statistical findings relevant to apparent bias and inefficiency in analyst forecasts presented in this section and the next are qualitatively similar when we do not impose the requirement that data be available to calculate unexpected accruals.[3]

2.2. The impact of asymmetries in the distribution of forecast errors on inferences concerning bias

One of the most widely held beliefs among accounting and finance academics is that incentives and/or cognitive biases induce analysts to produce generally optimistic forecasts (see, e.g., reviews by Brown (1993) and Kothari, 2001). This view is repeatedly reinforced when studies that employ analysts' forecasts as a measure of expected earnings present descriptive statistics and refer casually to negative mean forecast errors as evidence of the purportedly "well-documented" phenomenon of optimism in analyst forecasts.[4] The belief is even more common among regulators (see, e.g., Becker, 2001) and the business press (see, e.g., Taylor, 2002). In spite of the prevalent view of analyst forecast optimism, summary statistics associated with forecast error distributions reported in Panel A of Table 1 raise doubts about this conclusion.

[2] As described in Section 4, we use a quarterly version of the modified Jones model to estimate accruals. For the purposes of sensitivity tests, we also examine a measure of unexpected accruals that excludes nonrecurring and special items (see, Hribar and Collins, 2002), and use this adjusted measure in conjunction with *Zacks*' consensus forecast estimates and actual reported earnings, which also exclude such items. All the results involving unexpected accruals reported in the paper are qualitatively unaltered using this alternative measure.

[3] The results are also qualitatively similar when data from alternative forecast providers (I/B/E/S and First Call) are employed, indicating that the findings we revisit in this study are not idiosyncratic to a particular data source (see, Abarbanell and Lehavy, 2002).

[4] The perception is also strengthened in a number of studies that place analyst forecasts and reported earnings numbers (i.e., the two elements that comprise the forecast error) on opposite sides of a regression equation. These studies uniformly find significant intercepts and either casually refer to them as consistent with analyst optimism or emphasize them in supporting their prediction of analyst bias. Evidence presented below, however, indicates a nonlinear relation between forecasts and earnings, which contributes to nonzero intercepts in OLS regressions.

Table 1
Descriptive statistics on quarterly distributions of forecast errors (Panel A), the tail asymmetry (Panel B), and the middle asymmetry (Panel C), 1985–1998

Panel A: Statistics on forecast error distributions

Number of observations	33,548
Mean	−0.126
Median	0.000
% Positive	48%
% Negative	40%
% Zero	12%

Panel B: Statistics on the "tail asymmetry" in forecast error distributions

P5	−1.333
P10	−0.653
P25	−0.149
P75	0.137
P90	0.393
P95	0.684

Panel C: Statistics on the "middle asymmetry" in forecast error distributions

Range of forecast errors (1)	Ratio of positive to negative forecast errors (2)	% of total number of observations (3)
Overall	1.19	100
Forecast errors = 0		12
[−0.1, 0) & (0, 0.1]	1.63*	29
[−0.2, −0.1) & (0.1, 0.2]	1.54*	18
[−0.3, −0.2) & (0.2, 0.3]	1.31*	10
[−0.4, −0.3) & (0.3, 0.4]	1.22*	7
[−0.5, −0.4) & (0.4, 0.5]	1.00	5
[−1, −0.5) & (0.5, 1]	0.83*	11
[Min, −1) & (1, Max]	0.40*	9

This table provides descriptive statistics on quarterly distributions of forecast errors for the period of 1985–1998. Analyst earnings forecasts and actual realized earnings are provided by *Zacks Investment Research*. Panel A provides the mean, median, and frequencies of quarterly forecast errors. Panel B provides percentile values of forecast error distributions. Panel C reports the ratio of positive to negative forecast errors for observations that fall into increasingly larger and nonoverlapping symmetric intervals moving out from zero forecast errors. For example, the forecast error range of [−0.1, 0) & (0, 0.1] includes all observations that are greater than or equal to −0.1 and (strictly) less than zero and observations that are greater than zero and less than or equal to 0.1. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price.

*A test of the difference in the frequency of positive to negative forecast errors is statistically significant at or below a 1% level.

As can be seen in Panel A, the only statistical indication that supports the argument for analyst optimism is a fairly large negative mean forecast error of −0.126. In contrast, the median error is zero, suggesting unbiased forecasts, while the percentage of positive errors is significantly greater than the percentage of negative errors (48% vs. 40%), suggesting apparent analyst pessimism.

To better understand the causes of this inconsistency in the evidence of analyst biases among the summary statistics, we take a closer look at the distribution of forecast errors. Panel A of Fig. 1 presents a plot of the 1st through the 100th percentiles of the pooled quarterly distributions of forecast errors over the sample period. Moving from left to right, forecast errors range from the most negative to the most positive.

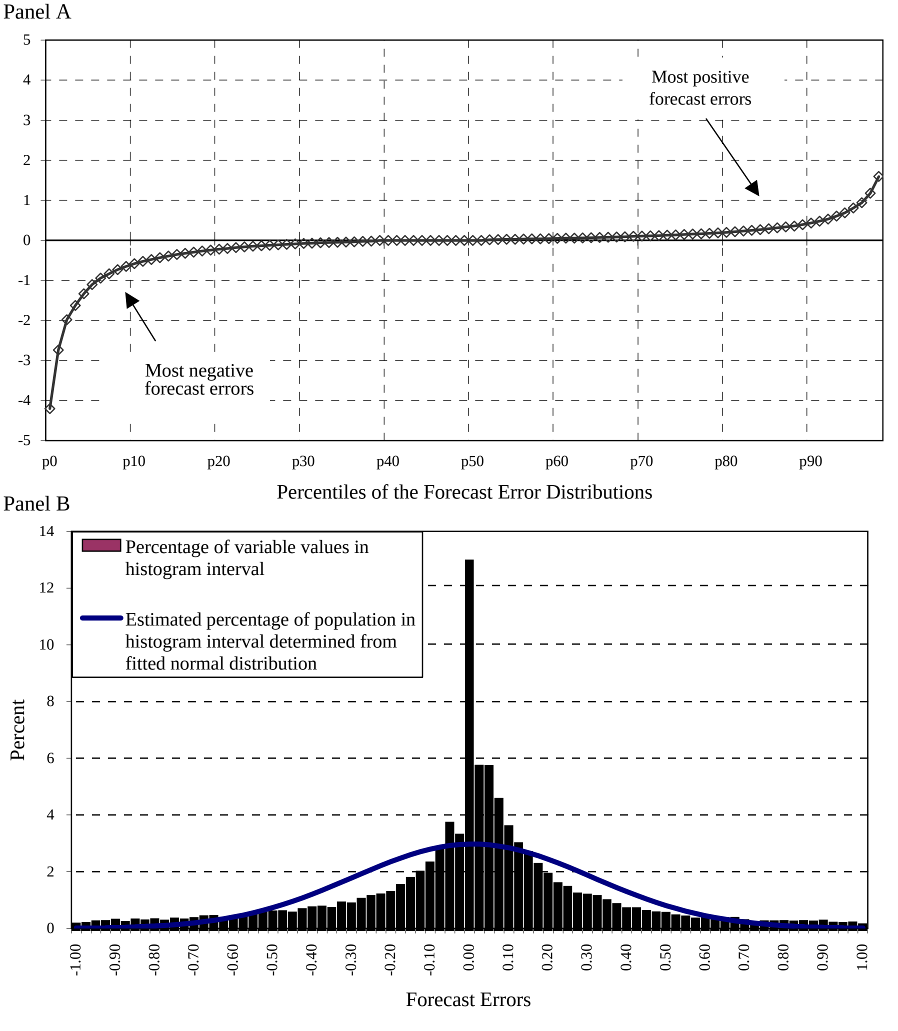

Fig. 1. Percentile values of quarterly distributions of analyst forecast errors (Panel A) and histogram of forecast errors for observations within forecast errors of -1 to $+1$ (Panel B). Panel A depicts percentile values of quarterly distributions of analyst forecast errors. Panel B presents percentage of forecast error values in histogram intervals for observations within a forecast error of -1% to $+1\%$ of the beginning-of-period stock price. Forecast error equals reported earnings minus the consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price ($N = 33,548$).

One distinctive feature of the distribution is that the left tail (ex-post bad news) is longer and fatter than the right tail, i.e., far more extreme forecast errors of greater absolute magnitude are observed in the ex-post ‘‘optimistic’’ tail of the distribution than in the ‘‘pessimistic’’ tail. We refer to this characteristic of the distribution as the *tail asymmetry*. Although Fig. 1 summarizes the distribution of observations over the entire sample period, unreported results indicate that a tail asymmetry is present in each quarter represented in the sample. To get a sense of the magnitude of the asymmetry, we return to Panel B of Table 1, where the 5th percentile (extreme negative forecast errors) is nearly twice the size observed for the 95th percentile (-1.333 vs. 0.684). Alternatively, we find that 13% of the observations fall below a negative forecast error of -0.5, while only 7% fall above a positive error of an equal magnitude (not reported in the table).

Closer visual inspection of the data reveals a second feature of the distribution depicted in Panel B of Fig. 1—a higher frequency of small positive forecast errors versus small negative errors. Specifically, the figure presents the frequencies of forecast errors that fall in fixed subintervals of 0.025 within the range of -1 to $+1$. Clearly, the *incidence* of small positive relative to small negative errors increases as forecast errors become smaller in absolute magnitude. We refer to this property of the distribution as the *middle asymmetry*.[5] Statistics on the magnitude of the middle asymmetry are reported in Panel C of Table 1. This panel presents the ratio of positive (i.e., apparently pessimistic) errors to negative errors for observations that fall into increasingly larger and nonoverlapping symmetric intervals moving out from zero forecast errors. Consistent with the visual evidence in Panel B of Fig. 1, this ratio increases for smaller, symmetric intervals of forecast errors, reaching 1.63 in the smallest interval examined (significantly different from 1, as well as significantly different from the ratios calculated for the larger intervals).[6] Another distinguishing feature of the distribution seen in Panel C of Table 1 and evident in both Panels A and B of Fig. 1 is the large number of exactly zero observations (12%). Depending on one's previous exposure to the data or instincts about the task of forecasting, the magnitude of the clustering at exactly zero may not seem

[5] The visual evidence in Panel B of Fig. 1 is consistent with specific circumstances in which analysts have incentives to produce forecasts that fall slightly short of reported earnings (see, e.g., Degeorge et al., 1999; Matsumoto, 2002; Brown, 2001; Burgstahler and Eames, 2002; Bartov et al., 2000; Dechow et al., 2003; Abarbanell and Lehavy, 2003a, b). However, prior studies have not considered the impact of observations that comprise the middle asymmetry on inferences concerning the *general* tendency of analysts to produce biased and/or inefficient forecasts.

[6] An analysis of unscaled forecast errors confirms that rounding down a greater number of negative than positive forecast errors to a value of zero when errors are scaled by price does not systematically induce the middle asymmetry (see, Degeorge et al., 1999). Similarly, there is no obvious link between the presence of the middle asymmetry and round-off errors induced by the application of stock-split factors to consensus forecast errors discussed in Baber and Kang (2002) and Payne and Thomas (2002). Abarbanell and Lehavy (2002) present evidence confirming the presence of the middle asymmetry in samples confined to firms with stock-split factors of less than 1.

surprising. Nevertheless, the large number of forecasts of exactly zero has important impacts on statistical inferences.[7]

The statistics presented above indicate that the tail asymmetry pulls the mean forecast error toward a negative value, supporting the case for analyst optimism. But, as shown in Panel C of Table 1, the excess of *small* positive over *small* negative errors associated with the middle asymmetry is largely responsible for a significantly higher overall incidence of positive to negative forecast errors in the distribution, thus supporting the case for analyst pessimism. Finally, a zero median forecast error, which supports an inference of analyst unbiasedness, reflects the countervailing effects of the middle asymmetry and tail asymmetries. A rough calculation pertaining to the nonzero forecast errors in the interval between [−0.1, 0) and (0, 0.1] gives a sense of these effects. There are 9662 observations in this region. If nonzero forecast errors were random, we would expect 4831 forecasts to be positive, when in fact 5928 are positive, indicating that small errors in the distribution of absolute magnitude less than or equal to 0.1 contribute 1097 more observations to the right of zero than would be expected if the distribution was symmetric. This region of the forecast error distribution contains 29% of all observations but contributes more than 42% of the total number of pessimistic errors in excess of optimistic errors and represents roughly 3.3% of the entire distribution. Their impact offsets, all else being equal, the contribution of approximately 2.5% of negative observations in excess of what would be expected if the distribution of errors were symmetric, arising from the tail asymmetry (relative to the extreme decile cutoffs of a fitted normal distribution). Because 12% of the forecast error sample has a value of exactly zero, the relative sizes of the tail and middle asymmetries are each sufficiently small (and offsetting) to ensure that the median error remains at zero.

The evidence in Table 1 and Fig. 1 yields two important implications for drawing inferences about the nature and extent of analyst bias. First, depending on which summary statistic the researcher chooses to emphasize, support can found for analyst optimism, pessimism, and even unbiasedness. Second, if a researcher relies on a given summary statistic to draw an inference about analyst bias, a relatively small percentage of observations in the distribution of forecast errors will be responsible for his or her conclusion. This is troublesome because extant hypotheses that predict analyst optimism or pessimism typically do not indicate how often the phenomenon will occur in the cross-section and often convey the impression that

[7] Because many factors can affect the process that generates the typical distribution of forecast errors, there is no reason to expect them to be normally or even symmetrically distributed. Supplemental analyses unreported in the tables reject normality on the basis of skewness and kurtosis. It is interesting to note, however, that kurtosis in the forecast error distribution does not align with the typical descriptions of leptokurtosis (high peak and fat tails) or platykurtosis (flat center and/or shoulders). Relative to decile cutoffs of the fitted normal distribution, we find that the most extreme negative decile of the actual distribution contains only 5% of the observations and the most extreme positive decile contains only 2.5% of the observations. Thus, even though the extreme negative tail is roughly twice the size of the extreme pessimistic tail, extreme observations are actually *underrepresented* in the distribution relative to a normal, especially in the positive tail. The thinner tails and shoulders of the distribution highlight the role of peakedness as a source of deviation from normality, a fact that is relevant to assessing the appropriateness of statistics used by researchers to draw inferences about analyst forecast bias.

bias will be pervasive in the distribution (see, studies suggesting that analysts are hard-wired or motivated to produce optimistic forecasts, e.g., Affleck-Graves et al. (1990), Francis and Philbrick (1993), and Kim and Lustgarten (1998), or that selection biases lead to hubris in analysts' earnings forecasts, e.g., McNichols and O'Brien, 1997).[8]

Some studies have explicitly recognized the disproportional impact of extreme negative forecast errors on conclusions drawn in the literature, but for the most part they have had little influence on general perceptions. For example, Degeorge et al. (1999) predict a tendency for pessimistic errors to occur but recognize the common perception that analyst forecasts are optimistic; they note in passing that extreme negative forecast errors are responsible for an optimistic mean forecast in their sample. Some studies also tend to deal with this feature of the data in an ad hoc manner. Keane and Runkle (1998), for example, recognize the impact of extreme negative forecast errors on statistical inferences concerning analyst forecast rationality and thus eliminate observations from their sample based on whether reported earnings contain large negative special items. However, Abarbanell and Lehavy (2002) show that there is a very high correlation between observations found in the extreme negative tail of forecast error distributions and firms that report large negative special items, even when special items are excluded from the reported earnings benchmark used to calculate the forecast error. Thus, by imposing rules that eliminate observations from their sample based on the size of negative special items, Keane and Runkle (1998) effectively truncate the extreme negative tail of forecast error distributions, and in so doing nearly eliminate evidence of mean optimism in their sample.

Some researchers are less explicit in justifying the removal of observations from the distribution of forecast errors when testing for forecast rationality, or are unaware that they have done so in a manner that results in sample distributions that deviate substantially from the population distribution. For example, many studies implicitly limit observations in their samples to those that are less extreme by choosing ostensibly symmetric rules for eliminating them, such as winsorization or truncations of values greater than a given absolute magnitude.[9] It should be evident from Panel A of Fig. 1 that such rules inherently mitigate the statistical impact of the

[8] A notable exception is the attribution of optimism in analysts' earnings forecasts to incentives to attract and maintain investment banking relationships (see, e.g., Lin and McNichols, 1998; Dugar and Nathan, 1995). Evidence consistent with this argument is based on fairly small samples of firms issuing equity. We emphasize that all the qualitative results in this paper are unaltered after eliminating observations for which an IPO or a seasoned equity offering took place within 1 year of the date of a forecast. Furthermore, the number of observations removed from the sample for this reason represents a very small percentage of those in each of the quarters in our sample period.

[9] For example, Kothari (2001) reports that Lim (2001) excludes absolute forecast errors of $10 per share or more, Degeorge et al. (1999) delete absolute forecast errors greater than 25 cents per share, Richardson et al. (1999) delete price-deflated forecast errors that exceed 10% in absolute value, and Brown (2001) winsorizes absolute forecast errors greater than 25 cents per share (which implies a much larger tail winsorization than typically undertaken to remove possible data errors). While none of these procedures, when applied to our data, completely eliminates the tail asymmetry, all of them substantially attenuate to varying degrees its statistical impact on our tests.

tail asymmetry and arbitrarily transform the distribution, frequently without a theoretical or institutional reason for doing so.[10]

One might justify truncating data on the grounds that the disproportional impact of the extreme tail makes it difficult detect general tendencies, or that such "errors" may not accurately reflect factors relevant to analysts' objective functions (see, e.g., Abarbanell and Lehavy, 2003b; Gu and Wu, 2003; Keane and Runkle, 1998). However, it is possible for researchers to "throw the baby out with the bathwater" if they assume that these observations do not reflect the effects of incentives or cognitive biases, albeit in a more noisy fashion than other observations in the distribution. Another concern that arises from transforming the distribution of errors without justification is that it may suppress one feature of the data (e.g., the tail asymmetry), leaving another unusual but more subtle feature of the distribution (e.g., the middle asymmetry) to dominate an inference that forecasts are generally biased or to offset the other and yield an inference that forecasts are generally unbiased. This is an important issue because there has been a tendency in the literature on forecast rationality for new hypotheses to crop up motivated solely by the goal of explaining "new" empirical results. For example, after truncating large absolute values of forecast errors, Brown (2001) finds that the mean and median forecasts in recent years indicate a shift away from analyst optimism and toward analyst pessimism. Increasing pessimism as a function of market sentiment as reflected in changes in price level or changes in analyst incentives has also been a subject of growing interest in the behavioral finance literature. Clearly, when data inclusion rules that systematically reduce the tail asymmetry are applied, empirical evidence in support of increasing or time-varying analyst pessimism will be affected by the size and magnitude of the remaining middle asymmetry.

Perhaps the most unsatisfying aspect of the evidence presented in Table 1 is the fact that general incentive and behavioral theories of analyst forecast errors are not sufficiently developed at this stage to predict that when forecast errors are extreme they are more likely to be *optimistic* and when forecast errors are small they are more likely to be *pessimistic*. That is, individual behavioral and incentive theories for analyst forecast errors do not account for the simultaneous presence of the two asymmetries that play such an important role in generating evidence consistent with analyst bias and, as we show in the next section, analyst forecast inefficiency with respect to prior information (see Abarbanell and Lehavy, 2003a, for an exception).

3. The effect of the two asymmetries on evidence of apparent analyst misreaction to prior stock returns, prior earnings changes, and prior forecast errors

In this section, we demonstrate how observations that comprise the tail and middle asymmetries in forecast error distributions *conditional on prior realizations of*

[10] For example, in our data an arbitrary symmetric truncation of the distribution at the 10th and the 90th percentiles reduces the measure of skewness in the remainder of the distribution to a level that does not reject normality and results in a mean forecast error near zero among the remaining observations. A similar effect occurs with an arbitrary one-sided truncation of the negative tail at a value as low as the 3rd percentile.

economic variables contribute to inconsistent inferences concerning the efficiency of analysts' forecasts. One important message of the ensuing analysis is that the likelihood that a forecast error observation falls into one or the other asymmetry varies by the sign and magnitude of the prior news. This feature of the data links the empirical literature on analyst inefficiency to the heretofore separate literature on analyst bias. This is because observations that comprise the two asymmetries and lead—depending on the statistic relied on—to inconsistent inferences concerning analyst bias also contribute to conflicting inferences concerning whether analysts underreact, overreact, or react efficiently to prior news.

We consider realizations of three economic variables: prior period stock returns, prior period earnings changes, and prior period analyst forecast errors. These three variables are those most often identified in previous studies of analyst forecast efficiency.[11] Consistent with the previous literature, we define prior abnormal returns (*PrAR*) as equal to the return between 10 days after the last quarterly earnings announcement to 10 days prior to the current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period.[12] Prior earnings changes (*PrEC*) are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by the price at the beginning of the period, and prior forecast errors (*PrFE*) are the prior quarter's forecast error.

The remainder of this section proceeds as follows: we first present evidence on the existence of the tail and middle asymmetries in distributions of forecast errors conditional on the sign of prior news variables. We then analyze the role of the asymmetries in producing indications of analyst inefficiency in both summary statistics and regression coefficients and discuss the robustness of these findings. Next, we show the disproportionate impact of observations that comprise the asymmetries in generating evidence of serial correlation in analyst forecast errors. Finally, we discuss the shortcomings of econometric "fixes" that intentionally or unintentionally ameliorate the impact of one or both asymmetries on inferences concerning analyst forecast rationality.

3.1. The tail and middle asymmetries in forecast error distributions conditional on prior news variables

Tests of analyst forecast efficiency typically partition distributions of forecast errors based on the sign of the prior news to capture potential differences in analyst reactions to prior good versus prior bad news. Accordingly, before we review the

[11] Studies that examine the issue of current period forecast efficiency with respect to prior period realization of returns or earnings (e.g., Abarbanell, 1991; Easterwood and Nutt, 1999) commonly frame the question in terms of whether analysts over- or underreact to prior news. In contrast, studies that examine the issue of current period forecast efficiency with respect to analysts' own past forecast errors are generally limited to the question of whether there is significant serial correlation in lagged forecast errors, without regard to how the sign and magnitude of prior forecast errors affect that correlation.

[12] All reported results are qualitatively similar when prior abnormal returns are measured between 10 days after the last quarterly earnings announcement to either 30 days prior or 1 day prior to the current quarter earnings announcement.

statistical evidence, we first examine the features of forecast error distributions conditional on the sign of prior news variables. Panels A–C of Fig. 2, which depict the percentiles of the distributions of forecast errors conditional on the sign of each of the three prior news variables, show that prior bad news partitions are characterized by larger tail asymmetries than prior good news partitions for all prior news variables.

Panels A–C of Fig. 3—which depict the frequencies of forecast errors that fall in fixed subintervals of 0.025 within the range of -0.5 to $+0.5$ for *PrAR*, *PrEC*, and *PrFE*, respectively—show that prior good news partitions are characterized by larger middle asymmetries than prior bad news partitions for all three prior news variables.[13]

Together, Figs. 2 and 3 suggest that distributions of forecast errors conditional on the sign of prior news retain the characteristic asymmetries found in the unconditional distributions in Section 2. However, the likelihood of a subsequent forecast error falling into the middle asymmetry is greater following prior good news, while the likelihood of a forecast error falling into the tail asymmetry is greater following prior bad news.[14] Below we investigate the impact of the variation in the size of the asymmetries in distributions of forecast errors conditional on the sign of news on inferences about analyst inefficiency that are drawn from summary statistics (Section 3.1.1) and regression coefficients (Section 3.1.2).

3.1.1. Inferences about analyst efficiency from summary statistics

Panel A of Table 2 shows how the two asymmetries impact summary statistics, including means, medians, and the percentages of negative to positive forecast errors in distributions of forecast errors conditional on the sign of prior news. We begin with the case of prior bad news. Prior bad news partitions for all three variables produce significantly negative mean forecast errors (-0.195 for *PrAR*, -0.291 for *PrEC*, and -0.305 for *PrFE*), supporting an inference of analyst underreaction (i.e., the mean forecast is too high following bad news). The higher percentages of negative than positive forecast errors in the bad news partitions of each variable (e.g., 50% vs. 40% for negative *PrEC*) are also consistent with a tendency for analysts to underreact to prior bad news. The charts in Figs. 2 and 3 foreshadow these results. The relatively larger tail asymmetry in prior bad news partitions drives parametric means to large negative values. Similarly, the larger negative relative to

[13] The concentration of small (extreme) errors among positive (negative) prior returns news is not induced by scaling by prices that are systematically higher (lower) following a period of abnormal positive (negative) returns, since the middle and tail asymmetries are still present in distributions of unscaled forecast errors and errors deflated by forecasts.

[14] Abarbanell and Lehavy (2003a) report the same patterns in forecast error distributions conditional on classification of ranked values of stock recommendations, P/E ratio, and market-to-book ratios into high and low categories. It is certainly possible that some form of irrationality or incentive effect leads to different forecast error regimes on either side of a demarcation point of zero, and therefore coincidentally sorts the two asymmetries that are located on either side of a zero. However, the continued presence of relatively small but statistically influential asymmetries in the conditional distributions may overwhelm the researcher's ability to detect these incentive or behavioral factors, or may give the false impression that such a factor is pervasive in the distribution when it is not.

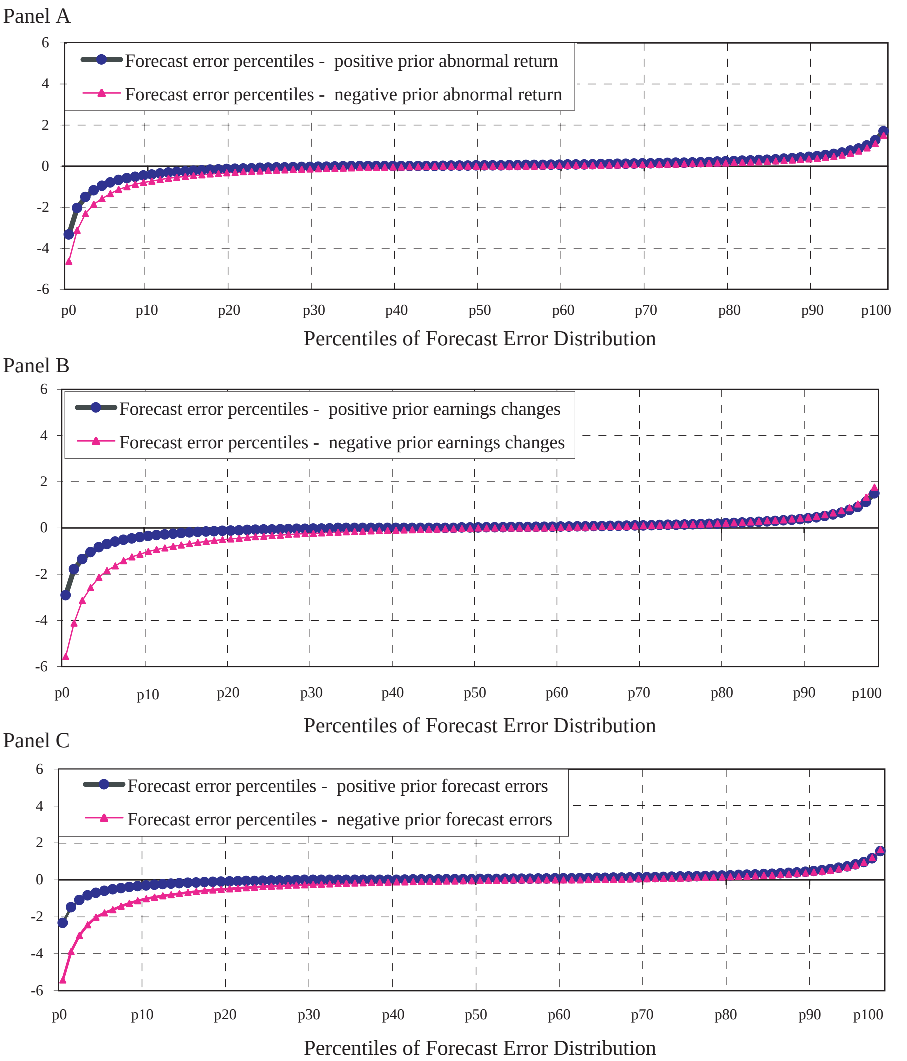

Fig. 2. Forecast error equals reported earnings minus consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price. Prior market-adjusted return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by the beginning-of-period price.

positive tails account for greater overall frequencies of negative than positive errors, consistent with underreaction to bad news for all three variables. This is so even though prior bad news distributions of forecast errors for *PrAR* and *PrEC* are characterized by middle asymmetries, which, all else equal, tend to push the ratio of positive to negative errors toward values greater than 1.

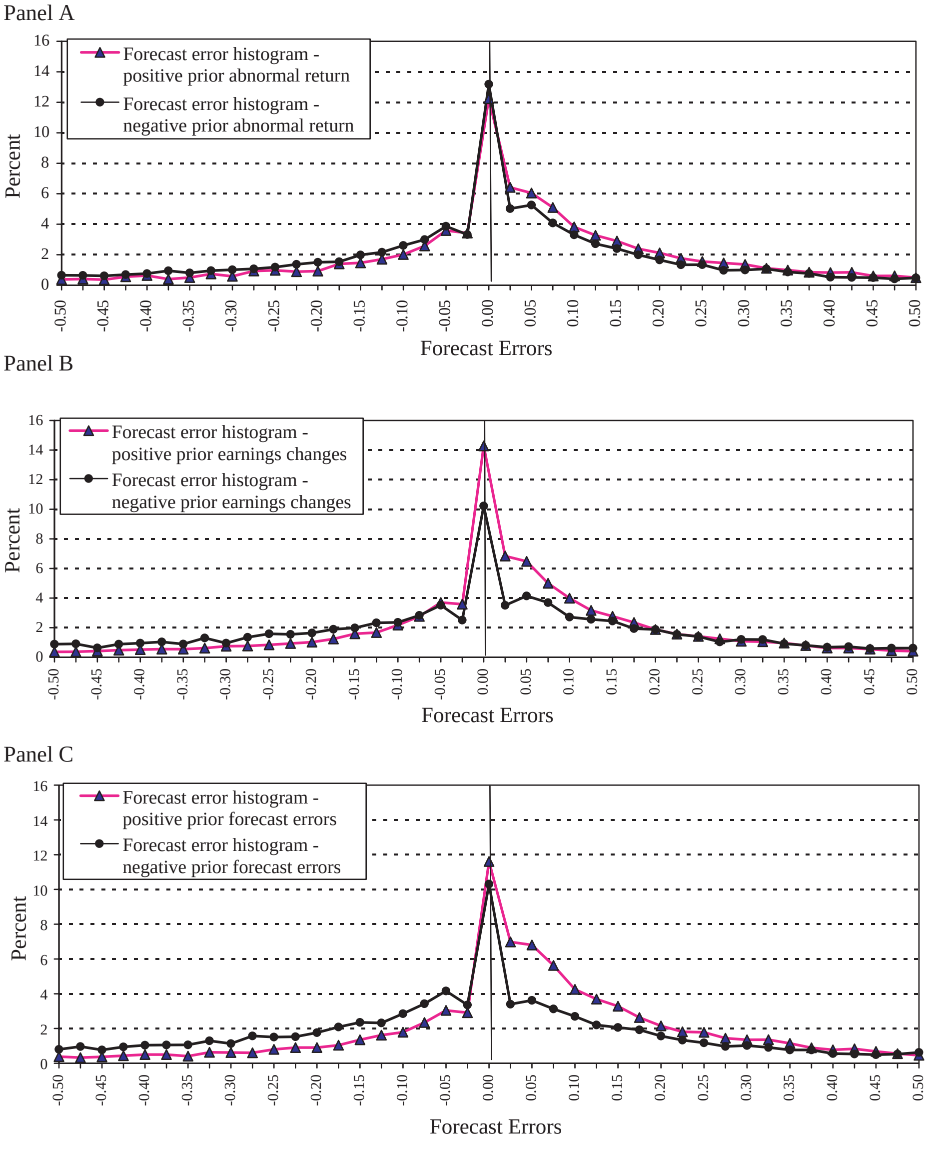

Fig. 3. Histogram of forecast errors by sign of prior abnormal returns (Panel A), prior earnings changes (Panel B), and prior forecast errors (Panel C). This figure presents the percentage of forecast error values in histogram intervals for observations within forecast error of -0.5 to $+0.5$ by sign of prior abnormal return (Panel A), prior earnings changes (Panel B), and prior forecast errors (Panel C). Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price. Prior abnormal return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by the beginning-of-period price.

Table 2
Mean, median, and frequency of forecast errors (Panel A), and ratio of positive to negative forecast errors in symmetric regions for bad (Panel B) and good (Panel C) prior news variables

Panel A: Mean, median, and frequency of forecast errors by sign of prior news variables

Statistic	Sign of prior abnormal return		Sign of prior earnings changes		Sign of prior forecast errors	
	Negative (1)	Positive (2)	Negative (3)	Positive (4)	Negative (5)	Positive (6)
Mean	−0.195*	−0.041*,#	−0.291*	−0.036*,#	−0.305*	0.017*,#
Median	0.000	0.028	−0.015	0.020	−0.043	0.042
% Zero forecast errors	13%	12%	10%	14%	10%	11%
% Positive forecast errors	42%	54%	40%	52%	36%	59%
% Negative forecast errors	45%	34%	50%	34%	54%	30%
N	16,940	13,833	11,526	21,062	12,999	15,415

Panel B: Ratio of positive to negative forecast errors for negative *realizations of prior news*

Range of forecast errors	Negative prior abnormal return		Negative prior earnings changes		Negative prior forecast errors	
	Ratio of positive to negative FE (1)	% of total (2)	Ratio of positive to negative FE (3)	% of total (4)	Ratio of positive to negative FE (5)	% of total (6)
Overall	0.94	100	0.81	100	0.66	100
Forecast errors = 0		13		10		10
[−0.1, 0) & (0, 0.1]	1.39	27	1.26	21	0.94	23
[−0.2, −0.1) & (0.1, 0.2]	1.27	17	1.15	17	0.94	17
[−0.3, −0.2) & (0.2, 0.3]	0.99	10	0.93	11	0.75	10
[−0.4, −0.3) & (0.3, 0.4]	0.96	7	0.93	8	0.72	7
[−0.5, −0.4) & (0.4, 0.5]	0.73	5	0.74	6	0.59	5
[−1, −0.5) & (0.5, 1]	0.60	11	0.56	14	0.52	14
[Min, −1) & (1, Max]	0.29	10	0.28	14	0.24	14

Panel C: Ratio of positive to negative forecast errors for positive *realizations of prior news*

Range of forecast errors	Positive prior abnormal return		Positive prior earnings changes		Positive prior forecast errors	
	Ratio of positive to negative FE (1)	% of total (2)	Ratio of positive to negative FE (3)	% of total (4)	Ratio of positive to negative FE (5)	% of total (6)
Overall	1.58	100	1.53	100	1.99	100
Forecast errors = 0		12		14		11
[−0.1, 0) & (0, 0.1]	1.86	31	1.82	33	2.33	33
[−0.2, −0.1) & (0.1, 0.2]	1.89	18	1.85	18	2.42	19
[−0.3, −0.2) & (0.2, 0.3]	1.85	10	1.66	9	2.22	10
[−0.4, −0.3) & (0.3, 0.4]	1.70	6	1.49	6	2.03	7
[−0.5, −0.4) & (0.4, 0.5]	1.52	5	1.28	4	1.70	4
[−1, −0.5) & (0.5, 1]	1.25	10	1.17	9	1.44	10
[Min, −1) & (1, Max]	0.62	8	0.58	7	0.83	6

Panel A provides statistics on forecast errors (FE) by sign of prior abnormal return, prior earnings changes, and prior forecast errors. Panel B (Panel C) reports the ratio of positive to negative forecast errors for observations that fall into increasingly larger and nonoverlapping symmetric intervals moving out from zero forecast errors for negative (positive) prior abnormal returns, prior earnings changes, and prior forecast errors. Prior abnormal return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by beginning-of-period price. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price.

*Significantly different than zero at a 1% level or better.

#Mean forecast error for positive prior news variables is significantly different than mean forecast error for negative prior news variables at a 1% level or better.

The impact of the tail asymmetry on the inference of underreaction to prior bad news can be seen in Panel B of Table 2, which presents the number of observations in increasingly larger nonoverlapping symmetric intervals starting from zero for the three prior bad news partitions. Even though large errors in the intervals [min, −1) and (1, max] make up a relatively small percentage of the observations in the bad news distributions of *PrAR*, *PrEC*, and *PrFE* (10%, 14%, and 14%, respectively), errors of these absolute magnitudes comprise 3.45 (=1/0.29) 3.57 (=1/0.28), and 4.17 (=1/0.24) bad news observations for every good news observation, respectively.

Apparent consistency across summary statistical indicators of analyst underreaction to prior bad news does not carry over to the case of prior good news. The mean error for the good news partitions of *PrAR* and *PrEC* reported in columns 2 and 4 of Panel A of Table 2 are negative, consistent with analyst *overreaction* (i.e., the mean forecast is too high following good news), but is positive in the case of good news *PrFE*, suggesting *underreaction*. These mixed parametric results are attributable to the fact that tail asymmetries, although relatively small compared to their bad news counterparts, are still sufficiently large to produce negative mean errors for both prior good news partitions of *PrAR* and *PrEC* (see Fig. 2). However, they are not large enough to generate a negative median for these variables because, as seen in Panel C of Table 2, there is an even greater *frequency* of small positive errors associated with middle asymmetries in the good news partitions than for unconditional distributions (e.g., the ratio of positive errors to negative errors is 1.86 in the interval [−0.1, 0), (0, 0.1] of the *PrAR* partition but only 1.63 in that same interval of the unconditional distribution). The middle asymmetries are thus sufficiently large to offset relatively small tail asymmetries in these good news partitions, leading to indications of underreaction to good news in nonparametric statistics.[15]

3.1.2. Inferences about analyst efficiency from regression analysis

While means, medians, and ratios of positive to negative forecast errors are viable statistics from which to draw inferences of analyst inefficiency, most studies rely on slopes of regressions of forecast errors on prior news variables. The most persistent findings from such regressions are significant positive slope coefficients that are consistent with overall analyst *underreaction* to prior news realizations. To examine

[15] In this study, as in any study that partitions prior news variables by sign, we treat all prior variables as if they were interchangeable for the purposes of drawing inferences concerning a general tendency toward analyst inefficiency. Clearly, partitioning on the sign of news is likely to lead to misclassification in the case of prior earnings news, since the average firm is *not* likely to have an expected change of zero. Moreover, both prior earnings changes and prior forecast errors entail the use of an earnings benchmark, which, as discussed in the next section, introduces another potential problem of classification associated with potential time-series correlations induced by earnings management. These are interesting issues worthy of further consideration. However, they do not preclude an analysis of how the tail and middle asymmetries in forecast error distributions have combined to generate inconsistent indications of analyst inefficiency in the existing literature. If anything, these issues further strengthen the case for adopting the approach of identifying salient features of distributions of forecast errors in an effort to develop more precise hypotheses and design more appropriate empirical tests.

Table 3
Slope coefficients from OLS and rank regressions of forecast errors on prior news variables

	Explanatory variable					
	Prior abnormal return		Prior earnings changes		Prior forecast errors	
	OLS	Ranked	OLS	Ranked	OLS	Ranked
Overall	0.744	0.162	0.819	0.160	0.238	0.253
	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Prior bad news	1.602	0.213	2.306	0.130	0.231	0.265
	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Prior good news	0.089	0.199	−0.835	0.157	0.045	0.170
	0.28	<0.01	0.01	<0.01	0.11	<0.01

This table reports slope coefficient estimates from OLS and rank regressions of forecast errors on prior abnormal return, prior earnings changes, and prior forecast errors with the White-corrected p-values. Prior abnormal return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by beginning-of-period price. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price.

the effect of the two asymmetries on this inference, we first estimate the slope coefficients for separate OLS and rank regressions of forecast errors on *PrAR*, *PrEC*, and *PrFE*. After applying White corrections suggested by the regression diagnostics, the estimates, as shown in the first row of Table 3, confirm that the typical finding reported in the prior literature of overall underreaction holds for all three prior news variables in our sample, inasmuch as all three coefficients are positive and reliably different from zero. Similarly, rank regressions produce significant positive slope coefficients in the case of all three prior news variables.

Next, we compare the inferences from regression slope coefficients estimated by the sign of prior news to assess their consistency with the parametric and nonparametric evidence presented in Panel A of Table 2 and the preceding regression results for the overall samples. These results are presented in Table 3. Consistent with regression results for the overall sample, prior bad news partitions of all three variables produce OLS and rank slope coefficients that are significantly positive, indicating once again analyst underreaction to prior bad news. These results are consistent with indications of underreaction in both the parametric and nonparametric summary statistics associated with all three bad news partitions reported in Panel A of Table 2. In sharp contrast, however, regression results for the prior good news partitions generate inconsistent indications across both OLS and rank regression slope coefficients and across prior news variables. The OLS slope coefficient is positive but insignificant in the case of good news *PrAR* and *PrFE*, resulting in a failure to reject efficiency in these cases, but it is reliably negative for the good news *PrEC* variable, consistent with analyst *overreaction* to prior good earnings news. That is, OLS performed on the prior good news partitions of forecast errors produces *no* evidence of apparent analyst underreaction observed both in the overall samples and in the prior bad news partitions. In contrast, and adding to the ambiguity, rank regressions do produce reliably positive slope coefficients consistent with underreaction for all three prior good news variables. This finding is also consistent with the rank regression results for both the overall samples and the prior bad news partitions for all three prior news variables that suggest analyst underreaction.

It is evident from the foregoing collection of parametric and nonparametric results that it is difficult to draw a clear inference regarding the existence and nature of analyst inefficiency with respect to prior news. These results are a microcosm of similar inconsistencies found in the literature on analyst efficiency with respect to prior news, examples of which are discussed below. In keeping with our goal of assessing the extent, to which theories that predict systematic errors in analysts forecasts are supported by the evidence, we next delve further into the robustness of specific findings concerning analyst-forecast efficiency. As in the case of inferences on bias in analysts' forecasts, we find inconsistencies and a lack of robustness of evidence, which are linked to the relative size of the two asymmetries present in forecast error distributions.

3.2. How robust is evidence of analyst underreaction to bad news?

To further isolate the disproportional influence of the asymmetries on statistics, we examine the relation between forecast errors and prior news variables in finer partitions of the prior news variables. Our goal is to demonstrate that while the statistical indications of analyst underreaction to prior bad news are largely consistent in Tables 2 and 3, the phenomenon is not robust in the distribution of forecast errors. Fig. 4 depicts the percentiles of the distributions of forecast errors for the lowest, highest, and the combined distribution of the 2nd through the 9th decile of each prior news variable. One pattern evident in all of the panels is that the most extreme prior bad news decile is always associated with the most extreme negative forecast errors.

The effect of this association is evident in Fig. 5, which summarizes the mean and median forecast errors by decile of prior news for all three variables: The largest negative mean error by far is produced in the 1st decile of all prior news variables. This finding helps explain why overall bad news partitions of prior news yield parametric means that are always consistent with analyst underreaction.[16]

To gauge the effect of observations in the lowest prior news decile (which, as seen in Fig. 4, are associated with extreme negative forecast errors), we reestimate the

[16] Furthermore, in unreported results we find that OLS regressions by individual deciles produce significant positive coefficients in *only* the 1st decile among all deciles associated with prior bad news for all three prior variables. The combination of greater (lower) variation in the independent variable and a strong linear (nonlinear) relation between prior news and forecast errors in the first decile (other deciles) contribute to these results, as we discuss later.

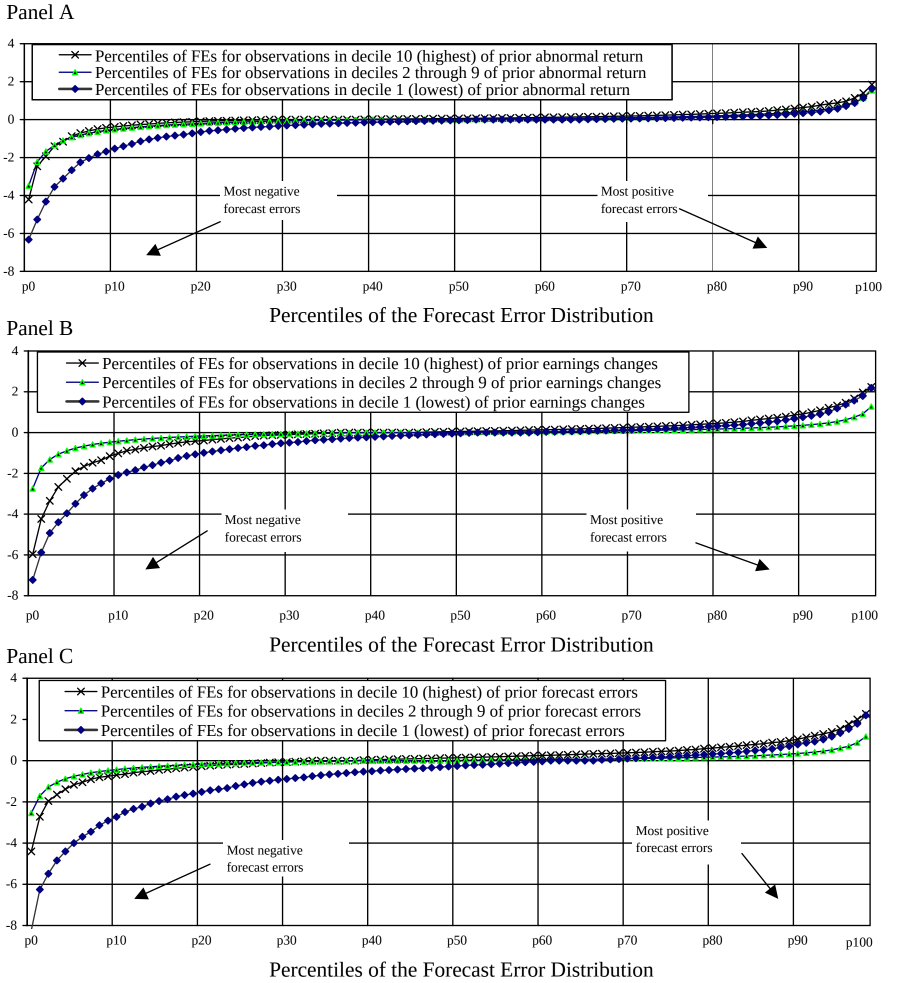

Fig. 4. The tail asymmetry in forecast errors within selected deciles of prior news variables. This figure depicts percentiles of quarterly distributions of analysts' forecast errors that fall in selected deciles (lowest, highest, and the combined distribution of the 2nd through the 9th decile) of prior abnormal returns (Panel A) prior earnings changes (Panel B) and prior forecast errors (Panel C). Forecast error equals reported earnings minus consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price. Prior market-adjusted return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by the beginning-of-period price.

OLS regressions for the overall sample after excluding observations in this decile (unreported in the tables). We find that removing the 1st decile of prior news results in declines in the overall coefficients from values of 0.744, 0.819, and 0.238, to values

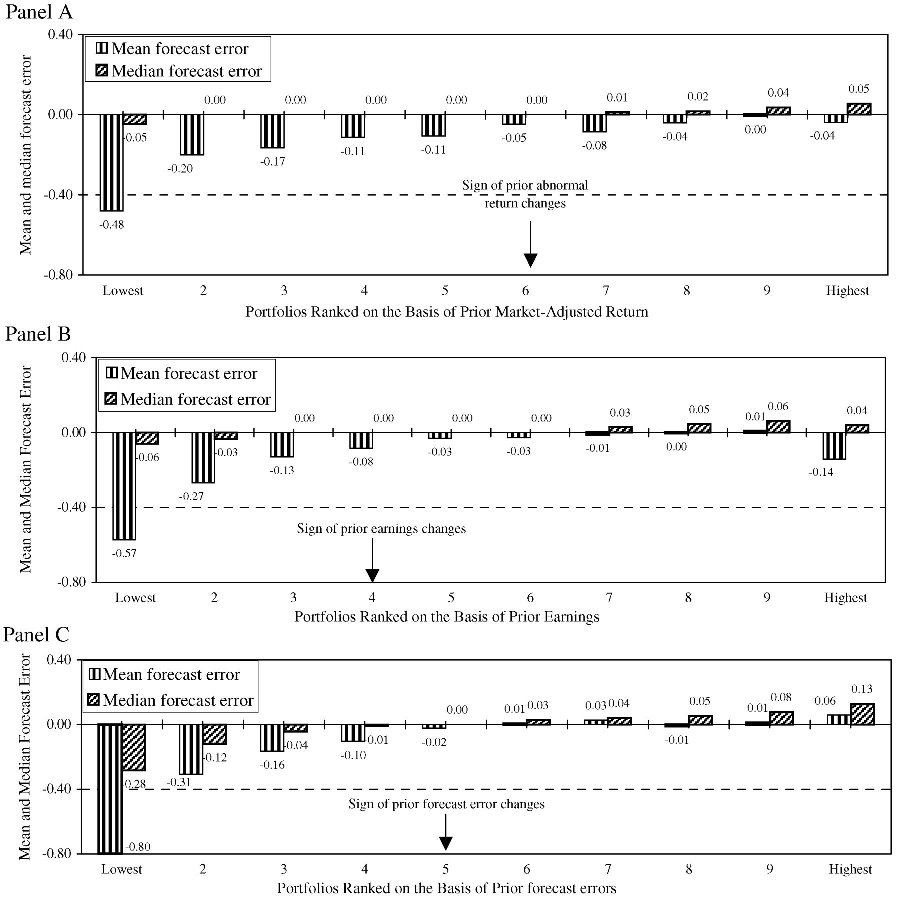

Fig. 5. Mean and median forecast errors by decile ranking of prior abnormal return (Panel A), prior earnings changes (Panel B), and prior forecast errors (Panel C). This figure depicts mean and median forecast errors for portfolios ranked on the basis of prior abnormal return (Panel A), prior earnings changes (Panel B), and prior forecast errors (Panel C). Prior abnormal return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by the beginning-of-period price. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price.

of 0.380, −0.559, and 0.194, for *PrAR*, *PrEC*, and *PrFE*, respectively, and *t*-statistics are significantly reduced in each case. Removal of individual deciles 2–9 before reestimating the regressions leads to virtually no change in the coefficients for all three prior news variables, whereas removal of the 10th decile actually leads to increases in the coefficients for all three variables. Notably, the disproportionate influence of extreme forecast error observations associated with extreme prior news is an effect that is not specifically predicted by extant behavioral or incentive-based theories of analyst inefficiency.[17]

The middle asymmetry also contributes, albeit more subtly than the tail asymmetry, to producing OLS regression coefficients that are consistent with underreaction to bad news. As seen in the first row of Panels A–C of Table 4 ("Overall"), which presents the ratio of positive to negative forecast errors by deciles of all three prior news variables, the percentage of positive errors increases as prior news improves. Consider, for example, in Panel A, the evidence for the first 5 deciles of *PrAR*, which only pertain to prior bad news realizations. The steadily increasing rate of small positive errors as *PrAR* improves will contribute to a positive slope coefficient in OLS regressions of forecast errors on prior bad news, reinforcing an inference of underreaction from this statistic. The concern raised by evidence in the remaining rows of Panel A of Table 4 is that less extreme prior bad news generates increasingly higher incidences of small positive versus small negative forecast errors—that is, observations that represent exactly the opposite of analyst underreaction.

Finally, recall that nonparametric statistics, including percentages of negative errors, rank regression slopes, and medians, also provide consistent indications of analyst underreaction to bad news. The nonparametric evidence in Panel A of Table 4 suggests however that this finding is also not as robust as it first appears. In the case of *PrAR*, for example, only the two most extreme negative deciles are associated with a reliably higher frequency of negative errors, which would not be expected if analyst underreaction to bad news was a pervasive phenomenon. In fact, there is a monotonic increase in the rate of positive to negative errors in the deciles that contain bad news realizations, with the 3rd decile containing a statistically equal number of each, and deciles 4–6 containing a reliably *greater* number of positive than negative errors.[18] Thus, observations that form the tail asymmetry, which is most pronounced in extreme bad news *PrAR*, even have a disproportional impact on some nonparametric evidence of underreaction to bad news, including indications from medians, percentages of negative errors, and rank regressions.[19]

[17] It is not well recognized that the inference of underreaction to prior bad news generated by the parametric tests favored in the literature is common to all prior news variables and is always driven by the concentration of extreme negative errors associated with extreme prior bad news. This conclusion can be drawn from studies investigating over/underreaction to prior returns (see, e.g., Brown et al., 1985; Klein, 1990; Lys and Sohn, 1990; Abarbanell, 1991; Elgers and Murray, 1992; Abarbanell and Bernard, 1992; Chan et al., 1996) and studies investigating over/underreaction to prior earnings changes (see, e.g., De Bondt and Thaler, 1990; Abarbanell and Bernard, 1992; Easterwood and Nutt, 1999).

[18] The 6th decile of *PrAR* includes small negative, small positive, and a limited number of zero observations. The demarcation point of zero occurs in the 4th decile of *PrEC*, reflecting a greater likelihood of positive earnings changes than negative earnings changes. The demarcation occurs in the 5th decile of *PrFE*, reflecting both a high percentage of zero prior forecast errors as well as the higher incidence overall of positive versus negative errors associated with the middle asymmetry. As suggested in footnote 15, simply partitioning prior news at the value of zero (as is done in the literature) may not lead to appropriate comparisons with respect to analyst efficiency across prior news variables in all situations.

[19] Recall that rank regressions of forecast errors and prior news produce large positive and significant slope coefficients, consistent with underreaction to bad news prior returns even though the incidence of positive errors is equal to or greater than the incidence of negative forecast errors in all but the most

Table 4
Ratio of small positive to small negative forecast errors in symmetric regions by decile ranking of prior abnormal return (Panel A), prior earnings changes (Panel B), and prior forecast error (Panel C)

Range of forecast errors	Lowest	2	3	4	5	6	7	8	9	Highest
Panel A: Ratio of small positive to small negative forecast errors and percentage of total decile observations within deciles of prior abnormal return										
Overall	0.66	0.78	0.97	1.08	1.17	1.27	1.33	1.39	1.76	2.12
[−0.1, 0) & (0, 0.1]	1.39	1.12	1.35	1.51	1.53	1.61	1.66	1.75	1.84	2.43
	24%	30%	32%	34%	35%	36%	38%	36%	34%	31%
[−0.2, −0.1) & (0.1, 0.2]	1.11	1.16	1.26	1.24	1.49	1.53	1.46	1.54	2.41	2.60
	18%	19%	21%	19%	20%	21%	20%	20%	21%	21%
[−0.3, −0.2) & (0.2, 0.3]	0.75	0.83	0.99	1.15	1.14	1.31	1.72	1.56	2.02	2.64
	10%	11%	11%	11%	12%	12%	11%	12%	12%	11%
Panel B: Ratio of small positive to small negative forecast errors and percentage of total decile observations within deciles of prior earnings changes										
Overall	0.75	0.77	0.86	0.91	1.16	1.53	1.83	1.87	1.83	1.45
[−0.1, 0) & (0, 0.1]	1.52	1.30	1.18	1.14	1.38	2.10	2.36	2.07	2.00	1.98
	16%	21%	28%	41%	56%	54%	45%	33%	25%	18%
[−0.2, −0.1) & (0.1, 0.2]	1.25	1.15	1.11	1.08	1.29	1.57	2.24	2.54	2.20	1.91
	13%	19%	21%	23%	19%	20%	24%	25%	22%	15%
[−0.3, −0.2) & (0.2, 0.3]	0.97	0.98	0.91	0.79	0.93	1.19	2.03	2.17	1.98	2.19
	9%	12%	13%	12%	7%	9%	11%	13%	13%	11%
Panel C: Ratio of small positive to small negative forecast errors and percentage of total decile observations within deciles of prior forecast errors										
Overall	0.53	0.58	0.70	0.74	1.32	2.25	2.06	1.91	1.95	1.82
[−0.1, 0) & (0, 0.1]	1.10	0.90	0.91	0.87	1.50	3.02	2.22	2.05	2.09	1.65
	8%	15%	24%	37%	65%	58%	46%	33%	24%	13%
[−0.2, −0.1) & (0.1, 0.2]	1.27	0.94	0.88	0.90	1.16	2.17	2.68	2.59	2.75	1.99
	10%	17%	23%	25%	18%	21%	24%	25%	23%	16%
[−0.3, −0.2) & (0.2, 0.3]	0.90	0.71	0.69	0.64	1.28	1.69	2.16	2.66	2.20	2.32
	9%	12%	14%	11%	7%	8%	10%	14%	15%	13%

This table reports the ratio of small positive to small negative forecast errors for observations that fall into increasingly larger and nonoverlapping symmetric intervals moving out from zero forecast errors and the percentage of observations that fall in these intervals of the total nonzero forecast errors in that decile. Prior abnormal return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Prior earnings changes are defined as the prior quarter seasonal earnings change (from quarter $t-5$ to quarter $t-1$) scaled by the beginning-of-period price. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price.

(*footnote continued*)
extreme deciles of bad news *PrAR*. This occurs because the most negative ranks of *PrAR* are paired with the most negative forecast errors, which when combined with the increasing incidence of pessimistic errors as bad news becomes less extreme (in principle, overreaction), accounts for an overall positive association in the rank slope coefficient that is consistent with apparent underreaction.

3.3. How robust is the evidence of misreaction to prior good news?

As seen in Tables 2 and 3, evidence can be found for either analyst underreaction or overreaction to prior good news, depending on the statistical approach and/or prior variable on which the researcher focuses. Our goal in this section is to examine the robustness of parametric evidence of analyst overreaction and nonparametric evidence of analyst underreaction to good news.

In Panel A of Fig. 4, the most extreme prior good news decile in the case of *PrAR* does not display a tail asymmetry substantially different from the combined deciles 2–9. In contrast, in the case of *PrEC* (in Panel B) the most extreme positive decile actually exhibits the second largest degree of tail asymmetry inasmuch the combined inner decile distribution (deciles 2–9) has a considerably smaller tail asymmetry. In the case of *PrFE*, depicted in Panel C, the most extreme positive decile displays a slightly greater degree of tail asymmetry than the combined deciles 2–9. Thus, although the tail asymmetry is always present in extreme prior good news deciles, there is considerable variation in the degree of tail asymmetry across extreme good news realizations of prior news variables—a phenomenon that once again is not contemplated by general incentive and behavioral theories.

The statistical impact of variation in the degree of tail asymmetries in extreme good news deciles across prior variables is reflected in the mean forecast errors by decile presented in Fig. 5. Notably, as seen in Panel B, the relatively large tail asymmetry associated with extreme good news *PrEC* leads to a negative mean error in the 10th decile (i.e., overreaction), which aligns with the large tail asymmetry observed in Panel B of Fig. 4. In contrast, mean forecast errors for the good news *PrEC* deciles 5–9 are small and in many cases significantly positive (i.e., consistent with underreaction) because the tail asymmetry associated with these observations is small. The disproportional influence of the 10th decile of *PrEC* is also evident in regression results. In addition to being responsible for the only overall prior good news partition that produces a significant OLS slope coefficient, it is the only individual decile comprising good news for any variable that produces a significant slope coefficient (unreported in the tables). We note that removal of the 10th decile from the overall regression of forecast errors on *PrEC* leads to an increase in the slope coefficient from a value of 0.819 to 3.17, with a corresponding increase in the t-statistic. That is, the strong negative association between forecast errors and prior good news in this decile, which contributes disproportionately to the finding of overreaction to good news, also introduces severe nonlinearity in the overall regression.[20]

[20] The increasing rate of small positive errors as good news becomes more extreme contributes to positive slope coefficients in OLS regressions of forecast errors on prior good news. This is analogous to the impact of increasing rates of positive errors as bad news becomes less extreme, an effect more evident when the most extreme decile of good news is removed. The concern here, however, is that more extreme prior news leads to higher incidences of less extreme positive forecast errors—a phenomenon that is not only counterintuitive but is not predicted by extant incentive and behavioral theories of analyst inefficiency.

The most extreme good news *PrEC* decile is, therefore, largely responsible for the negative slope coefficient and the negative mean observed for good news *PrEC* partitions, suggesting the dominant influence of a small number of observations from the left tail of the distribution of forecast errors in producing parametric evidence of overreaction to good news prior earnings changes. Easterwood and Nutt (1999) refer to regression results that indicate a combination of underreaction to bad news and overreaction to good news as *generalized optimism*. From the evidence presented thus far it is clear that a small number of extreme negative forecast error observations associated with both extreme bad and extreme good news *PrEC* realizations are largely responsible for this finding. The question of the robustness of the finding of generalized optimism is magnified in the case of statistical indications of overreaction to good news because, as was reported in Table 2, good news *PrAR* and *PrFE* do not generate consistent parametric evidence of generalized optimism, even in the extreme deciles. This lends a "razor's edge" quality to the result that hinges on whether there is a sufficiently large number of extreme bad and good news realizations associated with extremely negative forecasts.[21] Furthermore, ambiguity in interpreting the evidence is introduced because there is no extant behavioral or incentive theory of analyst inefficiency that predicts that, when overreaction occurs, it will be concentrated among extreme prior news and come in the form of extreme analyst overreaction.

Finally, just as in the case of prior bad news, the presence of asymmetries also raises questions about the robustness of nonparametric evidence of analyst misreaction to prior good news. Recall from Section 3.1.1 that, in contrast to parametric statistics, nonparametric statistics suggested analyst *underreaction* to prior good news for all three prior news variables. The evidence in Tables 2 and 4 indicates that large middle asymmetries reinforce nonparametric indications of underreaction—in particular, the increasing relation between the magnitude of good news and the likelihood of small positive forecast errors, a relation that is monotonic in the case of *PrAR* and *PrFE*. Thus, the middle asymmetry, and its variation with the magnitude of prior good news, has a disproportionate impact on the inference of underreaction to good news from nonparametric statistics, including indications from medians, percentages of negative errors, and rank regressions. Notably, the percentage of positive forecast errors is substantially larger than the percentage of negative errors even in the most extreme *PrEC* decile. That is, the decile largely responsible for producing the only statistical evidence that analysts overreact to good news displays a strong tendency for errors that are consistent with underreaction.

3.4. The tail and middle asymmetries and serial correlation in analysts' forecasts

The preceding results indicate that regression evidence of underreaction is disproportionately influenced by apparent extreme underreaction to extreme bad

[21] Easterwood and Nutt (1999) eliminate the middle third of the prior earnings news distribution before estimating OLS slope coefficients, which provide the statistical support for their conclusion that analysts underreact to bad news and overreact to good news. Clearly, this test design gives even greater weight to observations that comprise the tail asymmetry.

prior news and is also impacted by the increase in the middle asymmetry as prior news improves. The asymmetries have important impacts on alternative (to regression) tests of analyst inefficiency in the literature. For example, as mentioned earlier, the analysis of the relation between current and prior forecast errors is typically not couched in terms of over- or underreaction to signed prior news, but rather in terms of overall serial correlation in lagged analyst forecast errors (see, e.g., Brown and Rozeff, 1979; Mendenhall, 1991; Abarbanell and Bernard, 1992; Ali et al., 1992; Shane and Brous, 2001; Alford and Berger, 1999). These studies focus almost exclusively on parametric measures of serial correlation and primarily on the first lag, or consecutive period errors.

Table 5 presents the Pearson and Spearman correlation between consecutive quarterly forecast errors for the overall sample and within each of the deciles of current forecast errors. The mean correlations for the entire sample are statistically significant, with yearly averages of 0.15 and 0.22, respectively. Note that the first decile, which includes the observations in the extreme left tail that are associated with the tail asymmetry, produces the greatest Pearson and Spearman correlations of 0.17 and 0.19, respectively. In contrast, the correlations in all other deciles are much smaller and most often statistically insignificant in the case of the Pearson measure. It is interesting to note that if distributions of forecast errors were symmetric, then forming deciles on the basis of current forecast errors (a procedure only followed in Table 5) would be expected to attenuate, relative to the overall sample serial correlation, the estimated correlation in every decile. However, the facts that correlation is not attenuated in the most extreme negative forecast error decile (in fact, it is larger than the overall correlation) and that the Pearson correlation is insignificant in the most extreme positive forecast error decile are additional indications of the important role the tail asymmetry plays in the findings of serial correlation. We note that when the deciles are formed based on *prior* forecast errors (that is they are sorted on the independent variable, as is done in all other tests performed in the paper) we still find that Pearson correlations are highest in the most extreme negative forecast error decile.[22]

Finally, we note that the strongest Spearman correlations in the table, other than the most extreme negative decile of current forecast errors, are found in deciles 6 and 7, i.e., those with a high concentration of current and prior small pessimistic forecast errors. The evidence is also inconsistent with what would be expected based on forming deciles on current forecast errors, where correlation in the middle deciles would be driven to zero. The higher correlations in deciles 6 and 7 are found whether deciles are formed on current or prior forecast errors. The evidence suggests the need for further exploration into the role of observations in the middle asymmetry in producing estimated serial correlation consistent with apparent analyst under-reaction to their own forecast errors.

[22] It is also interesting to note from columns 4 and 5 that the first decile is not only associated with the largest mean values for current forecast errors, but is also associated with the largest mean value among the prior (i.e., lagged) forecast error deciles.

Table 5
Serial correlation in consecutive-period forecast errors

Decile ranking of forecast errors (1)	Pearson correlation in consecutive forecast errors (2)	Spearman correlation in consecutive forecast errors (3)	Mean forecast errors (4)	Mean prior quarter forecast errors (5)
Lowest	0.17#	0.19#	−2.08	−0.79
2	0.04&	0.07#	−0.44	−0.26
3	0.03	0.06#	−0.17	−0.12
4	0.06#	0.05&	−0.06	−0.04
5	0.06#	0.03&	0.00	−0.07
6	−0.01	0.09#	0.03	0.04
7	0.01	0.08#	0.08	0.04
8	−0.02	0.04&	0.15	−0.01
9	0.00	0.04&	0.29	0.02
Highest	0.00	0.04&	0.90	−0.12
Overall	0.15#	0.22#	−0.13	−0.13

This table reports the Pearson and Spearman correlation coefficients and means of current and prior quarter forecast errors *within* deciles of the ranked (current) forecast error distribution. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by beginning-of-period price.
#(&) Represents a statistically significant correlation at a 1% (5%) level.

3.5. Summary and implications of the tail and middle asymmetries on inferences of analyst efficiency

An important conclusion from the analysis of conditional forecast error distributions is that the sign of prior news variables sorts observations from the tail and middle asymmetries in a manner that (1) reinforces the inference of underreaction found in parametric statistics for all prior *bad* news partitions, an inference that is largely the result of the dominant impact of the tail asymmetry; and (2) can create offsetting or reinforcing effects that contribute to producing conflicting signs of means and regression slope coefficients within and across different prior *good* news partitions of the variables. Thus, the presence of middle and tail asymmetries in conditional distributions of forecast errors helps explain why evidence of underreaction to bad news appears to be so robust in the literature while evidence of under- and overreaction to good news is not. Attenuation of means and slope coefficients due to the relatively greater impact of the middle asymmetry in good news distributions of forecast errors also helps explain why, in every study to date that employs parametric tests and concludes that analysts' forecasts are inefficient, the magnitude of misreaction to bad news is always found to be greater than the magnitude of misreaction to good news.

It is tempting to infer from the insignificance of slope coefficients pertaining to regressions of forecast errors on prior news generated for some good news partitions reported in Table 3 and in all inner deciles of distributions of all prior news variables that, apart from cases of extreme prior news, analysts produce efficient forecasts (see, footnote 16). However, the sensitivity of statistical findings in prior good news partitions documented above suggests that we exercise caution in reaching this conclusion. Results in Fig. 4 and Table 4, along with unreported results, verify that all decile partitions of *PrAR* and *PrEC* are characterized by both middle and tail asymmetries, and that every good (bad) news decile of *PrFE* is characterized by a middle (tail) asymmetry. While it is possible that failure to reject zero slope coefficients in the inner deciles is the result of a general tendency for analyst forecasts to be efficient when prior news is not extreme, we must concede the possibility that the lower variation in the independent variable and small numbers of observations associated with tail and middle asymmetries *within deciles* combine to produce nonlinearities and lower power in a manner that obscures evidence of analyst inefficiency. That is, slicing up the data into greater numbers of partitions does not appear to eliminate the potential impact of both asymmetries in influencing inferences concerning the existence and nature of analyst inefficiency in parametric tests.[23]

The evidence in this section reveals how asymmetries can produce and potentially obscure indications of analyst inefficiency, depending on the statistical approach adopted by the researcher. Next, we describe examples of procedures that (perhaps unintentionally) mitigate the impact of observations that comprise the asymmetries, but may not necessarily shed new light on the question of whether analysts' forecasts are efficient.

3.6. Data transformations, nonlinear statistical methods, and alternative loss functions

Apart from partitioning forecast errors in parametric tests and applying nonparametric tests, some studies implicitly or explicitly adjust the underlying data in order to attenuate the disproportional impacts and nonlinearities induced by the tail asymmetry. Two such approaches are truncating and winsorizing forecast errors. As in the case of inferences concerning bias discussed in Section 2, the effects of arbitrary truncations on inferences concerning analyst under- and overreaction can be significant. Keane and Runkle (1998), for example, argue that evidence of misreaction to prior earnings news is overstated as a result of uncontrolled cross-correlation in forecast errors. However, they explicitly state that their finding of efficiency—after applying GMM to control for bias in standard errors induced by cross-correlation—rests on having first imposed a

[23] Severe heteroscedasticity in the decile regression residuals are consistent with this argument. In addition, while we do not advocate arbitrary truncations of the data to mitigate the impact of the asymmetries we find that small symmetric truncations of tail observations within decile distributions similar to those described in the previous section for the unconditional distribution of forecast errors result in significant slope coefficients in many of the inner deciles of prior returns and prior earnings changes. Because small truncations of extreme observations reduce the number of observations in each decile and further reduce variation in the independent variable, it is possible that the statistical significance of the coefficients after truncation in these cases reflects the presence of analyst inefficiency and/or the elimination of the offsetting impact of the tail asymmetry in a manner that allows the middle asymmetry to dominate an inference of inefficiency.

sample selection criterion that results in the truncation of large forecast error observations in the extreme negative tail of the distribution. Their argument for doing so is that the Compustat reported earnings used to benchmark forecasts for such observations includes large negative transitory items that analysts do not forecast. Abarbanell and Lehavy (2002) show that tail asymmetries also characterize distributions of forecast errors based on the earnings reported by commercial forecast data sources such as I/B/E/S, Zacks, and First Call, which are, in principle, free of such special items. They also report a high correlation between the observations that fall into the extreme negative tail of the distribution of forecast errors calculated with Compustat-reported earnings and those that fall into the extreme negative tail of distributions calculated with earnings provided by forecast data services. Thus, it remains to be seen whether the finding of analyst forecast rationality continues to hold when GMM procedures are applied to untruncated distributions of forecast error based on "cleaned" reported earnings numbers rather than truncated distributions of forecast errors based on Compustat earnings.[24]

An alternative to arbitrarily truncating a subset of observations is to transform the entire distribution of forecasts, a common procedure used to eliminate nonlinearities, stabilize variances, or induce a normal distribution of forecast errors to avoid violating the assumptions of the standard linear model. For example, log and power transformations mitigate skewness and the disproportionate impact of extreme observations when the dependent variable is forecast errors. However, each type of transformation alters the structure of the data in a unique way, and it is possible for different transformations to yield different inferences concerning analyst inefficiency. That is, transformations of distributions of forecast error are not likely to lead to greater consensus in the literature unless strong a priori grounds for preferring one transformation to another can be agreed upon. Such grounds can only be found by gaining a better understanding of what factors are responsible for creating relevant features of the untransformed data—an understanding that in turn would require more exacting theories than have thus far been produced as well as more institutional research into the analysts' actual forecasting task.

Finally, instead of adapting the data to fit the model the researcher may choose to adapt the model to fit the data. Disproportionate variation in the degree of tail asymmetry as a function of the sign and magnitude of prior news suggests, at a minimum, that parametric tests of analyst inefficiency should be adapted to allow for the nonlinear relationship between forecast errors and prior news. For example, after Basu and Markov (2003) replaced the quadratic assumption in their standard OLS regression with a linear loss function assuming that analysts minimize absolute forecast errors, they found little evidence to support analyst inefficiency. Imposing this loss function has an effect similar to truncating extreme observations, since such

[24] We note that although arbitrarily truncating the dependent variable (e.g., Keane and Runkle, 1998) may seem to be a more egregious form of biasing a test, the evidence presented earlier suggests that arbitrarily truncating observations in the middle of the distribution of the prior earnings news (e.g., Easterwood and Nutt, 1999) can also create problems when researchers draw inferences about the tendency for analysts to misreact to prior news, inasmuch as this procedure can further accentuate the already disproportionate impact of the tail asymmetry.

observations are given less weight in the regression (as opposed to being removed outright from the distribution).[25]

Clearly there is something to be learned from examining how inferences change under different assumed loss functions. However, at this stage in the literature, the approach will have limited benefits for a number of reasons. First, while a logical case can be made for one loss function that leads to the failure to reject unbiasedness and efficiency, an equally strong case for a loss function that leads to a rejection of unbiasedness and efficiency can also be made, without either assumption being inconsistent with existing empirical evidence of how analysts are compensated. In such cases, the conclusion about whether analyst forecasts are rational will hinge on which assumption best describes analysts' true loss function—a subject about which we know surprisingly little.[26] Second, it is possible that some errors are actually partially explained by cognitive or incentive factors that are coincidental with or are exacerbated by other factors that give rise to the same errors the researcher underweights by assuming a given loss function. Finally, although assuming a given loss function—like the choice of alternative test statistics or data truncations—may lead to a statistical inference consistent with rationality, such an approach ignores the empirical fact that the two notable asymmetries are present in the distribution. Given their influence on inferences, providing compelling reasons for these asymmetries is a prerequisite for judging whether and in what circumstances incentives or cognitive biases induce analyst forecast errors.

In the next section we take a step toward understanding how the asymmetries in forecast error distributions arise by identifying a link between the presence of observations that comprise the two asymmetries and unexpected accruals included in the reported earnings used to benchmark forecasts. This link suggest the possibility that some "errors" in the distribution of forecast errors may arise only because the forecast was inappropriately benchmarked with *reported* earnings, when in fact the analyst had targeted a different earnings number.

4. Linking bias in reported earnings to apparent bias and inefficiency in analyst forecasts

4.1. Accounting conservatism and unexpected accruals

Abarbanell and Lehavy (2003a) argue that an important factor affecting the recognition of accounting accruals is the conservative bent of GAAP. Because

[25] Note that, as discussed earlier, there may be greater difficulty detecting irrationality (alternatively, a greater likelihood of failing to reject efficiency) using regression analysis once procedures that attenuate the impact of left tail observations are introduced because the middle asymmetry is still present.

[26] The fact that the evidence of misreaction to even extreme good news is mixed for different definitions of prior news and different parametric statistics presents a challenge to adapting behavioral theories to better fit the data. Unless we can identify a common cognitive factor that explains why differences in apparent misreaction depend on the extremeness of prior news, the empirical case for any form of generalized bias or inefficiency will hinge on a relatively small number of observations comprising the tail and middle asymmetries that are not predicted by the theory.

conservative accounting principles facilitate the immediate recognition of economic losses but restrict the recognition of economic gains, the maximum amount of possible income-decreasing accruals that a typical firm can recognize in a given accounting period will be larger than the maximum amount of income-increasing accruals (see, e.g., Watts, 2003). Table 6 provides evidence that supports this intuition.

The table presents selected summary statistics associated with cross-sectional distributions of firms' quarterly unexpected accruals over the sample period.[27] The mean unexpected accrual over the sample period is -0.217. While the distribution is negatively skewed, the median is 0.023 and the percentage of positive and negative unexpected accruals is nearly equal. It is evident from Table 6 that, while the unexpected accrual distribution is relatively symmetric in the middle, it is characterized by a longer negative than positive tail. For example, the magnitude of the average values at the 25th and 75th percentiles is nearly identical. However, symmetric counterpart percentiles outside these values begin to diverge by relatively large amounts, beginning with a comparison of the values at the 10th and 90th percentiles. The differences become progressively larger with comparisons of counterpart percentiles farther out in the tails. For example, the average 5th and 3rd percentile values are approximately 1.17 times larger than the average 95th and 97th percentiles, and the average value of the 1st percentile is 1.30 times larger than the average value of the 99th percentile. We stress that, although the percentile values of unexpected accruals vary from quarter to quarter, the basic shape of the distribution is similar in every quarter.

4.2. Linking unexpected accruals to asymmetry in tails of forecast error distributions

The measure of unexpected accruals we employ is based on historical relations known prior to the quarter for which earnings are forecast. Although the term "unexpected" is used, it is possible—in fact likely—that analysts will acquire new information about changes in the relations between sales and accruals that occurred during the quarter before they issue their last forecast for a quarter. Nevertheless, we can use the measure of unexpected accruals to identify, ex-post, cases in which significant changes in accrual relations did take place, and then assess whether the evidence is consistent with analysts' issuing a final forecast of earnings for the quarter either unaware of some of these changes or unmotivated to forecast them.

If analysts' forecasts do not account for the fact that some firms will recognize accruals placing them in the extreme negative tails of the distribution of unexpected accruals, then there will be a direct link between the negative tail of this distribution and the extreme negative tail of the forecast error distribution. The conjectured link

[27] Unexpected accruals reported in the tables are the measure produced by the modified Jones model applied to quarterly data (see Appendix A for calculations). To facilitate comparison with our forecast error measure, we express unexpected accruals on a per share basis scaled by price and multiplied by 100. As indicated earlier, the qualitative results are unaltered when we employ the unmodified Jones model and other estimation techniques found in the literature, including one that excludes nonrecurring and special items.

Table 6
Descriptive statistics on quarterly distributions of unexpected accrual, 1985–1998

Unexpected accrual	
Number of observations	33,548
Mean	−0.217
Median	0.023
Standard deviation	5.600
Skewness	−1.399
Kurtosis	16.454
% Positive	50.8
% Negative	49.2
% Zero	0.0
P1	−20.820
P3	−11.547
P5	−8.386
P10	−4.574
P25	−1.349
P75	1.350
P90	4.185
P95	7.148
P97	9.891
P99	15.945

This table reports descriptive statistics on quarterly distributions of unexpected accruals. Unexpected accruals are calculated using the modified Jones model as described in the appendix (expressed as unexpected accrual per share scaled by price and multiplied by 100).

is depicted in Fig. 6. The figure shows mean forecast errors in intervals of (+/−) 0.5% centered on the percentiles of unexpected accruals. For example, the mean forecast error corresponding to the Xth percentile of unexpected accruals is computed using observations that fall in the interval of $X-0.5$ to $X+0.5$ percentiles of the unexpected accruals distribution.

It is clear from Fig. 6 that extreme negative forecast errors are associated with extreme negative unexpected accruals. That is, the evidence suggests a direct connection between the tail asymmetry in the forecast error distribution (documented in earlier sections) and an asymmetry in tails of the unexpected accrual measure.[28] This link continues to be observed even when we employ consensus earnings estimates and reported earnings that are, in principle, stripped of

[28] Another example of this link relates to the evidence on serial correlation in forecast errors presented earlier. Recall from Table 5 that the most extreme prior forecast error decile is also associated with the most negative mean current forecast errors. In unreported results we find that this decile is also characterized by the largest negative lagged and current unexpected accruals observed for these deciles (whether forecast error deciles are formed on the current or prior forecast errors). Thus, consecutive quarters of large, negative unexpected accruals go hand-in-hand with consecutive quarters of extreme negative forecast error observations that, in turn, are associated with high levels of estimated serial correlation.

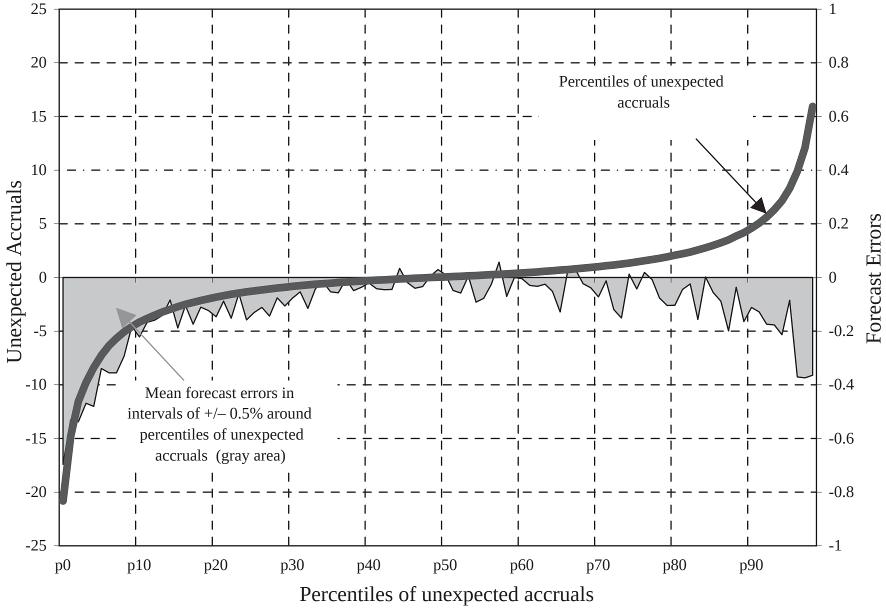

Fig. 6. Linking unexpected accruals and the asymmetry in tails of forecast error distributions. This figure depicts percentiles of unexpected accruals and mean forecast errors (gray area) in intervals of (+/−) 0.5% around unexpected accruals percentiles. For example, the mean forecast errors corresponding to the Xth percentile of unexpected accruals is computed using observations that fall in the interval of $X-0.5$ to $X+0.5$ percentiles of the unexpected accruals distribution. Forecast error equals reported earnings minus consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price. Unexpected accruals are the measure produced by the modified Jones model as described in the appendix (expressed as percentage of unexpected accrual per share scaled by price and multiplied by 100).

nonrecurring items and special charges (because Zacks indicates that analysts do not attempt to forecast these items), and a measure of unexpected accruals that also strips such items (see, Hribar and Collins, 2002). This suggests that an association exists between extreme negative accruals deemed "special or nonrecurring" and extreme negative accruals that do not fit this description. One possible reason for this association is that firms take an "unforecasted earnings bath," recognizing operating expenses larger than justified by the firm's actual performance for the period at the same time as they recognize large discretionary or nondiscretionary negative transitory operating and nonoperating items (see, Abarbanell and Lehavy, 2003b).

A second explanation for the association between large negative unexpected accruals and large negative forecast errors is that all the models of unexpected accruals examined in this study are prone to misclassifying nondiscretionary accruals as discretionary in periods when firms are recognizing large, negative transitory items. Combining the misclassification argument with a cognitive based argument that analysts react too slowly to extreme current performance would account for the observed link between unexpected accruals and forecast errors. While a more detailed analysis is beyond the scope of this paper, the evidence in Fig. 6 sheds additional light on the question of misclassification. It is seen in the figure that the largest percentiles of *positive* unexpected accruals are actually associated with fairly large negative mean forecast errors. The upside down U-shape that characterizes mean forecast errors over the range of unexpected accruals is inconsistent with a straightforward misclassification argument.[29] This is because if extreme positive unexpected accruals reflected misclassification in the case of firms that experience strong current performance, these would be the same cases in which analysts' forecasts would tend to underreact to extreme current good news and issue forecasts that fall short of reported earnings. The association between firm recognition of large negative transitory items and large negative operating items and the association between forecast errors and unexpected accruals are empirical phenomena that clearly deserve further exploration.

4.3. Linking unexpected accruals and the asymmetry in the middle of forecast error distributions

Table 7 provides evidence suggesting that unexpected accruals are also associated with the middle asymmetry in forecast error distributions. Column 2 presents a comparison of the ratio of positive to negative errors in narrow intervals centered on a zero forecast error (as reported in Panel B of Table 1) to the analogous ratio when forecast errors are based on reported earnings after "backing out" the realization of unexpected accruals for the quarter. In sharp contrast to the results reported in Table 1, the results in Table 7 indicate that after controlling for unexpected accruals, the number of small positive forecast errors *never* exceeds the number of small negative forecast errors in any interval. For example, the ratio of good to bad earnings surprises in the interval between [−0.1, 0) and (0, 0.1] is 1.63 (a value reliably different from 1) when errors are computed using earnings as reported by the firm, compared to 0.95 (statistically indistinguishable from 1) when errors are based on reported earnings adjusted for unexpected accruals. Thus, as in the case of the tail asymmetry, there is an empirical link between firms' recognition of unexpected accruals and the middle asymmetry. Given the impact of the tail and middle asymmetries on inferences concerning analyst bias and inefficiency described in Sections 2 and 3, researchers should take into account the role of unexpected accruals in the reported earnings typically used to benchmark forecast.

[29] The plot of *median* forecast errors around unexpected accrual percentiles also displays an upside down U-shape. However, as one might expect from the summary statistics describing the forecast error distributions in Table 1, the magnitude of these median errors is much smaller than mean errors, and large negative median forecast errors are only found in the most extreme positive and negative unexpected accrual percentiles.

Table 7
Linking unexpected accruals and the asymmetry in the middle of forecast error distributions

Range of forecast errors (1)	Ratio of positive to negative forecast errors based on *reported* earnings (2)	Ratio of positive to negative forecast errors based on earnings adjusted for unexpected accruals (3)
Overall	1.19*	0.96*
[−0.1, 0) & (0, 0.1]	1.63*	0.95
[−0.2, −0.1) & (0.1, 0.2]	1.54*	0.97
[−0.3, −0.2) & (0.2, 0.3]	1.31*	1.09
[−0.4, −0.3) & (0.3, 0.4]	1.22*	0.97
[−0.5, −0.4) & (0.4, 0.5]	1.00	0.99
[−1, −0.5) & (0.5, 1]	0.83*	0.95*
[Min, −1) & (1, Max]	0.40*	0.95*

This table provides the ratio of positive to negative forecast errors for observations that fall into increasingly larger and nonoverlapping symmetric intervals moving out from zero forecast errors. For example, the forecast error range of [−0.1, 0) & (0, 0.1] includes all observations that are greater than or equal to −0.1 and (strictly) less than zero and observations that are greater than zero and less than or equal to 0.1. Forecast error is reported earnings minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by the beginning-of-period price. Earnings before unexpected accruals (used to compute the forecast error ratios in column 3) are calculated as the difference between reported earnings and the empirical measure of unexpected accruals.
*A test of the difference in the frequency of positive to negative forecast errors is statistically significant at or below a 1% level.

4.4. Explanations for a link between asymmetries in forecast error distributions and unexpected accruals

One general explanation for the link between unexpected accruals and the presence of asymmetries in forecast error distributions is that incentive or judgment factors that affect analysts' forecasts are exacerbated when estimates of unexpected accruals are likely to be unusual. For example, it is possible that cases of underreaction that appear to be concentrated among firms with the most extreme bad news reflect situations in which analysts have the weakest (strongest) incentives to lower (inflate) forecasts or suffer from cognitive obstacles that prevent them from revising their forecasts downward. At the same time, it has been argued in the accounting literature that unexpected accrual models produce biased downward estimates in exactly the same circumstances, i.e., when firms are experiencing extremely poor performance (see, e.g., Dechow et al., 1995).[30] This combination of

[30] The controversy over bias in unexpected accrual estimates relates to the issue of whether they truly reflect the exercise of discretion on the part of management. The conclusion that such measures are flawed is generally based on results from misclassification tests in which the maintained assumption is that historical data have not been affected by earnings management. This assumption can be challenged on logical grounds and, somewhat circularly, on the grounds that no evidence in the empirical literature supports this assumption.

potentially unrelated factors could account for the fact that extreme negative unexpected accruals accompany analysts' final forecasts for quarters characterized by prior bad news. Analogously, a higher incidence of small positive versus small negative errors as news improves is consistent with a greater likelihood of a *fixed* amount of judgment-related underreaction or incentive-based inflation of forecasts the better the prior news. The fact that unexpected accruals also appear to be related to the presence of the middle asymmetry may be coincidental to a slight tendency for unexpected accrual estimates to be positive in cases of firms experiencing high growth and positive returns (see, e.g., McNichols, 2000).[31]

Clearly there is a long list of possible combinations of unrelated factors that can simultaneously give rise to the two asymmetries in forecast error distributions and their apparent link to unusual unexpected accruals, which makes it difficult to pinpoint their source. Nevertheless, researchers still have good reason to consider these empirical facts when developing empirical test designs, choosing test statistics, and formulating and refining analytical models. One important reason is that if analysts' incentives or errors in judgment are responsible for systematic errors, it should be recognized that these factors appear to frequently produce very specific kinds of errors; i.e., small positive and extreme negative errors. To date, however, individual incentive and cognitive-based theories do not identify the economic conditions, such as extreme good and bad prior performance, that would be more likely to trigger or exacerbate incentive or judgment issues in a manner leading to exactly these types of errors. These explanations are also not easily reconciled with an apparent schizophrenia displayed by analysts who tend to slightly underreact to extreme good prior news with great regularity, but overreact extremely in a limited number of extreme good news cases. Finally, current behavioral and incentive-based theories do not account for actions undertaken by *firms* that produce reported earnings associated with forecast errors of the type found in the tail and middle asymmetries. Until such theories begin to address these issues it is not clear how observations that fall into the observed asymmetries should be treated in statistical tests of general forms of analyst irrationality. The identification of specific types of influential errors and their link to unexpected accruals documented in this paper provides a basis or expanding and refining behavioral and incentive theories of forecast errors.

A second reason for focusing on the empirical properties of forecast error distributions and their link to unexpected accruals is because it supports an alternative perspective on the cause of apparent forecast errors; i.e., the possibility that analysts either lack the ability or motivation to forecast discretionary biases in reported earnings. If so, then earnings manipulations undertaken to beat forecasts or to create reserves (e.g., earnings baths) that *are not* anticipated in analysts' forecasts

[31] McNichols (2000) argues that a positive association between unexpected accruals and growth reflects a bias in unexpected accrual models, but she does not perform tests to distinguish between this hypothesis and the alternative that high-growth firms are more likely to recognize a positive discretionary accrual to meet an earnings target, as argued in Abarbanell and Lehavy (2003a). We note that the presence of the middle asymmetry among firms with prior bad news returns and earnings changes is inconsistent with the misclassification argument.

may in part account for concentrations of small positive and large negative observations in distributions of forecast errors.[32] This suggests that evidence previously inferred to indicate systematic errors in analysts' forecasts might actually reflect the inappropriate benchmarking of forecasts.[33] An important implication of this possibility is that researchers may be formulating and testing new incentive and cognitive theories or turning to more advanced statistical methods and data transformations in order to explain forecast errors that are apparent, not real.

5. Summary and conclusions

In this paper we reexamine the evidence in the literature on analyst-forecast rationality and incentives and assess the extent to which extant theories for analysts' forecast errors are supported by the accumulated empirical evidence. We identify two relatively small asymmetries in cross-sectional distributions of forecast error observations and demonstrate the important role they play in generating statistical results that lack robustness or lead to conflicting conclusions concerning the existence and nature of analyst bias and inefficiency with respect to prior news. We describe how inferences in the literature have been affected, but these examples by no means enumerate all of the potential problems faced by the researcher using earnings surprise data. Our examples do demonstrate how some widely held beliefs about analysts' proclivity to commit systematic errors (e.g., the common belief that analysts generally produce optimistic forecasts) are not well supported by a broader analysis of the distribution of forecast errors. After four decades of research on the rationality of analysts' forecasts it is somewhat disconcerting that the most definitive statements observers and critics of earnings forecasters appear willing to agree on are ones for which there is only tenuous empirical support.

We stress that the evidence presented in this paper is not inconsistent with forecast errors due to analysts' errors in judgment and/or the effects of incentives. However, it does suggest that refinements to extant incentive and cognitive-based theories of systematic errors in analysts' forecasts may be necessary to account for the *joint* existence of both a tail asymmetry and a middle asymmetry in cross-sectional

[32] Abarbanell and Lehavy (2003b) offer theoretical, empirical, and anecdotal support for the assumption that analysts may not be motivated to account for or capable of anticipating earnings management in their forecasts. Based on this assumption they develop a framework in which analysts always forecast unmanaged earnings and firms undertake extreme income-decreasing actions or manipulations that leave reported earnings slightly above outstanding forecasts to inform investors of their private information. They describe a setting in which neither analysts nor managers behave opportunistically and investors are rational, where the two documented asymmetries in forecast error distributions arise and are foreshadowed by the sign and magnitude of stock returns before the announcement of earnings. In their setting, prior news predicts biases in the reported earnings benchmark, not biases in analysts' forecasts.

[33] Gu and Wu (2003) offer a variation on this argument suggesting that the analysts forecast the median earnings of the firm's ex-ante distribution, which also suggests that for some firms ultimate reported earnings (reports that differ from median earnings) are not the correct benchmark to use to assess whether analysts' forecasts are biased.

distributions of forecast errors. At the very least, researchers attempting to assess the descriptiveness of such theories should be mindful of the disproportionate impact of relatively small numbers of observations in the cross-section on statistical inferences.[34]

The evidence we present also highlights an empirical link between unexpected accruals embedded in the reported earnings benchmark to forecasts and the presence of the tail and middle asymmetries in forecast error distributions. Such biases in reported earnings benchmarks may point the way toward expanding and refining incentive and cognitive-based theories of analyst errors in the future. However, these results also raise questions about whether analysts are expected or motivated to forecast discretionary manipulations of reported earnings by firms. Thus, these results also highlight the fact that research to clarify the true target at which analyst forecasts are aimed is a prerequisite to making a compelling case for or against analyst rationality. Organizing our thinking around the salient properties of forecast error distributions and how they arise has the potential to improve the chaotic state of our current understanding of analyst forecasting and the errors analysts may or may not systematically commit.

Appendix A. The calculation of unexpected accruals

Our proxy for firms' earnings management, quarterly unexpected accruals, is calculated using the modified Jones (1991) model (Dechow et al., 1995); see Weiss (1999) and Han and Wang (1998) for recent applications of the Jones model to estimate quarterly unexpected accruals. All required data (as well as earnings realizations) are taken from the 1999 Compustat Industrial, Full Coverage, and Research files.

According to this model, unexpected accruals (scaled by lagged total assets) equal the difference between the predicted value of the scaled expected accruals ($NDAP$) and scaled total accruals (TA). Total accruals are defined as

$$TA_t = (\Delta CA_t - \Delta CL_t - \Delta Cash_t + \Delta STD_t - DEP_t)/A_{t-1},$$

where ΔCA_t is the change in current assets between current and prior quarter, ΔCL_t the change in current liabilities between current and prior quarter, $\Delta Cash_t$ the change in cash and cash equivalents between current and prior quarter, ΔSTD_t the change in debt included in current liabilities between current and prior quarter, DEP_t the current-quarter depreciation and amortization expense, and A_t the total assets.

[34] For example, given the recent attention in the literature to incentive factors that give rise to small, apparently pessimistic forecast errors (see footnote 5), it is important that researchers testing general behavioral theories understand that the middle asymmetry has the ability to produce evidence consistent with cognitive failures or, potentially, to obscure it. Similarly, the tail asymmetry has played a role in producing both parametric and nonparametric evidence that supports incentive-based theories of bias and inefficiency. However, such theories identify no role for extreme news or extreme forecast errors in generating predictions and do not acknowledge or recognize their crucial role in providing support for hypotheses.

The predicted value of expected accruals is calculated as

$$NDAP_t = \alpha_1(1/A_{t-1}) + \alpha_2(\Delta REV_t - \Delta REC_t) + \alpha_3 PPE_t,$$

where ΔREV_t is the change in revenues between current and prior quarter scaled by prior quarter total assets, ΔREC_t the change in net receivables between current and prior quarter scaled by prior quarter total assets, and PPE_t the gross property plant and equipment scaled by prior quarter total assets.

We estimate the firm-specific parameters, α_1, α_2, and α_3, from the following regression using firms that have at least ten quarters of data:

$$TA_{t-1} = a_1(1/A_{t-2}) + a_2\Delta REV_{t-1} + a_3 PPE_{t-1} + \varepsilon_{t-1}.$$

The modified Jones model resulted in 35,535 firm-quarter measures of quarterly unexpected accruals with available forecast errors on the Zacks database.

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Analyst Conflicts and Research Quality*

Anup Agrawal
University of Alabama

Mark A. Chen
Georgia State University

June 2012

*Agrawal: Culverhouse College of Business, Tuscaloosa, AL 35487-0224, Tel: (205) 348-8970, aagrawal@cba.ua.edu, http://www.cba.ua.edu/personnel/AnupAgrawal.html. Chen: Robinson College of Business, Department of Finance, Atlanta, GA 30303-3083, Tel: (404) 413-7339, machen@gsu.edu. We thank Dan Bernhardt, Utpal Bhattacharya, Jonathan Clarke, Doug Cook, Rob Hansen, Paul Irvine, Jeff Jaffe, Prem Jain, Chuck Knoeber, Junsoo Lee, Kai Li, Felicia Marston, Erik Peek, Gordon Phillips, Mike Rebello, David Reeb, Jay Ritter, seminar participants at Indiana University, Tulane University, University of Alabama, University of New Orleans, the 2004 EFA-Maastricht meetings, the 2005 AFA meetings, and the 2006 ALEA-UC Berkeley meetings for helpful comments and suggestions. Special thanks are due to Fernando Zapatero, the editor. We also thank Thomson Financial for providing analyst forecast data via the Institutional Brokers Estimates System (I/B/E/S). Agrawal acknowledges financial support from the William A. Powell, Jr. Chair in Finance and Banking.

Analyst Conflicts and Research Quality

Abstract

This paper examines whether the quality of stock analysts' forecasts is related to conflicts of interest from their employers' investment banking (IB) and brokerage businesses. We consider four aspects of forecast quality: accuracy, bias, and revision frequency of quarterly earnings per share (EPS) forecasts and relative optimism in long-term earnings growth (LTG) forecasts. Using a unique dataset that contains the annual revenue breakdown of analysts' employers among IB, brokerage, and other businesses, we uncover two main findings. First, accuracy and bias in quarterly EPS forecasts appear to be unrelated to conflict magnitudes, after controlling for forecast age, firm resources and analyst characteristics. Second, relative optimism in LTG forecasts and the revision frequency of quarterly EPS forecasts are positively related to the importance of brokerage business to analysts' employers. Additional tests suggest that the frequency of quarterly forecast revisions is positively related to analysts' trade generation incentives. Our findings suggest that reputation concerns keep analysts honest with respect to short-term earnings forecasts but not long-term growth forecasts. In addition, conflicts from brokerage appear to play a more important role in shaping analysts' forecasting behavior than has been previously recognized.

Keywords: Stock analysts, Security analysts, Analyst conflicts, Analyst forecasts, Investment banking, Brokerage commissions, Conflicts of interest

JEL Classifications: G24, G28, G34, G38, K22, M41

Analyst Conflicts and Research Quality

1. Introduction

In April 2003, ten of the largest Wall Street firms reached a landmark settlement with the New York State Attorney General, the U.S. Securities and Exchange Commission (SEC), and other federal and state securities regulators on the issue of conflicts of interest faced by sell-side analysts. The firms agreed to pay a record $1.4 billion in penalties to settle government charges that their analysts had routinely issued optimistic stock research in order to win investment banking (IB) business from the companies they covered. Regulators cited the behavior of analysts such as Jack Grubman, perhaps the most influential telecom stock analyst during the late 1990s stock market boom. In November 1999, Grubman, then an analyst with Salomon Smith Barney, raised his rating on AT&T stock from a 'hold' to a 'strong buy' in an apparent bid to court AT&T's large IB business (see Gasparino (2002)).[1]

The settlement forced the participating securities firms to make structural changes in the production and dissemination of equity research (see Smith, Craig and Solomon (2003)). For example, analysts are no longer allowed to accompany investment bankers in making sales presentations, and securities firms are required to maintain separate reporting and supervisory structures for their research and IB operations. Firms must tie an analyst's pay to the quality and accuracy of his research rather than to the amount of IB business the research generates. In addition, an analyst's written report on a company must disclose whether his firm conducts IB business with the researched company.[2] Of the total settlement amount, $430 million is earmarked for providing investors with stock research from independent research firms.

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[1]Other instances of alleged conflicts of interest were commonplace. One example involved Phua Young, a Merrill Lynch analyst who followed Tyco International, Ltd. Merrill reportedly hired Young in September 1999 at the suggestion of Dennis Kozlowski, Tyco's then-CEO. Whereas the previous Merrill analyst had been highly critical of Tyco, Young embraced his role as a cheerleader for the company. See Maremont and Bray (2004).

[2]Throughout the paper, we refer to an analyst's employer as a 'firm' and a company followed by an analyst as a 'company'.

The settlement was fundamentally grounded on the premise that analysts who are free from potential conflicts of interest produce superior, unbiased stock research. In this paper, we provide empirical evidence on whether the quality of analysts' research is related to the magnitude of their conflicts of interest. We focus on an important product of analyst research: forecasts of corporate earnings per share (EPS) and earnings growth. We address four questions. First, how is the accuracy of analysts' quarterly EPS forecasts related to the magnitude of conflicts with IB or brokerage business? Second, are conflicts related to the bias in quarterly forecasts? Third, how are conflicts related to the revision frequency of quarterly forecasts? And finally, what is the relation between analyst conflicts and the relative optimism in long-term earnings growth (LTG) forecasts?

Answers to these questions are important not only to regulators and academics, but also to a broad range of stock market participants. Retail and institutional investors alike use analyst reports to form expectations about the future prospects of a company. In fact, institutional investors seem to rely so much on analysts' opinions that they generally avoid investing in stocks without analyst coverage (see, e.g., O'Brien and Bhushan (1990)). Prior academic studies have found that analysts' earnings forecasts and stock recommendations have investment value (see, e.g., Givoly and Lakonishok (1979), Stickel (1991), Womack (1996), Barber, Lehavy, McNichols and Trueman (2001), Jegadeesh, Kim, Krische and Lee (2004), and Loh and Mian (2006)). Moreover, analysts are widely quoted in the news media on major corporate events, and their pronouncements on television can lead stock prices to respond within seconds (see Busse and Green (2002)).

To conduct our empirical analysis, we assemble a unique dataset that contains the revenue breakdown for analyst employers (most of which are private firms not subject to the usual disclosure requirements for publicly-traded companies) into revenues from IB, brokerage, and other businesses. This information allows us to examine in detail the relation between the quality of analyst research and potential conflicts arising from IB and brokerage businesses. We perform univariate and panel regression analyses using a sample of more than 170,000 quarterly EPS forecasts and more than 38,000 LTG forecasts for about 7,400 U.S. public companies during the January 1994 to March 2003 time period. These forecasts were issued by about 3,000 analysts employed by 39 publicly-traded securities firms and 124 private securities firms.

Prior academic research has focused on conflicts faced by analysts in the context of pre-existing underwriting relationships.[3] For instance, Lin and McNichols (1998) and Michaely and Womack (1999) find that analysts employed by underwriters in security offerings tend to be more optimistic than other analysts about the prospects of the issuing company. Kadan, Madureira, Wang, and Zach (2009) document that recommendations of analysts whose employers have underwriting relationships with the covered companies are less optimistic and more informative following the enactment of recent U.S. conflict-of-interest regulations. Our paper contributes to this line of research in several ways. First, our approach takes into account both actual as well as potential conflicts from IB activities. As long as an analyst's employer has an IB business, even if the employer does not *currently* do business with the followed company, it might aspire to do so in the future. Second, we examine the conflict of interest arising from IB in general, rather than solely from security offerings. In addition to offering underwriting services, an investment bank can offer advisory services on mergers and corporate restructuring. Third, while prior academic research, the news media, and regulators have generally focused on conflicts from IB business, our data allow us to examine conflicts from brokerage business as well. As discussed in Section 2 below, IB and brokerage operations are two distinct sources of potential conflicts of interest, and they may influence analyst behavior in different ways.

Fourth, the prior empirical finding that underwriter analysts tend to be more optimistic than other analysts is consistent with two alternative interpretations: (a) underwriter analysts issue optimistic reports on companies to reward them for past IB business or to curry favor to win future IB business, and (b) companies select underwriters whose analysts already have favorable views of their stocks to begin with. The second interpretation recognizes that underwriter choice is endogenous and that underwriter analyst optimism by itself does not necessarily imply a conflict of interest. We sidestep this issue of endogeneity by broadening the focus beyond the existence of

[3] See Ramnath, Rock, and Shane (2006) and Mehran and Stulz (2007) for excellent reviews of the literature on analyst conflicts.

underwriting relations between analyst employers and followed companies. Specifically, we capture the overall importance of IB and brokerage businesses to analyst employers by measuring the percentages of total annual revenues derived from these businesses. Unlike measures based on underwriting relations between analysts' employers and followed companies, the percentages of total revenues from IB or brokerage businesses are arguably exogenous in that they would be largely unaffected by an individual analyst's forecasting behavior. Finally, our approach yields substantially larger sample sizes than those used in prior research, leading to greater statistical reliability of the results.

Several papers study analyst conflicts using methods that are somewhat related to our approach. For example, Barber, Lehavy, and Trueman (2007) find that recommendation upgrades (downgrades) by brokerage houses that have IB business under-perform (outperform) similar recommendations by non-IB brokerages and independent research firms. Cowen, Groysberg and Healy (2006) find that full-service securities firms, which have both IB and brokerage businesses, issue less optimistic forecasts and recommendations than do non-IB brokerage houses. Finally, Jacob, Rock and Weber (2008) find that short-term earnings forecasts made by investment bank analysts are more accurate and less optimistic than those made by analysts at independent research firms. We extend this line of research by quantifying the reliance of a securities firm on IB and brokerage businesses. This is an important feature of our paper for at least two reasons. First, given that many securities firms operate in multiple lines of business, it can be difficult to unambiguously classify them according to business lines. By separately measuring the magnitudes of both IB and brokerage conflicts in each firm, our approach avoids the need to rely on a classification scheme. Second, since the focus of this research is on the consequences of analysts' conflicts, measuring the magnitude of conflict, and not simply its existence, is important. Our conclusions sometimes differ from classification-based studies.

Our main findings can be summarized as follows. We find no evidence that the accuracy or bias in individual analysts' quarterly EPS forecasts is related to the magnitude of their IB or brokerage conflicts, after controlling for forecast age, firm resources, analyst experience and analyst workloads. This result also holds for technology stocks and during the late-1990s stock market boom, settings in which analysts may have faced particularly severe conflicts. The result holds for both publicly-traded and private analyst employers, and it is robust to the use of alternate measures of conflict magnitude. However, we find that the importance of brokerage conflicts is positively related to both the level of LTG forecasts and the revision frequency of quarterly EPS forecasts. In further tests, we find that greater brokerage conflicts make it less likely that forecast revisions are intended to provide investors with timely and accurate information. That is, trade-generation motives appear to drive forecast revisions to a greater degree as brokerage conflicts increase.

Our findings provide two important insights into the forecasting behavior of analysts who face potential conflicts of interest. First, while analysts do not appear to systematically respond to conflicts by biasing short-term (quarterly EPS) forecasts, they do appear to succumb to conflicts when making long-term earnings growth forecasts. This difference may be because analysts are more concerned about a possible loss of reputation from issuing easily-refuted short-term forecasts than from issuing long-term growth forecasts. Second, despite obvious instances of abuse that have been reported in the media, we find no systematic relationship between the magnitude of IB conflicts and several aspects of analysts' forecasting behavior. Brokerage conflicts, on the other hand, appear to play a more important role in shaping analysts' forecasting behavior than has been previously recognized.[4]

The remainder of the paper is organized as follows. Section 2 discusses the potential effects of conflicts of interest on analyst forecasts. Section 3 describes our sample and data. Section 4 presents our main empirical results. Section 5 examines two alternative explanations of our results on forecast revision frequency. Section 6 presents

[4] In a companion paper (Agrawal and Chen (2008)), we find that analysts with greater IB and brokerage conflicts issue more positive stock recommendations, particularly during the late-1990s stock bubble. But the reactions of stock prices and trading volumes to recommendation revisions suggest that investors adjust for these biases by discounting the opinions of more conflicted analysts, even during the bubble. Furthermore, the one-year investment performance of recommendation revisions is unrelated to conflict magnitudes, suggesting that the marginal investor is not systematically misled by analyst advice. In related research, Malmendier and Shanthikumar (2007) show that while small investors appear to naively follow optimistic recommendations by underwriter analysts, institutions appear to rationally discount recommendations for underwriting bias.

additional results from two partitions of the sample: the technology sector versus other industry sectors; and the late 1990s versus other time periods. Section 7 concludes.

2. Potential effects of conflicts of interest

This section discusses the potential effects of conflicts of interest on four aspects of analysts' behavior and performance: accuracy, bias, and revision frequency of quarterly EPS forecasts, and optimism in long-term earnings growth projections. Section 2.1 deals with IB conflicts, and Section 2.2 deals with brokerage conflicts.

2.1 Investment banking conflicts

The most widely-discussed type of analyst conflict arises from the fact that securities firms can use optimistic research to try to win or keep lucrative underwriting business.[5] Several academic studies have reported evidence of analyst optimism in the context of existing underwriting relationships. For example, Dugar and Nathan (1995) and Lin and McNichols (1998) find that analysts whose employers have underwritten seasoned equity offerings issue more favorable earnings forecasts and stock recommendations about clients than do non-underwriter analysts. Dechow, Hutton, and Sloan (2000) document a positive bias in underwriter analysts' long-term growth (LTG) forecasts for firms conducting seasoned equity offerings. Michaely and Womack (1999) find that underwriter analysts in initial public offerings are generally more optimistic in recommending a client firm's stock than are non-underwriter analysts, but underwriter recommendations exhibit particularly poor long-run stock performance. And O'Brien, McNichols and Lin (2005) find that underwriter analysts in equity offerings are slower to downgrade stocks - but faster to upgrade them - than non-underwriter analysts.

Securities firms seek not only to maintain the goodwill of existing IB clients, but also to attract new corporate clients. Corporate managers may award underwriting or merger advisory mandates to securities firms that issue consistently optimistic earnings forecasts. This incentive implies that EPS forecasts of analysts subject to pressure from

[5] Ljungqvist, Marston and Wilhelm (2006, 2009) find that while optimistic recommendations do not help the analyst's firm win the lead underwriter or co-manager positions in general, they do help the firm win the co-manager position in deals where the lead underwriter is a commercial bank.

IB should exhibit a positive bias relative to forecasts of analysts at independent firms. Likewise, the long-term (three to five year) earnings growth estimates of analysts at IB firms should be rosier than the growth projections of independent analysts.

Alternatively, pressure from IB business can lead to a *pessimistic* bias in analyst forecasts. A widely-held belief among market participants is that corporations often seek to meet or beat analysts' quarterly estimates, regardless of the absolute level of performance. Whether or not a company meets its quarterly estimates can serve as a rule of thumb by which boards of directors and investors evaluate managers (see, e.g., Degeorge, Patel, and Zeckhauser (1999) and Farrell and Whidbee (2003)). Indeed, Bartov, Givoly, and Hayn (2002) find that companies that exceed the threshold set by analyst estimates subsequently experience higher abnormal stock returns. Chan, Karceski, and Lakonishok (2007) document that the frequency of non-negative earnings surprises has grown in recent years, particularly for growth firms and for analysts employed by firms with no IB business. Therefore, 'lowering the bar' with pessimistic forecasts, especially near the earnings announcement date, may be a way for conflicted analysts to win favor with potential IB clients.

If optimistic or pessimistic forecast biases are important, then, *ceteris paribus*, the overall accuracy of conflicted analysts should be lower than that of independent analysts. However, there are at least three mitigating forces that can reduce bias among analysts at large investment banks. First, compared to an independent research firm, an investment bank may provide an analyst with an environment that is more conducive to making high-quality forecasts. Possible advantages include access to greater resources and research support (Clement (1999)) and to information generated by the underwriting and due diligence process (Michaely and Womack (1999)). Second, firms with large IB operations can attract analysts with better forecasting ability. As Hong and Kubik (2003) find, more accurate analysts tend to move to more prestigious securities firms, which are more likely than small, regional firms to have significant IB operations.

Finally, reputation concerns can reduce analysts' response to IB conflicts. As in the model of Bolton, Freixas, and Shapiro (2007), financial intermediaries that provide misleading advice to investors can suffer a loss of market share in the presence of competition from other information providers. Indeed, empirical evidence suggests that optimism in lead underwriters' stock recommendations is mitigated when a larger number of unaffiliated analysts cover the same stock (see Sette (2011)). It therefore stands to reason that an analyst who wants to avoid the risk of a tarnished reputation or loss of career prospects will be less inclined to issue biased and misleading earnings forecasts. Overall, then, the effect of IB conflicts on EPS and LTG forecasting behavior can be expected to depend on multiple and sometimes opposing forces. It is the net effect of these forces that we seek to understand in our empirical analysis below.

2.2 Brokerage conflicts

When a securities firm has significant brokerage operations, its analysts face direct or indirect incentives to use their research to generate trading commissions.[6] For example, an analyst may be able to increase his firm's trading volume by issuing optimistic projections.[7] A new earnings forecast that is particularly positive should lead to trading by both new investors and current shareholders, provided that investors ascribe at least some information content to the forecast. On the other hand, since short-sale constraints can prevent most investors from reacting to negative information unless they already hold a stock, a negative forecast should generate trading from a narrower set of investors.[8]

An analyst can also increase trading volume by revising his earnings forecasts frequently. Analysts' forecast revisions have been shown to increase share trading volume (see, e.g., Ajinkya, Atiase, and Gift (1991)) and to significantly affect stock

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[6]Some brokerage firms acknowledge explicitly tying their analysts' compensation to the magnitude of trading commission revenues that their research generates. See, for example, the case of Soleil Research, Inc., discussed in Vickers (2003).

[7]Carleton, Chen and Steiner (1998) find that brokerage analysts appear to inflate their stock recommendations. Jackson (2005) shows theoretically that analysts' incentives for trade generation can lead to an optimistic forecast bias. Hayes (1998) develops a model to analyze how commission-based incentives and short-sale constraints can affect analysts' information gathering decisions. Ljungqvist, et al. (2007) find that analysts employed by larger brokerages issue more optimistic recommendations and more accurate earnings forecasts.

[8]Numerous regulations in the United States increase the cost of selling shares short (see Dechow, Hutton, Meulbroek and Sloan (2001)). Furthermore, traditional mutual funds that qualify as SEC-registered investment companies cannot derive more than 30% of their profits from short sales. Thus, it is not surprising that the vast majority of stock trades are regular purchases and sales rather than short sales. For example, over the 1994-2001 period, short sales comprised only about ten percent of the annual New York Stock Exchange trading volume (see NYSE (2002)).

prices apart from earnings news, dividends, or other corporate announcements (see, e.g., Stickel (1991)). From one perspective, a positive relation between trading volume and the frequency of forecast revisions can be beneficial to investors. For example, if revising forecasts is a costly, then analysts whose compensation is tied (directly or indirectly) to commission revenue may be more willing to issue timely revisions that reflect his changing earnings expectations. Indeed, previous work has established a link between analysts' forecasting frequency and their ultimate accuracy (see, e.g., Stickel (1992) and Clement and Tse (2003)).

However, the prospect of boosting commissions may lead an analyst to revise his forecasts too frequently even when there is little or no new information. This perverse 'churning' behavior, despite being anticipated by rational investors, could be profitable for an analyst if investors assign a positive probability of genuine information content to the revisions.[9] If churning incentives are important, then one would expect that, relative to independent analysts, conflicted analysts will revise their forecasts more frequently and substantially and yet will not end up being more accurate.

As in the case of IB conflicts, concerns about loss of reputation can limit abusive analyst behavior stemming from brokerage conflicts. The importance of reputational concerns may depend on market conditions, on the time period in question, and on characteristics of analysts and their employers. Hence, the net relation between the magnitude of brokerage conflicts and the quality of LTG or quarterly EPS forecasts is ultimately an empirical issue.

3. Sample and data

We obtain data on revenues of analyst employers from annual filings made with the SEC. Under Section 17 of the Securities Exchange Act of 1934, all registered broker-dealer firms in the United States, whether public or private, are required to file annual audited financial reports with the SEC. The requisite filings, referred to as x-17a-5 filings, must contain a statement of financial condition (balance sheet), a statement of

[9] Irvine (2004), using transactions data from the Toronto Stock Exchange, documents that a brokerage firm's market share of trading in a stock tends to increase when its analyst issues a forecast further away from the consensus. He also finds, however, that greater forecast bias by itself does not increase market share.

income, a statement of changes in financial condition, and a statement detailing net capital requirements.

Our sample construction begins with the set of all broker-dealer firms listed in the May 2003 version of Thomson Financial's I/B/E/S Broker Translation File, which contains 1,257 entries. Of these entries, 159 correspond to forecast-issuing firms that chose to withhold their names from the Broker Translation File. For each of the remaining 1,098 firms with names available, we conduct a manual keyword search for x-17a-5 forms using Thomson Financial's Global Access database and the public reading room of the SEC. Electronic form filing was first mandated by the SEC in 1994, so the availability of x-17a-5 filings before 1994 is extremely limited. Therefore, we restrict our sample to the 1994-2003 time period.

Out of the 1,098 firms for which we have names, 318 firms did not file an x-17a-5 form with the SEC during our sample period, either because they were based in a jurisdiction outside of the U.S. or because they were not active broker-dealers during the period. The filings for an additional 81 firms were not available electronically through Global Access. Finally, because the revenue breakdown of broker-dealers is a key data item used in this study, we exclude 454 firms for which this data is not available. These firms chose to withhold the income statement portion of their x-17a-5 filings from the public under the SEC's confidential treatment provision.[10]

Because broker-dealer firms enter our sample only when they choose to publicly disclose their income statements, we face a potential sample selection bias if firms' tendency toward disclosure is systematically related to the nature of the firms' conflicts of interest. But this bias does not appear to be serious for our purposes for two reasons. First, the average levels of forecast characteristics of interest in this study (i.e., the bias, error, and revision frequency of quarterly EPS forecasts and the level of LTG estimates) are similar between private securities firms that either report or withhold their revenue breakdown information. Second, we conduct all of our main tests separately for forecasts issued by private broker-dealers and those issued by publicly-traded broker-dealers.

[10]Under the Securities Exchange Act, broker-dealers are permitted to obtain confidential treatment of the income statement portion of an x-17a-5 filing if disclosure of the income statement to investors could harm the firm's business condition or competitive position.

There is no selection bias for the latter sub-sample because all publicly-traded firms are required to disclose their income statements in annual 10-K filings. The results for the two groups of firms are very similar.

The above selection procedure yields a sample of 245 firms. We further eliminate 20 instances in which the same firm appears in the Broker Translation File under multiple names or codes. Thus, for 225 unique firms we have data on total revenue and its key components for at least one year during the sample period.

We augment the sample by identifying all broker-dealer firms in I/B/E/S that were publicly-traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or Nasdaq. Of the 44 firms identified as publicly traded, 21 firms do not disclose revenue information in their x-17a-5 filings. For these 21 firms, we use annual 10-K filings to gather financial data on revenues, revenue components, and balance-sheet items. Thus, the sample of firms for which we have revenue breakdown[11] data includes 246 broker-dealers, of which 44 are publicly traded. Of these, 163 broker-dealers (including 39 public companies) issued at least one forecast on I/B/E/S during our sample period.

Table 1 shows descriptive statistics for our sample of broker-dealers, analysts, and forecasts. Panel A describes the size and revenue breakdown for broker-dealers for the 2002 fiscal year. The first three columns are for the full sample, and the next three columns are for the sub-sample of publicly-traded firms. The median securities firm is quite small, with total revenue of only $3.25 million. The majority of firms have no IB revenue. The median revenue from brokerage commissions is $1.6 million. Not surprisingly, the publicly-traded securities firms in the sample are much larger, with median IB revenue of $31 million and median brokerage commission revenue of $50 million.

Panel B of Table 1 reports statistics, both for the full sample of firms and for the sub-sample of publicly-traded firms, on the fraction of total revenue coming from either IB or brokerage commission. For the full sample of all firm-years, about half of the typical

[11] Securities firms report revenue breakdown into revenues from investment banking, from brokerage, and from other businesses. The last category includes asset management, proprietary trading, market making, and margin lending.

firm's total revenue comes from brokerage; the revenue from IB is negligible. The fraction of IB (brokerage) revenue ranges from 0 to 1 with a median of .004 (.488) and mean of .112 (.506). For the sub-sample of publicly-traded securities firms, the corresponding range for the IB (brokerage) revenue fraction is from 0 (.005) to .913 (.999) with a median of .114 (.362) and mean of .137 (.393). Thus, compared to private securities firms, publicly-traded firms derive a substantially greater proportion of their revenue from IB.

We obtain forecasts and reported earnings per share (EPS) numbers from the I/B/E/S U.S. Detail History File for the time period from January 1, 1994 to June 30, 2003. All EPS forecast and reported EPS numbers are converted to primary EPS numbers using the dilution factors provided by I/B/E/S. Our sample includes all quarterly EPS and LTG forecasts made by individual analysts working for broker-dealer firms for which we have revenue information; it excludes forecasts made by analyst teams.

In Panel C, characteristics of EPS and LTG forecasts are reported for the entire sample period. Following much of the literature on analysts' earnings forecasts, we compute forecast bias as the difference between actual EPS and forecasted EPS, divided by the stock price twelve months before quarter-end. We define forecast inaccuracy as the absolute value of forecast bias. Bias, inaccuracy, and forecast age are all computed from an analyst's latest forecast for a company during a quarter. The median EPS forecast is slightly pessimistic, but the magnitude of the pessimism is not large—roughly 1.3 cents on a $50 stock for forecasts made over the one-month or three-month period before quarter-end. The median forecast inaccuracy is much larger, about 5.5 cents on a $50 stock for both forecast periods. For long-term earnings growth projections, the median forecast level is strikingly high, about 16% per year.[12] Over the three (six) month period preceding quarter-end, the median analyst following a company issues just one quarterly EPS forecast; the mean number of forecasts is 1.3 (1.7).

Panel D reports characteristics of individual analysts and their employers. The number of analysts employed by the analyst's firm, number of companies covered, and number of I/B/E/S industry groups covered, are all measured over the calendar year in

[12] I/B/E/S defines a long-term growth forecast as the expected annual growth in operating earnings over a company's next full business cycle, usually a period of three to five years.

which forecasts occur. We exclude analysts that are present in the EPS detail file in 1983 (the first year for which quarterly EPS forecasts are available through I/B/E/S) because we cannot fully observe the employment histories of these analysts. Overall, analysts in our sample do not appear to cover companies for long periods of time. The median company-specific forecasting experience of an analyst is about 1.1 years; her median general forecasting experience is about three years.[13] The median analyst works for a securities firm that employs 61 analysts and tracks nine companies in two different four-digit I/B/E/S S/I/G[14] industry groups.

Appendix Table A.1 lists, for fiscal year 2002, the largest analyst employers as well as the largest employers with either no IB or no brokerage business. As Panel A shows, Adams, Harkness, & Hill, Inc. is the largest employer in our sample without any IB business. The firm employs 23 analysts and has total revenue of about $62 million, all of which consists of brokerage commissions.[15]

Analyst research is typically financed via a firm's brokerage business. Consequently, almost all sell-side analysts are employed by firms with at least some commission revenue. Analyst employers with no such revenue tend to be tiny boutique firms. Panel B indicates that there were only two such firms in 2002. Both firms were start-ups. One employed eight analysts, the other employed one. Finally, Panel C lists the five largest employers of analysts. Not surprisingly, these firms are among the most prominent and well-capitalized Wall Street securities firms. Merrill Lynch is the largest employer, employing 231 forecast-issuing analysts. Of Merrill Lynch's total 2002 revenues of $18.6 billion, $2.4 billion is from IB, $4.7 billion from brokerage commissions, and the rest from other businesses such as asset management and proprietary trading.

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[13]Analyst experience appears to be short for several reasons. First, we only measure experience issuing quarterly EPS forecasts. Any additional experience issuing LTG forecasts or stock recommendations is not included in our measure. Second, securities firms hired a number of new analysts during the late 1990s stock market boom, a time period included in our sample. Third, company-specific forecasting experience is low because of large turnover in the portfolio of stocks followed by an analyst. This happens particularly after analysts change employers, which occurs quite frequently.

[14]Sector / Industry / Group code.

4. Empirical results

We present our results on forecast accuracy in section 4.1, forecast bias in section 4.2, the level of LTG forecasts in section 4.3 and revisions in quarterly forecasts in section 4.4.

4.1. Forecast accuracy

We begin with univariate comparisons of forecast accuracy. Table 2 compares quarterly EPS forecast inaccuracy for analysts employed at firms with and without significant IB (or brokerage) business. We define a broker-dealer firm to have significant (insignificant) IB business if, at the end of the preceding fiscal year, its IB revenue as a percentage of its total revenue was in the top (bottom) quartile among all broker-dealers in the sample. A similar definition applies for brokerage commission business. All of the univariate comparisons are conducted at the level of the company. In other words, for each company in each quarter, we compute the mean forecast error for each type of securities firm; we then compare the resulting sets of matched pairs. Only the latest forecast made by an analyst during a quarter is used in the computation.

Panel A shows results for forecasts issued over the period of one month prior to quarter-end. Each set of two rows in the panel shows the mean and median values of our forecast accuracy measure for firms without and with significant IB (or brokerage) business. These are followed by a row showing p-values for differences between the two rows. The rows labeled 1 and 2 are for firms without and with significant IB business. The rows labeled 3 and 4 are for firms without and with significant brokerage business. Rows 5 and 6 and rows 7 and 8 conduct comparisons between firms with and without a particular type of business, conditional on the absence of the other type of business. The basic message from Panel A is that forecasts of analysts employed by firms with significant brokerage business (row 4) are somewhat less accurate than forecasts made by the control group of analysts (row 3). This finding holds even if IB business is insignificant (row 6 versus row 5).

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[15] Commission revenue slightly exceeds total revenue, which includes a loss from the firm's proprietary trading activities.

Panel B shows corresponding results for forecasts made over the three-month period prior to quarter-end. Here, the results for firms with versus without significant brokerage operations mirror those in Panel A. In addition, analysts employed by firms with significant IB but no significant brokerage business (row 8) make forecasts that are somewhat more accurate than forecasts made by the control group of analysts (row 7).

We next conduct regression analyses linking forecast inaccuracy to our measures of conflict severity. In these regressions, we include variables that have been found in prior research (e.g., Mikhail, Walther and Willis (1997), Clement (1999), and Jacob, Lys and Neale (1999)) to affect analysts' forecast accuracy, such as forecast age, employer size, forecasting experience, and workload. Since the publicly-traded and private securities firms in our sample likely differ in ways that are not fully captured by size, we also control for public versus private status. Our basic model is the following:

(1) $$NAFE_{ijt} = b_0 + b_1\ IB_{it} + b_2\ COM_{it} + b_3\ AGE_{ijt} + b_4\ SIZE_{it} + b_5\ CEXP_{ijt} + b_6\ GEXP_{it} + b_7\ NCOS_{it} + b_8\ NIND_{it} + b_9\ PUBLIC_{it} + e_{ijt},$$

where the subscripts denote analyst i following company j for year-quarter t and the variables are defined as follows:

NAFE = Normalized absolute forecast error = forecast inaccuracy, as defined in section 3,

IB (or COM) = IB (or commission) revenue as a percentage of total revenues of an analyst's employer,

AGE = Number of days between forecast date and earnings release,

SIZE = Natural log of one plus the number of analysts employed by a firm in year t,

CEXP = An analyst's company-specific forecasting experience = Number of years an analyst has been following the company,

GEXP = General experience as analyst = Number of years an analyst has been issuing forecasts to I/B/E/S,

NCOS = Number of companies followed by an analyst over the calendar year,

NIND = Number of different 4-digit I/B/E/S S/I/G industries followed by an analyst over the calendar year, PUBLIC =1, if a securities firm is publicly-traded on NYSE, AMEX or NASDAQ, 0 otherwise, and

e = the error term.

The main explanatory variables of interest in equation (1) are our measures of conflicts faced by an analyst, IB and COM. These variables are measured at the level of a securities firm. We implicitly assume that from the perspective of an individual analyst, IB and COM are given, exogenous quantities that cannot be affected directly by the choice of a forecast. We use three alternative econometric approaches to estimate equation (1). The first approach is a pooled OLS regression, where t-statistics are computed using White's (1980) correction for heteroskedasticity. The unit of observation in the regression is an analyst-company-year-quarter (e.g., the Salomon analyst following IBM for the quarter ended March 2003). Our second approach follows Fama and MacBeth (1973), where we estimate cross-sectional regressions for each year-quarter and make inferences based on the time-series of coefficient estimates.[16] In both of these approaches, we include industry dummies as well as the natural logarithm of the followed company's market capitalization one year prior to quarter end. Finally, in the third approach, we estimate panel regressions where we treat company-year-quarter effects as fixed, because we are only interested in determining whether a particular analyst characteristic (namely, independence) is related to forecast inaccuracy. By focusing on differences across analysts following a given company for a given year-quarter (e.g., the March 2003 quarter for Microsoft), this approach avoids the need to control for characteristics of the company and the time period in question.[17] The regressions exclude a small number of observations for which an employer's total revenues are zero or negative due to securities trading losses.

Table 3 shows the results of our regressions on forecast inaccuracy. For each of the three estimation approaches, the table shows two variants of model (1): one excluding the PUBLIC dummy variable and the other including it. Panel A (B) shows results for

[16]In the Fama-MacBeth regressions reported in Tables 3 and 5, we exclude three quarters that have an insufficient number of observations to perform the estimation.

[17]See Wooldridge (2002) for an exposition of the fixed effects panel regression model. This approach has been employed by several studies of analyst forecasts (see, e.g., Clement (1999) and Agrawal, Chadha and Chen (2006)).

forecasts made within one month (three months) before quarter-end. Notably, the coefficients of the IB and COM variables are statistically indistinguishable from zero in all six estimations.[18] In other words, there is no indication in either panel that an analyst's forecast accuracy is related to the proportion of his employer's revenues coming from either IB or brokerage business.[19] While conflicts with IB or brokerage may affect the accuracy of analyst forecasts in particular cases, the effect does not show up systematically in the data. As expected, the regressions show that forecast inaccuracy is greater for older forecasts and is smaller for larger companies. There is only limited evidence that forecast inaccuracy is different for analysts employed by publicly-traded versus private securities firms.

4.2. Forecast bias

Table 4 shows univariate comparisons, similar to the accuracy comparisons in Table 2, of forecast bias between different types of employers. Differences in mean bias between different employer types are mostly insignificant. Based on comparisons of median values, analysts at firms with significant IB (brokerage) business appear to be slightly more pessimistic (optimistic) in both forecast periods.

Table 5 shows estimated coefficients from regressions of forecast bias using the three econometric approaches employed in Table 3. The explanatory variables are the same as in equation (1). Here too, the unit of observation in the pooled OLS and fixed effects regressions is an analyst-company-year-quarter. In both panels, the coefficients of IB and COM variables are insignificant under each of the three estimation approaches. There is no evidence that an analyst's forecast bias is systematically related to the magnitude of potential conflicts with his employer's IB or brokerage business. Forecasts made earlier are more optimistic, consistent with the pattern found by prior studies (e.g., Brown, Foster and Noreen (1985) and Richardson, Teoh and Wysocki (2004)). An

[18]The correlation between IB and COM is -.17. Throughout the paper, results are similar when we include IB and COM variables one at a time in the regressions.

[19]These and subsequent results are generally similar when we replace the continuous IB and COM variables in each regression with binary dummy variables indicating either positive revenue or revenue over $10 million.

analyst's optimism increases with his company-specific forecasting experience and decreases with company size. All of these relations are statistically significant.

4.3. Long-term earnings growth (LTG) forecasts

The univariate comparisons in Table 6 of long-term (three to five year) earnings growth forecasts reveal some notable differences. For example, mean growth forecasts are slightly less optimistic for analysts employed by firms with significant IB business (row 2) compared to the control group of analysts (row 1). For analysts employed by firms with substantial brokerage business (rows 4 or 6), LTG forecasts are higher than forecasts of the control group. For analysts employed by firms with significant IB but insignificant brokerage business (row 8), LTG forecasts are higher than forecasts for the control group (row 7). But the sample sizes in this last comparison are quite small, so they do not warrant strong conclusions.

Table 7 shows the results of Fama-MacBeth regressions and fixed effects regressions explaining LTG levels. We do not use pooled OLS regressions here because of a natural quarter-to-quarter serial dependence in the level of growth forecasts for a company. The unit of observation in the panel regressions is an analyst-company-year-quarter. The explanatory variables are the same as in equation (1), except that the forecast AGE variable is no longer relevant and is hence excluded. In the fixed effects regressions, the level of analysts' LTG forecasts increases with the proportion of their employers' revenues from brokerage business (COM). The magnitude of this effect is non-trivial. For instance, an increase in COM from the first to the third quartile of the sample is associated with an increase in the level of LTG of about 0.82%[20]. The level of LTG forecasts decreases with the size of the analyst's employer. In the Fama-MacBeth regressions, the level of LTG forecasts decreases in an analyst's company-specific forecasting experience and the number of companies followed by the analyst; it increases in the number of industry groups the analyst follows. All these relations are statistically significant.

4.4. Frequency of forecast revision

Table 8 shows results of panel regressions explaining a fourth aspect of analysts' forecasts, namely, the frequency of quarterly EPS forecast revisions. The dependent variable in the OLS specification (column (1)) and the Poisson specification (column (3)) is the number of EPS forecasts an individual analyst issues for a given company during the three-month period preceding the end of a quarter. The dependent variable in the logistic regressions (column (2)) is an indicator variable that equals one if an analyst issues multiple forecasts during the period; it equals zero otherwise. The unit of observation in the regressions is an analyst-company-year-quarter. All three specifications include industry and year-quarter dummies.[21] The explanatory variables are the same as in equation (1), except that the IB and AGE variables are excluded because we have no *a priori* reason to expect a systematic relation between these variables and the frequency of forecast revision. T-statistics are computed using White's correction for heteroskedasticity.

Under each of the three specifications, we find that analysts employed by firms with greater proportions of revenue from brokerage business (COM) issue more frequent forecast updates over the course of the quarter. This result is highly statistically significant. Moreover, the magnitude of this effect appears to be non-trivial. For example, in the OLS specification, an increase in COM from the first to the third quartile of the sample leads to an increase of about .04 in the number of forecasts, or about 3% of the sample mean. Table 8 also reveals that an analyst is likely to revise his forecast more often when the followed company is larger, when his employer is larger, when he has more company-specific forecasting experience, when he follows more companies, when he has less general forecasting experience, or when he covers fewer industries. All of these relations are statistically significant.

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[20]While an increase in the annual earnings growth rate of 0.8% may seem inconsequential, equity values (e.g., in dividend growth models) tend to be quite sensitive to even small changes in expectations of growth rates of dividends and earnings.

5. Interpretation of results on forecast revision frequency

As discussed in section 2.2, the positive relation we find between COM and forecast revision frequency in section 4.4 above is consistent with two distinct motives. On the one hand, an analyst who is compensated for generating commission revenue should be more willing to devote time and effort to making timely forecast revisions that reflect updated expectations about earnings. We refer to this as the 'investor welfare' motive. Alternatively, the prospect of boosting commissions can lead an analyst to revise his forecasts frequently even with little or no new information. Frequent forecast revisions can be particularly effective in getting investors to churn their portfolios if the absolute magnitudes of successive changes in forecasts are large. We call this the 'churning' motive. While the investor welfare and churning motives are not mutually exclusive, the first is consistent with maximization of investors' interests, and the second is not. We attempt to distinguish between these two motives by conducting three tests, presented in sections 5.1 through 5.3.

5.1 Commission incentives, earnings uncertainty and revision frequency

As a first test of the two motives for making frequent forecast revisions, we add a measure of earnings uncertainty to the explanatory variables in the Table 8 regressions of forecast revision frequency. The more uncertain are a company's earnings for a given quarter, the greater will be investor demand for frequent forecast updates. Following Johnson (2004), we measure earnings uncertainty by the dispersion (i.e., standard deviation) of analyst forecasts at the beginning of the quarter. A positive coefficient on forecast dispersion would tend to confirm the investor welfare motive. At the same time, if the coefficient of COM is still positive after controlling for dispersion, this finding would be consistent with the churning motive.

We find that the coefficients of both forecast dispersion and COM are positive and statistically significant at the .001 level or better in the extended versions of all six models in Table 8. Our evidence thus suggests that the frequency of forecast updates is partly driven by investor demand for updated information. But, after controlling for this

[21]We do not treat company-year-quarter effects as fixed here because doing so results in the loss of a large number of groups with no variation in the dependent variable.

effect, commission incentives still play an important role in an analyst's decision on how frequently to revise his forecast. To save space, we do not report these results in a table.

5.2 Commission incentives and churning

For our second test of the motives underlying frequent forecast revisions, we devise two simple measures of churning,[22] denoted $CHURN_1$ and $CHURN_2$, and estimate the following regression:

(2) $$CHURN_{ijt} = bo + b_1\ COM_{it} + b_2\ SIZE_{it} + e_{ijt},$$

where the subscripts denote Analyst i following Company j for Year-quarter t, COM and SIZE are as defined as in section 4.1 above, and the churning measure is defined as follows:

CHURN = $CHURN_1$ or $CHURN_2$,

$CHURN_1$ = Mean absolute forecast revision = $\sum_{k=2}^{n} |d_k - d_{k-1}| / (n-1)$,

$CHURN_2$ = Mean squared forecast revision = $\sum_{k=2}^{n} (d_k - d_{k-1})^2 / (n-1)$,

$d_k = F_k / S$,

F_k = kth forecast of EPS made by an analyst for a given company-year-quarter,

S = Stock price 12 months before quarter-end,

n = Number of forecasts made by an analyst for a given company-year-quarter over the 6-month period prior to quarter-end, and

e = the error term.

The churning story suggests that the stronger is the commission incentive, the larger should be the absolute magnitude of successive changes in forecasts. This implies that the coefficient b_1 in equation (2) should be positive. On the other hand, the investor welfare story, under which forecast revisions are aimed purely at providing updated information to investors in a timely fashion, implies no particular relation between the strength of commission incentives and the magnitude of successive changes in an analyst's forecasts.

[22]Both measures capture a salient aspect of churning, namely the average distance between successive changes in an analyst's forecast, without regard to gains in forecast accuracy.

We estimate equation (2) in a pooled OLS regression with robust standard errors. The estimate of the coefficient b_1 is significantly positive using either $CHURN_1$ or $CHURN_2$ as the dependent variable, with t-values of 2.68 and 2.81, respectively. In other words, the absolute magnitude of successive changes in an analyst's forecasts appears to be positively related to the strength of brokerage conflicts.

These churning variables measure the magnitude, rather than the frequency, of successive forecast revisions by an analyst. We next examine churning measures that take into account both, by multiplying each measure by (n-1). We then re-estimate equation (2) as earlier. Once again, the estimate of the coefficient b_1 is significantly positive, with t-values of 4.62 and 3.08, respectively, for the two churning measures. Overall, this evidence is consistent with the idea that analysts employed by firms where brokerage business is more important issue forecast updates that are more frequent and larger in magnitude in an attempt to generate trades. These results are not shown in a table to save space.

5.3. Boldness, trade generation and forecast accuracy

One characteristic of a forecast revision that is generally related to both accuracy and trade generation is boldness, i.e., how much the new forecast departs from the consensus. Compared to forecasts that herd with the consensus, bold forecasts tend to be more accurate (see, e.g., Clement and Tse (2005)), and they generate more trades for the analyst's firm (Irvine (2004)). In addition, Clement and Tse find that a bold revision tends to be more accurate than the original forecast. Motivated by these prior findings, we conduct tests examining the link between the boldness of a revised forecast and the incremental change in forecast accuracy for analysts facing different degrees of brokerage conflicts. Specifically, we estimate the following pooled regression by OLS:

(3) $$\Delta NAFE_{ijt} = b_0 + b_1\, BOLDNESS_{ijt} * HCOM_{it} + b_2\, BOLDNESS_{ijt} * LCOM_{it} + b_3\, NDAYS_{ijt} + e_{ijt},$$

where the subscripts denote analyst i following company j for year-quarter t, NAFE is forecast inaccuracy as defined in section 4.1 above, and the other variables are defined as follows:

$\Delta NAFE_{ijt} = NAFE_{ijt} - NAFE_{ij,t-1}$,

$BOLDNESS_i = |F_i - F| / S$,

F_i = Forecast of analyst i for a given company-year-quarter,

F = Consensus forecast for the company-year-quarter,

S= Stock price twelve months before quarter-end,

$HCOM_i$ = 1, if analyst i works for an employer with high (above-median) COM,

= 0 otherwise,

$LCOM_i = 1 - HCOM_i$,

NDAYS = Number of days between the current forecast and prior forecast of an analyst about a company-year-quarter, and

e = the error term.

The investor welfare story predicts that $b_1 = b_2 < 0$, while the churning story predicts that $b_1 > b_2$. In other words, if forecast revisions are aimed purely at providing timely and accurate information to investors, then the relation between forecast inaccuracy and boldness should be negative and of the same magnitude for analysts facing high or low degrees of brokerage conflicts. But if frequent revisions are at least partly aimed at inducing investors to churn their portfolios, then the relation between forecast inaccuracy and boldness should be less (more) negative for analysts who face higher (lower) degrees of brokerage conflict.

Our estimation of equation (3) indicates that $\hat{b}_1$ = -.13 and $\hat{b}_2$ = -.31; both coefficients are significantly different from zero. The test of the null hypothesis that $b_1 = b_2$ has an associated p-value of less than .0001. In other words, bold forecast revisions do tend to increase forecast accuracy, but this gain in accuracy is significantly greater for analysts with lower brokerage conflicts. These results suggest that, although the investor welfare story holds, churning is also an important motive for forecast revisions. We obtain qualitatively similar results if we replace the boldness variable by the change in boldness or if we replace the continuous measure of boldness in equation (3) with a binary measure used in Clement and Tse (2005). Once again, we do not show these results in a table to save space.

6. Sub-sample results

We next examine two interesting partitions of our sample. We present the results for technology versus other sectors in section 6.1 and the results for the late 1990s versus other time periods in section 6.2.

6.1 Technology versus other industry sectors

Numerous stories in the media suggest that conflicts of interest may have been more pronounced in the technology sector than in other industry sectors during our sample period. We examine this idea by replacing the IB variable in model (1) of Tables 3, 5 and 7 by two variables, IB*TECH and IB*NTECH, and replacing the COM variable in Tables 3, 5, 7 and 8 by COM*TECH and COM*NTECH. The binary variable TECH equals 1 if the first two digits of the I/B/E/S S/I/G code of a followed company are '08' (i.e., the company belongs to the technology sector); otherwise, TECH equals zero. NTECH is defined as 1 - TECH.

We find no significant relation between the accuracy or bias in an analyst's quarterly earnings forecasts and the importance to her employer of IB or brokerage business either in the technology sector or in other industry sectors. The frequency of an analyst's forecast updates is positively related to the importance of brokerage business to her employer in each sector, with no significant difference in the coefficient estimates. But the level of analysts' long-term growth (LTG) forecasts is positively related to the importance of IB and brokerage business only for the technology sector; it is insignificant for the remaining sectors as a group. This difference is statistically significant. To save space, we do not tabulate these results.

6.2 Late 1990s versus other time periods

The late 1990s was a period of booming stock prices. Media accounts and the timing of regulatory actions suggest that conflicts of interest were particularly severe during this period. To examine this idea, we replace the IB variable in model (1) of Tables 3, 5 and 7 by two variables: IB*LATE90S and IB*NLATE90S. Similarly, we replace the COM variable in Tables 3, 5, 7 and 8 by COM*LATE90S and

COM*NLATE90S. The variable LATE90S equals 1 for forecasts made for time periods ending during 1995-99; it equals zero otherwise. NLATE90S equals 1 - LATE90S.

There is no significant relation between the accuracy or bias in an analyst's quarterly earnings forecasts and the importance to his employer of IB or brokerage business for either the late 1990s or other time periods in our sample. The level of LTG forecasts is unrelated to IB during both time periods. LTG is positively related to COM during the late 1990s and is unrelated to it during other time periods, but the difference is statistically insignificant. The probability of forecast revision is positively related to COM during both time periods, but the coefficient of COM is significantly lower during the late 1990s than during other periods. Once again, we do not show these results in a table to save space.

7. Summary and conclusions

The landmark settlement that prominent Wall Street firms reached with regulators in April 2003 mandated sweeping changes in the production and dissemination of sell-side analyst research. Among its key provisions, the settlement required securities firms to create and maintain greater separation between equity research and IB activities, and to provide brokerage customers with research reports produced by independent research firms. The basic premise underlying such requirements is that independent analysts do in fact produce research that is superior to that of analysts who face potential conflicts of interest from their employers' other businesses.

In this paper, we empirically examine whether the quality of analysts' forecasts of earnings or earnings growth is related to the magnitude of potential conflicts of interest arising from their employers' IB and brokerage businesses. Using a unique dataset containing the breakdown of securities firms' revenues from IB, brokerage, and other businesses, we investigate the effects of analyst conflicts on four aspects of their forecasts: accuracy and bias in quarterly earnings forecasts, optimism in LTG forecasts, and the frequency of quarterly forecast revisions.

Our investigation reveals that quarterly EPS forecast bias and accuracy do not appear to be systematically related to the importance of IB or brokerage business to analysts' employers. This result also holds for forecasts made for companies within the technology sector as well as forecasts made during the late-1990s stock market boom, contexts in which conflicts of interest may have been particularly severe. In addition, the absence of a link between analyst conflicts and quarterly forecast bias or accuracy holds for publicly-traded as well as private analyst employers, and it is robust to several alternative measures of conflict severity.

We find, however, that the degree of relative optimism in analysts' LTG forecasts tends to increase with the share of their employers' revenues derived from brokerage commissions. We also find that the frequency of forecast revisions bears a significant positive relationship with the share of revenues from brokerage business. We conduct several tests to distinguish between alternative explanations of this finding on forecast revision frequency. The results of these tests suggest that analysts' trade generation incentives can indeed impair the quality of stock research. Our findings imply that distortions in analyst research are unlikely to be completely eliminated by regulations that focus solely on IB conflicts. The precise nature of trade generation incentives, how they impact analyst behavior, and how they might be mitigated all appear to be fruitful avenues for future research.

Our findings also highlight a key difference in analysts' short-term (quarterly EPS) versus long-term (EPS growth) forecasting behavior. While analysts do not appear to systematically respond to conflicts by biasing short-term forecasts, they do appear to succumb to conflicts when making long-term growth projections. What accounts for this difference? One possibility is that short-term forecasts allow the labor market to assess an analyst's performance against an objective, well-defined benchmark. If an analyst allows his short-term forecasts to be affected by the conflicts he faces, his deception can be revealed with the very next earnings release, damaging his reputation and livelihood. But with long-term forecasts, analysts may not face the same degree of market scrutiny. Investors' memories may be short, and analysts may be able to get away with revising their initial flawed projections. A second possible explanation, suggested by dividend growth models, is that equity valuations depend more on long-term growth rates than on the next quarter's earnings, and analysts use the most effective means available to prop up a stock. We leave a complete resolution of this issue to future research.

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Table 1
Sample Characteristics

This table provides descriptive statistics on broker-dealers, analysts, and forecasts. The sample includes I/B/E/S quarterly earnings and long-term earnings growth (LTG) forecasts made between January 1994 and June 2003 and corresponding annual financial information for broker-dealer firms. Panel A contains statistics on revenue components for broker-dealer firms for fiscal years ending in 2002. A broker-dealer is public if it is traded on the NYSE, Nasdaq, or AMEX. Panel B shows, over the sample period 1994-2003, the distribution of the fraction of total revenues generated from investment banking (IB) or brokerage businesses. N is the number of firm-years. Panel C reports characteristics of long-term growth forecasts and quarterly EPS forecasts over the entire sample period. Bias is computed as (actual EPS-forecast EPS) divided by the stock price twelve months before quarter-end. Forecast error is measured as the absolute value of forecast bias. Statistics for bias, accuracy and forecast age are based on the latest forecast made by each analyst over the relevant period. Forecast age is the number of days between the forecast date and the earnings release. In Panels B and C, forecasts and broker-years are excluded when total revenues are negative or when fractions of revenue exceed one. In Panels B, C, and D, analyst teams and analysts for which forecasting experience could not be determined are excluded. In Panel C, the periods of one, three and six months refer to periods before quarter-end. Panel D reports analysts' experience and workload characteristics measured on an annual basis over the entire sample period.

Panel A: Broker-Dealer Firm Characteristics, 2002

	All Broker-Dealers			Public Broker-Dealers		
	Mean	**Median**	**# of Firms**	**Mean**	**Median**	**# of Firms**
Revenue ($ millions)	848.35	3.25	151	4953.32	176.15	25
Investment Banking Revenue ($ millions)	97.28	0	151	572.17	30.73	25
Brokerage Commission Revenue ($ millions)	154.16	1.60	151	847.06	49.80	25
Other Revenue ($ millions)	596.90	0.43	151	3534.09	76.68	25

Panel B: IB and Commission Revenues Divided by Total Revenue, 1994-2003

	Distribution of the Fraction of Total Revenue							
Source of Revenue	***N***	**Min**	**1st Quart.**	**Median**	**3rd Quart.**	**Max**	**Mean**	**Std. Dev.**
All broker-dealers								
IB fraction	972	0	0	0.004	0.136	1	0.112	0.194
Brokerage commission	972	0	0.207	0.488	0.853	1	0.506	0.341
Public broker-dealers								
IB fraction	227	0	0.069	0.114	0.154	0.913	0.137	0.137
Brokerage commission	227	0.005	0.160	0.362	0.494	0.999	0.393	0.276

Table 1 (cont.)

Panel C: Forecast Characteristics, 1994-2003				
	Mean	**Median**	**Sample Size**	**Unit of Observation**
Bias in Quarterly EPS Forecasts				
One-Month Period	-0.00017	0.00026	54,369	Forecast
Three-Month Period	-0.00039	0.00027	171,915	Forecast
Inaccuracy in Quarterly EPS Forecasts				
One-Month Period	0.0037	0.0011	54,369	Forecast
Three-Month Period	0.0039	0.0011	171,915	Forecast
LTG Forecasts (%)	19.61	16	38,209	Forecast
Number of Quarterly Earnings Forecasts				
Over Prior three months	1.325	1	188,658	Analyst-company-qtr.
Over Prior six months	1.740	1	239,102	Analyst-company-qtr.
Forecast Age (# of days)				
One-Month Period	14.001	14	59,699	Forecast
Three-Month Period	45.89	52	188,664	Forecast

Panel D: Analyst Characteristics, 1994-2003				
	Mean	**Median**	**Sample Size**	**Unit of Observation**
Company-specific forecasting experience (years)	2.25	1.11	87,244	Analyst-company-year
General forecasting experience (years)	4.32	2.97	9,387	Analyst-year
Number of analysts employed by firm	76.55	61	9,387	Analyst-year
Number of companies covered	10.19	9	9,387	Analyst-year
Number of 4-digit I/B/E/S SIG industry groups covered	2.39	2	9,378	Analyst-year

Table 2
Forecast Accuracy of Analysts Employed by Firms with Versus without Significant Investment Banking or Brokerage Business

This table presents univariate comparisons of quarterly EPS forecast inaccuracy between different groups of analysts classified according to whether their employer has significant investment banking (IB) or brokerage business. Panel A (B) presents results for forecasts made within one (three) month(s) of quarter-end. Forecast inaccuracy is computed as the absolute value of (actual EPS – forecast EPS) divided by the stock price measured 12 months before quarter end. Forecasts are drawn from the January 1994-June 2003 period. A broker-dealer is defined to have significant (insignificant) IB business in a given calendar year if its IB revenue as a percentage of its total revenue is in the top (bottom) quartile among all broker-dealers in the sample. Significant or insignificant brokerage business is defined similarly based on commission revenue as a percentage of total revenue. Comparisons are conducted at the level of the company-year-quarter unit. For each publicly-traded company in the I/B/E/S U.S. detail history file for which adequate data are available, forecast errors are averaged for each different type of broker-dealer firm; these averages are then compared using matched-pair t-tests for differences in means and Wilcoxon signed-rank tests for differences in distributions. *N* corresponds to the number of matched pairs. Only the latest forecasts made by individual analysts over the relevant forecast period are used. Revenue data are obtained from x-17a-5 or 10-k filings with the U.S. Securities and Exchange Commission. Forecasts are matched with annual broker-dealer financial data corresponding to the latest fiscal year preceding the date of the forecast.

Type of Firm	**A. One-month Forecast Period**			**B. Three-month Forecast Period**		
	N	**Mean**	**Median**	***N***	**Mean**	**Median**
1. Firms with no significant IB business	3683	0.0029	0.0010	16789	0.0032	0.0010
2. Firms with significant IB business	3683	0.0028	0.0010	16789	0.0031	0.0010
p-value of t-test/signed-rank test (1 vs. 2)		0.433	0.059		0.132	0.160
3. Firms with no significant brokerage business	3370	0.0026	0.0009	13982	0.0029	0.0009
4. Firms with significant brokerage business	3370	0.0029	0.0010	13982	0.0031	0.0010
p-value of t-test/signed-rank test (3 vs. 4)		0.006	0.000		0.000	0.000
5. Firms with no significant IB and no significant brokerage business	998	0.0025	0.00078	4161	0.0024	0.0008
6. Firms with significant brokerage but with no significant IB business	998	0.0029	0.00082	4161	0.0028	0.0008
p-value of t-test/signed-rank test (5 vs. 6)		0.056	0.025		0.002	0.000
7. Firms with no significant IB and no significant brokerage business	549	0.0026	0.00073	2837	0.0025	0.00082
8. Firms with significant IB but no significant brokerage business	549	0.0027	0.00073	2837	0.0023	0.00076
p-value of t-test/signed-rank test (7 vs. 8)		0.818	0.581		0.024	0.084

Table 3
Panel Regression Analysis of Quarterly Earnings Forecast Accuracy

This table reports coefficient estimates from regressions explaining errors in individual analysts' quarterly EPS forecasts made over the January 1994-June 2003 period. Panel A (B) presents results for forecasts made within one (three) month(s) of quarter-end. Only company quarters ending in March, June, September, or December are included. Forecast and reported numbers are based on primary EPS. Forecast error is computed as |reported EPS – forecast EPS| divided by the stock price twelve months before quarter-end. For each forecast period, only the latest forecast made by an analyst is included. The regressions in (1) are pooled OLS regression estimates using White's correction for heteroskedasticity. The pooled OLS regressions include industry and calendar-quarter dummies (not reported). (2) reports average coefficients obtained from Fama-MacBeth (1973) regressions performed on individual calendar quarters over the sample period. Each regression includes unreported industry dummies. In the fixed-effects regressions in (3), company-year-quarter effects are treated as fixed. Revenue data are obtained from x-17a-5 or 10-K filings with the U.S. Securities and Exchange Commission. Each forecast issued by an analyst is matched with broker-dealer revenue data corresponding to the latest fiscal year preceding the date of the forecast. Forecast age is measured as the number of days between the report date and the forecast date. Company-specific and general forecasting experience are measured as the number of years since an analyst first began issuing I/B/E/S EPS forecasts on a particular company or in general. The number of analysts employed by a firm, the number of companies covered by an analyst, and the number of industry groups covered by an analyst are measured over the calendar year of the earnings forecast. Industry groupings are based on I/B/E/S 4-digit S/I/G codes. Company market capitalization is measured in millions of dollars one year prior to quarter-end. The public brokerage dummy equals unity if a broker-dealer is traded on NYSE, AMEX, or Nasdaq and equals zero otherwise. T-statistics for coefficient estimates are in parentheses.

	Pooled OLS (1)		**Fama-MacBeth (2)**		**Company-Quarter Fixed Effects (3)**	
Panel A: One-Month Forecast Period						
Constant	-0.0083	-0.0083	-0.0040	-0.0049	0.0030	0.0030
	(-6.99)[a]	(-6.99)[a]	(-2.25)[b]	(-2.44)[b]	(8.82)[a]	(8.82)[a]
IB revenue as fraction of total revenue	-0.0009	-0.00089	-0.0015	0.0012	-0.00020	-0.00020
	(-0.67)	(-0.66)	(-1.10)	(0.52)	(-0.52)	(-0.52)
Commission revenue as fraction of total revenue	0.00036	0.00036	0.00076	-0.00018	0.00014	0.00014
	(0.76)	(0.75)	(1.82)	(-0.33)	(0.69)	(0.70)
Forecast age	0.00009	0.00009	0.00009	0.0001	0.00003	0.00003
	(9.15)[a]	(9.16)[a]	(8.07)[a]	(8.02)[a]	(7.18)[a]	(7.18)[a]
Ln (1+Number of analysts employed by brokerage)	0.00015	0.00011	0.0002	0.00015	-0.00012	-0.00013
	(1.51)	(0.89)	(2.00)[b]	(1.19)	(-2.41)[b]	(-2.19)[b]
Company-specific forecasting experience * 10^{-3}	0.1799	0.1804	0.1750	0.1750	-0.0250	-0.0248
	(6.31)[a]	(6.31)[a]	(5.14)[a]	(5.23)[a]	(-1.81)	(-1.81)
General forecasting experience * 10^{-3}	-0.0552	-0.0558	-0.0276	-0.02667	0.034	0.0341
	(-2.27)[b]	(-2.28)[b]	(-1.36)	(-1.34)	(3.27)[a]	(3.27)[a]
Number of companies followed * 10^{-3}	0.00075	0.00067	0.0075	0.0086	-0.0041	-0.0041
	(-0.07)	(-0.06)	(0.51)	(0.58)	(-0.82)	(-0.83)
Number of industry groups followed * 10^{-3}	0.0526	0.0538	-0.0222	-0.0272	-0.0421	-0.0416
	(0.81)	(0.83)	(-0.29)	(-0.36)	(-1.47)	(-1.46)
Ln (Market capitalization of company)	-0.00127	-0.00127	-0.0013	-0.0013		
	(-18.71)[a]	(-18.63)[a]	(-14.54)[a]	(-14.57)[a]		
Public broker-dealer dummy		0.00018		0.0016		0.00003
		(0.59)		(2.25)[b]		(0.25)
Number of Observations	45374	45374	45267	45267	45374	45374
Number of Groups					27704	27704
Model P-value	0.0000	0.0000			0.0000	0.0000
R^2	0.036	0.035	0.002	0.002	0.0043	0.0043

Table 3 (cont.)

Panel B: Three-Month Forecast Period

Constant	-0.0039 (-6.38)[a]	-0.0038 (-6.38)[a]	-0.0018 (-1.78)	-0.0029 (-2.64)[a]	0.0031 (20.21)[a]	0.0031 (20.19)[a]
IB revenue as fraction of total revenue	-0.00015 (-0.27)	-0.00015 (-0.28)	-0.0013 (-1.28)	0.0004 (0.26)	-0.00009 (-0.53)	-0.0001 (-0.53)
Commission revenue as fraction of total revenue	0.00019 (0.73)	0.00019 (0.74)	0.0005 (0.90)	0.00017 (0.66)	0.00004 (0.37)	0.00004 (0.38)
Forecast age	0.00003 (11.61)[a]	0.00003 (11.61)[a]	0.00003 (7.73)[a]	0.00003 (7.64)[a]	0.00002 (25.87)[a]	0.00002 (25.87)[a]
Ln (1+Number of analysts employed by brokerage)	0.00017 (2.93)[a]	0.00013 (1.98)[b]	0.00015 (2.30)[b]	0.00006 (0.79)	-0.00011 (-4.41)[a]	-0.00011 (-3.91)[a]
Company-specific forecasting experience * 10^{-3}	0.1392 (5.86)[a]	0.1397 (5.85)[a]	0.1551 (6.06)[a]	0.00015 (6.04)[a]	-0.0153 (-2.13)[b]	-0.0155 (-2.12)[b]
General forecasting experience * 10^{-3}	-0.0021 (-0.12)	-0.0026 (-0.15)	0.00053 (0.04)	0.00039 (0.03)	0.0109 (2.08)[b]	0.0109 (2.07)[b]
Number of companies followed * 10^{-3}	-0.0315 (-5.40)[a]	-0.0315 (-5.40)[a]	-0.0203 (-2.06)[b]	-0.0194 (-1.97)[b]	-0.00146 (-0.59)	-0.00147 (-0.59)
Number of industry groups followed * 10^{-3}	0.0607 (1.67)	0.0617 (1.71)	0.0228 (0.46)	0.0198 (0.39)	-0.0193 (-1.33)	-0.0191 (-1.32)
Ln (Market capitalization of company)	-0.0015 (-32.69)[a]	-0.0015 (-32.67)[a]	-0.0014 (-20.39)[a]	-0.0014 (-20.44)[a]		
Public broker-dealer dummy		0.00014 (0.80)		0.0014 (3.02)[a]		0.00002 (0.30)
Number of Observations	143477	143477	143318	143318	143477	143477
Number of Groups					61996	61996
Model P-value	0.0000	0.0000			0.0000	0.0000
R^2	0.026	0.026	0.001	0.001	0.009	0.009

[a,b] denote statistical significance in two-tailed tests at the 1% and 5% levels, respectively.

Table 4
Forecast Bias of Analysts Employed by Firms with Versus without Significant Investment Banking or Brokerage Business

This table presents univariate comparisons of quarterly EPS forecast bias between different groups of analysts classified according to whether their employer has significant investment banking (IB) or brokerage business. Panel A (B) presents results for forecasts made within one (three) month(s) of quarter-end. Forecast bias is measured as (reported EPS – forecast EPS) divided by the stock price measured twelve months before quarter end. Forecasts are drawn from the January 1994-June 2003 period. A broker-dealer is defined to have significant (insignificant) IB business in a given calendar year if its IB revenue as a percentage of its total revenue is in the top (bottom) quartile among all broker-dealers in the sample. Significant or insignificant brokerage business is defined similarly based on commission revenue as a percentage of total revenue. Comparisons are conducted at the level of the company-year-quarter unit. For each publicly-traded company in the I/B/E/S U.S. detail history file for which adequate data are available, forecast bias is averaged for each different type of broker-dealer firm; these averages are then compared using matched-pair t-tests for differences in means and Wilcoxon signed-rank tests for differences in distributions. *N* corresponds to the number of matched pairs. Only the latest forecasts made by individual analysts over the relevant forecast period are used. Revenue data are obtained from x-17a-5 or 10-k filings with the U.S. Securities and Exchange Commission. Forecasts are matched with annual broker-dealer financial data corresponding to the latest fiscal year preceding the date of the forecast.

Type of Firm	**A. One-month Forecast Period**			**B. Three-month Forecast Period**		
	N	**Mean**	**Median**	***N***	**Mean**	**Median**
1. Firms with no significant IB business	3683	0.00007	0.0002	16789	$-5.6*10^{-6}$	0.00026
2. Firms with significant IB business	3683	0.00011	0.0003	16789	0.00003	0.00029
p-value of t-test/signed-rank test (1 vs. 2)		0.747	0.028		0.493	0.0001
3. Firms with no significant brokerage business	3370	0.00003	0.00025	13982	0.00008	0.00027
4. Firms with significant brokerage business	3370	-0.00013	0.00020	13982	-0.00006	0.00025
p-value of t-test/signed-rank test (3 vs. 4)		0.138	0.0005		0.017	0.000
5. Firms with no significant IB and no significant brokerage business	998	-0.0002	0.00022	4161	0.00026	0.00026
6. Firms with significant brokerage but with no significant IB business	998	-0.0002	0.00017	4161	0.00035	0.00029
p-value of t-test/signed-rank test (5 vs. 6)		0.709	0.074		0.395	0.470
7. Firms with no significant IB and no significant brokerage business	549	-0.00037	0.0000	2837	0.00002	0.00022
8. Firms with significant IB but no significant brokerage business	549	-0.00044	0.0000	2837	0.00009	0.00025
p-value of t-test/signed-rank test (7 vs. 8)		0.620	0.934		0.447	0.008

Table 5
Panel Regression Analysis of Quarterly Earnings Forecast Bias

This table shows coefficient estimates from regressions explaining the degree of bias in individual analysts' quarterly EPS forecasts made over the January 1994-June 2003 period. Panel A (B) presents results for forecasts made within one (three) month(s) of quarter-end. Only company quarters ending in March, June, September, or December are included. Forecast and reported numbers are based on primary EPS. Forecast bias is computed as (reported EPS – forecast EPS) divided by the stock price twelve months before quarter-end. The sample includes only the latest forecast made by an analyst for a company during a given forecast period. Columns (1) show results of pooled OLS regressions that include industry and calendar-quarter dummies (not reported) and t-statistics using White's correction for heteroskedasticity. Columns (2) report average coefficient estimates from Fama-MacBeth (1973) regressions that include unreported industry dummies, performed on individual calendar quarters over the sample period. In the fixed-effects regressions in (3), company-year-quarter effects are treated as fixed. Revenue data are obtained from x-17a-5 or 10-K filings with the SEC. Each forecast issued by an analyst is matched with broker-dealer revenue data corresponding to the latest fiscal year preceding the date of the forecast. Forecast age is measured as the number of days between the report date and the forecast date. Company-specific and general forecasting experience are (continuous) measures of the number of years since an analyst first began issuing I/B/E/S EPS forecasts on a particular company or in general. The number of analysts employed by a firm, the number of companies covered by an analyst, and the number of industry groups covered by an analyst are measured over the calendar year of the earnings forecast. Industry groupings are based on I/B/E/S 4-digit S/I/G codes. Company market capitalization is measured in millions of dollars one year prior to quarter-end. The public brokerage dummy equals one if a broker-dealer firm is publicly-traded on NYSE, AMEX, or Nasdaq and equals zero otherwise. T-statistics for coefficient estimates are shown in parentheses.

	Pooled OLS (1)		**Fama-MacBeth (2)**		**Company-Quarter Fixed Effects (3)**	
Panel A: One-Month Forecast Period						
Constant	0.0045	0.0045	0.0050	0.0048	0.00086	0.00085
	(3.55)[a]	(3.54)[a]	(2.79)[a]	(2.59)[a]	(2.29)[b]	(2.27)[b]
IB revenue as fraction of total revenue	0.00088	0.00087	-0.00027	0.00026	0.00019	0.00019
	(0.64)	(0.63)	(-0.16)	(0.14)	(0.47))	(0.47)
Commission revenue as fraction of total revenue	-0.00017	-0.00016	-0.00097	-0.0006	-0.00019	-0.0002
	(-0.34)	(-0.32)	(-1.71)	(-1.09)	(-0.88)	(-0.92)
Forecast age	-0.00006	-0.00006	-0.00006	-0.00006	-0.00003	-0.00003
	(-5.67)[a]	(-5.68)[a]	(-4.52)[a]	(-4.51)[a]	(-5.76)[a]	(-5.78)[a]
Ln (1 + Number of analysts employed by brokerage)	0.00015	0.00023	0.00009	0.00025	0.00006	0.00009
	(1.49)	(1.93)	(0.65)	(1.52)	(1.16)	(1.48)
Company-specific forecasting experience * 10^{-3}	-0.1149	-0.1158	-0.1193	-0.1187	-0.0073	-0.0075
	(-3.86)[a]	(-3.89)[a]	(-3.18)[a]	(-3.18)[a]	(-0.49)	(-0.49)
General forecasting experience * 10^{-3}	0.0448	0.0458	0.0391	0.0381	0.026	0.0262
	(1.76)	(1.80)	(1.49)	(1.48)	(2.27)[b]	(2.28)[b]
Number of companies followed * 10^{-3}	-0.0125	-0.0126	-0.0211	-0.0219	-0.0038	-0.0037
	(-1.10)	(-1.11)	(-1.37)	(-1.46)	(-0.70)	(-0.68)
Number of industry groups followed * 10^{-3}	-0.060	-0.0621	-0.0492	-0.0474	-0.0737	-0.0754
	(-0.90)	(-0.93)	(-0.67)	(-0.65)	(-2.34)[b]	(-2.39)[b]
Ln (Market capitalization of company)	0.00024	0.00024	0.00028	0.00028		
	(3.48)[a]	(3.48)[a]	(3.72)[a]	(3.71)[a]		
Public broker-dealer dummy		-0.0003		-0.00026		-0.00013
		(-0.97)		(-0.79)		(-0.95)
Number of Observations	45374	45374	45267	45267	45374	45374
Number of Groups					27704	27704
Model P-value	0.0000	0.0000			0.0000	0.0000
R^2	0.008	0.008	0.001	0.001	0.003	0.003

Table 5 (cont.)

Panel B: Three-Month Forecast Period

Constant	0.0025 (3.87)[a]	0.0025 (3.86)[a]	0.0021 (2.63)[a]	0.0030 (3.28)[a]	0.0002 (1.19)	0.0002 (1.22)
IB revenue as fraction of total revenue	-0.00066 (-1.18)	-0.00065 (-1.17)	-0.0050 (-1.08)	-0.0065 (-1.48)	0.00016 (0.78)	0.00016 (0.78)
Commission revenue as fraction of total revenue	-0.00012 (-0.43)	-0.00012 (-0.44)	-0.00054 (-1.13)	-0.00024 (-0.75)	0.00002 (0.21)	0.00003 (0.24)
Forecast age	-0.00003 (-9.39)[a]	-0.00003 (-9.39)[a]	-0.00003 (-6.04)[a]	-0.00003 (-6.01)[a]	-0.00001 (-14.88)[a]	-0.00001 (-14.89)[a]
Ln (1+Number of analysts employed by brokerage)	0.00014 (2.33)[b]	0.00017 (2.39)[b]	0.00036 (2.31)[b]	0.00042 (2.26)[b]	0.00009 (3.36)[a]	0.00008 (2.55)[b]
Company-specific forecasting experience * 10^{-3}	-0.0606 (-2.50)[b]	-0.0610 (-2.50)[b]	-0.0778 (-3.47)[a]	-0.0769 (-3.42)[a]	0.012 (1.47)	0.0121 (1.49)
General forecasting experience * 10^{-3}	-0.0126 (-0.73)	-0.0122 (-0.70)	-0.0100 (-0.70)	-0.0097 (-0.67)	0.00343 (0.59)	0.0034 (0.58)
Number of companies followed * 10^{-3}	0.0245 (4.07)[a]	0.0245 (4.08)[a]	0.0129 (1.36)	0.0121 (1.27)	-0.0019 (-0.69)	-0.0195 (-0.70)
Number of industry groups followed * 10^{-3}	-0.0920 (-2.46)[b]	-0.0928 (-2.49)[b]	-0.0808 (-1.62)	-0.0779 (-1.56)	-0.0414 (-2.55)[b]	-0.041 (-2.53)[b]
Ln (Market capitalization of company)	0.00035 (7.68)[a]	0.00035 (7.68)[a]	0.00043 (5.99)[a]	0.00043 (6.01)[a]		
Public broker-dealer dummy		-0.00011 (-0.61)		-0.0011 (-2.72)[a]		-0.00004 (0.58)
Number of Observations	143477	143477	143318	143318	143477	143477
Model P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.005	0.005	0.001	0.001	0.003	0.003

[a,b] denote statistical significance in two-tailed tests at the 1% and 5% levels, respectively.

Table 6
Long-term Earnings Growth Forecasts of Analysts Employed by Firms with Versus Without Significant Investment Banking or Brokerage Business

Univariate comparisons of long-term (3 to 5 years) growth forecasts between different groups of analysts classified according to whether their employer has significant investment banking (IB) or brokerage business. The sample period is from January 1994 through June 2003. A broker-dealer is defined to have significant (insignificant) IB business in a given calendar year if its IB revenue as a percentage of its total revenue is in the top (bottom) quartile among all broker-dealers in the sample. Significant or insignificant brokerage business is defined similarly based on commission revenue as a percentage of total revenue. Comparisons are conducted at the level of the company-year-quarter unit. For each publicly-traded company in the I/B/E/S U.S. detail history file for which adequate data are available, LTG forecast levels are averaged for each different type of broker-dealer firm; these averages are then compared using matched-pairs t-tests for differences in means and Wilcoxon signed-rank tests for differences in distributions. *N* corresponds to the number of matched pairs. Only the latest company forecast made by an individual analyst over the appropriate quarter (March, June, September, or December) is used. Revenue data are obtained from x-17a-5 or 10-k filings with the U.S. Securities and Exchange Commission. Forecasts are matched with annual broker-dealer financial data corresponding to the latest fiscal year preceding the date of the forecast.

Type of Firm	*N*	Mean	Median
1. Firms with no significant IB business	1508	20.74	17.88
2. Firms with significant IB business	1508	19.83	17.5
p-value of t-test/signed-rank test (1 vs. 2)		0.002	0.112
3. Firms with no significant brokerage business	1578	18.58	15.9
4. Firms with significant brokerage business	1578	19.73	17
p-value of t-test/signed-rank test (3 vs. 4)		0.000	0.000
5. Firms with no significant IB and no significant brokerage business	246	16.58	15
6. Firms with significant brokerage but with no significant IB business	246	17.83	15
p-value of t-test/signed-rank test (5 vs. 6)		0.014	0.001
7. Firms with no significant IB and no significant brokerage business	52	19.40	20
8. Firms with significant IB but no significant brokerage business	52	21.66	20
p-value of t-test/signed-rank test (7 vs. 8)		0.033	0.016

Table 7
Analysis of Long-Term Earnings Growth Forecasts

This table reports coefficient estimates from regressions explaining the level of long-term earnings growth (LTG) forecasts made over the January 1994-June 2003 period. The sample period is partitioned into calendar quarters ending March, June, September and December. The sample includes only the latest forecast made in a quarter by an analyst for a company. The Fama-MacBeth regressions include unreported industry dummies. In the fixed-effects regressions, company-year-quarter effects are treated as fixed. Revenue data are obtained from x-17a-5 or 10-K filings with the U.S. Securities and Exchange Commission. Each forecasting period is matched with broker-dealer revenue data corresponding to the latest fiscal year preceding the date of the forecast. Company-specific and general forecasting experience are measured as the number of years since an analyst first began issuing I/B/E/S EPS forecasts on a particular company or in general. The number of analysts employed by a firm, the number of companies covered by an analyst, and the number of industry groups covered by an analyst are measured over the calendar year of the earnings forecast. Industry groupings are based on I/B/E/S 4-digit S/I/G codes. Company market capitalization is measured in millions of dollars one year prior to quarter-end. The public brokerage dummy equals unity if a broker-dealer is traded on NYSE, AMEX, or Nasdaq and equals zero otherwise. T-statistics for coefficient estimates are in parentheses.

	Fama-MacBeth (1)		**Company-Quarter Fixed Effects (2)**	
Constant	20.17	17.33	21.54	21.58
	(3.16)[a]	(2.37)[b]	(28.87)[a]	(28.64)[a]
IB revenue as fraction of total revenue	3.53	8.86	0.151	0.158
	(0.29)	(0.61)	(0.14)	(0.15)
Commission revenue as fraction of total revenue	6.68	-2.16	1.27	1.257
	(0.64)	(-0.68)	(2.39)[b]	(2.37)[b]
Ln (1+Number of analysts employed by brokerage)	-0.498	-0.22	-0.516	-0.543
	(-0.65)	(-0.27)	(-3.61)[a]	(-3.28)[a]
Company-specific forecasting experience	-0.649	-0.65	0.026	0.026
	(-17.03)[a]	(-16.90)[a]	(0.78)	(0.79)
General forecasting experience	-0.003	-0.005	-0.005	-0.005
	(-0.08)	(-0.15)	(-0.26)	(-0.27)
Number of companies followed	-0.032	-0.034	-0.007	-0.007
	(-2.05)[b]	(-2.11)[b]	(-0.73)	(-0.74)
Number of industry groups followed	0.185	0.185	0.035	0.035
	(3.03)[a]	(2.97)[a]	(0.54)	(0.54)
Public broker-dealer dummy		3.459		0.090
		(1.05)		(0.32)
Number of Observations	35258	35258	35319	35319
Number of Groups			26870	26870
R^2	0.008	0.008	0.007	0.007

[a,b] denote statistical significance in 2-tailed tests at the 1% and 5% levels, respectively.

Table 8
Analysis of Quarterly Earnings Forecast Frequency

The dependent variable in the OLS and Poisson regressions in columns (1) and (3) is the number of EPS forecasts issued by an individual analyst on a given company during the three months preceding the end of the quarter. The dependent variable in the logistic regressions in column (2) is an indicator variable equal to one if an analyst issued more than one forecast during the three-month forecasting period, and equal to zero otherwise. The sample consists of quarterly EPS forecasts made over the January 1994-June 2003 period. Company quarters not ending March, June, September, or December are excluded from the analysis. Regressions are performed on the pooled sample of observations and include unreported industry and calendar-quarter dummies. Revenue data from x-17a-5 or 10-K filings with the U.S. Securities and Exchange Commission are used to construct a variable measuring the potential degree of analysts' conflict of interest. Each forecast period is matched with broker-dealer revenue data corresponding to the latest fiscal year ending before the forecast period. Company-specific and general forecasting experience are measured as the number of years since an analyst first began issuing EPS forecasts through I/B/E/S on a particular company or in general. The number of analysts employed by a firm, the number of companies covered by an analyst, and the number of industry groups covered by an analyst are measured over the calendar year of the earnings forecast. Industry groupings are based on I/B/E/S 4-digit S/I/G codes. Company market capitalization is measured in millions of dollars one year prior to quarter-end. The public brokerage dummy equals unity if a broker-dealer is traded on NYSE, AMEX, or Nasdaq and equals zero otherwise. Heteroskedasticity-consistent t-statistics and z-statistics are in parentheses.

	OLS Specification (1)		**Logistic Specification (2)**		**Poisson Specification (3)**	
Constant	1.4321	1.4324	-0.9397	-2.2965	0.3521	0.0784
	(17.29)[a]	(17.29)[a]	(-3.38)[a]	(-6.37)[a]	(5.94)[a]	(1.32)
Commission revenue as fraction of total revenue	0.0606	0.0607	0.2008	0.1995	0.0465	0.0467
	(6.75)[a]	(6.77)[a]	(5.49)[a]	(5.46)[a]	(6.81)[a]	(6.84)[a]
Ln (1+Number of analysts employed by brokerage)	0.0140	0.0121	0.0838	0.0895	0.0114	0.0101
	(6.67)[a]	(4.79)[a]	(9.56)[a]	(8.56)[a]	(7.11)[a]	(5.27)[a]
Company-specific forecasting experience	0.0088	0.0088	0.0265	0.0265	0.0062	0.0062
	(12.51)[a]	(12.53)[a]	(10.75)[a]	(10.71)[a]	(12.12)[a]	(12.14)[a]
General forecasting experience	-0.0015	-0.0016	-0.0049	-0.0049	-0.0011	-0.0011
	(-3.24)[a]	(-3.29)[a]	(-2.63)[a]	(-2.59)[a]	(-3.16)[a]	(-3.20)[a]
Number of companies followed	0.0011	0.0011	0.0042	0.0042	0.0009	0.0009
	(6.39)[a]	(6.39)[a]	(5.70)[a]	(5.70)[a]	(6.64)[a]	(6.64)[a]
Number of industry groups followed	-0.0080	-0.0079	-0.0268	-0.0270	-0.0060	-0.0059
	(-7.91)[a]	(-7.86)[a]	(-6.26)[a]	(-6.30)[a]	(-7.74)[a]	(-7.69)[a]
Ln (Market capitalization of company)	0.0291	0.0291	0.1071	0.1072	0.0222	0.0221
	(30.67)[a]	(30.65)[a]	(28.75)[a]	(28.76)[a]	(31.15)[a]	(31.12)[a]
Public broker-dealer dummy		0.0077		-0.0230		0.0052
		(1.46)		(-1.00)		(1.27)
Number of Observations	143474	143474	143474	143474	143474	143474
Model P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.067	0.067	0.045	0.045	0.008	0.008

[a,b] denote statistical significance in 2-tailed tests at the 1% and 5% levels, respectively.

Appendix Table A.1
Firms Employing the Most Analysts for Fiscal Years Ending in 2002

Panel A: Largest Analyst Employers with No IB Business

Firm name	Number of Analysts	Total Revenue ($ millions)	Commission Revenue ($ millions)
Adams, Harkness, & Hill, Inc.	23	61.78	63.84
BB&T Capital Markets	21	52.31	9.01
SWS Securities	17	22.78	22.42
Buckingham Research	17	28.69	27.23

Panel B: Largest Analyst Employers with No Commission Revenue

Firm name	Number of Analysts	Total Revenue ($ millions)	IB Revenue ($ millions)
Paradigm Capital, Inc.	8	0.0017	0
Hudson River Analytics, Inc.	1	0.0014	0

Panel C: Largest Analyst Employers

Firm name	Number of Analysts	Total Revenue ($ millions)	IB Revenue ($ millions)	Commission Revenue ($ millions)
Merrill Lynch & Co., Inc.	231	18,608	2,413	4,657
Morgan Stanley, Dean Witter & Co.	199	32,415	2,527	3,280
Salomon Smith Barney Holdings, Inc.	139	21,250	3,420	3,845
Goldman Sachs & Co.	133	22,854	2,572	4,950
Bear Stearns & Co.	122	6,891	833	1,110

CHAPTER 18

The Valuation of Common Stocks

In Chapter 17 it was noted that one purpose of financial analysis is to identify mispriced securities. Fundamental analysis was mentioned as one approach for conducting a search for such securities. With this approach the security analyst makes estimates of such things as the firm's future earnings and dividends. If these estimates are substantially different from the average estimates of other analysts but are felt to be more accurate, then from the viewpoint of the security analyst, a mispriced security will have been identified. If it is also felt that the market price of the security will adjust to reflect these more accurate estimates, then the security will be expected to have an abnormal rate of return. Accordingly, the analyst will issue either a buy or sell recommendation, depending on the direction of the anticipated price adjustment. Based on the capitalization of income method of valuation, dividend discount models have been frequently used by fundamental analysts as a means of identifying mispriced stocks. This chapter will discuss dividend discount models and how they can be related to models based on price-earnings ratios.

18.1 CAPITALIZATION OF INCOME METHOD OF VALUATION

There are many ways to implement the fundamental analysis approach to identifying mispriced securities. A number of them are either directly or indirectly related to what is sometimes referred to as the **capitalization of income method of valuation.**[1] This method states that the "true" or "intrinsic" value of any asset is based on the cash flows that the investor expects to receive in the future from owning the asset. Because these cash flows are expected in the future, they are adjusted by a **discount rate** to reflect not only the time value of money but also the riskiness of the cash flows.

Algebraically, the intrinsic value of the asset V is equal to the sum of the present values of the expected cash flows:

$$
\begin{aligned}
V &= \frac{C_1}{(1+k)^1} + \frac{C_2}{(1+k)^2} + \frac{C_3}{(1+k)^3} + \cdots \\
&= \sum_{t=1}^{\infty} \frac{C_t}{(1+k)^t} \qquad (18.1)
\end{aligned}
$$

where C_t denotes the expected cash flow associated with the asset at time t and k is the appropriate discount rate for cash flows of this degree of risk. In this equation the discount rate is assumed to be the same for all periods. Because the symbol ∞ above the summation sign in the equation denotes infinity, all expected cash flows, from immediately after making the investment until infinity, will be discounted at the same rate in determining V.[2]

18.1.1 Net Present Value

For the sake of convenience, let the current moment in time be denoted as zero, or $t = 0$. If the cost of purchasing an asset at $t = 0$ is P, then its **net present value** (NPV) is equal to the difference between its intrinsic value and cost, or:

$$
\begin{aligned}
\text{NPV} &= V - P \\
&= \left[\sum_{t=1}^{\infty} \frac{C_t}{(1+k)^t}\right] - P. \qquad (18.2)
\end{aligned}
$$

The NPV calculation shown here is conceptually the same as the NPV calculation made for capital budgeting decisions that has long been advocated in introductory finance textbooks. Capital budgeting decisions involve deciding whether or not a given investment project should be undertaken. (For example, should a new machine be purchased?) In making this decision, the focal point is the NPV of the project. Specifically, an investment project is viewed favorably if its NPV is positive, and unfavorably if its NPV is negative. For a simple project involving a cash outflow now (at $t = 0$) and expected cash inflows in the future, a positive NPV means that the present value of all the expected cash inflows is greater than the cost of making the investment. Conversely, a negative NPV means that the present value of all the expected cash inflows is less than the cost of making the investment.

The same views about NPV apply when financial assets (such as a share of common stock), instead of real assets (such as a new machine), are being considered for purchase. That is, a financial asset is viewed favorably and said to be underpriced (or undervalued) if NPV > 0. Conversely, a financial asset is viewed unfavorably and said to be overpriced or (overvalued) if NPV < 0. From Equation (18.2), this is equivalent to stating that a financial asset is underpriced if $V > P$:

$$
\sum_{t=1}^{\infty} \frac{C_t}{(1+k)^t} > P. \qquad (18.3)
$$

Conversely, the asset is overvalued if $V < P$:

$$\sum_{t=1}^{\infty} \frac{C_t}{(1+k)^t} < P.$$

18.1.2 Internal Rate of Return

Another way of making capital budgeting decisions in a manner that is similar to the NPV method involves calculating the **internal rate of return** (IRR) associated with the investment project. With IRR, NPV in Equation (18.2) is set equal to zero and the discount rate becomes the unknown that must be calculated. That is, the IRR for a given investment is the discount rate that makes the NPV of the investment equal to zero. Algebraically, the procedure involves solving the following equation for the internal rate of return k^*:

$$0 = \sum_{t=1}^{\infty} \frac{C_t}{(1+k^*)^t} - P. \tag{18.5}$$

Equivalently, Equation (18.5) can be rewritten as:

$$P = \sum_{t=1}^{\infty} \frac{C_t}{(1+k^*)^t}. \tag{18.6}$$

The decision rule for IRR involves comparing the project's IRR (denoted by k^*) with the required rate of return for an investment of similar risk (denoted by k). Specifically, the investment is viewed favorably if $k^* > k$, and unfavorably if $k^* < k$. As with NPV, the same decision rule applies if either a real asset or a financial asset is being considered for possible investment.[3]

18.1.3 Application to Common Stocks

This chapter is concerned with using the capitalization of income method to determine the intrinsic value of common stocks. Because the cash flows associated with an investment in any particular common stock are the dividends that are expected to be paid throughout the future on the shares purchased, the models suggested by this method of valuation are often known as **dividend discount models** (DDMs).[4] Accordingly, D_t will be used instead of C_t to denote the expected cash flow in period t associated with a particular common stock, resulting in the following restatement of Equation (18.1):

$$\begin{aligned} V &= \frac{D_1}{(1+k)^1} + \frac{D_2}{(1+k)^2} + \frac{D_3}{(1+k)^3} + \cdots \\ &= \sum_{t=1}^{\infty} \frac{D_t}{(1+k)^t} \end{aligned} \tag{18.7}$$

Usually the focus of DDMs is on determining the "true" or "intrinsic" value of one share of a particular company's common stock, even if larger size purchases are being contemplated. This is because it is usually assumed that larger size purchases can be made at a cost that is a simple multiple of the cost of one share. (For example, the cost of 1,000 shares is usually assumed to be 1,000 times the cost of one share.) Thus the numerator in DDMs is the cash dividends per share that are expected in the future.

However, there is a complication in using Equation (18.7) to determine the intrinsic value of a share of common stock. In particular, in order to use this equation the investor must forecast *all* future dividends. Because a common stock does not have a fixed lifetime, this suggests that an infinitely long stream of dividends must be forecast. Although this may seem to be an impossible task, with the addition of certain assumptions, the equation can be made tractable (that is, usable).

These assumptions center on dividend growth rates. That is, the dividend per share at any time t can be viewed as being equal to the dividend per share at time $t - 1$ times a dividend growth rate of g_t,

$$D_t = D_{t-1}(1 + g_t) \tag{18.8}$$

or, equivalently:

$$\frac{D_t - D_{t-1}}{D_{t-1}} = g_t. \tag{18.9}$$

For example, if the dividend per share expected at $t = 2$ is \$4 and the dividend per share expected at $t = 3$ is \$4.20, then $g_3 = (\$4.20 - \$4)/\$4 = 5\%$.

The different types of tractable DDMs reflect different sets of assumptions about dividend growth rates, and are presented next. The discussion begins with the simplest case, the zero-growth model.

18.2 THE ZERO-GROWTH MODEL

One assumption that could be made about future dividends is that they will remain at a fixed dollar amount. That is, the dollar amount of dividends per share that were paid over the past year D_0 will also be paid over the next year D_1, and the year after that D_2, and the year after that D_3, and so on—that is,

$$D_0 = D_1 = D_2 = D_3 = \cdots = D_\infty.$$

This is equivalent to assuming that all the dividend growth rates are zero, because if $g_t = 0$, then $D_t = D_{t-1}$ in Equation (18.8). Accordingly, this model is often referred to as the **zero-growth** (or no-growth) **model.**

18.2.1 Net Present Value

The impact of this assumption on Equation (18.7) can be analyzed by noting what happens when D_t is replaced by D_0 in the numerator:

$$V = \sum_{t=1}^{\infty} \frac{D_0}{(1 + k)^t}. \tag{18.10}$$

Fortunately, Equation (18.10) can be simplified by noting that D_0 is a fi[xed dol]lar amount, which means that it can be written outside the summation sign:

$$V = D_0\left[\sum_{t=1}^{\infty} \frac{1}{(1+k)^t}\right]. \tag{18.11}$$

The next step involves using a property of infinite series from mathematics. If $k > 0$, then it can be shown that:

$$\sum_{t=1}^{\infty} \frac{1}{(1+k)^t} = \frac{1}{k}. \tag{18.12}$$

Applying this property to Equation (18.11) results in the following formula for the zero-growth model:

$$V = \frac{D_0}{k_0}. \tag{18.13}$$

Because $D_0 = D_1$, Equation (18.13) is written sometimes as:

$$V = \frac{D_1}{k}. \tag{18.14}$$

Example

As an example of how this DDM can be used, assume that the Zinc Company is expected to pay cash dividends amounting to \$8 per share into the indefinite future and has a required rate of return of 10%. Using either Equation (18.13) or Equation (18.14), it can be seen that the value of a share of Zinc stock is equal to \$80 (= \$8/.10). With a current stock price of \$65 per share, Equation (18.2) would suggest that the NPV per share is \$15 (= \$80 − \$65). Equivalently, as V = \$80 > P = \$65, the stock is underpriced by \$15 per share and would be a candidate for purchase.

18.2.2 Internal Rate of Return

Equation (18.13) can be reformulated to solve for the IRR on an investment in a zero-growth security. First, the security's current price P is substituted for V, and second, k^* is substituted for k. These changes result in:

$$P = \frac{D_0}{k^*}$$

which can be rewritten as:

$$k^* = \frac{D_0}{P} \tag{18.15a}$$

$$= \frac{D_1}{P}. \tag{18.15b}$$

Example

Applying this formula to the stock of Zinc indicates that $k^* = 12.3\%$ ($= \$8/\$65$). Because the IRR from an investment in Zinc exceeds the required rate of return on Zinc ($12.3\% > 10\%$), this method also indicates that Zinc is underpriced.[5]

18.2.3 Application

The zero-growth model may seem quite restrictive. After all, it seems unreasonable to assume that a given stock will pay a fixed dollar-size dividend forever. Although such a criticism has validity for common stock valuation, there is one particular situation where this model is quite useful.

Specifically, whenever the intrinsic value of a share of high-grade preferred stock is to be determined, the zero-growth DDM will often be appropriate. This is because most preferred stock is nonparticipating, meaning that it pays a fixed dollar-size dividend that will not change as earnings per share change. Furthermore, for high-grade preferred stock these dividends are expected to be paid regularly into the foreseeable future. Why? Because preferred stock does not have a fixed lifetime, and, by restricting the application of the zero growth model to high-grade preferred stocks, the chance of a suspension of dividends is remote.[6]

18.3 THE CONSTANT-GROWTH MODEL

The next type of DDM to be considered is one that assumes that dividends will grow from period to period at the same rate forever, and is therefore known as the **constant growth model.**[7] Specifically, the dividends per share that were paid over the previous year D_0 are expected to grow at a given rate g, so that the dividends expected over the next year D_1 are expected to be equal to $D_0(1+g)$. Dividends the year after that are again expected to grow by the same rate g, meaning that $D_2 = D_1(1+g)$. Because $D_1 = D_0(1+g)$, this is equivalent to assuming that $D_2 = D_0(1+g)^2$ and, in general:

$$D_t = D_{t-1}(1+g) \tag{18.16a}$$

$$= D_0(1+g)^t. \tag{18.16b}$$

18.3.1 Net Present Value

The impact of this assumption on Equation (18.7) can be analyzed by noting what happens when D_t is replaced by $D_0(1+g)^t$ in the numerator:

$$V = \sum_{t=1}^{\infty} \frac{D_0(1+g)^t}{(1+k)^t}. \tag{18.17}$$

Fortunately, Equation (18.17) can be simplified by noting that D_0 is a [illegible] lar amount, which means that it can be written outside the summation [illegible]

$$V = D_0\left[\sum_{t=1}^{\infty} \frac{(1+g)^t}{(1+k)^t}\right].$$

The next step involves using a property of infinite series from mathe[illegible] If $k > g$, then it can be shown that:

$$\sum_{t=1}^{\infty} \frac{(1+g)^t}{(1+k)^t} = \frac{1+g}{k-g}. \qquad (18.19)$$

Substituting Equation (18.19) into Equation (18.18) results in the valuation [illegible] mula for the constant-growth model:

$$V = D_0\left(\frac{1+g}{k-g}\right). \qquad (18.20)$$

Sometimes Equation (18.20) is rewritten as:

$$V = \frac{D_1}{k-g} \qquad (18.21)$$

because $D_1 = D_0(1 + g)$.

Example

As an example of how this DDM can be used, assume that during the past year the Copper Company paid dividends amounting to $1.80 per share. The forecast is that dividends on Copper stock will increase by 5% per year into the indefinite future. Thus dividends over the next year are expected to equal $1.89 [= $1.80 × (1 + .05)]. Using Equation (18.20) and assuming a required rate of return k of 11%, it can be seen that the value of a share of Copper stock is equal to $31.50 [= $1.80 × (1 + .05)/(.11 − .05) = $1.89/(.11 − .05)]. With a current stock price of $40 per share, Equation (18.2) would suggest that the NPV per share is −$8.50 (= $31.50 − $40). Equivalently, as V = $31.50 < P = $40, the stock is overpriced by $8.50 per share and would be a candidate for sale if currently owned.

18.3.2 Internal Rate of Return

Equation (18.20) can be reformulated to solve for the IRR on an investment in a constant-growth security. First, the current price of the security P is substituted for V and then k^* is substituted for k. These changes result in:

$$P = D_0\left(\frac{1+g}{k^*-g}\right). \qquad (18.22)$$

which can be rewritten as:

$$k^* = \frac{D_0(1 + g)}{P} + g \tag{18.23a}$$

$$= \frac{D_1}{P} + g. \tag{18.23b}$$

Example

Applying this formula to the stock of Copper indicates that $k^* = 9.72\%$ {= [\$1.80 × (1 + .05)/\$40] + .05 = (\$1.89/\$40) + .05}. Because the required rate of return on Copper exceeds the IRR from an investment in Copper (11% > 9.72%), this method also indicates that Copper is overpriced.

18.3.3 Relationship to the Zero-Growth Model

The zero-growth model of the previous section can be shown to be a special case of the constant-growth model. In particular, if the growth rate g is assumed to be equal to zero, then dividends will be a fixed dollar amount forever, which is the same as saying that there will be zero growth. Letting $g = 0$ in Equations (18.20) and (18.23a) results in two equations that are identical to Equations (18.13) and (18.15a), respectively.

Even though the assumption of constant dividend growth may seem less restrictive than the assumption of zero dividend growth, it may still be viewed as unrealistic in many cases. However, as will be shown next, the constant-growth model is important because it is embedded in the multiple-growth model.

18.4 THE MULTIPLE-GROWTH MODEL

A more general DDM for valuing common stocks is the **multiple-growth model.** With this model, the focus is on a time in the future (denoted by T) after which dividends are expected to grow at a constant rate g. Although the investor is still concerned with forecasting dividends, these dividends do not need to have any specific pattern until this time, after which they will be assumed to have the specific pattern of constant growth. The dividends up until T ($D_1, D_2, D_3, \ldots, D_T$) will be forecast individually by the investor. (The investor also forecasts when this time T will occur.) Thereafter dividends are assumed to grow by a constant rate g that the investor must also forecast, meaning that:

$$D_{T+1} = D_T(1 + g)$$
$$D_{T+2} = D_{T+1}(1 + g) = D_T(1 + g)^2$$
$$D_{T+3} = D_{T+2}(1 + g) = D_T(1 + g)^3$$

and so on. Figure 18.1 presents a time line of dividends and growth rates associated with the multiple-growth model.

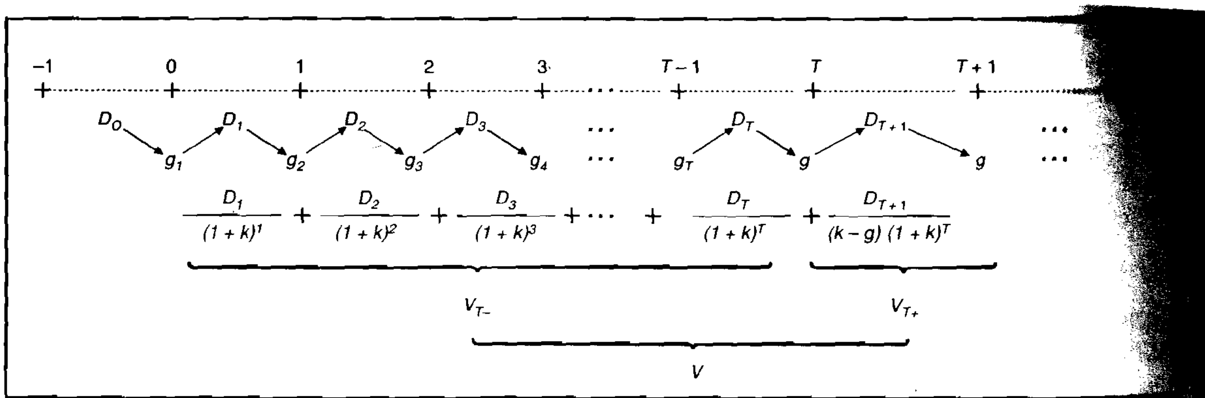


Figure 18.1
Time Line for Multiple-Growth Model

18.4.1 Net Present Value

In determining the value of a share of common stock with the multiple-growth model, the present value of the forecast stream of dividends must be determined. This can be done by dividing the stream into two parts, finding the present value of each part, and then adding these two present values together.

The first part consists of finding the present value of all the forecast dividends that will be paid up to and including time T. Denoting this present value by V_{T-}, it is equal to:

$$V_{T-} = \sum_{t=1}^{T} \frac{D_t}{(1 + k)^t}. \tag{18.24}$$

The second part consists of finding the present value of all the forecast dividends that will be paid after time T, and involves the application of the constant-growth model. The application begins by imagining that the investor is not at time zero but is at time T, and has not changed his or her forecast of dividends for the stock. This means that the next period's dividend D_{T+1} and all those thereafter are expected to grow at the rate g. Thus the investor would be viewing the stock as having a constant growth rate, and its value at time T, V_T, could be determined with the constant-growth model of Equation (18.21):

$$V_T = D_{T+1}\left(\frac{1}{k - g}\right). \tag{18.25}$$

One way to view V_T is that it represents a lump sum that is just as desirable as the stream of dividends after T. That is, an investor would find a lump sum of cash equal to V_T, to be received at time T, to be equally desirable as the stream of dividends D_{T+1}, D_{T+2}, D_{T+3}, and so on. Now given that the investor is at time zero, not at time T, the present value at $t = 0$ of the lump sum V_T must be determined. This is done simply by discounting it for T periods at the rate k, resulting in the following formula for finding the present value at time zero for all dividends after T, denoted V_{T+}:

$$V_{T+} = V_T\left[\frac{1}{(1+k)^T}\right] \tag{18.26}$$
$$= \frac{D_{T+1}}{(k-g)(1+k)^T}.$$

Having found the present value of all dividends up to and including time T with Equation (18.24), and the present value of all dividends after time T with Equation (18.26), the value of the stock can be determined by summing up these two amounts:

$$V = V_{T-} + V_{T+}$$
$$= \sum_{t=1}^{T} \frac{D_t}{(1+k)^t} + \frac{D_{T+1}}{(k-g)(1+k)^T}. \tag{18.27}$$

Figure 18.1 illustrates the valuation procedure for the multiple-growth DDM that is given in Equation (18.27).

Example

As an example of how this DDM can be used, assume that during the past year the Magnesium Company paid dividends amounting to $.75 per share. Over the next year, Magnesium is expected to [illegible] $D_0)/D_0 = (\$2 - \$.75)/\$.75 = 167\%$. The year after that, dividends are expected to amount to $3 per share, indicating that $g_2 = (D_2 - D_1)/D_1 = (\$3 - \$2)/\$2 = 50\%$. At this time, the forecast is that dividends will grow by 10% per year indefinitely, indicating that $T = 2$ and $g = 10\%$. Consequently, $D_{T+1} = D_3 = \$3(1 + .10) = \$3.30$. Given a required rate of return on Magnesium shares of 15%, the values of V_{T-} and V_{T+} can be calculated as follows:

$$V_{T-} = \frac{\$2}{(1+.15)^1} + \frac{\$3}{(1+.15)^2}$$
$$= \$4.01$$
$$V_{T+} = \frac{\$3.30}{(.15-.10)(1+.15)^2}$$
$$= \$49.91.$$

...ing V_{T-} and V_{T+} results in a value for V of $\$4.01 + \$49.91 = \$53.92$. With ...ent stock price of $55 per share, Magnesium appears to be fairly priced. ... Magnesium is not significantly mispriced because V and P are nearly of ...ze.

18.4.2 Internal Rate of Return

The zero-growth and constant-growth models have equations for V that reformulated in order to solve for the IRR on an investment in a stock. U nately, a convenient expression similar to Equations (18.15a), (18.15b), (1 and (18.23b) is not available for the multiple-growth model. This can be noting that the expression for IRR is derived by substituting P for V, and k^* in Equation (18.27):

$$P = \sum_{t=1}^{T} \frac{D_t}{(1 + k^*)^t} + \frac{D_{T+1}}{(k^* - g)(1 + k^*)^T}. \qquad (18.28)$$

This equation cannot be rewritten with k^* isolated on the left-hand side, meaning that a closed-form expression for IRR does not exist for the multiple-growth model.

However, all is not lost. It is still possible to calculate the IRR for an investment in a stock conforming to the multiple-growth model by using an "educated" trial-and-error method. The basis for this method is in the observation that the right-hand side of Equation (18.28) is simply equal to the present value of the dividend stream, where k^* is used as the discount rate. Hence the larger the value of k^*, the smaller the value of the right-hand side of Equation (18.28). The trial-and-error method proceeds by initially using an estimate for k^*. If the resulting value on the right-hand side of Equation (18.28) is larger than P, then a larger estimate of k^* is tried. Conversely, if the resulting value is smaller than P, then a smaller estimate of k^* is tried. Continuing this search process, the investor can hone in on the value of k^* that makes the right-hand side equal P on the left-hand side. Fortunately, it is a relatively simple matter to program a computer to conduct the search for k^* in Equation (18.28). Most spreadsheets include a function that does so automatically.

Example

Applying Equation (18.28) to the Magnesium Company results in:

$$\$55 = \frac{\$2}{(1 + k^*)^1} + \frac{\$3}{(1 + k^*)^2} + \frac{\$3.30}{(k^* - .10)(1 + k^*)^2}. \qquad (18.29)$$

Initially a rate of 14% is used in attempting to solve this equation for k^*. Inserting 14% for k^* in the right-hand side of Equation (18.29) results in a value of \$67.54. Earlier 15% was used in determining V and resulted in a value of \$53.92. This means that k^* must have a value between 14% and 15%, since \$55 is between \$67.54 and \$53.92. If 14.5% is tried next, the resulting value is \$59.97, suggesting that a higher rate should be tried. If 14.8% and 14.9% are subsequently tried, the respective resulting values are \$56.18 and \$55.03. As \$55.03 is the closest to P, the IRR associated with an investment in Magnesium is 14.9%. Given a required return of 15% and an IRR of approximately that amount, the stock of Magnesium appears to be fairly priced.

18.4.3 Relationship to the Constant-Growth Model

The constant-growth model can be shown to be a special case of the multiple-growth model. In particular, if the time when constant growth is assumed to begin is set equal to zero, then:

$$V_{T-} = \sum_{t=1}^{T} \frac{D_t}{(1+k)^t} = 0$$

and

$$V_{T+} = \frac{D_{T+1}}{(k-g)(1+k)^T} = \frac{D_1}{k-g}$$

because $T = 0$ and $(1 + k)^0 = 1$. Given that the multiple-growth model states that $V = V_{T-} + V_{T+}$, it can be seen that setting $T = 0$ results in $V = D_1/(k - g)$, a formula that is equivalent to the formula for the constant-growth model.

18.4.4 Two-Stage and Three-Stage Models

Two dividend discount models that investors sometimes use are the two-stage model and the three-stage model.[8] The two-stage model assumes that a constant growth rate g_1 exists only until some time T, when a different growth rate g_2 is assumed to begin and continue thereafter. The three-stage model assumes that a constant growth rate g_1 exists only until some time T_1, when a second growth rate is assumed to begin and last until a later time T_2, when a third growth rate is assumed to begin and last thereafter. By letting V_{T+} denote the present value of all dividends after the last growth rate has begun and V_{T-} the present value of all the preceding dividends, it can be seen that these models are just special cases of the multiple-growth model.

In applying the capitalization of income method of valuation to common stocks, it might seem appropriate to assume that the stock will be sold at some point in the future. In this case the expected cash flows would consist of the dividends up to that point as well as the expected selling price. Because dividends after the selling date would be ignored, the use of a dividend discount model may seem to be improper. However, as will be shown next, this is not so.

18.5 VALUATION BASED ON A FINITE HOLDING PERIOD

capitalization of income method of valuation involves discounting all dividends that are expected throughout the future. Because the simplified models growth, constant growth, and multiple growth are based on this method, involve a future stream of dividends. Upon reflection it may seem that models are relevant only for an investor who plans to hold a stock forever, such an investor would expect to receive this stream of future dividends.

But what about an investor who plans to sell the stock in a year?[9] In this situation, the cash flows that the investor expects to receive from purchasing a share of the stock are equal to the dividend expected to be paid one year from now (for ease of exposition, it is assumed that common stocks pay dividends annually) and the expected selling price of the stock. Thus it would seem appropriate to determine the intrinsic value of the stock to the investor by discounting these two cash flows at the required rate of return as follows:

$$
\begin{aligned}
V &= \frac{D_1 + P_1}{1 + k} \\
&= \frac{D_1}{1 + k} + \frac{P_1}{1 + k}
\end{aligned}
\tag{18.30}
$$

where D_1 and P_1 are the expected dividend and selling price at $t = 1$, respectively.

In order to use Equation (18.30), the expected price of the stock at $t = 1$ must be estimated. The simplest approach assumes that the selling price will be based on the dividends that are expected to be paid after the selling date. Thus the expected selling price at $t = 1$ is:

$$
\begin{aligned}
P_1 &= \frac{D_2}{(1 + k)^1} + \frac{D_3}{(1 + k)^2} + \frac{D_4}{(1 + k)^3} + \cdots \\
&= \sum_{t=2}^{\infty} \frac{D_t}{(1 + k)^{t-1}}.
\end{aligned}
\tag{18.31}
$$

Substituting Equation (18.31) for P_1 in the right-hand side of Equation (18.30) results in:

$$
\begin{aligned}
V &= \frac{D_1}{1 + k} + \left[\frac{D_2}{(1 + k)^1} + \frac{D_3}{(1 + k)^2} + \frac{D_4}{(1 + k)^3} + \cdots\right]\left(\frac{1}{1 + k}\right) \\
&= \frac{D_1}{(1 + k)^1} + \frac{D_2}{(1 + k)^2} + \frac{D_3}{(1 + k)^3} + \frac{D_4}{(1 + k)^4} + \cdots \\
&= \sum_{t=1}^{\infty} \frac{D_t}{(1 + k)^t}
\end{aligned}
$$

which is exactly the same as Equation (18.7). Thus valuing a share of common stock by discounting its dividends up to some point in the future and its expected selling price at that time is equivalent to valuing stock by discounting all future dividends. Simply stated, the two are equivalent because the expected selling price is itself based on dividends to be paid after the selling date. Thus Equation (18.7), as well as the zero-growth, constant-growth, and multiple-growth models that are based on it, is appropriate for determining the intrinsic value of a share of common stock regardless of the length of the investor's planned holding period.

Example

As an example, reconsider the common stock of the Copper Company. Over the past year it was noted that Copper paid dividends of $1.80 per share, with the forecast that the dividends would grow by 5% per year forever. This means that dividends over the next two years (D_1 and D_2) are forecast to be \$1.89 [= \$1.80 × (1 + .05)] and \$1.985 [= \$1.89 × (1 + .05)], respectively. If the investor plans to sell the stock after one year, the selling price could be estimated by noting that at $t = 1$, the forecast of dividends for the forthcoming year would be D_2, or \$1.985. Thus the anticipated selling price at $t = 1$, denoted P_1, would be equal to \$33.08 [= \$1.985/(.11 − .05)]. Accordingly, the intrinsic value of Copper to such an investor would equal the present value of the expected cash flows, which are D_1 = \$1.89 and P_1 = \$33.08. Using Equation (18.30) and assuming a required rate of 11%, this value is equal to \$31.50 [= (\$1.89 + \$33.08)/(1 + .11)]. Note that this is the same amount that was calculated earlier when all the dividends from now to infinity were discounted using the constant-growth model: $V = D_1/(k - g)$ = \$1.89/(.11 − .05) = \$31.50.

18.6 MODELS BASED ON PRICE-EARNINGS RATIOS

Despite the inherent sensibility of DDMs, many security analysts use a much simpler procedure to value common stocks. First, a stock's earnings per share over the forthcoming year E_1 are estimated, and then the analyst (or someone else) specifies a "normal" **price-earnings ratio** for the stock. The product of these two numbers gives the estimated future price P_1. Together with estimated dividends D_1 to be paid during the period and the current price P, the estimated return on the stock over the period can be determined:

$$\text{Expected return} = \frac{(P_1 - P) + D_1}{P} \tag{18.32}$$

where $P_1 = (P_1/E_1) \times E_1$.

Some security analysts expand this procedure, estimating earnings per share and price-earnings ratios for optimistic, most likely, and pessimistic scenarios to produce a rudimentary probability distribution of a security's return. Other analysts determine whether a stock is underpriced or overpriced by comparing the stock's actual price-earnings ratio with its "normal" price-earnings ratio, as will be shown next.[10]

In order to make this comparison, Equation (18.7) must be rearranged and some new variables introduced. To begin, it should be noted that earnings per share E_t are related to dividends per share D_t by the firm's **payout ratio** p_t,

$$D_t = p_t E_t. \tag{18.33}$$

...more, if an analyst has forecast earnings-per-share and payout ratios, ...she has implicitly forecast dividends.

...ion (18.33) can be used to restate the various DDMs where the focus is ...ing what the stock's price-earnings ratio should be instead of on esti-... intrinsic value of the stock. In order to do so, $p_t E_t$ is substituted for D_t

in the right-hand side of Equation (18.7), resulting in a general formula for determining a stock's intrinsic value that involves discounting earnings:

$$V = \frac{D_1}{(1+k)^1} + \frac{D_2}{(1+k)^2} + \frac{D_3}{(1+k)^3} + \cdots$$
$$= \frac{p_1E_1}{(1+k)^1} + \frac{p_2E_2}{(1+k)^2} + \frac{p_3E_3}{(1+k)^3} + \cdots$$
$$= \sum_{t=1}^{\infty} \frac{p_tE_t}{(1+k)^t}. \tag{18.34}$$

Earlier it was noted that dividends in adjacent time periods could be viewed as being "linked" to each other by a dividend growth rate g_t. Similarly, earnings per share in any year t can be "linked" to earnings per share in the previous year $t - 1$ by a growth rate in earnings per share, g_{et},

$$E_t = E_{t-1}(1 + g_{et}). \tag{18.35}$$

This implies that

$$E_1 = E_0(1 + g_{e1})$$
$$E_2 = E_1(1 + g_{e2}) = E_0(1 + g_{e1})(1 + g_{e2})$$
$$E_3 = E_2(1 + g_{e3}) = E_0(1 + g_{e1})(1 + g_{e2})(1 + g_{e3})$$

and so on, where E_0 is the actual level of earnings per share over the past year, E_1 is the expected level of earnings per share over the forthcoming year, E_2 is the expected level of earnings per share for the year after E_1, and E_3 is the expected level of earnings per share for the year after E_2.

These equations relating expected future earnings per share to E_0 can be substituted into Equation (18.34), resulting in:

$$V = \frac{p_1[E_0(1 + g_{e1})]}{(1+k)^1} + \frac{p_2[E_0(1 + g_{e1})(1 + g_{e2})]}{(1+k)^2} + \frac{p_3[E_0(1 + g_{e1})(1 + g_{e2})(1 + g_{e3})]}{(1+k)^3} + \cdots. \tag{18.36}$$

As V is the intrinsic value of a share of stock, it represents what the stock would be selling for if it were fairly priced. It follows that V/E_0 represents what the price-earnings ratio would be if the stock were fairly priced, and is sometimes referred to as the stock's "normal" price-earnings ratio. Dividing both sides of Equation (18.36) by E_0 and simplifying results in the formula for determining the "normal" price-earnings ratio:

$$\frac{V}{E_0} = \frac{p_1(1 + g_{e1})}{(1+k)^1} + \frac{p_2(1 + g_{e1})(1 + g_{e2})}{(1+k)^2} + \frac{p_3(1 + g_{e1})(1 + g_{e2})(1 + g_{e3})}{(1+k)^3} + \cdots. \tag{18.37}$$

This shows that, other things being equal, a stock's "normal" price-earnings ratio will be higher:

The *greater* the expected payout ratios ($p_1, p_2, p_3, \ldots$),
The *greater* the expected growth rates in earnings per share ($g_{e1}, g_{e2}, g_{e3}, \ldots$),
The *smaller* the required rate of return (k).

The qualifying phrase "other things being equal" should not be overlooked. For example, a firm cannot increase the value of its shares by simply making greater payouts. This will increase $p_1, p_2, p_3, \ldots$, but will decrease the expected growth rates in earnings per share $g_{e1}, g_{e2}, g_{e3}, \ldots$. Assuming that the firm's investment policy is not altered, the effects of the reduced growth in its earnings per share will just offset the effects of the increased payouts, leaving its share value unchanged.

Earlier it was noted that a stock was viewed as underpriced if $V > P$ and overpriced if $V < P$. Because dividing both sides of an inequality by a positive constant will not change the direction of the inequality, such a division can be done here to the two inequalities involving V and P, where the positive constant is E_0. The result is that a stock can be viewed as being underpriced if $V/E_0 > P/E_0$ and overpriced if $V/E_0 < P/E_0$. Thus a stock will be underpriced if its "normal" price-earnings ratio is greater than its actual price-earnings ratio, and overpriced if its "normal" price-earnings ratio is less than its actual price-earnings ratio.

Unfortunately, Equation (18.37) is intractable, meaning that it cannot be used to estimate the "normal" price-earnings ratio for any stock. However, simplifying assumptions can be made that result in tractable formulas for estimating "normal" price-earnings ratios. These assumptions, along with the formulas, parallel those made previously regarding dividends and are discussed next.

18.6.1 The Zero-Growth Model

The zero-growth model assumed that dividends per share remained at a fixed dollar amount forever. This is most likely if earnings per share remain at a fixed dollar amount forever, with the firm maintaining a 100% payout ratio. Why 100%? Because if a lesser amount were assumed to be paid out, it would mean that the firm was retaining part of its earnings. These retained earnings would be put to some use, and would thus be expected to increase future earnings and hence dividends per share.

Accordingly, the zero-growth model can be interpreted as assuming $p_t = 1$ for all time periods and $E_0 = E_1 = E_2 = E_3$ and so on. This means that $D_0 = E_0$ and $D_1 = E_1 = D_2 = E_2$ and so on, allowing valuation Equation (18.13) to be restated as:

$$V = \frac{E_0}{k}. \tag{18.38}$$

Dividing Equation (18.38) by E_0 results in the formula for the "normal" price-earnings ratio for a stock having zero growth:

$$\frac{V}{E_0} = \frac{1}{k}. \tag{18.39}$$

Example

Earlier it was assumed that the Zinc Company was a zero-growth firm idends of $8 per share, selling for $65 a share, and having a required turn of 10%. Because Zinc is a zero-growth company, it will be assum has a 100% payout ratio which, in turn, means that E_0 = $8. At this po tion (18.38) can be used to note that a "normal" price-earnings ratio for $1/.10 = 10$. As Zinc has an actual price-earnings ratio of $65/$8 = 8.1, cause $V/E_0 = 10 > P/E_0 = 8.1$, it can be seen that Zinc stock is underpric

18.6.2 The Constant-Growth Model

Earlier it was noted that dividends in adjacent time periods could be viewed being connected to each other by a dividend growth rate g_t. Similarly, it was noted that earnings per share can be connected by an earnings growth rate g_e. The constant-growth model assumes that the growth rate in dividends per share will be the same throughout the future. An equivalent assumption is that earnings per share will grow at a constant rate g_e throughout the future, with the payout ratio remaining at a constant level p. This means that:

$$
\begin{aligned}
E_1 &= E_0(1 + g_e) = E_0(1 + g_e)^1 \\
E_2 &= E_1(1 + g_e) = E_0(1 + g_e)(1 + g_e) = E_0(1 + g_e)^2 \\
E_3 &= E_2(1 + g_e) = E_0(1 + g_e)(1 + g_e)(1 + g_e) = E_0(1 + g_e)^3
\end{aligned}
$$

and so on. In general, earnings in year t can be connected to E_0 as follows:

$$E_t = E_0(1 + g_e)^t. \tag{18.40}$$

Substituting Equation (18.40) into the numerator of Equation (18.34) and recognizing that $p_t = p$ results in:

$$
\begin{aligned}
V &= \sum_{t=1}^{\infty} \frac{pE_0(1 + g_e)^t}{(1 + k)^t} \\
&= pE_0\left[\sum_{t=1}^{\infty} \frac{(1 + g_e)^t}{(1 + k)^t}\right].
\end{aligned} \tag{18.41}
$$

The same mathematical property of infinite series given in Equation (18.19) can be applied to Equation (18.41), resulting in:

$$V = pE_0\left(\frac{1 + g_e}{k - g_e}\right). \tag{18.42}$$

It can be noted that the earnings-based constant-growth model has a numerator that is identical to the numerator of the dividend-based constant-growth model, because $pE_0 = D_0$. Furthermore, the denominators of the two models are identical. Both assertions require that the growth rates in earnings and dividends be the same (that is, $g_e = g$). Examination of the assumptions of the models reveals that these growth rates must be equal. This can be seen by recalling that constant earnings growth means:

$$E_t = E_{t-1}(1 + g_e).$$

Now when both sides of this equation are multiplied by the constant payout ratio, the result is:

$$pE_t = pE_{t-1}(1 + g_e).$$

Because $pE_t = D_t$ and $pE_{t-1} = D_{t-1}$, this equation reduces to:

$$D_t = D_{t-1}(1 + g_e)$$

which indicates that dividends in any period $t - 1$ will grow by the earnings growth rate, g_e. Because the dividend-based constant-growth model assumed that dividends in any period $t - 1$ would grow by the dividend growth rate g, it can be seen that the two growth rates must be equal for the two models to be equivalent.

Equation (18.42) can be restated by dividing each side by E_0, resulting in the following formula for determining the "normal" price-earnings ratio for a stock with constant growth:

$$\frac{V}{E_0} = p\left(\frac{1 + g_e}{k + g_e}\right). \tag{18.43}$$

Example

Earlier it was assumed that the Copper Company had paid dividends of \$1.80 per share over the past year, with a forecast that dividends would grow by 5% per year forever. Furthermore, it was assumed that the required rate of return on Copper was 11%, and the current stock price was \$40 per share. Now assuming that E_0 was \$2.70, it can be seen that the payout ratio was equal to 66⅔% (= \$1.80/\$2.70). This means that the "normal" price-earnings ratio for Copper, according to Equation (18.43), is equal to 11.7 [= .6667 × (1 + .05) /(.11 −.05)]. Because this is less than Copper's actual price-earnings ratio of 14.8 (= \$40/\$2.70), it follows that the stock of Copper Company is overpriced.

18.6.3 The Multiple-Growth Model

Earlier it was noted that the most general DDM is the multiple-growth model, where dividends are allowed to grow at varying rates until some point in time T, after which they are assumed to grow at a constant rate. In this situation the present value of all the dividends is found by adding the present value of all dividends up to and including T, denoted by V_{T-}, and the present value of all dividends after T, denoted by V_{T+}:

$$\begin{aligned} V &= V_{T-} + V_{T+} \\ &= \sum_{t=1}^{T} \frac{D_t}{(1 + k)^t} + \frac{D_{T+1}}{(k - g)(1 + k)^T}. \end{aligned} \tag{18.27}$$

In general, earnings per share in any period t can be expressed as equal to E_0 times the product of all the earnings growth rates from time zero to time t:

$$E_t = E_0(1 + g_{e1})(1 + g_{e2}) \cdots (1 + g_{et}). \tag{18.44}$$

Because dividends per share in any period t are equal to the payout ratio for that period times the earnings per share, it follows from Equation (18.44) that:

$$\begin{aligned} D_t &= p_t E_t \\ &= p_t E_0(1 + g_{e1})(1 + g_{e2}) \cdots (1 + g_{et}). \end{aligned} \tag{18.45}$$

Replacing the numerator in Equation (18.37) with the right-hand side of Equation (18.45) and then dividing both sides by E_0 gives the following formula for determining a stock's "normal" price-earnings ratio with the multiple-growth model:

$$\begin{aligned} \frac{V}{E_0} &= \frac{p_1(1 + g_{e1})}{(1 + k)^1} + \frac{p_2(1 + g_{e1})(1 + g_{e2})}{(1 + k)^2} + \cdots \\ &+ \frac{p_T(1 + g_{e1})(1 + g_{e2}) \cdots (1 + g_{eT})}{(1 + k)^T} \\ &+ \frac{p(1 + g_{e1})(1 + g_{e2}) \cdots (1 + g_{eT})(1 + g)}{(k - g)(1 + k)^T}. \end{aligned} \tag{18.46}$$

Example

Consider the Magnesium Company again. Its share price is currently \$55, and per share earnings and dividends over the past year were \$3 and \$.75, respectively. For the next two years, forecast earnings and dividends, along with the earnings growth rates and payout ratios, are:

$$\begin{array}{llll} D_1 = \$2.00 & E_1 = \$5.00 & g_{e1} = 67\% & p_1 = 40\% \\ D_2 = \$3.00 & E_2 = \$6.00 & g_{e2} = 20\% & p_2 = 50\%. \end{array}$$

Constant growth in dividends and earnings of 10% per year is forecast to begin at $T = 2$, which means that $D_3 = \$3.30$, $E_3 = \$6.60$, $g = 10\%$, and $p = 50\%$.

Given a required return of 15%, Equation (18.46) can be used as follows to estimate a "normal" price-earnings ratio for Magnesium:

$$\begin{aligned} \frac{V}{E_0} &= \frac{.40(1 + .67)}{(1 + .15)^1} + \frac{.50(1 + .67)(1 + .20)}{(1 + .15)^2} + \frac{.50(1 + .67)(1 + .20)(1 + .10)}{(.15 - .10)(1 + .15)^2} \\ &= .58 + .76 + 16.67 \\ &= 18.01. \end{aligned}$$

Because the actual price-earnings ratio of 18.33 (= \$55/\$3) is close to the "normal" ratio of 18.01, the stock of the Magnesium Company can be viewed as fairly priced.

18.7 SOURCES OF EARNINGS GROWTH

So far no explanation has been given as to why earnings or dividends will be expected to grow in the future. One way of providing such an explanation uses the constant-growth model. Assuming that no new capital is obtained externally and no shares are repurchased (meaning that the number of shares outstanding does not increase or decrease), the portion of earnings not paid to stockholders as dividends will be used to pay for the firm's new investments. Given that p_t denotes the payout ratio in year t, then $(1 - p_t)$ will be equal to the portion of earnings not paid out, known as the **retention ratio.** Furthermore, the firm's new investments, stated on a per-share basis and denoted by I_t, will be:

$$I_t = (1 - p_t)E_t. \tag{18.47}$$

If these new investments have an average return on equity of r_t in period t and every year thereafter, they will add r_tI_t to earnings per share in year $t + 1$ and every year thereafter. If all previous investments also produce perpetual earnings at a constant rate of return, next year's earnings will equal this year's earnings plus the new earnings resulting from this year's new investments:

$$\begin{aligned} E_{t+1} &= E_t + r_tI_t \\ &= E_t + r_t(1 - p_t)E_t \\ &= E_t[1 + r_t(1 - p_t)]. \end{aligned} \tag{18.48}$$

Because it was shown earlier that the growth rate in earnings per share is:

$$E_t = E_{t-1}(1 + g_{et}) \tag{18.35}$$

it follows that:

$$E_{t+1} = E_t(1 + g_{et+1}). \tag{18.49}$$

A comparison of Equations (18.48) and (18.49) indicates that:

$$g_{et+1} = r_t(1 - p_t). \tag{18.50}$$

If the growth rate in earnings per share g_{et+1} is to be constant over time, then the average return on equity for new investments r_t and the payout ratio p_t must also be constant over time. In this situation Equation (18.50) can be simplified by removing the time subscripts:

$$g_e = r(1 - p). \tag{18.51a}$$

Because the growth rate in dividends per share g is equal to the growth rate in earnings per share g_e, this equation can be rewritten as:

$$g = r(1 - p). \tag{18.51b}$$

From this equation it can be seen that the growth rate g depends on (1) the proportion of earnings that is retained $1 - p$, and (2) the average return on equity on the earnings that are retained r.

The constant-growth valuation formula given in Equation (18.20) can be modified by replacing g with the expression on the right-hand side of Equation (18.51b), resulting in:

$$V = D_0\left(\frac{1+g}{k-g}\right)$$

$$= D_0\left[\frac{1+r(1-p)}{k-r(1-p)}\right].$$

$$= D_1\left[\frac{1}{k-r(1-p)}\right].$$

Under these assumptions, a stock's value (and hence its price) should be greater, the greater its average return on equity for new investments, other things being equal.

Example

Continuing with the Copper Company, recall that $E_0 = \$2.70$ and $p = 66\frac{2}{3}\%$. This means that $33\frac{1}{3}\%$ of earnings per share over the past year were retained and reinvested, an amount equal to \$.90 (= .3333 × \$2.70). The earnings per share in the forthcoming year E_1 are expected to be \$2.835 [= \$2.70 × (1 + .05)] because the growth rate g for Copper is 5%.

The source of the increase in earnings per share of \$.135 (= \$2.835 − \$2.70) is the \$.90 per share that was reinvested at $t = 0$. The average return on equity for new investments r is 15%, because \$.135/\$.90 = 15%. That is, the reinvested earnings of \$.90 per share can be viewed as having generated an annual increase in earnings per share of \$.135. This increase will occur not only at $t = 1$, but also at $t = 2$, $t = 3$, and so on. Equivalently, a \$.90 investment at $t = 0$ will generate a perpetual annual cash inflow of \$.135 beginning at $t = 1$.

Expected dividends at $t = 1$ can be calculated by multiplying the expected payout ratio p of $66\frac{2}{3}\%$ times the expected earnings per share E_1 of \$2.835, or .6667 × \$2.835 = \$1.89. It can also be calculated by multiplying 1 plus the growth rate g of 5% times the past amount of dividends per share D_0 of \$1.80, or 1.05 × \$1.80 = \$1.89.

It can be seen that the growth rate in dividends per share of 5% is equal to the product of the retention rate ($33\frac{1}{3}\%$) and the average return on equity for new investments (15%), an amount equal to 5% (= .3333 × .15).

Two years from now ($t = 2$), earnings per share are anticipated to be \$2.977 [= \$2.835 × (1 + .05)], a further increase of \$.142 (= \$2.977 − \$2.835) that is due to the retention and reinvestment of \$.945 (= .3333 × \$2.835) per share at $t = 1$. This expected increase in earnings per share of \$.142 is the result of earning (15%) on the reinvestment (\$.945), because .15 × \$.945 = \$.142.

The expected earnings per share at $t = 2$ can be viewed as having three components. The first is the earnings attributable to the assets held at $t = 0$, an amount equal to \$2.70. The second is the earnings attributable to the reinvestment of \$.90 at $t = 0$, earning \$.135. The third is the earnings attributable to the reinvestment of \$.945 at $t = 1$, earning \$.142. These three components, when summed, can be seen to equal E_2 = \$2.977 (= \$2.70 + \$.135 + \$.142).

Dividends at $t = 2$ are expected to be 5% larger than at $t = 1$, or \$1.985 (= 1.05 × \$1.89) per share. This amount corresponds to the amount calculated by multiplying the payout ratio times the expected earnings per share at $t = 2$, or \$1.985 (= .6667 × \$2.977). Figure 18.2 summarizes the example.

−1		0		1		2	→∞
	E_0 = $2.70		$2.700		$2.700		...
		$.90 x .15 =	.135		.135		...
		E_1 =	$2.835	$.945 x .15 =	.142		...
				E_2 =	$2.977		...
I_0 =	$ .90	I_1 =	$ .945	I_2 =	$ .992		...
D_0 =	1.80	D_1 =	1.890	D_2 =	1.985		...
E_0 =	$2.70	E_1 =	$2.835	E_2 =	$2.977		...

Figure 18.2
Growth in Earnings for Copper Company

18.8 A THREE-STAGE DDM

As this chapter's Institutional Issues discusses, the three-stage DDM is the most widely applied form of the general multiple-growth DDM. Consider analyzing the *ABC* Company.

18.8.1 Making Forecasts

Over the past year, *ABC* has had earnings per share of $1.67 and dividends per share of $.40. After carefully studying ABC, the security analyst has made the following forecasts of earnings per share and dividends per share for the next five years:

$E_1 = \$2.67 \quad E_2 = \$4.00 \quad E_3 = \$6.00 \quad E_4 = \$8.00 \quad E_5 = \$10.00$
$D_1 = \$\ .60 \quad D_2 = \$1.60 \quad D_3 = \$2.40 \quad D_4 = \$3.20 \quad D_5 = \$\ 5.00.$

These forecasts imply the following payout ratios and earnings-per-share growth rates:

$p_1 = 22\% \quad p_2 = 40\% \quad p_3 = 40\% \quad p_4 = 40\% \quad p_5 = 50\%$
$g_{e1} = 60\% \quad g_{e2} = 50\% \quad g_{e3} = 50\% \quad g_{e4} = 33\% \quad g_{e5} = 25\%.$

Furthermore, the analyst believes that *ABC* will enter a transition stage at the end of the fifth year (that is, the sixth year will be the first year of the transition stage), and that the transition stage will last three years. Earnings per share and payout ratio for year 6 are forecast to be E_6 = $11.90 and p_6 = 55%. {Thus g_{e6} = 19% [= ($11.90 − $10.00)/$10.00] and D_6 = $6.55 (= .55 × $11.90)}.

The last stage, known as the maturity stage, is forecast to have an earnings-per-share growth rate of 4% and a payout ratio of 70%. Now it was shown in equation (18.51b) that with the constant-growth model, $g = r(1 - p)$, where r is the average return on equity for new investment and p is the payout ratio. Given

Applying Dividend Discount Models

Over the last 30 years, dividend discount models (DDMs) have achieved broad acceptance among professional common stock investors. Although few investment managers rely solely on DDMs to select stocks, many have integrated DDMs into their security valuation procedures.

The reasons for the popularity of DDMs are twofold. First, DDMs are based on a simple, widely understood concept: The fair value of any security should equal the discounted value of the cash flows expected to be produced by that security. Second, the basic inputs for DDMs are standard outputs for many large investment management firms—that is, these firms employ security analysts who are responsible for projecting corporate earnings.

Valuing common stocks with a DDM technically requires an estimate of future dividends over an infinite time horizon. Given that accurately forecasting dividends three years from today, let alone 20 years in the future, is a difficult proposition, how do investment firms actually go about implementing DDMs?

One approach is to use constant or two-stage dividend growth models, as described in the text. However, although such models are relatively easy to apply, institutional investors typically view the assumed dividend growth assumptions as overly simplistic. Instead, these investors generally prefer three-stage models, believing that they provide the best combination of realism and ease of application.

Whereas many variations of the three-stage DDM exist, in general, the model is based on the assumption that companies evolve through three stages during their lifetimes. (Figure 18.3 portrays these stages.)

1. **Growth stage:** Characterized by rapidly expanding sales, high profit margins, and abnormally high growth in earnings per share. Because of highly profitable expected investment opportunities, the payout ratio is low. Competitors are attracted by the unusually high earnings, leading to a decline in the growth rate.
2. **Transition stage:** In later years, increased competition reduces profit margins and earnings growth slows. With fewer new investment opportunities, the company begins to pay out a larger percentage of earnings.

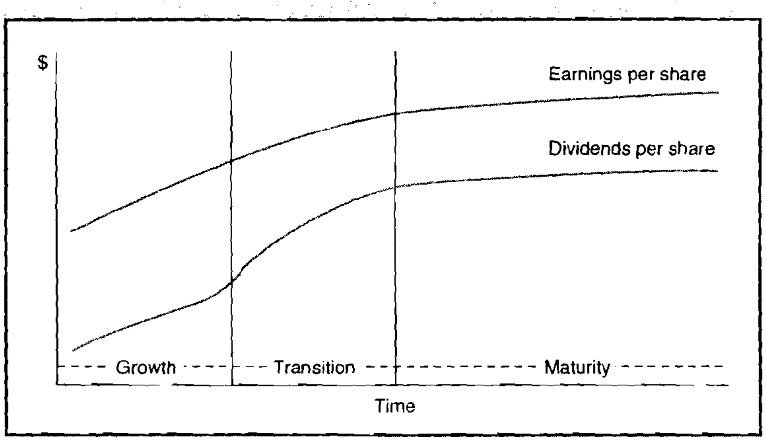


Figure 18.3
The Three Stages of the Multiple-Growth Model
Source: Adapted from Carmine J. Grigoli, "Demystifying Dividend Discount Models," *Merrill Lynch Quantitative Research*, April 1982.

3. **Maturity (steady-state) stage:** Eventually the company reaches a position where its new investment opportunities offer, on average, only slightly attractive returns on equity. At that time its earnings growth rate, payout ratio, and return on equity stabilize for the remainder of its life.

The forecasting process of the three-stage DDM involves specifying earnings and dividend growth rates in each of the three stages. Although one cannot expect a security analyst to be omniscient in his or her growth forecast for a particular company, one can hope that the forecast pattern of growth—in terms of magnitude and duration—resembles that actually realized by the company, particularly in the short run.

Investment firms attempt to structure their DDMs to make maximum use of their analysts' forecasting capabilities. Thus the models emphasize specific forecasts in the near term, when it is realistic to expect security analysts to project earnings and dividends more accurately. Conversely, the models emphasize more general forecasts over the longer term, when distinctions between companies' growth rates become less discernible. Typically, analysts are required to supply the following for their assigned companies:

1. expected annual earnings and dividends for the next several years;
2. after these specific annual forecasts end, earnings growth and the payout ratio forecasts until the end of the growth stage;
3. the number of years until the transition stage is reached;
4. the duration (in years) of the transition stage—that is, once abnormally high growth ends, the number of years until the maturity stage is reached.

Most three-stage DDMs assume that during the transition stage, earnings growth declines and payout ratios rise linearly to the maturity-stage steady-state levels. (For example, if the transition stage is ten years long, earnings growth at the maturity stage is 5% per year, and earnings growth at the end of the growth stage is 25%, then earnings growth will decline 2% in each year of the transition stage.) Finally, most three-stage DDMs make standard assumptions that all companies in the maturity stage have the same growth rates, payout ratios, and return on equity.

With analysts' inputs, plus an appropriate required rate of return for each security, all the necessary information for the three-stage DDM is available. The last step involves merely calculating the discounted value of the estimated dividends to determine the stock's "fair" value.

The seeming simplicity of the three-stage DDM should not lead one to believe that it is without its implementation problems. Investment firms must strive to achieve consistency across their analysts' forecasts. The long-term nature of the estimates involved, the substantial training required to make even short-term earnings forecasts accurately, and the coordination of a number of analysts covering many companies severely complicate the problem. Considerable discipline is required if the DDM valuations generated by a firm's analysts are to be sufficiently comparable and reliable to guide investment decisions. Despite these complexities, if successfully implemented, DDMs can combine the creative insights of security analysts with the rigor and discipline of quantitative investment techniques.

that the maturity stage has constant growth, this equation can be reformulated and used to determine r:

$$r = g/(1 - p).$$

Thus r for *ABC* has an implied value of 13.33% [$= 4\%/(100\% - 70\%)$], which is assumed to be consistent with the long-run growth forecasts for similar companies.

At this point there are only two missing pieces of information that are needed to determine the value of *ABC*—the earnings-per-share growth rates and the payout ratios for the transition stage. Taking earnings per share first, forecast that $g_{e6} = 19\%$ and $g_{e9} = 4\%$. One method of determining how "decay" to 4% is to note that there are three years between the sixth and years, and 15% between 19% and 4%. A "linear decay" rate would be determined by noting that 15%/3 years = 5% per year. This rate of 5% would be subtracted from 19% to get g_{e7}, resulting in 14% (= 19% − 5%). Then it would be subtracted from 14% to get g_{e8}, resulting in 9% (= 14% − 5%). Finally, as a check, be noted that 4% (= 9% − 5%) is the value that was forecast for g_{e9}.

A similar procedure can be used to determine how the payout ratio of in year 6 will grow to 70% in year 9. The "linear growth" rate will be (70% − 55%)/3 years = 15%/3 years = 5% per year, indicating that p_7 = 60% (= 55% + 5%) and p_8 = 65% (= 60% + 5%). Again a check indicates that 70% (= 65% + 5%) is the value that was forecast for p_9.

With these forecasts of earnings-per-share growth rates and payout ratios in hand, forecasts of dividends per share can now be made:

$$
\begin{aligned}
D_7 &= p_7E_7 \\
&= p_7E_6(1 + g_{e7}) \\
&= .60 \times \$11.90 \times (1 + .14) \\
&= .60 \times \$13.57 \\
&= \$8.14 \\
D_8 &= p_8E_8 \\
&= p_8E_6(1 + g_{e7})(1 + g_{e8}) \\
&= .65 \times \$11.90 \times (1 + .14) \times (1 + .09) \\
&= .65 \times \$14.79 \\
&= \$9.61 \\
D_9 &= p_9E_9 \\
&= p_9E_6(1 + g_{e7})(1 + g_{e8})(1 + g_{e9}) \\
&= .70 \times \$11.90 \times (1 + .14) \times (1 + .09) \times (1 + .04) \\
&= .70 \times \$15.38 \\
&= \$10.76.
\end{aligned}
$$

18.8.2 Estimating the Intrinsic Value

Given a required rate of return on *ABC* of 12.4%, all the necessary inputs for the multiple-growth model have been determined. Hence it is now possible to estimate *ABC*'s intrinsic (or fair) value. To begin, it can be seen that $T = 8$, indicating that V_{T-} involves determining the present value of D_1 through D_8,

$$
\begin{aligned}
V_{T-} &= \left[\frac{\$.60}{(1 + .124)^1}\right] + \left[\frac{\$1.60}{(1 + .124)^2}\right] + \left[\frac{\$2.40}{(1 + .124)^3}\right] \\
&+ \left[\frac{\$3.20}{(1 + .124)^4}\right] + \left[\frac{\$5.00}{(1 + .124)^5}\right] + \left[\frac{\$6.55}{(1 + .124)^6}\right] \\
&+ \left[\frac{\$8.14}{(1 + .124)^7}\right] + \left[\frac{\$9.61}{(1 + .124)^8}\right] \\
&= \$18.89.
\end{aligned}
$$

Then V_{T+} can be determined using D_9:

$$V_{T+} = \frac{\$10.76}{(.124 - .04)(1 + .124)^8}$$
$$= \$50.28.$$

Combining V_{T-} and V_{T+} results in the intrinsic value of *ABC:*

$$\begin{aligned} V &= V_{T-} + V_{T+} \\ &= \$18.89 + \$50.28 \\ &= \$69.17. \end{aligned}$$

Given a current market price for *ABC* of \$50, it can be seen that its stock is underpriced by \$19.17 (= \$69.17 − \$50) per share. Equivalently, it can be noted that the actual price-earnings ratio for *ABC* is 29.9 (= \$50/\$1.67) but that a "normal" price-earnings ratio would be higher, equal to 41.4 (= \$69.17/\$1.67), again indicating that *ABC* is underpriced.

18.8.3 Implied Returns

As shown with the previous example, once the analyst has made certain forecasts, it is relatively straightforward to determine a company's expected dividends for each year up through the first year of the maturity stage. Then the present value of these predicted dividends can be calculated for a given required rate of return. However, many investment firms use a computerized trial-and-error procedure to determine the discount rate that equates the present value of the stock's expected dividends with its current price. Sometimes this long-run internal rate of return is referred to as the security's **implied return.** In the case of *ABC*, its implied return is 14.8%.

18.8.4 The Security Market Line

After implied returns have been estimated for a number of stocks, the associated beta for each stock can be estimated. Then for all the stocks analyzed, this information can be plotted on a graph that has implied returns on the vertical axis and estimated betas on the horizontal axis.

At this point there are alternative methods for estimating the security market line (SML).[11] One method involves determining a line of best fit for this graph by using a statistical procedure known as simple regression (as discussed in Chapter 17). That is, the values of an intercept term and a slope term are determined from the data, thereby indicating the location of the straight line that best describes the relationship between implied returns and betas.[12]

Figure 18.4 provides an example of the estimated SML. In this case the SML has been determined to have an intercept of 8% and a slope of 4%, indicating that, in general, securities with higher betas are expected to have higher implied returns in the forthcoming period. Depending on the sizes of the implied returns, such lines can have steeper or flatter slopes, or even negative slopes.

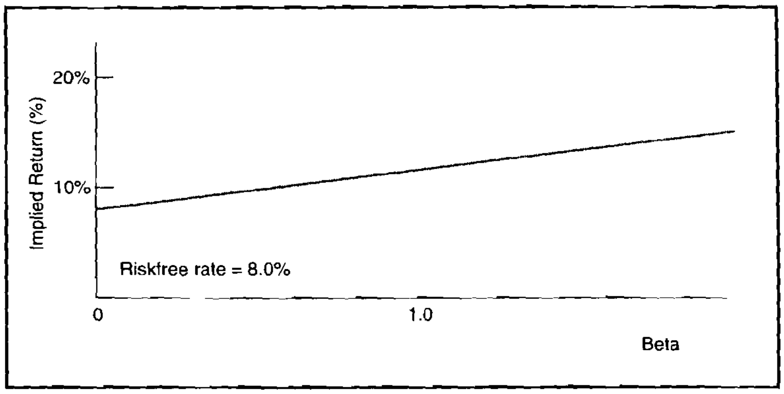


Figure 18.4
A Security Market Line Estimated from Implied Returns

The second method of estimating the SML involves calculating the implied return for a portfolio of common stocks. This is done by taking a value-weighted average of the implied returns of the stocks in the portfolio, with the resulting return being an estimate of the implied return on the market portfolio. Given this return and a beta of 1, the "market" portfolio can be plotted on a graph having implied returns on the vertical axis and betas on the horizontal axis. Next the riskfree rate, having a beta of 0, can be plotted on the same graph. Finally, the SML is determined by simply connecting these two points with a straight line.

Either of these SMLs can be used to determine the required return on a stock. However, they will most likely result in different numbers, as the two lines will most likely have different intercepts and slopes. For example, note that in the first method the SML may not go through the riskfree rate, whereas the second method forces the SML to go through this rate.

18.8.5 Required Returns and Alphas

Once a security's beta has been estimated, its required return can be determined from the estimated SML. For example, the equation for the SML shown in Figure 18.4 is:

$$k_i = 8 + 4\beta_i.$$

Thus if *ABC* has an estimated beta of 1.1, then it would have a required return equal to 12.4% [= 8 + (4 × 1.1)].

Once the required return on a stock has been determined, the difference between the stock's implied return (from the DDM) and this required return can be calculated. This difference is then viewed as an estimate of the stock's *alpha* and represents "... the degree to which a stock is mispriced. Positive alphas indicate undervalued securities and negative alphas indicate overvalued securities."[13] In the case of *ABC*, its implied and required returns were 14.8% and 12.4%, respectively. Thus its estimated alpha would be 2.4% (= 14.8% − 12.4%). Because this is a positive number, *ABC* can be viewed as being underpriced.

18.8.6 The Implied Return on the Stock Market

Another product of this analysis is that the implied return for a portfolio of stocks can be compared with the expected return on bonds. (The latter is typically represented by the current yield-to-maturity on long-term Treasury bonds.) Specifically, the difference between stock and bond returns can be used as an input for recommendations concerning asset allocation between stocks and bonds. That is, it can be used to form recommendations regarding what percent of an investor's money should go into stocks and what percent should go into bonds. For example, the greater the implied return on stocks relative to bonds, the larger the percentage of the investor's money that should be placed in common stocks.

18.9 DIVIDEND DISCOUNT MODELS AND EXPECTED RETURNS

The procedures described here are similar to those employed by a number of brokerage firms and portfolio managers.[14] A security's implied return, obtained from a DDM, is often treated as an expected return, which in turn can be divided into two components—the security's required return and alpha.

However, the expected return on a stock over a given holding period may differ from its DDM-based implied rate k^*. A simple set of examples will indicate why this difference can exist.

Assume that a security analyst predicts that a stock will pay a dividend of \$1.10 per year forever. On the other hand, the consensus opinion of "the market" (most other investors) is that the dividend will equal \$1.00 per year forever. This suggests that the analyst's prediction is a deviant or nonconsensus one.

Assume that both the analyst and other investors agree that the required rate of return for a stock of this type is 10%. Using the formula for the zero-growth model, the value of the stock is $D_1/.10 = 10D_1$, meaning that the stock should sell for ten times its expected dividend. Because other investors expect to receive \$1.00 per year, the stock has a current price P of \$10 per share. The analyst feels that the stock has a value of \$1.10/.10 = \$11 and thus feels that it is underpriced by \$11 − \$10 = \$1 per share.

18.9.1 Rate of Convergence of Investors' Predictions

[illegible] this situation the implied return according to the analyst is \$1.10/\$10 = 11%. [illegible] the analyst buys a share now with a plan to sell it a year later, what rate of re[illegible] might the analyst expect to earn? The answer depends on what assumption [illegible]de regarding the *rate of convergence of investors' predictions*—that is, the an[illegible] depends on the expected market reaction to the mispricing that the analyst [illegible] currently exists.

[illegible] cases shown in Table 18.1 are based on an assumption that the analyst is [illegible]t that his or her forecast of future dividends is correct. That is, in all of [illegible] the analyst expects that at the end of the year, the stock will pay the [illegible] dividend of \$1.10.

TABLE 18.1

ALPHA AND THE CONVERGENCE OF PREDICTIONS

	Expected Amount of Convergence		
	0% (A)	100% (B)	50% (C)
Dividend predictions D_2			
Consensus of other investors	1.00	1.10	1.05
Analyst	1.10	1.10	1.10
Expected stock price P_1	10.00	11.00	10.50
Expected return:			
Dividence yield D_1/P	11%	11%	11%
Capital gain $(P_1 - P)/P$	0	10	5
Total expected return	11%	21%	16%
Less required return	10	10	10
Alpha	1%	11%	6%

Note: P_1 is equal to the consensus dividend prediction at $t = 1$ divided by the required return of 10%. The example assumes that the current stock price P is \$10, and dividends are forecast by the consensus at $t = 0$ to remain constant at \$1.00 per share, whereas the analyst forecasts the dividends at $t = 0$ to remain constant at \$1.10 per share.

No Convergence

In column (A), it is assumed that other investors will regard the higher dividend as a fluke and steadfastly refuse to alter their projections of subsequent dividends from their initial estimate of \$1.00. As a result, the security's price at $t = 1$ can be expected to remain at \$10 (= \$1.00/.10). In this case the analyst's total return is expected to be 11% (= \$1.10/\$10), which will be attributed entirely to dividends as no capital gains are expected.

The 11% expected return can also be viewed as consisting of the required return of 10% plus an alpha of 1% that is equal to the portion of the dividend unanticipated by other investors, \$.10/\$10. Accordingly, if it is assumed that there will be no convergence of predictions, the expected return would be set at the implied rate of 11% and the alpha would be set at 1%.

Complete Convergence

Column (B) shows a very different situation. Here it is assumed that the other investors will recognize their error and completely revise their predictions. At the end of the year, it is expected that they too will predict future dividends of \$1.10 per year thereafter; thus the stock is expected to be selling for \$11 (= \$1.10/.10) at $t = 1$. Under these conditions, the analyst can expect to achieve a total return of 21% by selling the stock at the end of the year for \$11, obtaining 11% (= \$1.10/\$10) in dividend yield and 10% (= \$1/\$10) in capital gains.

The 10% expected capital gains result directly from the expected repricing of the security because of the complete convergence of predictions. In this case the fruits of the analyst's superior prediction are expected to be obtained all in one year. Instead of 1% "extra" per year forever, as in column (A), the analyst expects to obtain 1% (= \$.10/\$10) in extra dividend yield plus 10% (= \$1/\$10) in capital gains this year. By continuing to hold the stock in subsequent years, the analyst would expect to earn only the required return of 10% over those years. Accordingly, the expected return is 21% and the alpha is 11% when it is assumed that there is complete convergence of predictions.

Partial Convergence

Column (C) shows an intermediate case. Here the predictions of the other investors are expected to converge only halfway toward those of the analyst (that is, from \$1.00 to \$1.05 instead of to \$1.10). Total return in the first year is expected to be 16%, consisting of 11% (= \$1.10/\$10) in dividend yield plus 5% (= \$.50/\$10) in capital gains.

Since the stock is expected to be selling for \$10.50 (= \$1.05/.10) at $t = 1$, the analyst will still feel that it is underpriced at $t = 1$ because it will have an intrinsic value of \$11 (= \$1.10/.10) at that time. To obtain the remainder of the "extra return" owing to this underpricing, the stock would have to be held past $t = 1$. Accordingly, the expected return would be set at 16% and the alpha would be set at 6% when it is assumed that there is halfway convergence of predictions.

In general, a security's expected return and alpha will be larger, the faster the assumed rate of convergence of predictions.[15] Many investors use the implied rate (that is, the internal rate of return k^*) as a surrogate for a relatively short-term (for example, one year) expected return, as in column (A). In doing so, they are assuming that the dividend forecast is completely accurate, but that there is no convergence. Alternatively, investors could assume that there is some degree of convergence, thereby raising their estimate of the security's expected return. Indeed, investors could further alter their estimate of the security's expected return by assuming that the security analyst's deviant prediction is less than perfectly accurate, as will be seen next.[16]

18.9.2 Predicted versus Actual Returns

An alternative approach does not simply use outputs from a model "as is," but *adjusts* them, based on relationships between previous predictions and actual outcomes. Panels (a) and (b) of Figure 18.5 provide examples.

Each point in Figure 18.5(a) plots a *predicted return* on the stock market as a whole (on the horizontal axis) and the subsequent *actual return* for that period (on the vertical axis). The line of best fit (determined by simple regression) through the points indicates the general relationship between prediction and outcome. If the current prediction is 14%, history suggests that an estimate of 16% would be superior.

Each point in Figure 18.5(b) plots a predicted alpha value for a security (on the horizontal axis) and the subsequent "abnormal return" for that period (on the vertical axis). Such a diagram can be made for a given security, or for all the securities that a particular analyst makes predictions about, or for all the securities that the investment firm makes predictions about. Again a line of best fit can be drawn through the points. In this case, if the current prediction of a security's

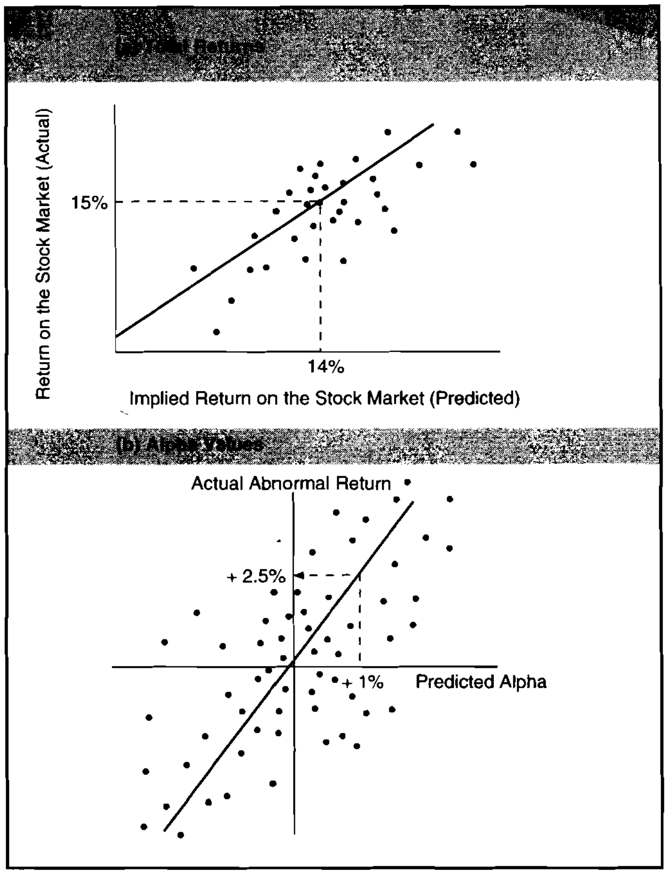


Figure 18.5
Adjusting Predictions

alpha is +1%, this relationship suggests that an "adjusted" estimate of +2.5% would be superior.

An important by-product of this type of analysis is the measure of correlation between predicted and actual outcomes, indicating the nearness of the points to the line. This **information coefficient** (IC) can serve as a measure of predictive accuracy. If it is too small to be significantly different from zero in a statistical sense, the value of the predictions is subject to considerable question.[17]

18.10 SUMMARY

1. The capitalization of income method of valuation states that the intrinsic value of any asset is equal to the sum of the discounted cash flows investors expect to receive from that asset.

2. Dividend discount models (DDMs) are a specific application of the capitalization of income method of valuation to common stocks.
3. To use a DDM, the investor must implicitly or explicitly supply a forecast of all future dividends expected to be generated by a security.
4. Investors typically make certain simplifying assumptions about the growth of common stock dividends. For example, a common stock's dividends may be assumed to exhibit zero growth or growth at a constant rate. More complex assumptions may allow for multiple growth rates over time.
5. Instead of applying DDMs, many security analysts use a simpler method of security valuation that involves estimating a stock's "normal" price-earnings ratio and comparing it with the stock's actual price-earnings ratio.
6. The growth rate in a firm's earnings and dividends depends on its earnings retention rate and its average return on equity for new investments.
7. Determining whether a security is mispriced using a DDM can be done in one of two ways. First, the discounted value of expected dividends can be compared with the stock's current price. Second, the discount rate that equates the stock's current price to the present value of forecast dividends can be compared with the required return for stocks of similar risk.
8. The rate of return that an analyst with accurate non-consensus dividend forecasts can expect to earn depends on the rate of convergence of other investors' predictions to the predictions of the analyst.

QUESTIONS AND PROBLEMS

1. Consider five annual cash flows (the first occurring one year from today):

Year	Cash Flow
1	\$5
2	\$6
3	\$7
4	\$8
5	\$9

Given a discount rate of 10%, what is the present value of this stream of cash flows?

2. Alta Cohen is considering buying a machine to produce baseballs. The machine costs \$10,000. With the machine, Alta expects to produce and sell 1,000 baseballs per year for \$3 per baseball, net of all costs. The machine's life is five years (with no salvage value). Based on these assumptions and an 8% discount rate, what is the net present value of Alta's investment?

3. Hub Collins has invested in a project that promised to pay \$100, \$200, and \$300, respectively, at the end of the next three years. If Hub paid \$513.04 for this investment, what is the project's internal rate of return?

4. Alton Products currently pays a dividend of \$4 per share on its common stock.

American Appraisal®

Equity Risk Premium QUARTERLY

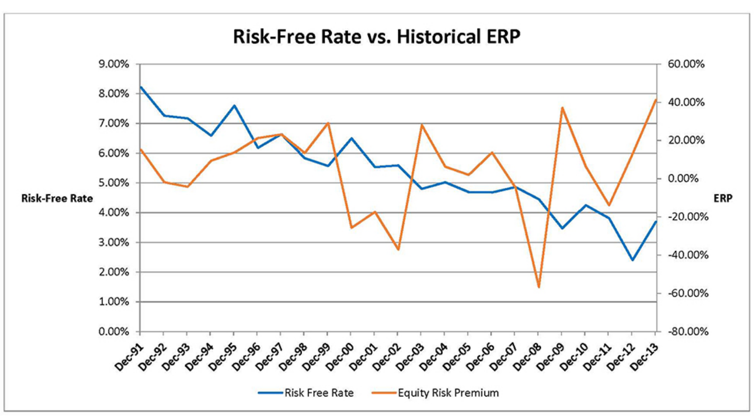
January 2015

US Equity Risk Premium

The equity risk premium ("ERP") is the extra return over the expected yield on risk-free securities that investors expect to receive from an investment in a diversified portfolio of common stocks.[1] It can also be thought to measure what investors demand over and above the risk-free rate for investing in equities as a class or the market price for taking on average equity risk.[2]

In recent years, US risk-free rates have reached levels near historic lows due to the perceived low risk of US treasuries relative to the sovereign debt of other developed nations. Additionally, the Federal Reserve and other Central Banks around the world have undertaken quantitative easing and other efforts to lower interest rates in response to economic conditions. This past quarter, the Federal Reserve announced it would conclude its asset purchase program; however, it will continue to maintain its existing bond holdings and reinvest principal payments. This effort, along with the current lending rate policy, will help maintain accommodative financial conditions. As a result, the capital asset pricing model ("CAPM"), which utilizes the ERP to calculate a cost of equity, has implied a below-average cost of equity when the market may have exhibited higher risk. Yields on US Treasury bonds, which were being manipulated by government intervention, were the primary driver for the implied below-average cost of equity. In the past year, US Treasury yields have been declining after returning to normal levels for a brief period of time late in 2013. Several reasons have been cited for the decline in US Treasury rates, most notably the shift from EU sovereign debt to US Treasuries, geopolitical unrest, pension funds protecting their status and, more recently, a sharp decline in worldwide energy prices. Another factor is the Federal Reserve signaling to the markets that rates may not be raised as previously expected until 2016. Yields on the 20-year US Treasury bond have declined to 2.47% as of December 31, 2014, from 3.08% as of June 30, 2014, and 3.72% as of December 31, 2013. It is too soon to determine whether this pullback trend will last throughout 2015.

Research has shown that the ERP is cyclical during business cycles and that the ERP can fluctuate within its historic range based on current and forecasted economic conditions. The ERP tends



to move in the opposite direction of the economy, so when the business cycle is at its peak, the ERP will be at the lower end of its historical range; conversely, during economic troughs, the ERP will be at the higher end of the range.[1] The historical risk-free rate and ERP are presented in the chart on the preceding page.

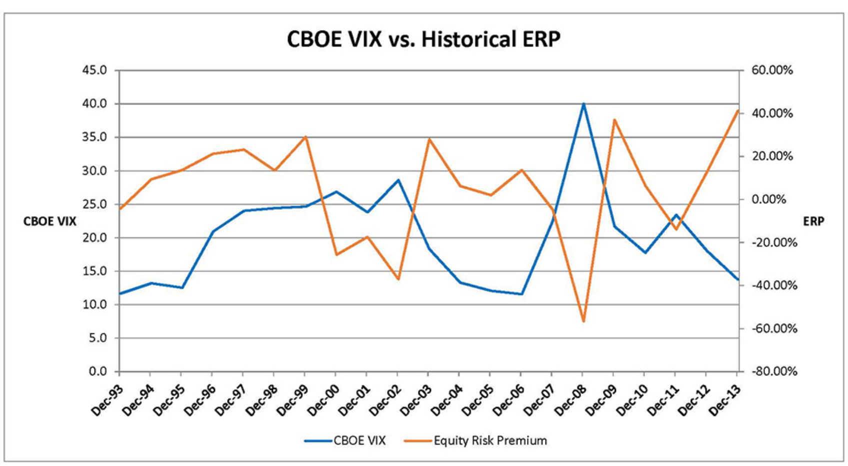
There is no single universally accepted methodology for estimating the ERP; thus, there is wide diversity in practice among academics and financial advisors with regard to recommended ERP estimates.

American Appraisal researched and analyzed various economic and market factors in order to determine where the current ERP should fall within a range of historical ERP. To determine which indicators were most relevant to the ERP, correlations were calculated for these indicators relative to the historical ERP. Long-term correlations greater than +/- 0.5 were considered meaningful.

Based on our research and analysis, American Appraisal utilizes a 6.0% US ERP combined with the actual risk-free rate as of January 2015, which is consistent with our conclusion for the prior quarter. Additional details of the factors we reviewed follow.

Economic/Market Indicators

The factors determined to display moderate or strong correlations with historical ERPs are the CBOE Volatility Index ("VIX"), Damodaran's implied premium, and Moody's Aaa and Baa 20-year corporate credit spreads. VIX is the ticker symbol for the Chicago Board Options Exchange ("CBOE") Volatility Index, which numerically expresses the market's expectations of 30-day volatility; it is constructed by using the implied volatilities of a wide range of S&P 500 Index options. The results are meant to be forward-looking and are calculated by using both call and put options.



1993-2013 Correlation (20 year):	-0.59
2003-2013 Correlation (10 year):	-0.74

The VIX is a widely used measure of market risk and often is referred to as the investor fear gauge. There are three variations of the volatility indexes: (1) the VIX, which tracks the S&P 500; (2) the VXN, which tracks the Nasdaq 100; and (3) the VXD, which tracks the Dow Jones Industrial Average. Damodaran's implied premium, developed by Aswath Damodaran, Professor of Finance at the Stern School of Business at New York University, is a forward-looking approach to calculating an expected ERP. It is based on using current market data to calculate an implied or residualized ERP.[3]

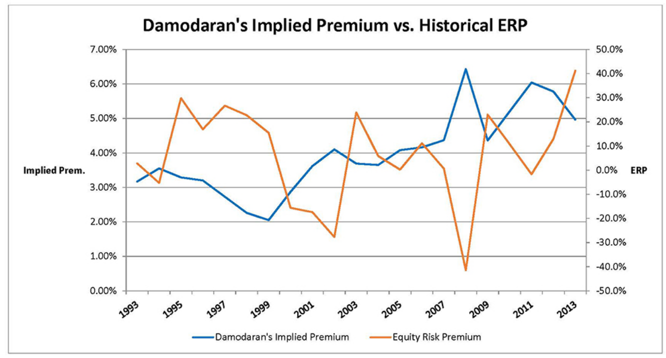
Moody's Aaa corporate credit spreads are calculated based on the difference in Aaa corporate yields vs. US treasuries with similar maturities.

Economic Indicators

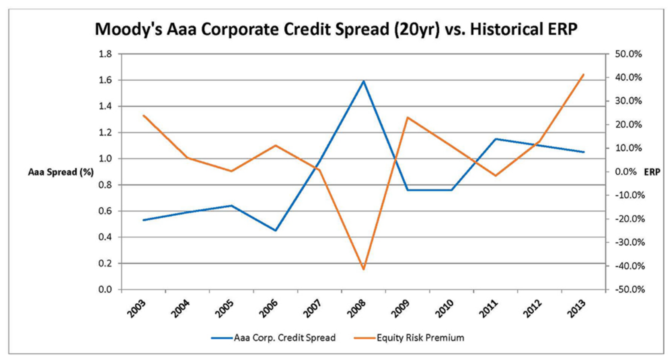
As described previously, the VIX, Damodaran's implied premium, and Moody's Aaa and Baa 20-year corporate credit spreads display meaningful correlations with historical ERPs. Each of the factors is briefly discussed below:

Damodaran's Implied Premium

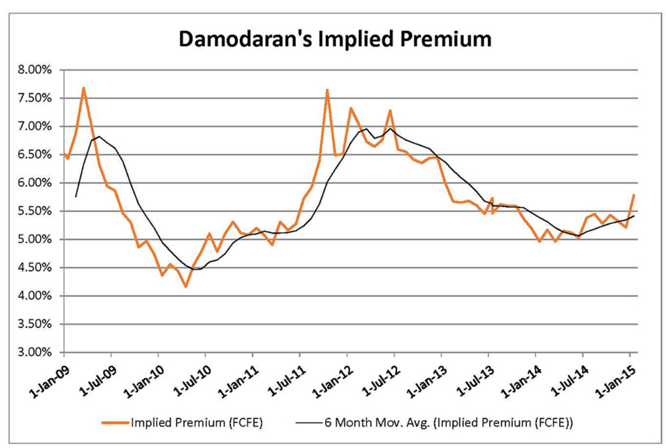
The six-month moving average trendline suggests that the implied premium has steadily trended down from 7.0% toward 6.0%, and dropped sharply - to slightly below 5% - at the end of 2013. It is now back up near 6% at the end of 2014.



1993-2013 Correlation (20 year):	-0.30
2003-2013 Correlation (10 year):	-0.49



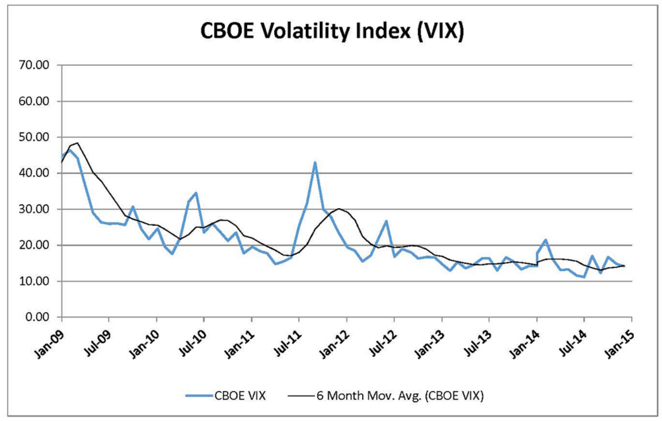
2003-2013 Correlation (10 year):	-0.55



Equity Risk Premium
QUARTERLY

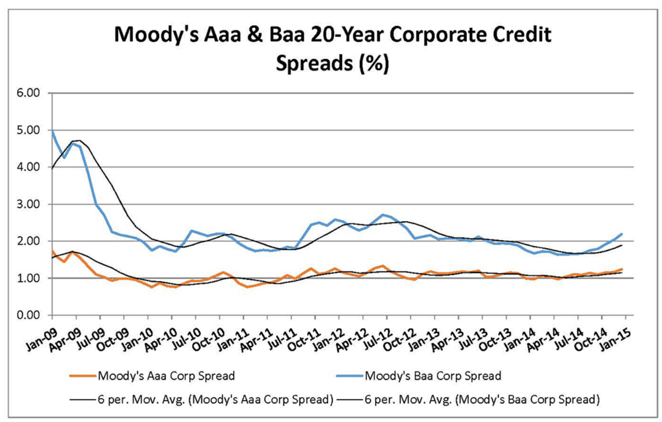
CBOE Volatility Index (VIX)

The VIX appears to be bouncing back from its lows, which approached low double digits, and increased to approximately 17 (long-term average near 20) at the end of September 2014. The VIX has fluctuated considerably over the past few years, spiking to over 40 in 2011. Since the first quarter of 2012, the six-month trendline has dipped down below 20 and is trending toward 15. The index is hovering close to the near-record lows throughout 2014 but toward the end of the year it trended toward 20, reflecting turmoil in the energy markets.



Moody's Aaa and Baa Corporate Credit Spreads (20-year)

In 2012, Aaa and Baa spreads fell, rose, fell, and rose again, while their six-month moving averages remained relatively flat. Since January 2013, corporate credit spreads have remained relatively flat; however, the corporate spreads began to widen slightly over the fourth quarter of 2014.

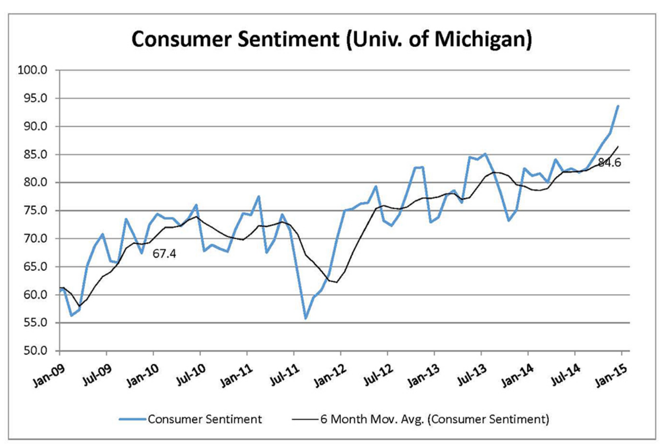


Additional Economic Indicators

In addition to the economic and market factors that display meaningful correlations with historical ERPs, the following economic indicators are monitored on a frequent basis to determine the current status of the US economy and help establish where the current ERP falls within the historical range.

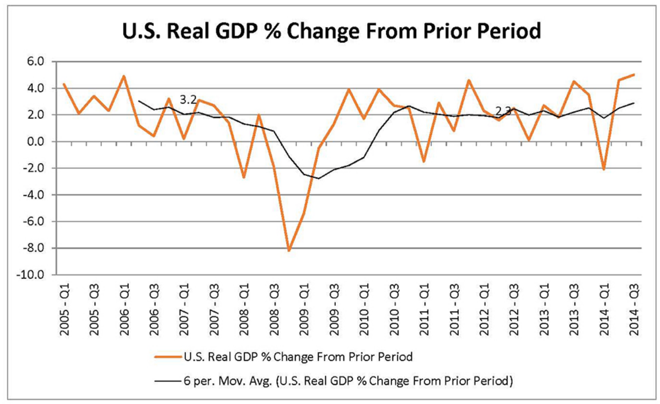
Consumer Sentiment

Consumer sentiment trends, as tracked by the University of Michigan, indicate improving consumer sentiment, which is typically preceded by positive economic trends. The survey has continued to trend toward new highs, with the latest survey posting a result of 93.6.



US Real GDP

The six-month moving average trendline for US real GDP indicates a relatively flat economy with slower growth trending above 2.0%. During the first quarter of 2014 the economy contracted at an annual rate of 2.9%. Economists cite much of the contraction to the bad weather that much of the country endured, which affected production, construction, and shipments. Many economists correctly projected improvement in the second quarter of 2014, with an annualized real growth rate of 4.6%. The economic growth observed in Q2 continued in Q3 with an annualized real growth rate of 5.0%. This is considered a coincident indicator by economists and is neither leading nor lagging.



Conclusion

As the ERP is cyclical and can fluctuate within its historical range based on current and economic conditions, please consult with your American Appraisal valuation advisor when developing a weighted average cost of capital or, more specifically, the cost of equity for your business.

Visit www.american-appraisal.com for more information.

Sources

[1]Shannon Pratt and Roger Grabowski, *Cost of Capital: Applications and Examples*, fourth edition (New York: John Wiley & Sons, 2010), pages 115, 137.

[2] Aswath Damodaran, "Risk Premiums: Looking backwards and forwards…" (presentation, October 2011).

[3] Aswath Damodaran, *Equity Risk Premiums (ERP): Determinants, Estimation and Implications - The 2013 Edition* (paper, updated March 2013).

Earnings Growth: The Two Percent Dilution

William J. Bernstein and Robert D. Arnott

Two important concepts played a key role in the bull market of the 1990s. Both represent fundamental flaws in logic. Both are demonstrably untrue. First, many investors believed that earnings could grow faster than the macroeconomy. In fact, earnings must grow slower than GDP because the growth of existing enterprises contributes only part of GDP growth; the role of entrepreneurial capitalism, the creation of new enterprises, is a key driver of GDP growth, and it does not contribute to the growth in earnings and dividends of existing enterprises. During the 20th century, growth in stock prices and dividends was 2 percent less than underlying macroeconomic growth. Second, many investors believed that stock buybacks would permit earnings to grow faster than GDP. The important metric is not the volume of buybacks, however, but net buybacks—stock buybacks less new share issuance, whether in existing enterprises or through IPOs. We demonstrate, using two methodologies, that during the 20th century, new share issuance in many nations almost always exceeded stock buybacks by an average of 2 percent or more a year.

The bull market of the 1990s was largely built on a foundation of two immense misconceptions. Whether their originators were knaves or fools is immaterial; the errors themselves were, and still are, important. Investors were told the following:

1. With a technology revolution and a "new paradigm" of low payout ratios and internal reinvestment, earnings will grow faster than ever before. Real growth of 5 percent will be easy to achieve.

Like the myth of Santa Claus, this story is highly agreeable but is supported by neither observable current evidence nor history.

2. When earnings are not distributed as dividends and not reinvested into stellar growth opportunities, they are distributed back to shareholders in the form of stock buybacks, which are a vastly preferable way of distributing company resources to the shareholders from a tax perspective.

William J. Bernstein is principal at Efficient Frontier Advisors, LLC, Eastford, Connecticut. Robert D. Arnott is chairman of First Quadrant, LP, and Research Affiliates, LLC, Pasadena, California.

Note: This article was accepted for publication prior to Mr. Arnott's appointment as editor of the Financial Analysts Journal.

True, except that over the long term, net buybacks (that is, buybacks minus new issuance and options) have been reliably negative.

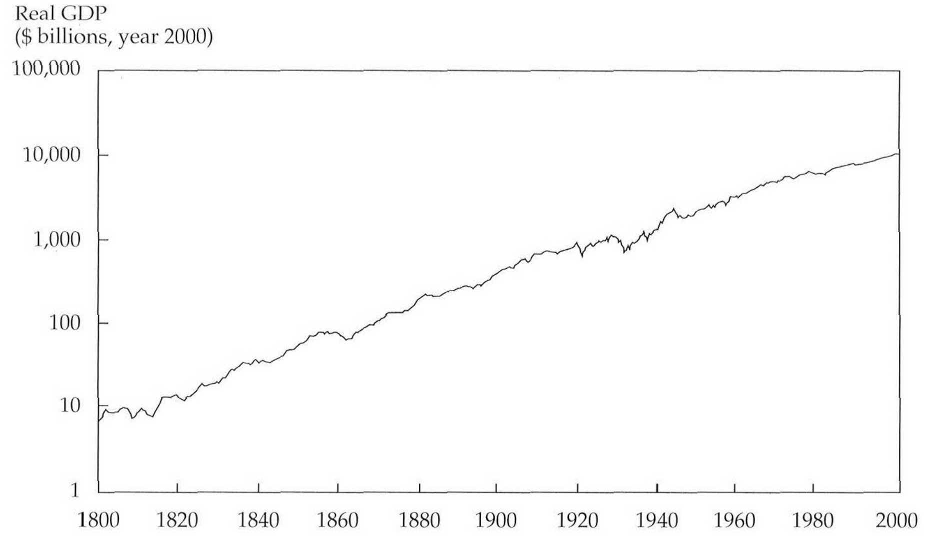
The vast majority of the institutional investing community has believed these untruths and has acted accordingly. Whether these tales are lies or merely errors, our implied indictment of these misconceptions is a serious one—demanding data. This article examines some of the data.

Big Lie #1: Rapid Earnings Growth

In the past two centuries, common stocks have provided a sizable risk premium to U.S. investors: For the 200 years from 1802 through 2001 (inclusive), the returns for stocks, bonds, and bills were, respectively, 8.42 percent, 4.88 percent, and 4.21 percent. In the most simplistic terms, the reason is obvious: A bill or a bond is a promise to pay interest and principal, and as such, its upside is sharply limited. Shares of common stock, however, are a claim on the future dividend stream of the nation's businesses. While the investor in fixed-income securities is receiving a modest fixed trickle from low-risk securities, the shareholder is the beneficiary of the ever-increasing fruits of innovation-driven economic growth.

Viewed over the decades, the powerful U.S. economic engine has produced remarkably steady growth. **Figure 1** plots the real GDP of the United States since 1800 as reported by the U.S. Department

Figure 1. Real U.S. GDP Growth, 1800–2000



of Commerce. From that year to 2000, the economy as measured by real GDP, averaging about 3.7 percent growth a year, has grown a thousandfold. The long-term uniformity of economic growth demonstrated in Figure 1 is both a blessing and a curse. To know that real U.S. GDP doubles every 20 years is reassuring. But it is also a dire warning to those predicting a rapid acceleration of economic growth from the computer and Internet revolutions. Such extrapolations of technology-driven increased growth are painfully oblivious to the broad sweep of scientific and financial history, in which innovation and change are constant and are neither new to the current generation nor unique.

The impact of recent advances in computer science pales in comparison with the technological explosion that occurred between 1820 and 1855. This earlier era saw the deepest and most far reaching technology-driven changes in everyday existence ever seen in human history. The changes profoundly affected the lives of those from the top to the bottom of the social fabric in ways that can scarcely be imagined today. At a stroke, the speed of transportation increased tenfold. Before 1820, people, goods, and information could not move faster than the speed of the horse. Within a generation, journeys that had previously taken weeks and months involved an order of magnitude less time, expense, danger, and discomfort. Moreover, important information that previously required the same long journeys could now be transmitted instantaneously.

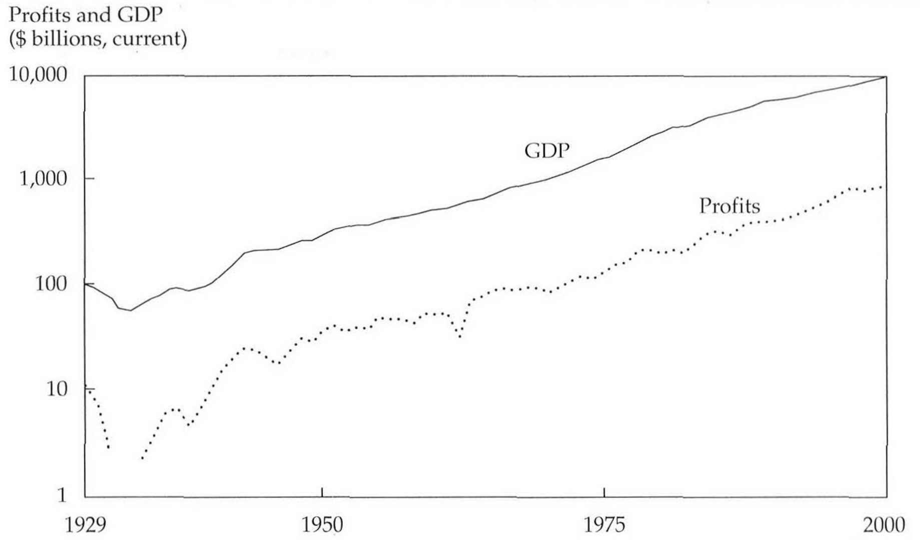
The average inhabitant of 1820 would have found the world 35 years later incomprehensible, whereas a person transported from 1967 to 2002 would have little trouble understanding the intervening changes in everyday life. From 1820 to 1855, the U.S. economy grew sixfold, four times the growth seen in the "tech revolution" of the past 35 years. More importantly, a close look at the right edge of Figure 1—the last decade of the 20th century—shows that the acceleration in growth during the "new paradigm" of the tech revolution of the 1990s was negligible when measured against the broad sweep of history.

The relatively uniform increase in GDP shown in Figure 1 suggests that corporate profits experienced a similar uniformity in growth. And, indeed, **Figure 2** demonstrates that, except for the Great Depression, during which overall corporate profits briefly disappeared, nominal aggregate corporate earnings growth has tracked nominal GDP growth, with corporate earnings remaining constant at 8–10 percent of GDP since 1929. The trend growth in corporate profits shown in Figure 2 is nearly identical, within a remarkable 20 bps, to the trend growth in GDP.[1]

Cannot stock prices also, then, be assumed to grow at the same rate as GDP? After all, a direct relationship between aggregate corporate profits and GDP has existed since at least 1929. The problem with this assumption is that per share earnings and dividends keep up with GDP *only if* no new shares are created. Entrepreneurial capitalism, however, creates a "dilution effect" through new enterprises and new stock in existing enterprises. So, per share earnings and dividends grow considerably slower than the economy.

In fact, since 1871, real stock prices have grown at 2.48 percent a year—versus 3.45 percent a year for GDP. Despite rising price–earnings ratios, we observe a "slippage" of 97 bps a year between stock

Figure 2. Nominal U.S. Corporate Profits and GDP, 1929–2000



prices and GDP. The true degree of slippage is much higher because almost half of the 2.48 percent rise in real stock prices after 1871 came from a substantial upward revaluation. The highly illiquid industrial stocks of the post–Civil War period rarely sold at more than 10 times earnings; often, they sold for multiples as low as 3 or 4 times earnings. These closely held industrial stocks gave way to instantly and cheaply tradable common shares, which today are priced nearly an order of magnitude more dearly.

Until the bull market of 1982–1999, the average stock was valued at 12–16 times earnings and 20–25 years' worth of dividends. By the peak of the bull market, both figures had tripled. Although the bull market was compressed into 18 years of the total period under discussion, this tripling of valuation levels was worth almost 100 bps a year—even when amortized over the full 130-year span. Thus, per share earnings and dividends grew 2 percent a year slower than the macroeconomy. If aggregate earnings and dividends grew as quickly as the economy while per share earnings and dividends were growing at an average of 2 percent a year slower, then shareholders have seen a slippage or dilution of 2 percent a year in the per share growth of earnings and dividends.

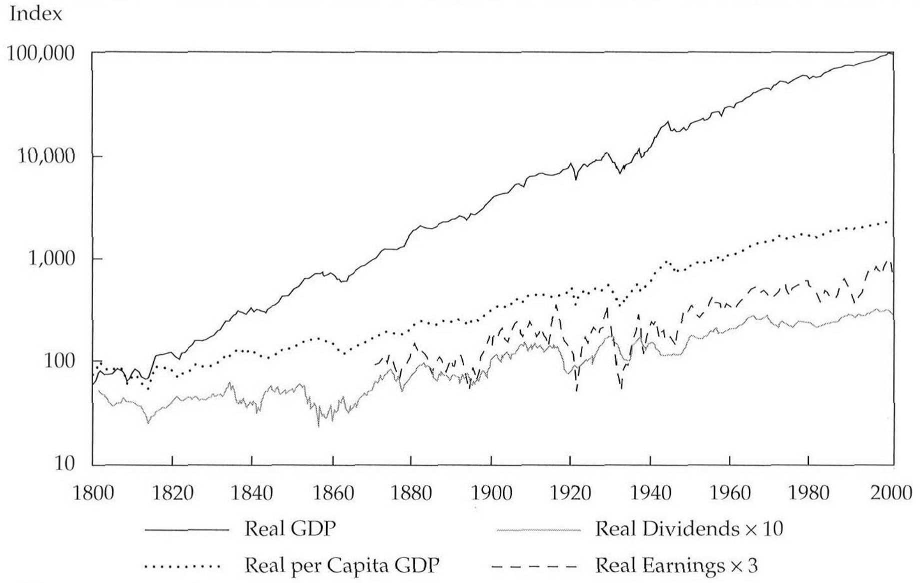
The dilution is the result of the net creation of shares as existing and new companies capitalize their businesses with equity. An often overlooked, but unsurprising, fact is that more than half of aggregate economic growth comes from new ideas and the creation of new enterprises, not from the growth of established enterprises. Stock investments can participate only in the growth of established businesses; venture capital participates only in the new businesses. The same investment capital cannot be simultaneously invested in both.

"Intrapreneurial capitalism," or the creation of new enterprises within existing companies, is a sound engine for economic growth, but it does not supplant the creation of new enterprises. Nor does it reduce the 2 percent gap between economic growth and earnings and dividend growth.

Note also that earnings and dividends grow at a pace very similar to that of per capita GDP (with some slippage associated with the "entrepreneurial" stock rewards to management). Consider that per capita GDP is a measure of productivity (with slight differences for changes in the work force) and aggregate economic wealth per capita can grow only in close alignment with productivity growth. Productivity growth is also the key driver of per capita income and of per share earnings and dividends. Accordingly, no one should be surprised that *per capita GDP, per capita income, per share earnings, and per share dividends—all grow in reasonably close proportion to productivity growth.*

If earnings and dividends grow faster than productivity, the result is a migration from return on labor to return on capital; if earnings and dividends grow more slowly, by a margin larger than the stock awards to management, then the economy migrates from rewarding capital to rewarding labor. Either way, such a change in the orientation of the economy cannot continue indefinitely. **Figure 3** demonstrates the close link between the growth of real corporate earnings and dividends and the growth of real per capita GDP; note that all of these measures exhibit growth far below the growth of real GDP.

Figure 3. Link of U.S. Earnings and Dividends to Economic Growth, 1802–2001



Note: Real GDP, real per capita GDP, and real stock prices were all constructed so that the series are on a common basis of January 1802 = 100.

A Global Laboratory

Is the United States unique? For an answer, we compared dividend growth, price growth, and total return with data on GDP growth and per capita GDP growth for the 16 countries covered by Dimson, Marsh, and Staunton (2002) spanning the 20th century.[2] The GDP data came from Maddison's (1995, 2001) world GDP survey for 1900–1998 and International Finance Corporation data for 1998–2000. The interrelationships of the data shown in **Table 1** are complex:

- The first column contains the real return (in U.S. dollars) of each national stock market.
- The second is real per share dividend growth.
- The third is real aggregate GDP growth for each nation (measured in U.S. dollars).
- The fifth is growth of real per capita GDP (measured in U.S. dollars).
- Thus, the fourth column measures the gap between growth in per share dividends and aggregate GDP—an excellent measure of the leakage that occurs between macroeconomic growth and the growth of stock prices.
- The last column represents the gap between the growth in per share dividends and per capita GDP.

For the full 16-nation sample in Table 1, the average gap between dividend growth and the growth in aggregate GDP is a startling 3.3 percent. The annual shortfall between dividend growth and per capita GDP growth is still 2.4 percent.

The 20th century was not without turmoil. Therefore, we divided the 16 nations into two groups according to the degree of devastation visited upon them by the era's calamities. The first group suffered substantial destruction of the countries' productive physical capital at least once during the century; the second group did not.

The nine nations in Group 1—Belgium, Denmark, France, Germany, Italy, Japan, the Netherlands, Spain, and the United Kingdom—were devastated by one or both of the two world wars or by civil war. The remaining seven—Australia, Canada, Ireland, South Africa, Sweden, Switzerland, and the United States—suffered relatively little direct damage. Even in this fortunate group, Table 1 shows dividend growth that is 2.3 percent less than GDP growth and 1.1 percent less than per capita GDP growth, on average. These gaps are close to the 2.7 percent and 1.4 percent figures observed in the United States during the 20th century.

The data for nations that were devastated during World Wars I and II and the Spanish Civil War are even more striking: The good news is that the economies in Group 1 repaired the devastations wrought by the 20th century; they enjoyed overall GDP growth and per capita GDP growth that rivaled the growth of the less-scarred Group 2 nations. The bad news is that the same cannot be said for per share equity performance; a 4.1 percent slippage occurred between the growth of their economies and per share corporate payouts. The

Table 1. Dilution of GDP Growth as It Flows Through to Dividend Growth: 16 Countries, 1900–2000

Country	Constituents of Real Stock Returns: Real Return	Constituents of Real Stock Returns: Dividend Growth	Real GDP Growth	Dilution in Dividend Growth (vis-à-vis GDP growth)	Real per Capita GDP Growth	Dilution in Dividend Growth (vis-à-vis per capita GDP growth)
Australia	7.5%	0.9%	3.3%	–2.4%	1.6%	–0.7%
Belgium	2.5	–1.7	2.2	–3.9	1.8	–3.5
Canada	6.4	0.3	4.0	–3.7	2.2	–1.9
Denmark	4.6	–1.9	2.7	–4.6	2.0	–3.9
France	3.6	–1.1	2.2	–3.3	1.8	–2.9
Germany	3.6	–1.3	2.6	–3.9	1.6	–2.9
Ireland	4.8	–0.8	2.3	–3.1	2.1	–2.9
Italy	2.7	–2.2	2.8	–5.0	2.2	–4.4
Japan	4.2	–3.3	4.2	–7.5	3.1	–6.4
Netherlands	5.8	–0.5	2.8	–3.3	1.7	–2.2
South Africa	6.8	1.5	3.4	–1.9	1.2	0.3
Spain	3.6	–0.8	2.7	–3.5	1.9	–2.7
Sweden	7.6	2.3	2.5	–0.2	2.0	0.3
Switzerland	5.0	0.1	2.5	–2.4	1.7	–1.6
United Kingdom	5.8	0.4	1.9	–1.5	1.4	–1.0
United States	6.7	0.6	3.3	–2.7	2.0	–1.4
Full-sample average	5.1	–0.5	2.8	–3.3	1.9	–2.4
War-torn Group 1 average	4.0	–1.4	2.7	–4.1	1.9	–3.3
Non-war-torn Group 2 average	6.4	0.7	3.0	–2.3	1.8	–1.1

creation of new enterprises in the wake of war was an even more important engine for economic recovery than in the Group 2 nations.

Thus, in Group 2 "normal nations" (i.e., those untroubled by war, political instability, and government confiscation of wealth), the natural ongoing capitalization of new technologies apparently produces a net dilution of outstanding shares of slightly more than 2 percent a year. The Group 1 nations scarred badly by war represent a more fascinating phenomenon; they can be thought of as experiments of nature in which physical capital is devastated and must be rebuilt. Fortunately, destroying a nation's intellectual, cultural, and human capital is much harder than destroying its economy; within little more than a generation, the GDP and per capita GDP of war-torn nations catch up with, and in some cases surpass, those of the undamaged nations. Unfortunately, the effort requires a high rate of equity recapitalization, which is reflected in the substantial dilution seen in Table 1 for the war-torn countries. This recapitalization savages existing shareholders.

In short, the U.S. experience was not unique. Around the world, every one of these countries except Sweden experienced dividend growth sharply slower than GDP growth, and only two countries experienced dividend growth even slightly faster than per capita GDP growth. The U.S. experience was better than most and was similar to that of the other nations that were not devastated by war.

The data for the individual countries in Table 1 show that the average real growth in dividends was negative for most countries. It also shows that dilution of GDP growth (the fourth column) was substantial for all the countries studied and that dilution of per capita GDP growth (the last column) was substantial for most countries but fit dividend growth with much less "noise" than did the dilution of overall GDP growth.

This analysis has disturbing implications for "paradigmistas" convinced of the revolutionary nature of biotechnology, Internet, and telecommunications/broadband companies. A rapid rate of technological change may, in effect, turn "normal" Group 2 nations into strife-torn Group 1 nations: An increased rate of obsolescence effectively destroys the economic value of plant and equipment as surely as bombs and bullets, with the resultant dilution of per share payouts happening much faster than the technology-driven acceleration of economic growth—if such acceleration exists. How many of the paradigmistas truly believe that the tech revolution will benefit the shareholders of existing enterprises remotely as much as it can benefit the entrepreneurs creating the new enterprises that make up the vanguard of this revolution?

Whatever the true nature of the interaction of technological progress and per share earnings, dividends, and prices, it will come as an unpleasant surprise to many that even in the Group 2 nations, average real per share dividend growth was only 0.66 percent a year (rounded in Table 1 to 0.7 percent); for the war-torn Group 1 nations, it was disturbingly negative.

In short, the equity investor in a nation blessed by prolonged peace cannot expect a real return greatly in excess of the much-maligned dividend yield; the investor cannot expect to be rescued by more rapid economic growth. Not only is outsized economic growth unlikely to occur, but even if it does, its benefits will be more than offset by the dilution of the existing investor's ownership interest by technology-driven increased capital needs.

Big Lie #2: Stock Buybacks

Stock buybacks are attractive to companies and beneficial to investors. They are a tax-advantaged means of providing a return on shareholder capital and preferable to dividends, which are taxed twice. Buybacks have enormous appeal. But contrary to popular belief, they did not occur in any meaningful way in the 1990s.

To support this contention, we begin with a remarkably simple measure of slippage in per share earnings and dividend growth: the ratio of the proportionate increase in market capitalization to the proportionate increase in stock price. For example, if over a given period, the market cap increases by a factor of 10 and the cap-weighted price index increases by a factor of 5, a 100 percent net share issuance has taken place in the interim. Formally,

$$\text{Net dilution} = \left(\frac{1+c}{1+r}\right) - 1,$$

where c is capitalization increase and r is price return. This relationship has the advantage of factoring out valuation changes, which are embedded in both the numerator and denominator, and neutralizing the impact of stock splits. Furthermore, it holds only for universal market indexes, such as the CRSP 1–10 or the Wilshire 5000, because less inclusive indexes can vary the ratio simply by adding or dropping securities. **Figure 4** contains plots of the total market cap and price indexes of the CRSP 1–10 beginning at the end of 1925.

The CRSP data contained NYSE-listed stocks until 1962. Even the CRSP data, however, can involve adding securities: CRSP added the Amex stocks in July 1962 and the Nasdaq stocks in July 1972, which created artificial discontinuities on those dates. The adjustment for these shifts is evident in **Figure 5**, for which we held the dilution ratio constant during the two months in question.[3] Note how market cap slowly and gradually pulls away from market price. The gap does not look large in Figure 4, but by the end of 2001, the cap index had grown 5.49 times larger than the price index, suggesting that for every share of stock extant in 1926, 5.49 shares existed in late 2001. The implication is that net new share issuance occurred at an annualized rate of 2.3 percent a year. Note that this rate is identical to the average dilution for non-war-torn countries during the 20th century given in Table 1. To give a better idea of how this dilution has proceeded over the past 75 years, Figure 5 provides a dilution index, defined as the ratio of capitalization growth to price index growth.

Figure 4. CRSP 1–10 Market Cap and Price Indexes, 31 December 1925–June 2002

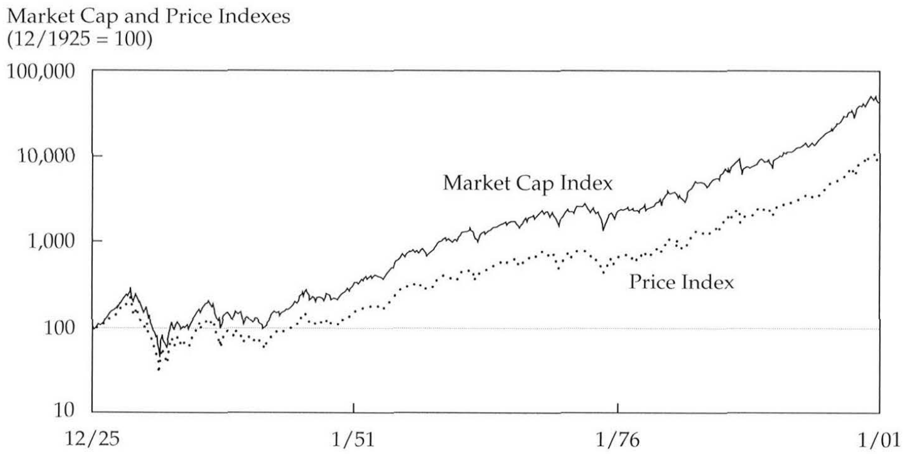


Figure 5. Cumulative Excess Growth of Market Cap Relative to Price Index, 31 December 1925 through June 2002

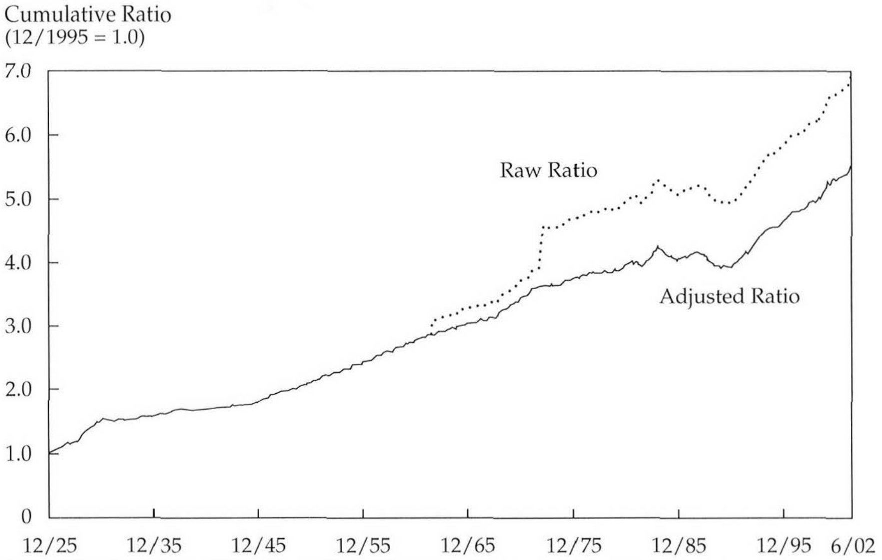
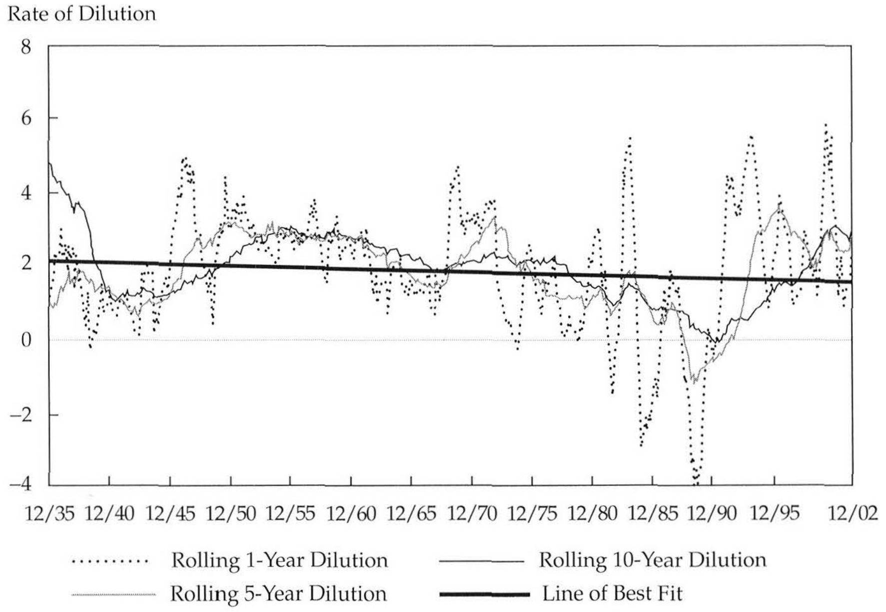


Figure 5 traces the growth in the ratio of the capitalization of the CRSP 1–10 Index as compared with the market-value-weighted price appreciation of these same stocks. The fact that this line rises nearly monotonically shows clearly that new-share issuance almost always sharply exceeds stock buybacks. The notable exception occurred in the late 1980s, when buybacks modestly outpaced new share issuance (evident from the fact that the line falls slightly during these "Milken years"). This development probably played a key role in precipitating the popular illusion that buybacks were replacing dividends. For a time, they did. But that stock buybacks were an important force in the 1990s is simply a myth. And belief in the myth may have been an important force in the bull market of the 1990s.

Figure 6 shows the rolling 1-year, 5-year, and 10-year dilution effect on existing equity shareholders as a consequence of a growth in the aggregate

Figure 6. Annualized Rate of Shareholder Dilution, 31 December 1935 through June 2002



supply of equity shares. Keep in mind that every 1 percent rise in equity capital is a 1 percent rise in market cap in which existing shareholders did not (could not) participate. Aside from the 1980s, this dilution effect on shareholders was essentially never negative—not even on a one-year basis. One can see how the myth of stock buybacks gained traction after the 1980s; even the 10-year average rate of dilution briefly dipped negative in the late 1980s. But then, during the late 1990s, stock buybacks were outstripped by new share issuance at a pace that was only exceeded in the IPO binge of 1926–1930. These conclusions hold true whether one is looking at net new share issuance on a 1-year, 5-year, or 10-year basis.

Those who argue that stock buybacks will allow future earnings growth to exceed GDP growth can draw scant support from history. Investors did see enormous earnings growth, far faster than real economic growth, from 1990 to 2000. But Figure 3 shows how tiny that surge of growth was in the context of 130 years of earnings history. Much of the earnings surge of the 1990s was dubious, at best.

The Eye of the Storm?

The big question today is whether the markets are likely to rebound into a new bull market or have merely been in the eye of the storm. We think the markets are in the eye.

The rapid earnings growth of the 1990s, which many pointed to as "proof" of a new paradigm, had several interesting characteristics:

1. A trough in earnings in the 1990 recession transformed into a peak in earnings in the 2000 bubble. Measuring growth from trough to peak is an obvious error; extrapolating that growth is even worse. This decade covered a large chunk of the careers of most people on Wall Street, many of whom have come to believe that earnings can grow very fast for a very long time. Part of conventional wisdom now is that earnings growth can outstrip macroeconomic growth.
2. Influenced by the new paradigm, analysts frequently ignored write-offs to focus increasingly on operating earnings. This practice is acceptable if write-offs are truly "extraordinary items," but it is not acceptable if write-offs become a recurring annual or biannual event, as was commonplace in the 1990s. Furthermore, what are extraordinary items for a single company are entirely ordinary for the economy as a whole. In some companies and some sectors, write-offs are commonplace. The focus on operating earnings for the broad market averages is misguided at best and deceptive at worst.
3. Those peak earnings of 1999–2000 consisted of three dubious components. The first is an underrecognition of the impact of stock options, which various Wall Street strategists estimated at 10–15 percent of earnings. The second is pension expense (or pension "earnings") based on assumptions of a 9.5 percent return, which were realistic then but are no longer; this factor pumped up earnings by approximately 15 percent at the peak and 20–30 percent from current depressed levels. The third component is Enron-style "earnings management," which various observers have estimated to be 5–10 percent of the peak earnings. (We suspect this percentage will turn out to be conservative.)

If these three sources of earnings overstatement (aggressive pension accounting, failure to expense management stock options, and outright fraud) are removed, the $54 peak earnings per share for the S&P 500 Index in 2000 turn out to be closer to $36. This figure implies normalized earnings a notch lower still. If the normalized earnings for the S&P 500 are in the $30–$36 range, as we suspect is the case, then the market at mid-year 2003 was still at a relatively rich 27–32 times normalized earnings. Using Shiller's (2000) valuation model (real S&P 500 level divided by 10-year average of real reported earnings) confirms this analysis. Shiller's model pegs the current multiple at nearly 30 times normalized earnings in mid-2003.

In principle, several conditions could allow earnings growth to exceed GDP growth. Massive stock buybacks are one. But we have demonstrated that buybacks in the 20th century were far more smoke than fire. Buybacks have been much touted as the basis for sustained earnings growth at unprecedented rates, but they simply do not show up in the data on market capitalization relative to market index price levels. Cross-holdings could also offer an interesting complication. But again, their impact does not show up in the objective shareholder dilution data. We have demonstrated that buybacks and cross-holdings do not yet show any signs of offsetting the historical 2 percent dilution, but the exploration of the possible impact of buybacks and cross-holdings is beyond the scope of this study.

Conclusion

Expected stock returns would be agreeable if dividend growth, and thus price growth, proceeded at the same rate as, or a higher rate than, aggregate economic growth. Unfortunately, dividends do not grow at such a rate: When we compared the Dimson et al. 20th century dividend growth series with aggregate GDP growth, we found that even in nations that were not savaged by the century's tragedies, dividends grew 2.3 percent more slowly, on average, than GDP. Similarly, by measuring the gap between the growth of market cap and share prices in the CRSP database, we found that between 1926 and the present, a 2.3 percent net annual dilution has occurred in the outstanding number of shares in the United States.

Two independent analytical methods point to the same conclusion: In stable nations, a roughly 2 percent net annual creation of new shares—the Two Percent Dilution—leads to a separation between long-term economic growth and long-term growth in dividends per share, earnings per share, and share price.

The markets are probably in the eye of a storm and can expect further turmoil as the rest of the storm passes over. If normalized S&P 500 earnings are \$30–\$36 per share, if payout ratios on those normalized earnings are at the low end of the historical range (implying lower-than-normal future earnings growth), if normal earnings growth is really only about 1 percent a year above inflation, if stock buybacks have been little more than an appealing fairy tale, if the credibility of earnings is at an all-time low, and if demographics suggest Baby Boomer dis-saving in the next 20 years, then we have a problem.

The authors would like to acknowledge the help, suggestions, and encouragement of Cliff Asness, Peter Bernstein, and Max Darnell.

Notes

1. In calculating "trend growth," we used a loglinear line of best fit to minimize the impact of distortions from an unusually high or low starting or ending date. The loss years of 1932 and 1933 were excluded because of loglinear calculation.
2. The Dimson et al. book is a masterwork. If you do not have a copy, you should.
3. We assumed the dilution factor to be zero in those two months. If a massive stock buyback or a massive new IPO occurred during one of these two months, we may have missed it. But net buybacks or net new share issuance during months in which the "index" saw a major reconstitution would be difficult to measure.

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alternative investment vehicles has recently been documented, no such evidence is available on the ability of investors to generate superior risk-adjusted returns based on timing among various hedge fund styles.

This article is, to the best of our knowledge, the first to document the existence of predictability in hedge fund index returns and to focus on its implications for tactical allocation decisions. Specifically, we examined (lagged) multifactor models for the return on nine hedge fund indexes. We chose factors that would measure the many dimensions of financial risk—market risks (proxied by stock prices, interest rates, and commodity prices), volatility risk (proxied by implicit volatilities from option prices), default risk (proxied by default spreads), and liquidity risk (proxied by trading volume). We show that a parsimonious set of models captures a significant amount of predictability for most hedge fund styles.

We also found that the benefits of tactical style allocation are potentially enormous. The article first provides evidence of the economic significance of the performance of hedge fund style-timing models by comparing the performance of a market timer with perfect forecasting ability in the alternative investment universe with the performance of a perfect market timer in the traditional universe. Then, the performance of a realistic style-timing model is presented. An equity-oriented portfolio that mixed traditional and alternative investment vehicles and a similar debt-oriented mixed portfolio produced spectacular results. Moreover, the results do not seem to be significantly affected by the presence of reasonably high transaction costs.

Some specific features of hedge fund investing do not facilitate the implementation of tactical allocation strategies. In particular, the absence of liquidity and the presence of lockup periods, which are typical of investments in hedge funds, are likely to prevent investors from implementing any kind of dynamic allocation among funds. We believe, however, that the future of hedge fund style timing is even brighter than its past or present. The hedge fund industry is still relatively new, and market conditions are evolving at an astounding pace. Although the world of alternative investing has consisted of a disparate set of managers following disparate specific strategies, significant attempts at structuring the markets have occurred in the past few years. Important, well-established firms are creating relatively liquid investment products designed to track the performance of hedge fund indexes. ◙

Keywords: Alternative Investments: hedge fund strategies; Portfolio Management: asset allocation; Portfolio Management: hedge fund strategies

Earnings Growth: The Two Percent Dilution

page 47

William J. Bernstein and Robert D. Arnott

The bull market of the 1990s was built largely on a foundation of two immense misconceptions:

- With a technology revolution and a "new paradigm" of low payout ratios and internal reinvestment, earnings will grow faster than ever before. Five percent real growth will be easy to achieve.
- When earnings are not distributed as dividends and not reinvested into stellar growth opportunities, they are distributed back to shareholders in the form of stock buybacks.

In fact, neither of these widespread beliefs stands up to historical scrutiny. Since 1800, the economy, as measured by real GDP, has grown a thousandfold, averaging about 3.7 percent a year. The long-term uniformity of economic growth is remarkable; it is both a blessing and a curse. To know that real U.S. GDP doubles every 20 years is reassuring. But this growth is also a dire warning to those predicting rapid acceleration of economic growth from the computer and Internet revolutions.

The relatively uniform increase in GDP implies a similar uniformity in the growth of corporate profits—which does, in fact, occur. Except for the Great Depression, during which overall corporate profits briefly disappeared, nominal aggregate corporate earnings have tracked nominal GDP growth, with corporate earnings staying at 8–10 percent of the GDP growth. The trend growth in corporate profits is identical, to within a remarkable 20 bps, to the trend growth in GDP.

For 16 countries, with data spanning the 20th century, we compared dividend growth, price growth, and total return with GDP data from the same period. We found that in stable, non-war-torn nations, per share dividend growth was 2.3 percent less than growth in aggregate GDP and 1.1 percent less than growth in per capita GDP. In the war-torn nations, the situation was far worse—per share dividend growth 4.1 percent less than growth in aggregate GDP and 3.3 percent less than growth in per capita GDP.

Data for the comprehensive CRSP 1–10 Index from 1926 to June 2002 show that, after adjustment for additions to the index, total U.S. market capitalization grew 2.3 percent faster than the price index. Thus, over the past 76 1/2 years, a 2.3 percent net new issuance of shares took place, which is the equivalent of *negative* buybacks. Although net buybacks occurred in the 1980s, by the 1990s, buyback activity had once again returned to historical norms.

Earnings growth was indeed high during the 1990s. But the persistence of this growth is dubious for three reasons:

- The market went from trough earnings in the 1990 recession to peak earnings in the 2000 bubble. Measuring growth from trough to peak is meaningless; extrapolating that growth is even worse.
- Analysts frequently ignored write-offs while increasing their focus on operating earnings. This behavior is acceptable if write-offs are truly "extraordinary items" but not if write-offs become an annual or biannual event, as was commonplace in the 1990s. Furthermore, what are extraordinary items for a single company are entirely ordinary for the economy as a whole.
- The peak earnings of 1999–2000 consisted of three dubious components. The first was an underrecognition of the impact of stock options, which various Wall Street strategists estimated at 10 percent or more of earnings. The second was pension expense (or pension "earnings") based on 9–10 percent return assumptions, which were realistic then but are no longer; this factor pumped up earnings by about 15 percent at the peak and 20–30 percent from recent, depressed levels. The third was Enron-style "earnings management," which various observers have estimated at 5–10 percent of the peak earnings.

In summary, in a dynamic, free-market economy, considerable capital is consumed funding new ventures. For this reason, per share growth of prices, earnings, and dividends will lag aggregate macroeconomic growth by an amount equal to the net issuance of new shares. In peaceful, stable societies, this gap appears to be about 2 percent a year. In war-torn nations, this gap is considerably larger. Although these nations' economies can recover relatively rapidly, the high degree of recapitalization that is required savages shareholders. ▪

Keywords: Portfolio Management: asset allocation; Economics: macroeconomics; Investment Industry: future directions and sources of change

Outlier-Resistant Estimates of Beta

page 56

R. Douglas Martin and Timothy T. Simin

Recent surveys show that many analysts continue to use the capital asset pricing model and that most of them purchase betas from commercial providers, which invariably use a raw or adjusted ordinary least-squares estimate of beta. The sanctified use of OLS is justified by the fact that the OLS beta is statistically the best estimate of the linear model parameters under idealized assumptions.

In practice, however, one of the ways these assumptions fail is associated with the occurrence of a small fraction of exceptionally large or small returns—that is, outliers. We show by using several examples that outliers can, depending on their location in the equity-market-returns space, substantially bias OLS estimates of beta. Furthermore, the weekly returns for 8,314 companies from the CRSP database that had at least two years of returns in the period January 1992 through December 1996 contained many examples in which the deletion of a few outliers, sometimes even a single outlier, dramatically affected the OLS beta.

The vast majority of commercial providers do nothing to deal with outliers; the few that do deal with this problem use some form of outlier treatment without a solid statistical rationale. We deal with the vulnerability of the OLS beta to outliers by introducing a new beta estimate that is resistant to the types of outliers that cause the most bias in OLS estimates but that produces estimates similar to OLS for outlier-free data. The outlier-resistant beta is an intuitively appealing weighted-least-squares estimate with data-dependent weights. It has several advantages over other commonly used "robust" techniques.

The outlier-resistant beta applied to the CRSP database shows that the absolute value of the difference between the resistant and OLS betas is greater than 0.5 for 13 percent of the companies and that this difference is considerably larger than 1.0 for 3.2 percent of the companies. Such extreme sensitivity of the OLS beta to outliers results in misleading interpretations of the risk and return characteristics of a company. This study shows that outlier distortion of the OLS beta is primarily a small-firm effect (i.e., there is a monotonic relationship between the median market capitalization of companies and the absolute difference between the resistant and OLS betas). Furthermore, the resistant beta has superior performance relative to the OLS beta for predicting future betas when influential outliers are present but suffers (at most) only a slight degradation in performance when no influential outliers are present.

What Risk Premium Is "Normal"?

Robert D. Arnott and Peter L. Bernstein

The goal of this article is an estimate of the objective forward-looking U.S. equity risk premium relative to bonds through history—specifically, since 1802. For correct evaluation, such a complex topic requires several careful steps: To gauge the risk premium for stocks relative to bonds, we need an expected real stock return and an expected real bond return. To gauge the expected real bond return, we need both bond yields and an estimate of expected inflation through history. To gauge the expected real stock return, we need both stock dividend yields and an estimate of expected real dividend growth. Accordingly, we go through each of these steps. We demonstrate that the long-term forward-looking risk premium is nowhere near the level of the past; today, it may well be near zero, perhaps even negative.

The investment management industry thrives on the expedient of forecasting the future by extrapolating the past. As a consequence, U.S. investors have grown accustomed to the idea that stocks "normally" produce an 8 percent real return and a 5 percent (that is, 500 basis point) risk premium over bonds, compounded annually over many decades.[1] Why? Because long-term historical returns have been in this range with impressive consistency. And because investors see these same long-term historical numbers year after year, these expectations are now embedded in the collective psyche of the investment community.[2]

Both the return and the risk premium assumptions are unrealistic when viewed from current market levels. Few have acknowledged that an important part of the lofty real returns of the past stemmed from rising valuation levels and from high dividend yields, which have since diminished. As we will demonstrate, the long-term forward-looking risk premium is nowhere near the 5 percent level of the past; indeed, today, it may well be near zero, perhaps even negative. Credible studies in and outside the United States are challenging the flawed conventional view. Well-researched studies by Claus and Thomas (2001) and Fama and French (2000) are just two (see also Arnott and Ryan 2001). Similarly, the long-term forward-looking real return from stocks is nowhere near history's 8 percent. We argue that, barring unprecedented economic growth or unprecedented growth in earnings as a percentage of the economy, real stock returns will probably be roughly 2–4 percent, similar to bond returns. In fact, even this low real return figure assumes that current near-record valuation levels are "fair" and likely to remain this high in the years ahead. "Reversion to the mean" would push future real returns lower still.

Robert D. Arnott is managing partner at First Quadrant, L.P., Pasadena, California. Peter L. Bernstein is president of Peter L. Bernstein, Inc., New York.

Furthermore, if we examine the historical record, neither the 8 percent real return nor the 5 percent risk premium for stocks relative to government bonds has ever been a realistic *expectation*, except from major market bottoms or at times of crisis, such as wartime. But this topic merits careful exploration. After all, according to the Ibbotson Associates data, equity investors earned 8 percent real returns and stocks have outpaced bonds by more than 5 percent over the past 75 years. Intuition suggests that investors should not require such outsized returns in order to bear equity market risk. Should investors have expected these returns in the past, and why shouldn't they continue to do so? We examine these questions expressed in a slightly different way. First, can we derive an objective estimate of what investors had good reasons to expect in the past? Second, why should we expect less in the future than we have earned in the past?

The answers to both questions lie in the difference between the *observed* excess return and the *prospective* risk premium, two fundamentally different concepts that, unfortunately, carry the same label—risk premium. If we distinguish between past excess returns and future expected risk premiums, the idea that future risk premiums should be different from past excess returns is not at all unreasonable.[3]

This complex topic requires several careful steps if it is to be evaluated correctly. To gauge the risk premium for stocks relative to bonds, we need an expected real bond return and an expected real stock return. To gauge the expected real bond return, we need both bond yields and an estimate of expected inflation through history. To gauge the expected real stock return, we need both stock dividend yields and an estimate of expected real dividend growth. Accordingly, we go through each of these steps, in reverse order, to form the building blocks for the final goal—an estimate of the objective forward-looking equity risk premium relative to bonds through history.

Has the Risk Premium Natural Limits?

For equities to have a zero or negative risk premium relative to bonds would be unnatural because stocks are, on average over time, more volatile than bonds. Even if volatility were not an issue, stocks are a secondary call on the resources of a company; bondholders have the first call. Because the risk premium is usually measured for corporate stocks as compared with government debt obligations (U.S. T-bonds or T-bills), the comparison is even more stark. Stocks should be priced to offer a superior return relative to *corporate* bonds, which should offer a premium yield (because of default risk and tax differences) relative to T-bonds, which should typically offer a premium yield (because of yield-curve risk) relative to T-bills. After all, long bonds have greater duration—hence, greater volatility of price in response to yield changes—so a capital loss is easier on a T-bond than on a T-bill.

In other words, the current circumstance, in which stocks appear to have a near-zero (or negative) risk premium relative to government bonds, is abnormal in the extreme. Even if we add 100 bps to the risk premium to allow for the impact of stock buybacks, today's risk premium relative to the more relevant corporate bond alternatives is still negligible or negative. This facet was demonstrated in Arnott and Ryan and is explored further in this article.

If zero is the natural minimum risk premium, is there a natural maximum? Not really. In times of financial distress, in which the collapse of a nation's economy, hyperinflation, war, or revolution threatens the capital base, expecting a large reward for exposing capital to risk is not unreasonable. Our analysis suggests that the U.S. equity risk premium approached or exceeded 10 percent during the Civil War, during the Great Depression, and in the wake of World Wars I and II. That said, however, it is difficult to see how one might objectively measure the forward-looking risk premium in such conditions.

A 5 percent excess return on stocks over bonds compounds so mightily over long spans that most serious fiduciaries, if they believed stocks were going to earn a 5 percent risk premium, would not even consider including bonds in a portfolio with a horizon of more than a few years: The probabilities of stocks outperforming bonds would be too high to resist.[4] Hence, under so-called normal conditions—encompassing booms and recessions, bull and bear markets, and "ordinary" economic stresses—a good explanation is hard to find for why expected long-term real returns should ever reach double digits or why the expected long-term risk premium of stocks over bonds should ever exceed about 5 percent. These upper bounds for expected real returns or for the risk premium, unlike the lower bound of zero, are "soft" limits; in times of real crisis or distress, the sky's the limit.

Expected versus "Hoped-For" Returns

Throughout this article, we deal with *expected* returns and *expected* risk premiums. This concept is rooted in objective data and defensible expectations for portfolio returns, rather than in the returns that an investor might *hope* to earn. The distinction is subtle; both represent expectations, but one is objective and the other subjective. Even at times in the past when valuation levels were high and when stockholders would have had no objective reason to expect any growth in real dividends over the long run, hopes of better-than-market short-term profits have always been the primary lure into the game.[5]

When we refer to expected returns or expected risk premiums, we are referring to the estimated future returns and risk premiums that an objective evaluation—based on past rates of growth of the economy, past and prospective rates of inflation, current stock and bond yields, and so forth—might have supported at the time. We explicitly do not include any extrapolation of past returns per se, because past returns are driven largely by changes in valuation levels (e.g., changes in yields), which in an efficient market, investors should not expect to continue into the indefinite future. By the same token, we explicitly do not presume any reversion to the mean, in which high yields or low yields are presumed to revert toward historical norms. We presume that the current yield is "fair" and is an unbiased estimator of future yields, both for stocks and bonds.

Few investors subjectively expect returns as low as the objective returns produced by this sort of analysis. In a recent study by Welch (2000), 236 financial economists projected, on average, a 7.2 percent risk premium for stocks relative to T-bills over the next 30 years. If we assume that T-bills offer the same 0.7 percent real return in the future that they have offered over the past 75 years, then stocks must be expected to offer a compounded geometric average real return of about 6.6 percent.[6] Given a dividend yield of roughly 1.5 percent in 1998–1999, when the survey was being carried out, the 236 economists in the survey were clearly presuming that dividend and earnings growth will be at least 5 percent a year above inflation, a rate of real growth three to five times the long-term historical norm and substantially faster than plausible long-term economic growth.

Indeed, even if ir vestors take seriously the real return estimates and risk premiums produced by the sort of objective analysis we propose, many of them will continue to believe that their own investments cannot fail to do better. Suppose they agree with us that stocks and bonds are priced to deliver 2–4 percent real returns before taxes.[7] Do they believe that *their* investments will produce such uninspired pretax real returns? Doubtful. If these kinds of projections were taken seriously, markets would be at far different levels from where they are. Consequently, if these objective expectations are correct, most investors will be wrong in their (our?) subjective expectations.

What Were Investors Expecting in 1926

Are we being reasonable to suggest that, after a 75-year span with 8 percent real stock returns and a 5 percent excess return over bonds (the Ibbotson findings), an 8 percent real return or a 5 percent risk premium is abnormal? Absolutely. The relevant question is whether the investors of 1926 would have had reason to *expect* these extraordinary returns. In fact, they would not. What they got was different from what they should have expected, which is a normal result in a world of uncertainty.

At the start of 1926, the beginning of the returns covered in the Ibbotson data, investors had no reason to expect the 8 percent real returns that have been earned over the past 75 years nor that these returns would provide a 5 percent excess return over bonds. As we will describe, these outcomes were the consequence of a series of historical accidents that uniformly helped stocks and/or helped the risk premium.

Consider what investors might objectively have expected at the start of 1926 from their long-term investments in stocks and bonds. In January that year, government bonds were yielding 3.7 percent. The United States was on a gold standard, government was small relative to the economy as a whole, and the price level of consumer goods, although volatile, had been trendless throughout most of U.S. history up to that moment; thus, inflation expectations were nil. It was a time of relative stability and prosperity, so investors would have had no reason to expect to receive less than this 3.7 percent government bond yield. Accordingly, the *real* return that investors would have expected on their government bonds was 3.7 percent, plain and simple.

Meanwhile, the dividend yield on stocks was 5.1 percent. We can take that number as the starting point to apply the sound theoretical notion that the real return on stocks is equal to

- the dividend yield
- plus (or minus) any change in the real dividend (now viewed as participation in economic growth)
- plus (or minus) any change in valuation levels, as measured by P/E multiples or dividend yields.

What did the investors expect of stocks in early 1926? The time was the tail end of the era of "robber baron" capitalism. As Chancellor (1999) observed, investors were accustomed to the fact that company managers would often dilute shareholders' returns if an enterprise was successful but that the shareholder was a full partner in any business decline. More important was the fact that the long-run history of the market was trendless. Thoughts of long-term economic growth, or long-run capital appreciation in equity holdings, were simply not part of the tool kit for return calculations in those days.

Investors generally did not yet consider stocks to be "growth" investments, although a few people were beginning to acknowledge the full import of Smith's extraordinary study *Common Stocks as Long-Term Investments*, which had appeared in 1924. Smith demonstrated how stocks had outperformed bonds over the 1901–22 period.[8] His work became the bible of the bulls as the bubble of the late 1920s progressed. Prior to 1926, however, investors continued to follow J.P. Morgan's dictum that the market would fluctuate, a traditional view hallowed by more than 100 years of stock market history. In other words, investors had no *trend* in mind. The effort was to buy low and to sell high, period.

Assuming that markets were fairly priced in early 1926, investors should have expected little or no benefit from rising valuation levels. Accordingly, the real long-term return that stock investors could reasonably have expected on average, or from the market as a whole, was the 5.1 percent dividend yield, give or take a little. Thus, stock investors would have expected roughly a 1.4 percent risk premium over bonds, not the 5 percent they actually earned in the next 75 years. The market exceeded objective expectations as a consequence of a series of historical accidents:

- *Historical accident #1: Decoupling yields from real yields.* The Great Depression (roughly 1929–1939) introduced a revolutionary increase in the role of government in peacetime economic policy and, simultaneously, drove the United States (and just about the rest of the world) off the gold standard. As prosperity came back in a big way after World War II, expected inflation became a normal part of bond valuation. This change created a one-time shock to bonds that decoupled nominal yields from real yields and drove nominal yields higher even as real yields fell. Real yields at year-end 2001 were 3.4 percent (the Treasury Inflation-Indexed Securities, commonly called TIPS, yield[9]), but nominal yields were 5.8 percent. This rise in nominal yields (with real yields holding steady) has cost bondholders 0.4 percent a year over 75 years. That accident alone accounts for nearly one-tenth of the 75-year excess return for stocks relative to bonds.
- *Historical accident #2: Rising valuation multiples.* Between 1926 and 2001, stocks rose from a valuation level of 18 times dividends to nearly 70 times dividends. This fourfold increase in the value assigned to each dollar of dividends contributed 180 bps to annual stock returns over the past 75 years, even though the entire increase occurred in the last 17 years of the period (we last saw 5.1 percent yields in 1984). This accident explains fully one-third of the 75-year excess return.
- *Historical accident #3: Survivor bias.* Since 1926, the United States has fought no wars on its own soil, nor has it experienced revolution. Four of the fifteen largest stock markets in the world in 1900 suffered a total loss of capital, a –100 percent return, at some point in the past century. The markets are China, Russia, Argentina, and Egypt. Two others came close—Germany (twice) and Japan. Note that war or revolution can wipe out bonds as easily as stocks (which makes the concept of "risk premium" less than relevant). U.S. investors in early 1926 would *not* have considered this likelihood to be zero, nor should today's true long-term investor.
- *Historical accident #4: Regulatory reform.* Stocks have gone from passing relatively little economic growth through to shareholders to passing much of the economic growth through to shareholders. This shift has led to 1.4 percent a year growth in real dividend payments and in real earnings since 1926. This accelerated growth in real dividends and earnings, which no one in 1926 could have anticipated, explains roughly one-fourth of the 75-year excess return.[10]

In short, the equity investors of 1926 probably expected to earn a real return little different from their 5.1 percent yield and expected to earn little more than the 140 bp yield differential over bonds. Indeed, an objective investor might have expected a notch less because of the greater frequency with which investors encountered dividend cuts in those days.

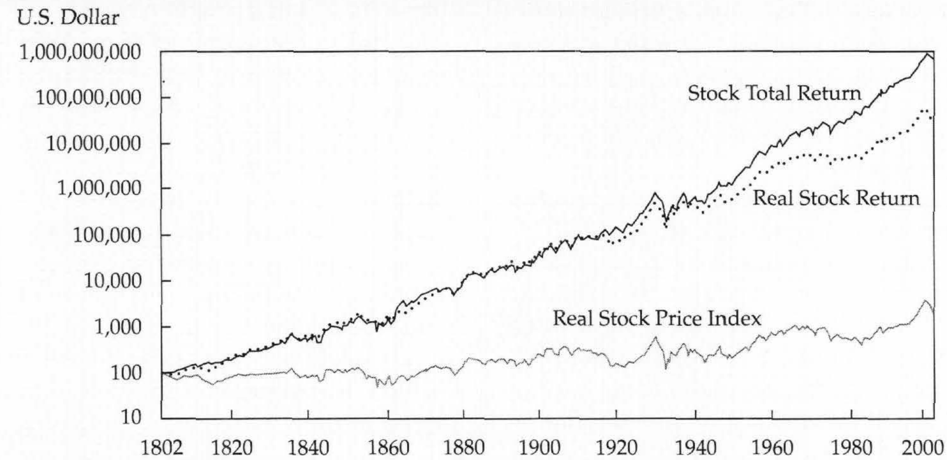
What Expectations Were Realistic in the Past?

To gauge what risk premium an investor might have objectively expected in the longer run past, we need to (1) estimate the real return that investors might reasonably have expected from stocks, (2) estimate the real return that investors might reasonably have expected from bonds, and (3) take the difference. From this exercise, we can gauge what risk premium an investor might reasonably have expected at any point in history, not simply an isolated snapshot of early 1926. A brief review of the sources of stock returns over the past two centuries should help lay a foundation for our work on return expectations and shatter a few widespread misconceptions in the process. The sources of the data are given in Appendix A.[11]

Step I: How Well Does Economic Growth Flow into Dividend Growth? Over the past 131 years, since reliable earnings data became available in 1870, the average earnings yield has been 7.6 percent and the average real return for stocks has been 7.2 percent; this close match has persuaded many observers to the view (which is wholly consistent with finance theory) that the best estimate for real returns is, quite simply, the earnings yield. On careful examination, this hypothesis turns out to be wrong. In the absence of changing valuation levels, real returns are systematically *lower* than earnings yields.

Figure 1 shows stock market returns since 1802 in a fashion somewhat different from that shown in most of the literature. The solid line in Figure 1 shows the familiar cumulative total return for U.S. equities since 1802, in which each $100 invested grows, with reinvestment of dividends, to almost $700 million in 200 years. To be sure, some of this growth came from inflation; as the line "Real Stock Return" shows, $700 million will not buy what it

Figure 1. Return from Inflation and Dividends: Growth of $100, 1801–2001

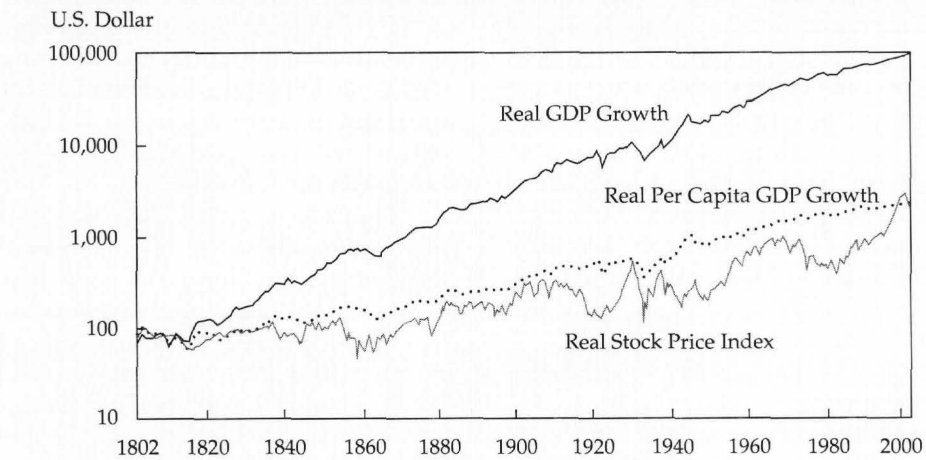


would have in 1802, when one could have purchased the entire U.S. GNP for less than that sum.[12] By removing inflation, we show in the "Real Stock Return" line that the $100 investment grew to "only" $37 million. Thus, adjusted for inflation, our fortune is much diminished but still impressive. Few portfolios are constructed without some plans for future spending, and the dividends that stocks pay are often spent. So, the "Real Stock Price Index" line shows the wealth accumulation from price appreciation alone, net of inflation and dividends. This bottom line (literally and figuratively) reveals that stocks have risen just 20-fold from 1802 levels. Put another way, if an investor had placed $100 in stocks in 1802 and received and spent the average dividend yield of 4.9 percent for the next 200 years, his or her descendants would today have a portfolio worth $2,099, net of inflation. So much for our $700 million portfolio!

Worse, the lion's share of the growth from $100 to $2,099 occurred in the massive bull market from 1982 to date. In the 180 years from 1802 to the start of 1982, the real value of the $100 portfolio had grown to a mere $400. If stocks were priced today at the same dividend yields as they were in 1802 and 1982, a yield of 5.4 percent, the $100 portfolio would be worth today, net of inflation and dividends, just $550. These data put the lie to the conventional view that equities derive most of their returns from capital appreciation, that income is far less important, if not irrelevant.

Figure 2 allows a closer look at the link between equity price appreciation and economic growth. It shows that the growth in share prices is much more closely tied to the growth in real *per capita* GDP (or GNP) than to growth in real GDP per se. The solid line shows that, compounding at about 4 percent in the 1800s and 3 percent in the 1900s, the economy itself delivered an impressive 1,000-fold growth.

Figure 2. The Link between Stock Prices and Economic Growth, 1802–2001



But net of inflation and dividend distributions, stock prices (the same "Real Stock Price Index" line in Figure 1) fell far behind, with cumulative real price appreciation barely 1/50 as large as the real growth in the economy itself.

How can this be? Can't shareholders expect to participate in the growth of the economy? No. Shareholders can expect to participate *only in the growth of the enterprises they are investing in.* An important engine for economic growth is the creation of new enterprises. The investor in today's enterprises does not own tomorrow's new enterprises—not without making a separate investment in those new enterprises with new investment capital.

Finally, the "Real Per Capita GDP Growth" line in Figure 2 shows the growth of the economy measured net of inflation *and population growth.* This growth in real per capita GDP tracks much more closely with the real price appreciation of stocks (the bottom line) than does real GDP itself.

Going one step further, **Figure 3** shows the internal growth of real dividends—that is, the growth that an index fund would expect to see in its own real dividends in the absence of additional investments, such as reinvestment of dividends.[13] Real dividends exhibit *internal* growth that is similar to the growth in real per capita GDP. Because growth in per capita GDP is a measure of productivity growth, the internal growth that can be sustained in a diversified market portfolio should closely match the growth of *productivity* in the economy, not the growth in the economy per se. Therefore, the dotted line traces per capita real GDP growth, the "Real Stock Price Index" line shows real stock prices, and the bottom line shows real dividends (× 10).[14] Figure 3 reveals the remarkable resemblance between real dividend growth and growth in real per capita GDP.

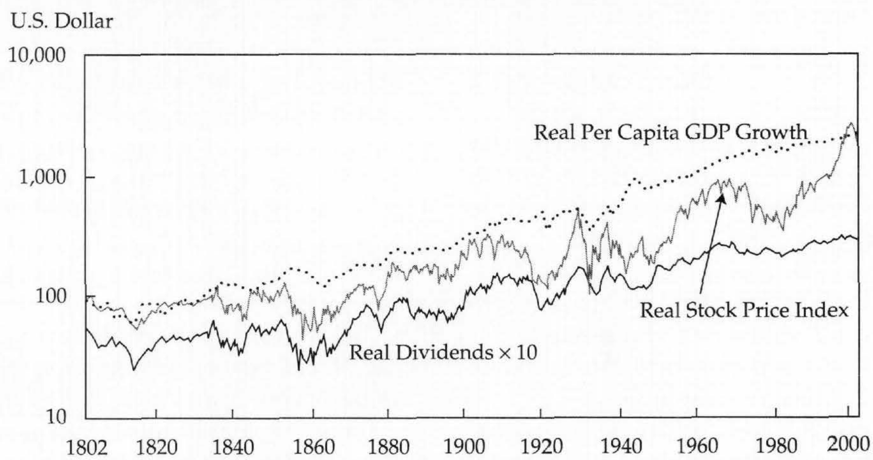
When we measure the internal growth of real dividends as in Figure 3, we see that real dividends have risen a modest fivefold from 1802 levels. In other words, the real dividends for a $100 portfolio invested in 1802 have grown merely 0.9 percent a year net of inflation. To be sure, the price assigned to each dollar of dividends has quadrupled, which leads to the 20-fold real price gain in the 200 years.

Although real dividends have tracked remarkably well with real per capita GDP, they have consistently fallen short of GDP gains. Not only have real dividends failed to match real GDP growth (as many equity investors seem to think is a *minimal* future growth rate for earnings and dividends), they have even had a modest shortfall, at an average of about 70 bps a year, relative to per capita economic growth.

In short, more than 85 percent of the return on stocks over the past 200 years has come from (1) inflation, (2) the dividends that stocks have paid, and (3) the rising valuation levels (rising P/Es and falling dividend yields) since 1982, not from growth in the underlying fundamentals of real dividends or earnings.[15] Furthermore, real dividends and real per capita GDP both grew faster in the 20th century than in the 19th century. Conversely, GDP grew faster in the 19th century than in the 20th century, *unless* we convert to per capita GDP.

Many observers think that earnings growth is far more important than dividend growth. We respectfully disagree. As noted by Hicks (1946), "... any increase in the present value of prospective net receipts must raise profits." In other words, properly stated, earnings should represent a proportional share of the net present value of all future

Figure 3. Dividends and Economic Growth, 1802–2001



profits. The problem is that reported earnings often do not follow this theoretical definition. For example, negative earnings should almost never be reported, yet reported operating losses are not uncommon. Furthermore, the quality of earnings reports prior to the advent of the U.S. SEC is doubtful at best; worse, we were unable to find any good source for earnings information prior to 1870. Accordingly, the dividend is the one reliable aspect of stock ownership over the past two centuries. It is the cash income returned to the shareholders; it is the means by which the long-term investor earns most of his or her internal rate of return. Finally, with earnings growth barely 0.3 percent faster than dividend growth over the past 131 years, an analysis based on earnings would reach conclusions nearly identical to our conclusions based on dividends.

Finance theory tells us that capital is fungible; that is, equity and debt, retained earnings and dividends—all should flow to the best use of capital and should (in the absence of tax-related arbitrages and other nonsystematic disruptions) produce a similar risk-adjusted return on capital. Thus, the retained earnings should deliver a return similar to the return an investor could have earned on that capital had it been paid out as dividends. Consider an example: If a company has an earnings yield of 5 percent (corresponding to a P/E of 20), it can pay out all of the earnings and thereby deliver a 5 percent yield to the shareholder. The real value of the company should not be affected by this full earnings distribution (unless the earnings are themselves being misstated), so the 5 percent earnings yield should also be the expected real return. Now, if the company, instead, pays a 2 percent yield and retains earnings worth 3 percent of the stock price, the company ought to achieve 3 percent real growth in earnings; otherwise, it should have distributed the cash to the shareholders. How does this theory stand up to reality?

Over the past 200 years, dividend yields have averaged 4.9 percent, yet real returns have been far higher, 6.6 percent. Since 1870, earnings yields have averaged 7.6 percent, close to the real returns of 7.2 percent over that span. This outcome is consistent with the notion of fungible capital, that the return on capital reinvested in an enterprise ought to match the return an investor might otherwise have earned on that same capital if it had been distributed as a dividend. However, if we take out the changes in valuation levels since 1982 (regardless of whether dividend yields or P/Es are used for those levels), the close match between earnings yield and real stock returns evaporates.

Moreover, with an average earnings yield of 7.6 percent and an average dividend yield of 4.7 percent since 1871, the average "retained earnings yield" has been nearly 3 percent. This retained earnings yield should have led to real earnings and dividend growth of 3 percent; otherwise, management ought to have paid this money out to the shareholders. Instead, real dividends and earnings grew at annual rates of, respectively, 1.2 percent and 1.5 percent. Where did the money go? The answer is that during the era of "pirate capitalism," success often led to dilution: Company managers issued themselves more stock![16]

Furthermore, retained earnings often chase poor internal reinvestment opportunities. If existing enterprises experienced only 1.2–1.5 percent internal growth of real dividends and earnings in the past two centuries, most of the 3.6 percent economic growth the United States has enjoyed has clearly not come from reinvestment in existing enterprises. In fact, it has stemmed from entrepreneurial capitalism, from the creation of new enterprises. Indeed, dividends on existing enterprises have fallen relative to GDP growth by approximately 100-fold in the past 200 years.[17]

The derring-do of the pirate capitalists of the 19th and early 20th centuries is not the only or even the most compelling explanation for this phenomenon. All the data we used are from indexes, which are a particular kind of sampling of the market. Old companies fading from view lose their market weight as the newer and faster growing companies gain a meaningful share in the economy. The older enterprises often have the highest earnings yield and the worst internal reinvestment opportunities, but the new companies do not materialize in the indexes the minute they start doing business or even the minute they go public. When they do enter the index, their starting weight is often small.

Furthermore, an index need only change the divisor whenever a new enterprise is added, whereas we cannot add a new enterprise to our portfolio without cost. The index changing the divisor is mathematically the same as selling a little bit of *all other* holdings to fund the purchase of a new holding, but when we add a new enterprise to our portfolios, we must commit some capital to effect the purchase. Whether through reinvestment of dividends or infusion of new capital, this new enterprise cannot enter our portfolio through the *internal* growth of an existing portfolio of assets. In effect, we must rebalance out of existing stocks to make room for the new stock—which produces the natural dilution that takes place as a consequence of the creation of new enterprises in a world of entrepreneurial capitalism: The same dollar cannot own an existing enterprise and simultaneously fund a new enterprise.[18]

The dynamics of the capitalist system inevitably lead to these kinds of results. Good business leads to expansion; in a competitive environment, expansion takes place on a wide scale; expansion on a wide scale intensifies the competitive environment; margins begin to decline; earnings growth slows; in time, earnings begin to decline; then, expansion slows, profit margins improve, and the whole thing repeats itself. We can see this drama playing out in the relationship between payout ratios in any given year and earnings growth: Since 1984, the payout ratio has explained more than half of the variation in five-year earnings growth rates with a *t*-statistic of 9.51.[19]

Few observers have noticed that much of the difference between stock dividend yields and the real returns on stocks can be traced directly to the upward revaluation of stocks since 1982. The historical data are muddied by this change in valuation levels—which is why we find the current fashion of forecasting the future by extrapolating the past to be so alarming. The earnings yield is a better estimate of future real stock returns than any extrapolation of the past. And the dividend yield plus a small premium for real dividend growth is even better, because in the absence of changes in valuation levels, the earnings yield systematically overstates future real stock returns.

If long-term real growth in dividends had been 0.9 percent, real stock returns would have been only 90 bps higher than the dividend yield if it were not for the enormous jump in the price-to-dividend ratio since 1982. Even if we adjust today's 1.4 percent dividend yield sharply upward to include "dividends by another name" (e.g., stock repurchases), making a case for real returns higher than the 3.4 percent currently available in the TIPS market would be a stretch.[20]

Step II: Estimating Real Stock Returns. To estimate the historical equity risk premium, we must compare (1) a realistic estimate of the *expected* real stock return that objective analysis might have supported in past years with (2) the *expected* real bond return available at the time. Future long-term real stock return is defined as[21]

$$RSR(t) = DY(t) + RDG(t) + \Delta PD(t) + \varepsilon, \quad (1)$$

where

$DY(t)$ = percentage dividend yield for stocks at time t

$RDG(t)$ = percentage real dividend growth rate over the applicable span starting at time t

$\Delta PD(t)$ = percentage change in the price assigned to each dollar of dividends starting at time t

ε = error term for sources of return not captured by the three key constituents (this term will be small because it will reflect only compounding effects)

Viewed from the perspective of forecasting future real returns, the $\Delta PD(t)$ term is a valuation term, which we deliberately exclude from our analysis. If markets exhibit reversion to the mean, valuation change should be positive when the market is inexpensive and negative when the market is richly priced. If markets are efficient, this term should be random. We choose not to go down the slippery slope of arguing valuation, even though we believe that valuation matters. Rather, we prefer to make the simplifying assumption that market valuations at any stage are "fair" and, therefore, that the real return stems solely from the dividend yield and real growth of dividends.

That said, the estimation process becomes more complex when we consider a sensible estimate for real dividend growth. For example, what real dividend growth rate might an investor in 1814 have expected on the heels of the terrible 1802–14 bear market and depression, during which real per capita GDP, real dividends, and real stock prices all contracted 40–50 percent? How can we objectively put ourselves in the position of an investor almost 200 years ago? For this purpose, we partition the real growth in dividends into two constituent parts, real economic growth and the growth of dividends relative to the economy.

Why not simply forecast dividend growth directly? Because countless studies have shown that analysts' forecasts are too optimistic, especially at market turning points. In fact, dividends (and earnings) in aggregate cannot grow as fast as the economy on a sustainable long-term basis, in large part because of the secular increase in shares outstanding and introduction of new enterprises. So, long-term dividend growth should be equal to long-term economic growth minus a haircut for dilution or entrepreneurial capitalism (the share of economic growth that is tied to new enterprises not yet available in the stock market) or plus a premium for hidden dividends, such as stock buybacks. So, real dividend growth is given by

$$RDG(t) = RGDP(t) + DGR(t) + \varepsilon, \quad (2)$$

where

$RGDP(t)$ = percentage real per capita GDP growth over the applicable span starting at time t

$DGR(t)$ = annual percentage dilution of real GDP growth as it flows through to real dividends starting at time t

ε = error term for compounding effects (it will be small)

Basically, in Equation 2, we are substituting $RGDP(t) + DGR(t)$ for $RDG(t)$ and rolling the $\Delta PD(t)$ term into the error term (to avoid getting into the debates about valuation and regression to the mean). With these two changes, and converting to an expectations model, our model for expected real stock market returns, *ERSR*, becomes

$$ERSR(t) = EDY(t) + ERGDP(t) + EDGR(t), \quad (3)$$

where

$EDY(t)$ = *expected* percentage dividend yield for stocks at time t

$ERGDP(t)$ = *expected* percentage real per capita GDP growth over the applicable span starting at time t

$EDGR(t)$ = *expected* annual percentage dilution of real per capita GDP growth as it flows through to real dividends starting at time t

A complication in this structure is the impact of recessions. In serious recessions, dividends are cut and GDP growth stops or reverses, possibly leading to a decline in even the long-term GDP growth. The result is a dividend yield that is artificially depressed, real per capita GDP growth that is artificially depressed, and long-term dividend growth relative to GDP growth that is artificially depressed, all three of which lead, in recessionary troughs, to understated expected real stock returns. The simplest way to deal with this issue is to use the last peak in dividends before a business downturn and the last peak in GDP before a business downturn in computing each of the three constituents of expected real stock returns.[22]

We illustrate how we constructed an objective real stock return forecast for the past 192 years in **Figure 4**; Panel A spans 1810 to 2001, and Panel B shows the same data after 1945. To explain these graphs, we will go through them line by line.

The easiest part of forecasting real stock returns, the "Estimated Real Stock Return" line in Figure 4, is the dividend yield: It is a known fact. We have adjusted dividends to correct for the artificially depressed dividends during recessions to get the $EDY(t)$ term shown as the "Dividend Yield" line in Figure 4. This step allows us to avoid understating the equity risk premium in recessions when dividends are artificially depressed. This adjustment boosts the expected dividend yield slightly relative to the raw dividend yield because the deepest recessions are often deeper than the average recessions of the prior 40 years. Against an average dividend yield of 4.9 percent, we found an average *expected* dividend yield of 5.0 percent.

Most long-run forecasts of earnings or dividend growth ignore the simple fact that aggregate earnings and dividends in the economy cannot sustainably grow faster than the economy itself. If new enterprise creation and secondary equity offerings dilute the share of the economy held by the shareholders in existing enterprises, then one sensible way to forecast dividend growth is to forecast economic growth and then forecast how rapidly this dilution will take place.[23] Stated another way, we want to know how much *less* rapidly dividends (and earnings) on existing enterprises can grow than the economy at large. The sum of real economic growth less this shortfall is the real growth in dividends.

The resulting line, "Dilution of GDP Growth in Dividends," in the two graphs of Figure 4 represents the $EDGR(t)$ term in our model (Equation 3). Note the persistent tendency for dividend growth to lag GDP growth: Real dividends have grown at 1 percent a year over the past 192 years, whereas the real economy has grown at 3.8 percent a year, and even real per capita GDP has grown at 1.8 percent a year. Why should real dividends have grown so much more slowly than the economy?

First, much of the growth in the economy has come from innovation and entrepreneurial capitalism. More than half of the capitalization of the Russell 3000 today consists of enterprises that did not exist 30 years ago. The 1971 buy-and-hold investor could not participate in this aspect of GDP growth or market growth because the companies did not exist. So, today's dividends and earnings on the existing companies from 1971 are only part of the dividends and earnings on today's total market.

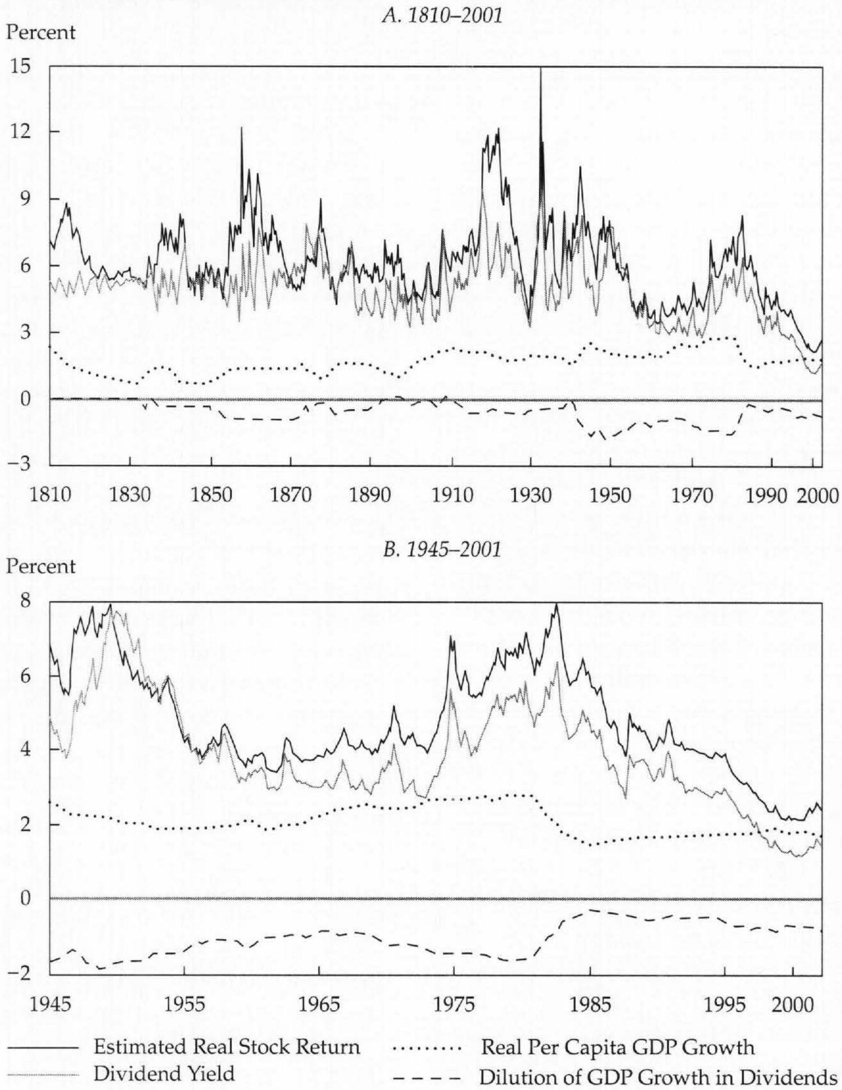
Second, as was demonstrated in Bernstein (2001b), retained earnings are often not reinvested at a return that rivals externally available investments; earnings and dividend growth are faster when payout ratios are high than when they are low, perhaps because corporate managers are then forced to be more selective about reinvestment alternatives.[24]

Finally, as we have emphasized, corporate growth typically leads to more shares outstanding, which automatically imposes a drag on the growth in dividends per share.

As a sensible estimate of the future dividend/GDP shortfall, the rational investor of any day might forecast dividend growth by using the prior 40-year shortfall in dividend growth relative to per capita GDP or might choose to use the cumulative (by now, 200-year) history. We chose the simple expedient of averaging the two.

The dilution effect we found from the 40-year and cumulative data for real dividends and real per capita GDP averages –60 bps. So, in the past 40 years, the dilution of dividend growth is almost

Figure 4. Estimating Real Stock Returns



exactly the same as the long-term average, –80 bps. With a standard deviation of just 0.5 percent, this shortfall of dividend growth relative to economic growth is the steadiest of any of the components of real stock returns or real bond returns. It has never been materially positive on a long-term sustained basis; it has never risen above +10 bps for any 40-year span in the entire history since 1810.

The history of dividend growth shows no evidence that dividends can ever grow materially faster than per capita GDP. Indeed, they almost always grow more slowly. Suppose real GDP growth in the next 40 years is 3 percent a year and population growth is 1 percent a year. These assumptions would appear to put an *upper limit* on real dividend growth at a modest 2 percent a year, far below consensus expectations. If the historical average dilution of dividend growth relative to real per capita GDP growth prevails, then the future real growth in dividends should be only about 1 percent, even with relatively robust, 2.5–3.0 percent, real GDP growth.

Now consider the third part of forecasting real stock returns in this fashion—the forecast of long-term real per capita GDP growth, *ERGDP(t)* in our model. How much real per capita GDP growth would an investor have expected at any time in the past 200 years? Again, a simple answer might come from the most recent 40 years' growth rate; another might come from the cumulative record going back as far as we have dividend and GDP data, to 1802. These historical data are shown in the "Real per Capita GDP Growth" line in Figure 4. And again, we chose the simple expedient of averaging the average of the two. Real per capita GDP growth has been remarkably stable over the past 200 years, particularly if we adjust it to correct for temporary dips during recessions. If we examine truly long-term results, the 40-year real growth rate in real per capita GDP has averaged 1.8 percent with a standard deviation of only 0.9 percent.[25]

Note from Figure 4 that the total economy grew faster during the 19th century than the 20th century whereas stock returns (and the underlying earnings and dividends) grew faster in the 20th century than the 19th. Why would the rapid growth of the 19th century flow through to the shareholder less than the slower growth of the 20th century? We see two possible answers. First, the base from which industrial growth started in the 19th century was so much smaller that much faster new enterprise creation occurred then than in the 20th century. Second, with nearly 3 percent growth in the population from 1800 to 1850, the growing talent and labor pool fueled a faster rate of growth than the 1.25 percent annual population growth rate of the most recent 50 years. It is not surprising that the pace of dilution, both from the creation of new enterprises and from secondary equity offerings, is faster when the population is growing faster. Population growth fuels growth in human capital, in available labor, and in both demand *and* supply of goods and services. As a result, when population growth is rapid, the pace of dilution of growth in the economy (as it flows through to a shareholder's earnings and dividends) is far more stable relative to real per capita GDP than relative to real GDP itself.

The simple framework we have presented for estimating real stock returns reveals few surprises. As Panels A and B of Figure 4 show, the expected stock return is the sum of the three constituent parts graphed in the other lines. We estimate that expected real stock returns for the past 192 years averaged about 6.1 percent with the following constituent parts: an expected yield averaging 5.0 percent plus real per capita GDP growth of 1.7 percent a year minus an expected *shrinkage* in dividends relative to real per capita GDP averaging –0.6 percent. Meanwhile, investors actually earned real returns of 6.8 percent. Most of this 70 bp difference from the 6.1 percent rational expectation over the past 192 years can be traced to the rise in valuation levels since 1982; the rest consists of the other happy accidents detailed previously.

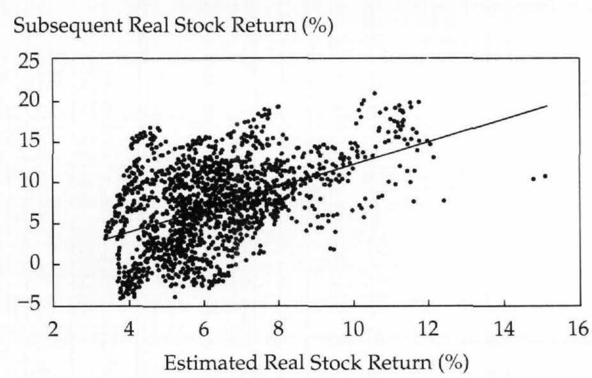
Expectations for real stock returns have soared above 6 percent often enough that many actuaries even today consider 8 percent a "normal" real return for equities. Our estimate for real stock returns, however, exceeds 8 percent only during the depths of the Great Depression, in the rebuilding following the War of 1812, the Civil War, World War I, and World War II, and in the Crash of 1877. In the past 50 years, expected real stock returns above 7 percent have been seen only in the aftermath of World War II, when many investors still feared a return to Depression conditions, and in the depths of the 1982 bear market.

When viewed from the vantage point of this formulation for expected real stock returns, the full 192-year record shows that expected real stock returns fell below 3.5 percent only once before the late 1990s, at the end of 1961 just ahead of the difficult 1962–82 span, real stock prices fell by more than 50 percent. Since 1997, expected real stock returns have fallen well below the 1961 levels, where they remain at this writing.

This formulation for expected real stock returns reveals the stark paradigm shift that took place in the 1950s. Until then, the best estimate for real dividend growth was rarely more than 1 percent, so the best estimate for real stock returns was approximately the dividend yield plus 100 bps—considerably less than the earnings yield! From the 1950s to date, as Panel B of Figure 4 shows, the shortfall of dividends relative to GDP growth improved (perhaps because the presence of the SEC discourages company managers from ignoring shareholder interests) and the real return that one could objectively expect from stocks finally and persuasively rose above the dividend yield. Today, it stands at almost twice the dividend yield, but it is still a modest 2.4 percent.

Figure 5 shows the strong correlation between our formulation for expected real stock returns and the actual real returns that stocks have delivered over the subsequent 10-year span. The correlation is good—at 0.62 during the modern market era after World War II and 0.46 for the full 182 years.[26] If we test the correlation between this simple metric of expected real stock returns and the actual subsequent 20-year real stock returns (not shown), the correlations grow to 0.95 and 0.60 for the post-1945 period and the full 182 years, respectively.

Figure 5. Estimated and Subsequent Actual Real Stock Returns, 1802–2001



The regression results given in Panel A **Table 1** show that the coefficient in the regression is larger than 1.00. So, that 100 bp increase in the expected real stock return, *ERSR*, is worth more than 100 bps in the subsequent 10-year actual real stock return, *RSR*. The implication is that some tendency for reversion to the mean does exist and that it will magnify the effect of unusually high or low expected real stock returns. This suggestion has worrisome implications for the recent record low levels for expected real stock returns.

Because rolling 10-year returns (and expected returns in our model) are highly serially correlated, the *t*-statistics given in Panel A of Table 1 are not particularly meaningful. One way to deal with overlapping data is to eliminate the overlap by using nonoverlapping samples—in this case, examining only our 19 nonoverlapping samples beginning December 1810. The Panel B results, with a coefficient larger than 1.00, confirm the previous results (and approach statistical significance, even with only 17 degrees of freedom).[27] One worrisome fact, in light of the recent large real stock returns, is that the nonoverlapping real stock returns by decades have a –31 percent serial correlation. Although it is not a statistically significant correlation, it is large enough to be interesting: It suggests that spectacular decades or wretched decades may be considerably more likely to reverse than to repeat.

Evaluating the real returns on stocks is clearly a useful exercise if the metric of success for a model is subsequent actual real returns, but we live in a relative world. The future real returns on all assets will rise and fall; so, real returns are an insufficient metric of success. What is of greater import is whether this metric of prospective real stock returns helps us identify the attractiveness of stocks *relative to other assets.*

Step III: Estimating Future Real Bond Returns. On the bond side, real realized returns are equal to the nominal yield minus inflation (or plus deflation) and plus or minus yield change times duration:

$$RBR(t) = BY(t) - INFL(t) + \Delta BY(t)DUR(t) + \varepsilon, \quad (4)$$

where

$BY(t)$ = percentage bond yield at time t

$INFL(t)$ = percentage inflation over the applicable span starting at time t

$\Delta BY(t)DUR(t)$ = annual change in yield over the applicable span times duration at time t (under the assumption that rolling reinvestment is in bonds of similar duration)

ε = error term (compounding effects lead to a small error term in this simple formulation)

As with stocks, we prefer to take current yields as a fair estimate of future bond yields. So, we eliminate the variable that focuses on changes in yields, $\Delta BY(t)DUR(t)$. We also need to shift our focus from measuring past real bond returns to forecasting future real bond returns. Therefore, our model is

$$ERBR(t) = BY(t) - EINFL(t), \quad (5)$$

where $BY(t)$ is the percentage bond yield at time t and $EINFL(t)$ is the expected percentage inflation over the applicable span starting at time t.

Equation 5 is difficult only in the sense that expectations for inflation in past economic environs are difficult to estimate objectively. How, for example, are we to gauge how much inflation an investor in February 1864 would have expected at a time when inflation had averaged 20 percent over the prior three years because of wartime shortages?

Table 1. Regression Results: Estimated Real Stock Return versus Actual 10-Year Real Stock Return
(*t*-statistics in parentheses)

Period	a	b	R^2	Correlation	Serial Correlation
A. Raw data: $RSR(t) = a + b[ERSR(t-120)]$					
1810–2001	–1.51%	1.38%	0.214	0.46	0.992
	(–4.2)	(24.4)			0.990
1945–2001	–7.80	3.15	0.391	0.62	0.996
	(–8.8)	(19.0)			0.995
B. Using 19 nonoverlapping samples, beginning December 1810					
1810–2000	–0.35%	1.22%	0.182	0.430	–0.315
	(–0.1)	(1.9)			0.021

Expectations would depend strongly on the outcome of the war: A victory by the North would have been expected to result in a restoration of the purchasing power of the dollar as wartime shortages disappeared; a victory by the South could have had severe consequences on the ultimate purchasing power of the North's dollar as a consequence of debt that could no longer be serviced. A rational expectation might have been for inflation greater than 0 (reflecting the possibility of victory by the South) but less than the 20 percent three-year inflation rate (reflecting the probability of victory by the North).

We based the estimate for expected future inflation on an *ex ante* regression forecast of 10-year future inflation based, in turn, on recent three-year inflation.[28] **Figure 6** shows how the expected rate of inflation has steadily become more closely tied to recent actual inflation in recent decades. Bond yields responded weakly to bursts of inflation up until the time of the Great Depression; they responded more strongly as inflation became a structural component of the economy in the past four decades.

Until the last 40 years, inflation was generally associated with wars and was virtually nonexistent—even negative—in peacetime. Figure 6 shows a burst of double-digit inflation on the heels of the War of 1812, in the late stages of the Civil War, during World War I, and in the rebuilding following World War II. And more recently, double-digit inflation characterized the "stagflation" of 1978–1981 that followed the Vietnam War and the oil shocks of the 1970s. The most notable changes since the Great Depression, especially since World War II, involve the magnitude and perceived role of government and loss of the automatic brakes once applied by the gold standard. From the end of World War II to the great inflationary crisis at the end of the 1970s, the dread of unemployment that was inherited from the Great Depression was the driving factor in both fiscal and monetary policy.

With the introduction of TIPS in January 1997, we finally have a U.S. government bond that pays a real return, which allows us to simplify the expected real bond returns to be the TIPS yield itself from that date forward; that is,

$$ERBR(t) = YTIPS(t), \tag{6}$$

where $YTIPS(t)$ is the percentage TIPS yield at time t.

Figure 7 shows how the current government bond yield (the "Bond Yield" line) minus expected inflation ("Estimated Inflation") leads to an estimate of the real bond return and hence the long-term expected real bond return ("Estimated Real Bond Yield"), which is the estimate through March of 1998 and the TIPS yield thereafter.[29] From the Equation 5 (or, more recently, Equation 6) formulation, expected real bond returns averaged 3.7 percent over the full period, a very respectable real yield, given the limited risk of government bonds, and good recompense for an investor's willingness to bear some bond-price volatility. Investors may not always have viewed government debt as the rock-solid investment, however, that it is generally considered today.

The 3.7 percent real bond return consists of an average nominal bond yield of 4.9 percent minus an expected inflation rate of 1.2 percent. For comparison, the average actual inflation rate has been 1.4 percent. In the years after World War II, the rate of peacetime inflation embedded in investors' memory banks was essentially zero, perhaps even slightly negative. Consequently, bond investors kept expecting inflation to go away, despite its persistence at a modest rate in the 1950s and early 1960s and an accelerating rate thereafter. As a result, bonds were badly priced for reality during most of

Figure 6. Estimating Future Inflation, 1810–2001

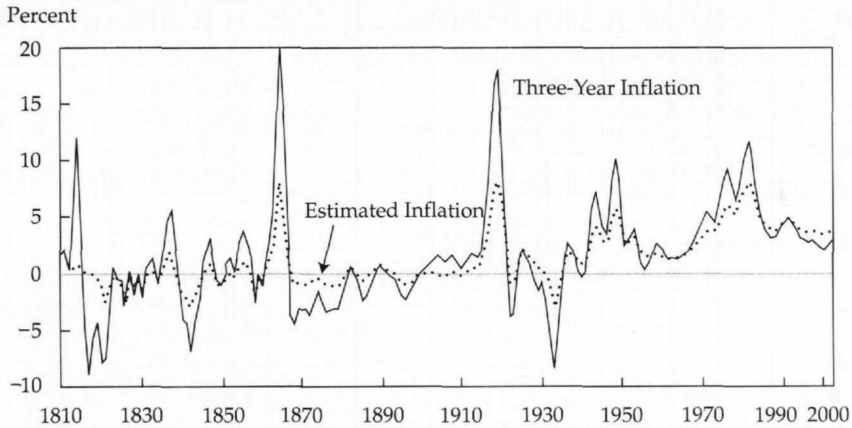
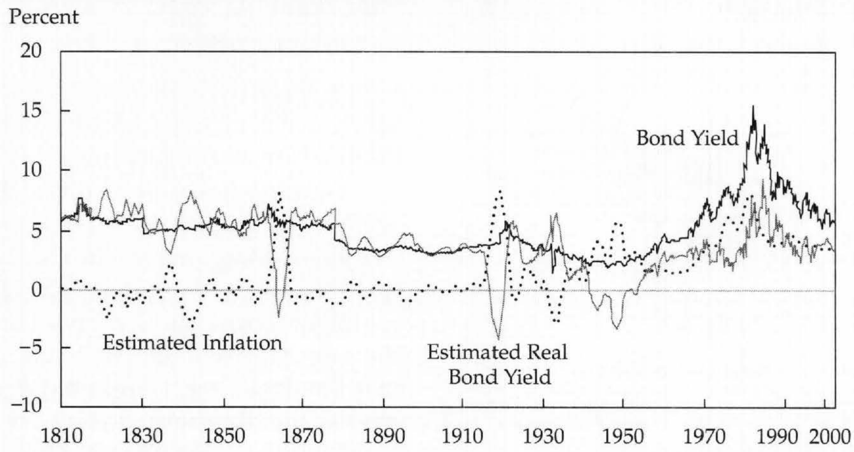


Figure 7. Estimating Real Bond Yields, 1810–2001



these two decades; they turned out to be certificates of confiscation for their holders until people finally woke up in the 1970s and 1980s. Actual inflation exceeded expected inflation with few exceptions from the start of World War II until roughly 1982; as can be seen in Figure 7, our model captures this phenomenon. Expectations are lower than actual outcomes during this span.

Figure 7 also shows several regimes of real yield with distinct structural change from one regime to the next. From the time the United States was in its infancy until the end of Reconstruction in the late 1870s, investors would not have viewed U.S. government bonds as a secure investment. They would have priced these bonds to deliver a 5–7 percent real yield, except during times of war. The overall stability of the yields is impressive: Unlike the history of stock prices, the surprise elements have been small.

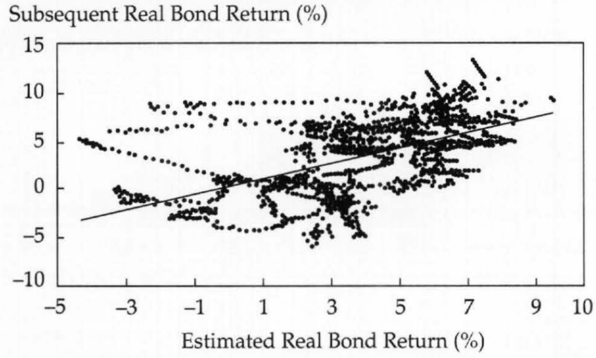
Once the United States had survived the Civil War and the security of U.S. government debt had been demonstrated repeatedly, investors began to price government debt at a 3–5 percent real yield. As Figure 7 shows, this level held, with a brief interruption in World War I, until the country went off the gold standard in 1933. This record is remarkable in view of the high rate of economic growth, but revolutionary technological change in those days, especially in transportation and agriculture, led to such stunning reductions in product costs that inflation was kept at bay except for very brief intervals.

For the next 20–25 years, the nation struggled with the Great Depression, World War II, and the war's aftermath. Investors slowly began to realize that deflationary price drops did not rebound fully after the trough of the Depression and that inflationary price increases did not retreat after the end of the war. The changed role of government plus the end of the gold standard had altered the picture, perhaps irrevocably. During this span, investors priced bonds to offer a 2–4 percent *notional* yield but a rocky −3 percent to +3 percent real yield. As Figure 7 shows, bond investors woke up late to the fact that inflation was now a normal part of life.

From the mid-1950s to date, investors have struggled with more structural inflation and more inflation uncertainty than ever before. Although investors sought to price bonds to deliver a real yield, inflation consistently exceeded their expectations. Only during the down cycle of the inflation roller coaster of 1980–1985 did bonds finally provide real yields to their owners. After this experience, bond investors developed an anxiety about inflation far greater than objective evidence would support. The result was a brief spike in real bond returns in 1984, as Figure 7 shows, with bond yields still hovering at 13.8 percent, even though three-year inflation had fallen to 4.7 percent (and our regression model for future inflation would have suggested expected inflation of 4.6 percent). The "expected" real yield was a most unusual 9.2 percent because investors were not yet prepared to believe that double-digit inflation was a thing of the past.

Another interesting fact is evident in **Figure 8**: The expected real bond returns produced by our formulation are highly correlated with the actual real returns earned over the subsequent decade. For 1810 to 1991, the expected real bond return has a 0.52 correlation with the actual real bond return earned over the next 10 years; from 1945 to date, the correlation rises to an impressive 0.63. Panel A of **Table 2** shows that the coefficient is reliably positive but not reliably more than 1.00, which suggests that, unlike expected real stock returns, no powerful tendency for reversion to the mean is at work in real bond yields. When we used the 19 available nonoverlapping samples (Panel B), we found the resulting correlation to be 0.64, which is a statistically significant relationship.[30]

Figure 8. Estimated and Subsequent Actual Real Bond Yield, 1802–2001



Why is the bond model a better predictor, when raw data are used, than the stock model for the two-century history? Two reasons seem evident. First, stocks have been more volatile than bonds for almost all 200 years of U.S. data. Therefore, any model for expected real stock returns should have a larger error term. Second, stocks are by their very nature longer term than bonds: A 10-year bond expires in 10 years; stocks have no maturity date.

The bond market correlations would be even better were it not for the negative real yields during times of war, when people tend to consider the inflation a temporary phenomenon. These episodes show up as the "loops" to the left of the body of the scatterplot in Figure 8. At these times, many U.S. investors apparently subordinated their own interests in a strong real yield to the needs of the nation: Long Treasury rates were essentially pegged during World War II and up to 1951, but that did not stop investors from buying them.

Step IV: Estimating the Equity Risk Premium. If we now take the difference between the expected real stock return and the expected real bond return, we are left with the expected equity risk premium:

$$ERP(t) = ERSR(t) - ERBR(t), \quad (7)$$

where $ERSR(t)$ is the expected real stock return starting at time t and $ERBR(t)$ is the expected real bond return starting at time t.

Figure 9 shows the results of this simple framework for estimating the risk premium over the past 192 years. Many observers may be startled to see that this estimate of the forward-looking risk premium for stocks has rarely been above 5 percent in the past 200 years; the exceptions are war, its aftermath, and the Great Depression. The historical average risk premium is a modest 2.4 percent, albeit with a rather wide range. The wide range is more a result of the volatility of expected real bond returns than the volatility of expected real stock returns, which are surprisingly steady except in times of crisis.[31]

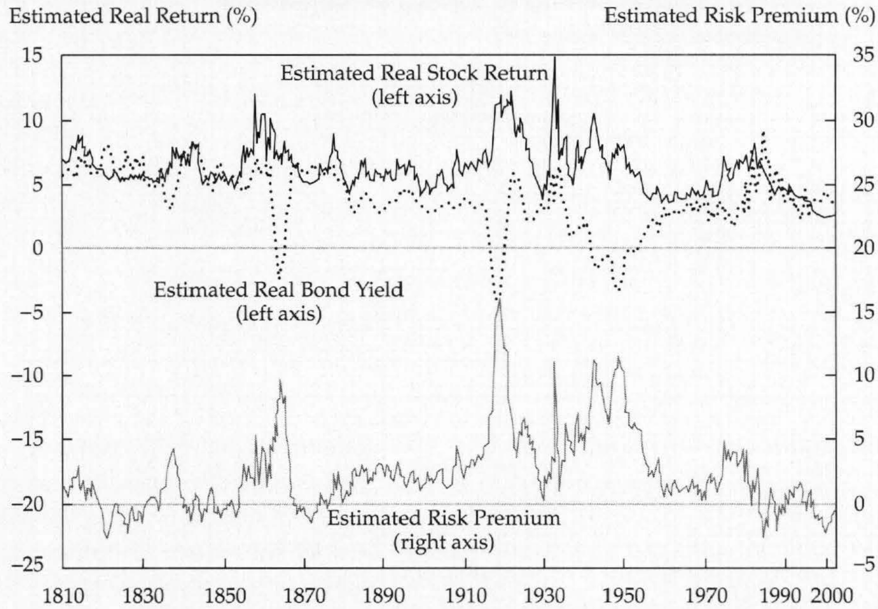
Over the past 192 years, our model (Equation 3) suggests that an objective evaluation would have pegged expected real stock returns at about 6.1 percent on average, only 120 bps higher than the average dividend yield. Investors have earned fully 70 bps more than this objective expectation, but they did not have objective reasons to expect to earn as much as they did. Our model suggests that an objective evaluation would have pegged expected real bond returns at about 3.7 percent. Investors have earned 20 bps less because of the inflationary shocks of the 1960s to 1980s; they expected more than they got.

The difference between the expected real returns for stocks and bonds reveals a stark reality. An objective estimate of the expected risk premium would have averaged 2.4 percent (240 bps) during this history (6.1 percent expected real stock returns minus 3.7 percent expected real bond returns), not the oft-cited 5 percent realized excess return that

Table 2. Regression Results: Estimated Real Bond Return versus Actual 10-Year Real Bond Return
(t-statistics in parentheses)

Period	a	b	R^2	Correlation	Serial Correlation
A. Raw data: RBR(t) = a + b[ERBR(t – 120)]					
1810–2001	0.45%	0.81%	0.266	0.52	0.999
	(3.5)	(28.1)			0.997
1945–2001	–0.74	1.05	0.399	0.63	0.997
	(–4.0)	(19.3)			0.980
B. Using 19 nonoverlapping samples, beginning December 1810					
1810–2001	–1.81%	1.31%	0.4120	0.64	0.182
	(–1.1)	(3.5)			0.677

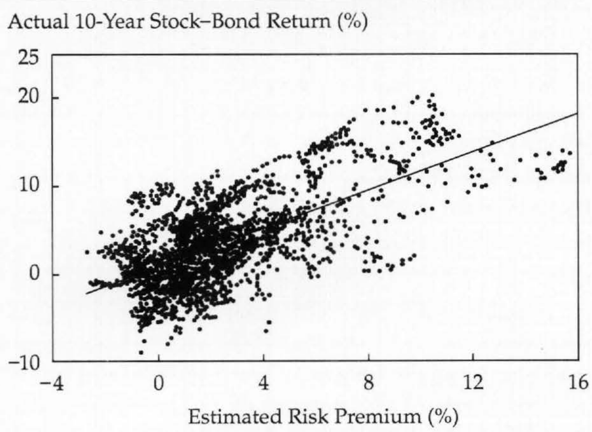
Figure 9. Estimating the Equity Risk Premium, 1810–2001



much of the investment world now depends on. Investors have *earned* a higher 3.3 percent (330 bps) excess return for stocks (6.8 percent actual real stock returns minus 3.5 percent for bonds), but the reason is the array of happy accidents for stocks and one extended unhappy accident for bonds.

All of this analysis is of mere academic interest, however, unless we can establish a link between our estimated risk premium and actual subsequent relative returns. Indeed, such a link does exist. The result of our formulation for the equity risk premium has a 0.79 correlation with the actual 10-year excess return for stocks over bonds since 1945 and a 0.66 correlation for the full span. This strong link is clear in **Figure 10**, for 1810–2001, and **Table 3**

Figure 10. Risk Premium and Subsequent 10-Year Excess Stock Returns: Correlations, 1810–1991



(where, for convenience, we have defined the 10-year excess return of stocks relative to bonds as *ERSB*); each 100 bp change in the equity risk premium is worth modestly more than 100 bps in subsequent annual excess returns for stocks relative to bonds over the next 10 years. As with the expected stock return model (Equation 3), the link for 20-year results is stronger, with correlations over the full span and since 1945 of, respectively, 0.64 and 0.95.

This strong link between objective measures of the risk premium and subsequent stock–bond excess returns is also clear for the 1945–2001 period shown in **Figure 11**, in which every wiggle of our estimate for the risk premium is matched by a similar wiggle in the subsequent 10-year excess return that stockholders earned relative to bondholders. Figure 11 shows that the excess returns on stocks relative to bonds became negative in the late 1960s on a 10-year basis, following low points in the risk premium, and again touched zero 10 years after the 1981 peak in bond yields.

We can also see in Figure 11 how the gap in 10-year results opened up sharply for the 10 years of the 1990s; it opened to unprecedented levels, even wider than in the early 1960s. Prior to this gap opening, the fit between the risk premium and subsequent excess returns is remarkably tight. The question is whether this anomaly is sustainable or is destined to be "corrected." History suggests that such anomalies are typically corrected, especially when the theoretical case to support them is so weak. This reminder should be sobering to investors who are depending on a large equity risk premium.

Table 3. Regression Results: Estimated Equity Risk Premium versus Actual 10-Year Excess Return of Stocks versus Bonds
(*t*-statistics in parentheses)

Period	a	b	R^2	Correlation	Serial Correlation
A. Raw data: ERSB(t) = a + b[ERP(t – 120)]					
1810–2001	0.91%	1.08%	0.430	0.66	0.993
	(8.8)	(40.6)			0.995
1945–2001	2.85	1.41	0.621	0.79	0.995
	(15.4)	(30.4)			0.996
B. Using 19 nonoverlapping samples, beginning December 1810					
1810–2001	0.84%	1.36%	0.490	0.70	0.055
	(0.8)	(4.0)			0.371

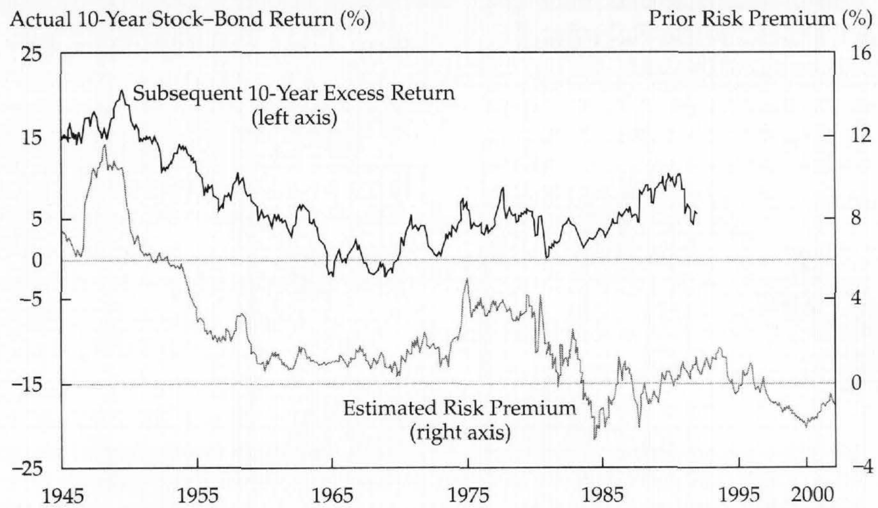
As with the models for real stock returns and for real bond returns, we also used nonoverlapping spans to take out the effect of the strong serial correlation in the estimated risk premium. For the 19 nonoverlapping spans (Panel B of Table 3), the correlation for the full period jumps to 0.70, with a highly significant *t*-statistic of 4.0.[32]

Conclusions

We have advanced several provocative assertions.

- The observed real stock returns and the excess return for stocks relative to bonds in the past 75 years have been extraordinary, largely as a result of important nonrecurring developments.
- It is dangerous to shape future expectations based on extrapolating these lofty historical returns. In so doing, an investor is tacitly assuming that valuation levels that have doubled, tripled, and quadrupled relative to underlying earnings and dividends can be expected to do so again.
- The investors of 75 years ago would not have had an objective basis for expecting the 8 percent real returns or 5 percent risk premium that stocks subsequently delivered. The estimated equity risk premium at the time was above average, however, which makes 1926 a better-than-average starting point for the historical risk premium.
- The real internal growth that companies generated in their dividends averaged 0.9 percent a year over the past 200 years, whereas earnings growth averaged 1.4 percent a year over the past 131 years.
- Dividends and earnings growth was slower than the increase in real per capita GDP, which averaged 1.6 percent over the past 200 years and 2.0 percent over the past 131 years. This internal growth is far less than the consensus expectations for future earnings and dividend growth.

Figure 11. Risk Premium and Subsequent 10-Year Excess Returns, 1945–2001



- The historical average equity risk premium, measured relative to 10-year government bonds as the risk premium investors might objectively have expected on their equity investments, is about 2.4 percent, half what most investors believe.
- The "normal" risk premium might well be a notch lower than 2.4 percent because the 2.4 percent objective expectation preceded *actual* excess returns for stocks relative to bonds that were nearly 100 bps higher, at 3.3 percent a year.
- The current risk premium is approximately zero, and a sensible expectation for the future real return for both stocks and bonds is 2–4 percent, far lower than the actuarial assumptions on which most investors are basing their planning and spending.[33]
- On the hopeful side, because the "normal" level of the risk premium is modest (2.4 percent or quite possibly less), current market valuations need not return to levels that can deliver the 5 percent risk premium (excess return) that the Ibbotson data would suggest. If reversion to the mean occurs, then to restore a 2 percent risk premium, the difference between 2 percent and zero still requires a near halving of stock valuations or a 2 percent drop in real bond yields (or some combination of the two). Either scenario is a less daunting picture than would be required to facilitate a reversion to a 5 percent risk premium.
- Another possibility is that the modest difference between a 2.4 percent normal risk premium and the negative risk premiums that have prevailed in recent quarters permitted the recent bubble. Reversion to the mean might not ever happen, in which case, we should see stocks sputter along delivering bondlike returns, but at a higher risk than bonds, for a long time to come.

The consensus that a normal risk premium is about 5 percent was shaped by deeply rooted naiveté in the investment community, where most participants have a career span reaching no farther back than the monumental 25-year bull market of 1975–1999. This kind of mind-set is a mirror image of the attitudes of the chronically bearish veterans of the 1930s. Today, investors are loathe to recall that the real total returns on stocks were negative for most 10-year spans during the two decades from 1963 to 1983 or that the excess return of stocks relative to long bonds was negative as recently as the 10 years ended August 1993.[34]

When reminded of such experiences, today's investors tend to retreat behind the mantra "things will be different this time." No one can kneel before the notion of the long run and at the same time deny that such circumstances will occur in the decades ahead. Indeed, such crises are more likely than most of us would like to believe. Investors greedy enough or naive enough to expect a 5 percent risk premium and to substantially overweight equities accordingly may well be doomed to deep disappointments in the future as the realized risk premium falls far below this inflated expectation.

What if we are wrong about today's low equity risk premium? Maybe real yields on bonds are lower than they seem. This chance is a frail reed to rely on for support. At this writing, at the end of 2001, an investor can buy TIPS, which provide government-guaranteed yields of about 3.4 percent, but inflation-indexed bond yields are a relatively recent phenomenon in the United States. So, we could not estimate historical real yields for prior years directly, only through a model such as the one described here. If we compare our model for real stock returns, at 2.4 percent in mid-2001, with a TIPS yield of 3.4 percent, we get an estimate for the equity risk premium of –100 bps.

Perhaps real earnings and dividend growth will exceed economic growth in the years ahead, or perhaps economic growth will sharply exceed the historical 1.6 percent real per capita GDP growth rate. These scenarios are certainly possible, but they represent the dreams of the "new paradigm" advocates. The scenarios are unlikely. Even if they prove correct, it will likely be in the context of unprecedented entrepreneurial capitalism, unprecedented new enterprise creation, and hence, unprecedented dilution of shareholders in existing enterprises.

The recurring pattern of history is that exceptionally poor or exceptionally rapid economic growth is never sustained for long. The best performance that dividend growth has ever managed, relative to real per capita GDP, is a scant 10 bp outperformance. This rate, the best 40-year real dividend growth *ever seen,* fell far short of real GDP growth: Real dividend growth was some 2 percent a year below real GDP growth during those same 40-year spans. So, history does not support those who hope that dividend growth will exceed GDP growth. This evidence is not encouraging for those who wish to see a 1.4 percent dividend yield somehow transformed into a 5 percent (or higher) real stock return.

The negative risk premium that precipitated the writing of "The Death of the Risk Premium" (Arnott and Ryan) in early 2000 was not without precedent, although most of the precedents, until recently, are found in the 19th century. In 1984 and again just before the 1987 market crash, real bond yields rose materially above the estimated real return on stocks. How well did this development predict subsequent relative returns? Stated more provocatively, why didn't our model work? Why didn't bonds beat stocks in the past decade? After all, with the 1984 peak in real bond returns and again shortly before the 1987 crash, the risk premium dipped even lower than the levels seen at the market peak in early 2000. Yet, stocks subsequently outpaced bonds. For an answer, recall that the context was a more than doubling of stock valuations, whether measured in price-to-book ratios, price-to-dividend ratios, or P/E multiples. If valuation multiples had held constant, the bonds would have prevailed.[35]

Appendix A. Estimating the Constituents of Return

An analysis of historical data is only as good as the data themselves. Accordingly, we availed ourselves of multiple data sources whenever possible. We were encouraged by the fact that the discrepancies between the various sources led to compounded rates of return that were no more than 0.2 percent different from one another.

Long Government Bond Yields, *BY*(*t*). Our data sources are as follows: for January 1800 to May 2001, 10-year government bond yields from Global Financial Data of the National Bureau of Economic Research (NBER) (data were annual until 1843 and were interpolated for monthly estimates); for June 2001 to December 2001, Bloomberg; and for January 1926 to December 2000, Ibbotson Associates, long-term government bond yields and returns. In cases of differences, we (1) averaged the yield data and (2) recomputed monthly total returns based on an assumed 10-year maturity standard.

Inflation, *INF*(*t*). We used two sources of inflation and U.S. Consumer Price Index data. For January 1801 to May 2001, NBER (annual until 1950; interpolated for monthly estimates); for June 2001 to December 2001, Bloomberg; and for January 1926 to December 2000, Ibbotson Associates. In cases of differences, we averaged the available data. Ibbotson data were given primary (two-thirds) weighting for 1926–1950 because the NBER data are annual through 1950.

Gross Domestic Product, *GDP*(*t*). For January 1800 to September 2001, NBER GNP data annually through 1920, interpolated July-to-July; for 1921–2001, quarterly GDP data; and for December 2001, *Wall Street Journal* consensus estimates.

Dividend Yield in Month *t*, *DY*(*t*), and Return on Stocks in Month *t*, *RS*(*t*). For January 1802 to December 1925, G. William Schwert (1990); for February 1871 to March 2001, Robert Shiller (2000); for January 1926 to December 2000, Ibbotson Associates (2001); and for April 2001 to December 2001, Bloomberg. In cases of differences, we averaged the available data. In Shiller's data, monthly dividend and earnings data are computed from the S&P four-quarter data for the quarter since 1926, with linear interpolation to monthly figures. Dividend and earnings data before 1926 are from Cowles (1939), interpolated from annual data.

Notes

1. The "bible" for the return assumptions that drive our industry is the work of Ibbotson Associates, building on the pioneering work of Ibbotson and Sinquefield (1976a, 1976b). The most recent update of the annual Ibbotson Associates data (2001) shows returns for U.S. stocks, bonds, bills, and inflation of, respectively, 11.0 percent, 5.3 percent, 3.8 percent, and 3.1 percent. These figures imply a real return for stocks of 7.9 percent and a risk premium over bonds of 5.7 percent (570 bps), both measured over a 75-year span. These data shape the expectations of the actuarial community, much of the consulting community, and many fund sponsors.
2. Fischer Black was fond of pointing out that examining the same history again and again with one new year added each passing year is an insidious form of data mining (see, for example, Black 1976). The past looks best when nonrecurring developments and valuation-level changes have distorted the results; extrapolating the past tacitly implies a belief that these nonrecurring developments can recur and that the changes in valuation levels will continue.
3. We strongly suggest that the investment community draw a distinction between past excess returns (observed returns from the past) and expected risk premiums (expected return differences in the future) to avoid continued confusion and to reduce the dangerous temptation to merely extrapolate past excess returns in shaping expectations for the risk premium. This habit is an important source of confusion that, quite literally, (mis)shapes decisions about the management of trillions in assets worldwide. We propose that the investment community begin applying the label "risk premium" *only* to expected future return differences and apply the label "excess returns" to observed historical return differences.
4. To see the effect of compounding at this rate, consider that if our ancestors could have earned a mere 1.6 percent real return on a $1 investment from the birth of Christ in roughly 4 B.C. to today, we would today have enough to buy more than the entire world economy. Similarly, the island of Manhattan was ostensibly purchased for $24 of goods, approximately the same as an ounce of gold when the dollar was first issued. This modest sum invested to earn a mere 5 percent real return would have grown to more than $20 billion in the 370 years since the transaction. At an 8 percent real return, as stocks earned from 1926 to 2000 in the Ibbotson data, this $24 investment would now suffice to buy more than the entire world economy.

5. No rational investor buys if he or she expects less than 1 percent real growth a year in capital, but objective analysis will demonstrate that this return is what stocks have actually delivered, plus their dividend yield, plus or minus any profits or losses from changes in yields. As Asness pointed out in "Bubble Logic" (2000), few buyers of Cisco would have *expected* a 1 percent internal rate of return at the peak, although the stock was priced to deliver just that, even if the overly optimistic consensus earnings and growth forecasts at the time were used. These buyers were focused on the view that the stock would produce handsome gains, as it had in the past, rather than on pursuing an objective evaluation, by using IRR or similar objective valuation tools, of expected returns. Such a focus plants the seeds of major disappointment.
6. The Welch study investigated an expected *arithmetic* risk premium for stocks relative to *cash*, not bonds. The difference between arithmetic and geometric returns is often illustrated by someone earning 50 percent in one year and –50 percent in the next. The arithmetic average is zero, but the person is down 25 percent (or 13.4 percent a year). Most practitioners think in terms of compounded geometric returns; in this example, practitioners would focus on the 13 percent a year loss, not on the zero arithmetic mean. If stocks have 16 percent average annual volatility (the average since World War II), the result is that the arithmetic mean is 130 bps higher than the geometric mean return (the difference is approximately half the variance, or 16 percent × 16 percent/2). Such a difference might be considered a "penalty for risk." If we add a 70 bp real cash yield (the historical average) plus a 720 bp risk premium minus a 130 bp penalty for risk, we find 6.6 percent to be the implied consensus of the economists for the geometric real stock return.
7. Such a return could easily fall to 0–2 percent net of taxes, especially in light of government's taxes on the inflation component of returns.
8. Smith's work even won a favorable review from John Maynard Keynes (for Keynes' approach, see his 1936 classic).
9. TIPS is the acronym for Treasury Inflation-Protected Securities, which have been replaced by Treasury Inflation-Indexed Securities.
10. In fairness, growth is now an explicit part of the picture. Dividend payout ratios are substantially lower than in the early 1920s and the 19th century as a result, at least in part, of corporate desires to finance growth. That said, our own evidence would suggest that internal reinvestment is not necessarily successful: High payout ratios precede higher growth than do low payout ratios.
11. We are indebted to G. William Schwert and Jeremy Siegel for some of the raw data for this analysis (see also Schwert 1990 and Siegel 1998). Although multiple sources exist for data after 1926 and a handful of sources provide data beginning in 1855 or 1870, Professor Schwert was very helpful in assembling these difficult early data. Professor Siegel provided earnings data back to 1870. We have not found a source for earnings data before 1870.
12. The U.S. Bureau of Labor Statistics maintains GDP data from 1921 to date; the earlier data are for GNP (gross national product). Because the two were essentially the same thing until international commerce became the substantial share of the economy that it is today, we used the GNP data from the Bureau of Labor Statistics for the 19th century and the first 20 years of the 20th century.
13. We stripped out reinvestment in the measure of real dividend growth shown in Figure 3 because investors are already receiving the dividend. To include dividends in the real dividend growth would double-count these dividends. What should be of interest to us is the internal growth in dividends stemming from reinvestment of the retained earnings.
14. We multiplied the real dividends by 10 to bring the line visually closer to the others; the result is that on those few occasions when the price line and dividend line touch, the dividend yield is 10 percent.
15. The fact that growth in real dividends and earnings is closer to per capita GDP growth than it is to overall GDP growth is intuitively appealing on one fundamental basis: Real per capita GDP growth measures the growth in productivity. It is sensible to expect real income, real per share earnings, and real per share dividends to grow with productivity rather than to mirror overall GDP growth.
16. This history holds a cautionary tale with regard to today's stock option practices.
17. This fall in dividends of existing enterprises is not surprising when one considers that the companies that existed in 1802 probably encompass, at most, 1 percent of the economy of 2001. The world has so changed that, at least from the perspective of the dominant stocks, today's economy would be unrecognizable in 1802.
18. Another way to think about this idea is to recognize the distinction between a market portfolio and a market index. The market portfolio shows earnings and dividend growth that are wholly consistent with growth in the overall economy (Bernstein 2001a). But if one were to unitize that market portfolio, the unit values would not grow as fast as the total capitalization and the earnings and dividends per unit (per "share" of the index) would not keep pace with the growth in the aggregate dollar earnings and dividends of the companies that compose the market portfolio. (When one stock is dropped and another added to a market index, typically the added stock is larger in capitalization than the deletion, which increases the divisor for constructing the index.) Precisely the same thing would happen in the management of an actual index fund. When a stock was replaced, the proceeds from the deleted stock would rarely suffice to fund the purchase of the added stock. So, all stocks would be trimmed slightly to fund that purchase; this consequence is implied by the change in the divisor for an index. It is this mechanism that drives the difference between the growth of the aggregate dollar earnings and dividends for the market portfolio, which will keep pace with GDP growth over time, and the growth of the "per share" earnings and dividends for the market *index* that creates the dilution we attribute to entrepreneurial capitalism. After all, entrepreneurial capitalism creates the companies that we must add to the market portfolio, thus changing our divisor and driving a wedge between the growth in market earnings or dividends and the growth in earnings and dividends per share in a market index.
19. See Bernstein (2001b). Over the past 131 years, the correlation between payout ratios and subsequent 10-year growth in real earnings has been 0.39; over the past 50 years, this correlation has soared to 0.66. Apparently, the larger the fraction of earnings paid out as dividends, the faster earnings subsequently grow, which is directly contrary to the Miller–Modigliani maxim (see Miller and Modigliani 1961 and Modigliani and Miller 1958).
20. To produce a 3.4 percent real return from stocks, matching the yield on TIPS, real growth in dividends needs to be 1.9 percent (twice the long-term historical real growth rate) while valuation levels remain where they are. Less than twice the historical growth in real dividends, or a return to the 3–6 percent yields of the past, will not get us there.
21. We have made the simplifying assumption that "long term" is a 10-year horizon. Redefining the long-term returns over a 5-year or 20-year horizon produces similar results.
22. Because this adjusted dividend is always at or above the true dividend, we have introduced a positive error into the average dividend yield. We offset this error by subtracting the 40-year average difference between the adjusted dividend and the true dividend. In this way, $EDY(t)$ is not overstated, on average, over time.

23. Of course, stock buybacks increase the share of the economy held by existing shareholders.
24. Arnott and Asness (2002) have shown that since 1945, the payout ratio has had a 77 percent correlation with subsequent real earnings growth. That is, higher retained earnings have historically led to slower, not faster, earnings growth.
25. Throughout this article, when we refer to a 10-year average or a 40-year average, we have used the available data if fewer years of data were available. For instance, for 1820, we used the 20-year GDP growth rate because 40 years of data were unavailable. We followed a convention of requiring at least 25 percent of the intended data; so, if the analysis was based on a 40-year average, we tolerated a 10-year average if necessary. To do otherwise would have forced us to begin our analysis in about 1840 and lose decades of interesting results. Because data before 1800 are very shaky and we required at least 10 years of data, our analysis begins, for the most part, in 1810.
26. We cannot know the 10-year returns from starting dates after 1991, so 192 years of expected return data lead to 182 years of correlation with subsequent 10-year actual returns.
27. Another way to deal with serially correlated data is to test correlations of differenced data. When we carried out such tests, we found that over the full span, the R^2 actually *rose* to 0.446 from the 0.214 shown in Panel A of Table 1; moreover, since 1945, the differenced results showed a still impressive 46 percent correlation. These results are available from the authors on request.
28. In an *ex ante* regression, the model is respecified for each monthly forecast with the use of all previously available data only.
29. We made the simplifying assumption that "long term" is a 10-year horizon. Redefining the long-term returns over a 5-year or 20-year horizon produced similar results.
30. Even when we considered successive differences to eliminate the huge serial correlation of real bond yields and 10-year real bond returns, the result from 1945 to date (available from the authors) was identical to the result for the raw data—a correlation of 0.63.
31. For investors accustomed to the notion that stock returns are uncertain and bond returns are assured over the life of the bond, this result will come as a surprise. But conventional bonds do *not* assure real returns; their expected real returns, therefore, should be highly uncertain. Stocks do, in a fashion, pass inflation through to the shareholder. So, nominal returns for stocks may be volatile and uncertain, but expected real stock returns are much more tightly defined than expected real bond returns.
32. Differencing caused the correlation for the full 182-year span to fall from 0.66 to 0.61 and, for the span following World War II, caused it to fall from 0.79 to 0.48.
33. For the taxable investor, the picture is worse, of course. In the United States, investors are even taxed on the inflation component of returns. From valuation levels that are well above historical norms, a negative real after-tax return is not at all improbable.
34. The excess return of stocks over bonds was negative also in the decades ended September 1991, November 1990, most 10-year spans ending August 1977 to June 1979, and the spans ending September 1974 to January 1975.
35. Consider the 10 years starting just before the stock market crash in September 1987. This span began with double-digit bond yields. The bond yield of 9.8 percent minus a regression-based inflation expectation of 3.6 percent led to an expected real bond return of 6.2 percent. The stock yield of 2.9 percent plus expected real per capita GDP growth of 1.6 percent minus an expected dividend shortfall relative to per capita GDP of 0.4 percent led to an expected real stock return of 4.0 percent. The risk premium was –2.0 percent. But stocks beat bonds by 4.9 percent a year over the next 10 years ending September 1997. What happened? The dividend yield plunged to 1.7 percent. This plunge in yields contributed 5.8 percent a year to stock returns; in the absence of this revaluation, stocks would have underperformed bonds by –0.9 percent. So, the –2.0 percent forecast was not bad; dividends rose a notch faster than normal, and more importantly, the price that the market was willing to pay for each dollar of dividends nearly doubled.

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Stocks versus Bonds: Explaining the Equity Risk Premium

Clifford S. Asness

From the 19th century through the mid-20th century, the dividend yield (dividends/price) and earnings yield (earnings/price) on stocks generally exceeded the yield on long-term U.S. government bonds, usually by a substantial margin. Since the mid-20th century, however, the situation has radically changed. In addressing this situation, I argue that the difference between stock yields and bond yields is driven by the long-run difference in volatility between stocks and bonds. This model fits 1871–1998 data extremely well. Moreover, it explains the currently low stock market dividend and earnings yields. Many authors have found that although both stock yields forecast stock returns, they generally have more forecasting power for long horizons. I found, using data up to May 1998, that the portion of dividend and earnings yields explained by the model presented here has predictive power only over the long term whereas the portion not explained by the model has power largely over the short term.

The dividend yield on the S&P 500 Index has long been examined as a measure of stock market value. For instance, the well-known Gordon growth model expresses a stock price (or a stock market's price) as the discounted value of a perpetually growing dividend stream:

$$P = \frac{D}{R-G}. \qquad (1)$$

where

P = price
D = dividends in Year 0
R = expected return
G = annual growth rate of dividends in perpetuity

Now, solving this equation for the expected return on stocks produces

$$R = \frac{D}{P} + G. \qquad (2)$$

Thus, if growth is constant, changes in dividends to price, D/P, are exactly changes in expected (or required) return. Empirically, studies by Fama and French (1988, 1989), Campbell and Shiller (1998), and others, have found that the dividend yield on the market portfolio of stocks has forecasting power for aggregate stock market returns and that this power increases as forecasting horizon lengthens.

Clifford S. Asness is president and managing principal at AQR Capital Management, LLC.

The market earnings yield or earnings to price, E/P (the inverse of the commonly tracked P/E), represents how much investors are willing to pay for a given dollar of earnings. E/P and D/P are linked by the payout ratio, dividends to earnings, which represents how much of current earnings are being passed directly to shareholders through dividends. Studies by Sorenson and Arnott (1988), Cole, Helwege, and Laster (1996), Lander, Orphanides, and Douvogiannis (1997), Campbell and Shiller (1998), and others, have found that the market E/P has power to forecast the aggregate market return.

Under certain assumptions, a bond's yield-to-maturity, Y, will equal the nominal holding-period return on the bond.[1] Like the equity yields examined here, the inverse of the bond yield can be thought of as a price paid for the bond's cash flows (coupon payments and repayment of principal). When the yield is low (high), the price paid for the bond's cash flow is high (low). Bernstein (1997), Ilmanen (1995), Bogle (1995), and others, have shown that bond yield levels (unadjusted or adjusted for the level of inflation or short-term interest rates) have power to predict future bond returns.

This article examines the relationship between stock and bond yields and, by extension, the relationship between stock and bond market returns (the difference between stock and bond expected returns is commonly called the equity risk premium). I hypothesize that the relative yield stocks must provide versus bonds today is driven by the experience of each generation of investors with each asset class.

The article also addresses the observation of many authors, economists, and market strategists that today's dividend and earnings yields on stocks are, by historical standards, shockingly low. I find they are not.

Finally, I report the results of decomposing stock yields into a fitted portion (i.e., stock yields explained by the model presented here) and a residual portion (i.e., stock yields not explained by the model).

Historical Yields on Stocks and Bonds

As far as yields are concerned, 1927–1998 tells a tale of two periods—as **Figure 1** clearly shows. Figure 1 plots the dividend yield for the S&P 500 and the yield to maturity for a 10-year U.S. T-bond from January 1927 through May 1998.[2] Prior to the mid-1950s, the stock market's yield was consistently above the bond market's yield. Anecdotally, investors of this era believed that stocks should yield more than bonds because stocks are riskier investments. Since 1958, the stock yield has been below the bond yield, usually substantially below. As of the latest data in Figure 1 (May 1998), the stock market yield was at an all-time low of 1.5 percent whereas the bond market yield was at 5.5 percent, not at all a corresponding low point. This observation has led many analysts to assert that the role of dividends has changed and that dividend yields in the late 1990s are not comparable to those of the past. Although this assertion may have some merit, I will argue that it is largely unnecessary to explain today's low D/P.

As did dividend yields, the stock market's earnings yields systematically exceeded bond yields early in the sample period, but as **Figure 2** shows, since the late-1960s, earnings yields have been comparable to bond yields and clearly strongly related (as are dividend yields, albeit from a lower level).[3] **Table 1** presents monthly correlation coefficients for various periods between the levels of D/P and *Y* and E/P and *Y*. The numbers in Table 1 clearly bear out what is seen in Figures 1 and 2. For the entire period, D/P and *Y* were negatively correlated because of their reversals; E/P was essentially uncorrelated with *Y*. For the later period, however, stock and bond yields show the strong positive relationship many economists and market strategists have noted.

Thus, we are left with several puzzles:

- Why did the stock market strongly outyield bonds for so long only to now consistently underyield bonds?
- Why did stock and bond yields move relatively independently, or even perversely, in the overall 1927–98 period but move strongly together in the later 40 years of this period?
- Perhaps most important, why are today's stock market yields so low and what does that fact mean for the future?

The rest of this article tries to answer these questions.

Figure 1. S&P 500 Dividend Yield and T-Bond Yield to Maturity, January 1927–May 1998

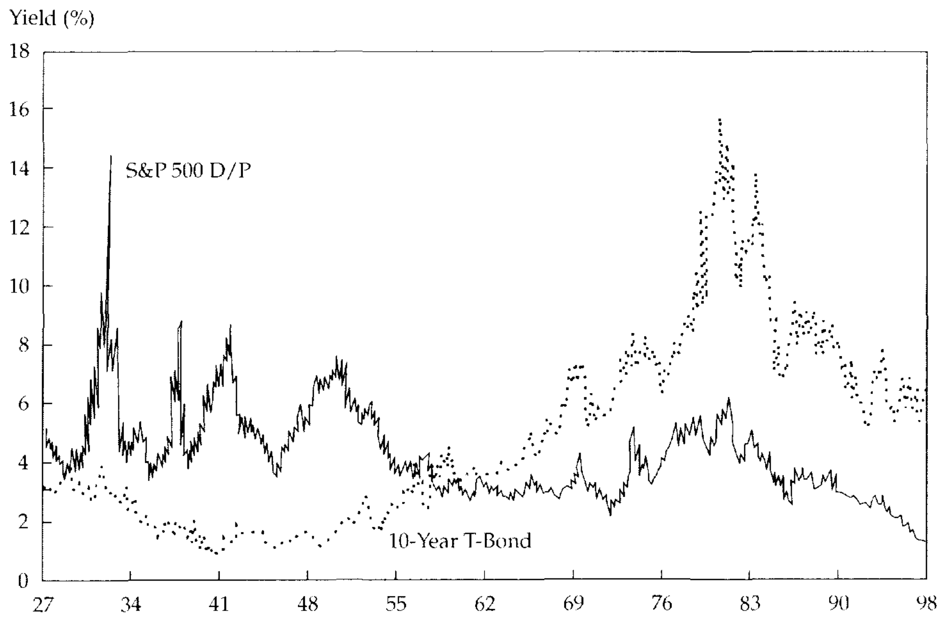


Figure 2. S&P 500 Earnings Yield and T-Bond Yield to Maturity, January 1927–May 1998

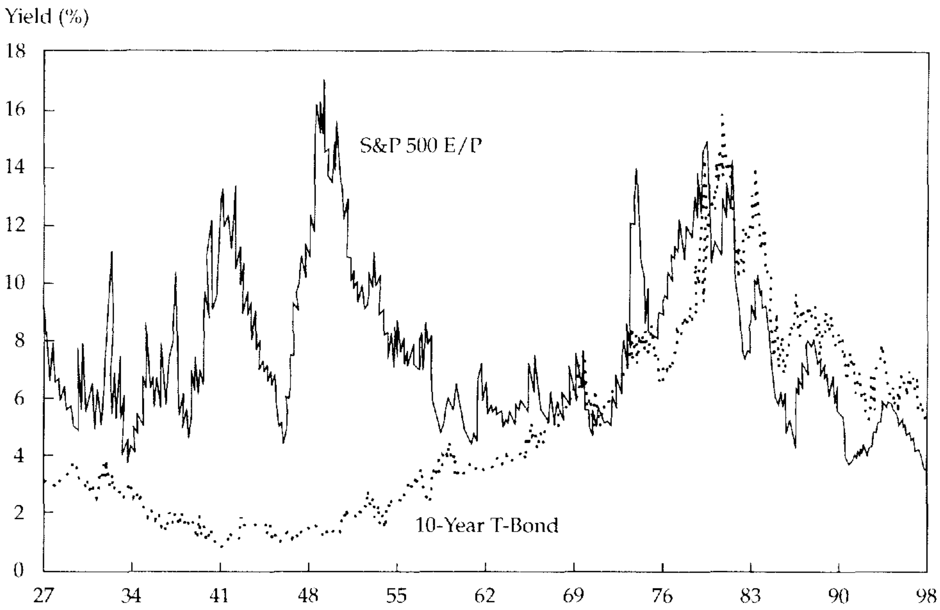


Table 1. Monthly Correlation Coefficients, Various Periods

Period	Correlation of D/P and Y	Correlation of E/P and Y
Full (January 1927–May 1998)	–0.28	+0.08
Early (January 1927–December 1959)	–0.23	–0.49
Late (January 1960–May 1998)	+0.71	+0.69

Model for Stock Market Yields

Researchers have shown a strong link between aggregate dividend and earnings yields and expected stock market returns, especially for long horizons. When stock market yields are high (low), expected future stock returns are high (low). This predictability has two possible explanations that are at least partly consistent with efficient markets (there are many *inefficient*-market explanations). One, investors' taste for risk varies. When investors are relatively less risk averse, they demand less in the way of an expected return premium to bear stock market risk. Fama and French (1988, 1989), among others, explored this hypothesis. Two, the perceived level of risk can change even if investors' taste for risk is constant.

I explore the hypothesis that the perceived level of risk can change (although the two hypotheses are not mutually exclusive). Note that investor perception of long-term risk need not be accurate for this hypothesis to be true. If investor perception of risk is accurate, then the evidence presented here may be consistent with an efficient market. If investor perception of risk is inaccurate but explains the pricing of stocks versus bonds, then the hypothesis may be deemed accurate but still pose a dilemma for fans of efficient markets.

Consider a simple model in which the required long-term returns on aggregate stocks and bonds vary through time. Expected stock returns, E(Stocks), are assumed to be proportional to dividend yields, whereas expected bond returns, E(Bonds), are assumed to move one-for-one with current bond yields; that is,

$$E(\text{Stocks})_t = a + b(\text{D/P}_t) + \varepsilon_{Stocks,t}, \quad (3)$$

$$E(\text{Bonds})_t = Y_t + \varepsilon_{Bonds}, \quad (4)$$

(where a is the intercept, b is the slope, D/P_t is dividend yield at time t, and ε is an error term). The hypothesis is that b is positive, so expected stock returns vary positively with current stock dividend yields, and that the ε terms are identically and independently distributed error terms representing the portion of expected returns not captured by the model.[4]

Now, I assume that expected stock and bond returns are linked through the long-run stock and bond volatility experienced by investors. So,

$$E(\text{Stocks})_t - E(\text{Bonds})_t = c + d\sigma(\text{Stocks})_t + e\sigma(\text{Bonds})_t. \quad (5)$$

The hypothesis is that d is positive whereas e is negative. That is, I assume that the expected (or required) return differential between stocks and bonds is a positive linear function of a weighted difference of their volatilities.[5] Although Equations 3, 4, and 5 do not represent a formal asset-pricing model, they do capture the spirit of allowing expected returns to vary through time as a function of volatility. Moreover, they yield empirically testable implications.[6]

Rearranging these equations (and aggregating coefficients) produces the following model:

$$D/P = \gamma_0 + \gamma_1 Y + \gamma_2\sigma(\text{Stocks}) + \gamma_3\sigma(\text{Bonds}) + \varepsilon_{D/P,t}. \quad (6)$$

Now, the hypothesis is that γ_1 is positive, γ_2 is positive, and γ_3 is negative. This model, and the precisely corresponding model for E/P, is tested in the following section.[7] Other authors (e.g., Merton 1980; French, Schwert, and Stambaugh 1987) have tested the link between expected stock returns and volatility by examining the relationship between realized stock returns and *ex ante* measures of volatility.[8] However, as these authors noted, realized stock returns are a noisy proxy for expected stock returns. I believe that linking Equations 3, 4, and 5 and focusing on the long term will reveal a clearer relationship between stock market volatility and expected stock market returns as represented by stock market yield (D/P or E/P).[9]

Preliminary Evidence

To investigate Equation 6, I defined a generation as 20 years and used a simple rolling 20-year annualized monthly return volatility for σ(Stocks) and σ(Bonds).[10] The underlying argument is that each generation's perception of the relative risk of stocks and bonds is shaped by the volatility it has experienced. For instance, Campbell and Shiller (1998) mentioned (but did not necessarily advocate) the argument that Baby Boomers are more risk tolerant "perhaps because they do not remember the extreme economic conditions of the 1930s." Another example is Glassman and Hassett (1999), who argued in *Dow 36,000* that remembrances of the Great Depression have led investors to require too high an equity risk premium.

A 20-year period captures the long-term generational phenomenon that I hypothesized.[11] The hypothesis is inherently behavioral because it states that the long-term, slowly changing relationship between stock and bond yields is driven by the long-term volatility of stocks and bonds experienced by the bulk of current investors. Although I believe a 20-year period is intuitively reasonable, given the hypothesis, I am encouraged by the fact that the results that follow are robust to alternative specifications of long-term volatility (i.e., from 10-year to 30-year trailing volatility) and still showed up significantly when windows as short as 5 years were used.

The regressions in this section are simple linear regressions that do not account for some significant econometric problems; for example, the following regressions have highly autocorrelated independent variables, dependent variables, and residuals. But the goal of these regressions is to initially establish the existence of an economically significant relationship. Because statistical inference is problematic, I do not focus on (but do report) the t-statistics. The focus is on the economic significance of the estimated coefficients and R^2 figures. (Subsequent sections explore the issue of statistical significance and report robustness checks.)

Because I required 20 years to estimate volatility and the monthly data began in 1926, I estimated Equation 6 by using monthly data from January 1946 through May 1998. Before examining this equation in full, I first examine the regression of D/P on bond yields only and D/P on the rolling volatility of stock and bond markets only for the 1946–98 period (the first data points are dividend and bond yields in January 1946 and stock and bond volatility estimated from January 1926 through December 1945; the t-statistics are in parentheses under the equations. The results are as follows:

$$\begin{aligned} D/P &= \underset{(40.72)}{4.10\%} - \underset{(-2.26)}{0.03Y} \end{aligned} \quad (7)$$

(with an adjusted R^2 of 0.7 percent) and

$$D/P = \underset{(11.87)}{2.02\%} + \underset{(18.96)}{0.14\sigma(\text{Stocks})} - \underset{(-5.24)}{0.07\sigma(\text{Bonds})} \quad (8)$$

(with an adjusted R^2 of 43.0 percent).[12]

Equation 7 shows that D/P and Y have a mildly negative relationship for 1946–1998, similar to what I found for the entire 1926–98 period (Table 1). Equation 8 shows that a significant amount of the variance of D/P (note the adjusted R^2) is explained by stock and bond volatility, with D/P rising with stock market volatility and falling with bond market volatility. This relationship is economically significant. An increase in stock market volatility from 15 percent to 20 percent, all else being equal, raises the required dividend yield on stocks by 70 basis points (bps). Now, note the estimate for Equation 6:

$$D/P = \underset{(-0.05)}{0.00\%} + \underset{(28.77)}{0.35Y} + \underset{(39.51)}{0.23\,\sigma(\text{Stocks})} - \underset{(-25.69)}{0.31\sigma(\text{Bonds})} \quad (9)$$

(with an adjusted R^2 of 75.4 percent).

This result supports the hypothesis. The dividend yield is mildly negatively related to the bond yield when measured alone (Equation 7), but this negative relationship is a highly misleading indicator of how stock and bond yields covary. When I adjusted for different levels of volatility, I found stock and bond yields to be strongly positively related. My interpretation of this regression is that stock and bond market yields are strongly positively related and the difference between stock and bond yields is a direct positive function of the weighted difference between stock and bond volatility. Intuitively, the more volatile stocks have been versus bonds, the higher the yield premium (or smaller a yield deficit) stocks must offer. In any case, when volatility is held constant, stock yields do rise and fall with bond yields.

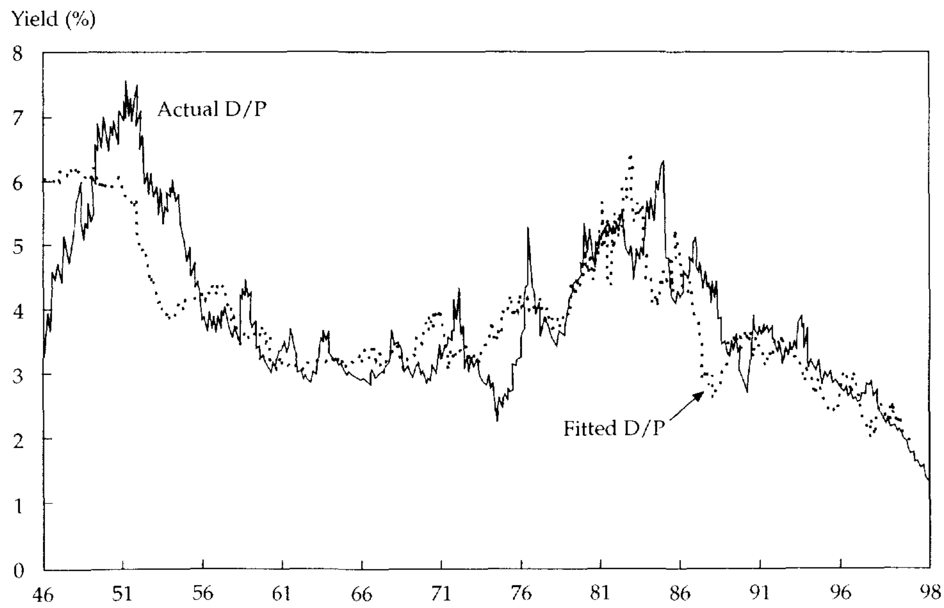
Again, these results are economically significant. For example, a 100 bp rise in bond yields translates to a 35 bp rise in the required stock market dividend yield, whereas a rise in stock market volatility from 15 percent to 20 percent leads to a rise of 115 bps in the required stock market dividend yield.

The fact that stock and bond yields are univariately unrelated (or even negatively related) over long periods (Table 1) is a result of changes in relative stock and bond volatility that obscure the strong positive relationship between stock and bond yields. The reason stock and bond yields are univariately positively related over shorter periods (e.g., 1960–1998) is because of the stable relationship between stock and bond volatility over short periods. In other words, a missing-variable problem is not much of a problem if the missing variable was not changing greatly during the period being examined (such as in 1960–1998). The problem is potentially destructive, however, if the missing variable varied significantly during the period (such as in 1927–1998).

Figure 3 presents the actual market D/P and the in-sample D/P fitted from the regression in Equation 9. **Figure 4** presents the residual from this regression (actual D/P minus fitted D/P). For today's reader, perhaps the most interesting part of Figures 3 and 4 is the latest results. The actual D/P at the end of May 1998 (the last data point) is 1.5 percent, a historic low. The forecasted D/P is also at a historic low, however—2.1 percent—which is a forecasting error of only 60 bps.

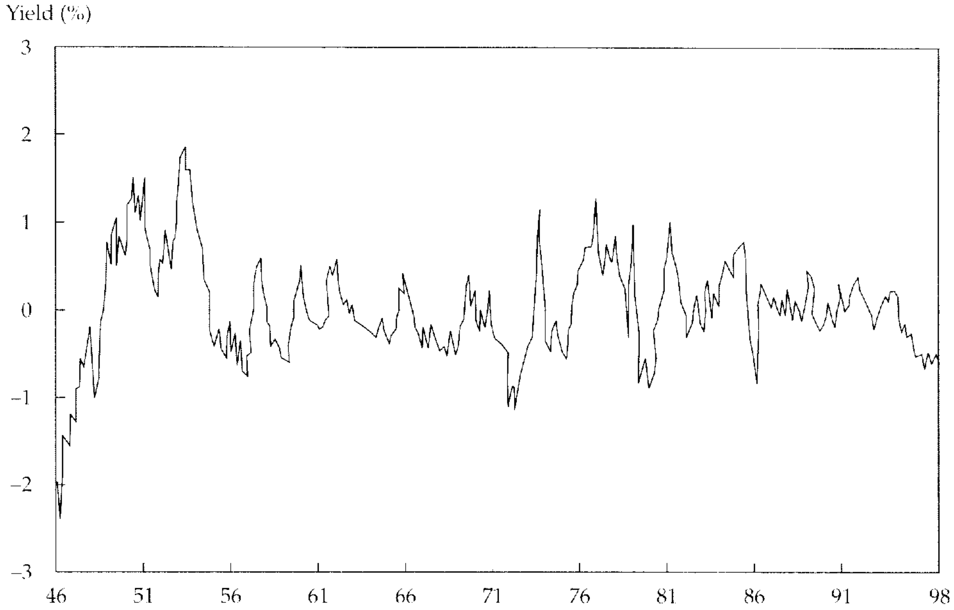
Simply examining the D/P series leads to a belief that recent D/Ps are shockingly low. These regressions suggest a different interpretation: Given the recent low bond yields and a low realized differential in volatility between stocks and bonds, I would forecast an all-time historically low D/P for stocks as of May 1998. The fact that the model does not forecast the actual low in dividend yield is not statistically anomalous (May's forecast error is about 1 standard deviation below zero) and may be a result of the stories other authors have cited to explain today's low D/P (e.g., stock buy-backs

Figure 3. Actual S&P 500 Dividend Yield and In-Sample Dividend Yield, January 1946–May 1998



Note: In-sample D/P fitted from the regression in Equation 9.

Figure 4. Regression Residual: Actual D/P minus Fitted D/P, January 1946–May 1998



replacing dividends). But these stories might not be at all necessary. For example, the story of stock buybacks replacing dividends has been around since at least the late 1980s (Bagwell and Shoven 1989), yet the average in-sample forecasting error of my model for D/P for 1990–1998 is only –9 bps. Apparently, nothing more than Equation 9 is needed to explain recent low dividend yields.

Running a similar regression for E/P, I obtained the following result:

$$\underset{(-3.70)}{E/P = -1.39\%} + \underset{(27.33)}{0.96Y} + \underset{(29.58)}{0.49\sigma(\text{Stocks})} - \underset{(-21.56)}{0.76\sigma(\text{Bonds})} \quad (10)$$

(with an adjusted R^2 of 64.8 percent). The model explains about as much of the variance for earnings yield as dividend yield. As of the end of May 1998, the E/P for the S&P 500 was 3.6 percent, corresponding to a P/E of 27.8. The forecasted E/P from the Equation 10 regression is 3.4 percent, or a forecasted P/E ratio of 29.1. Unlike the case for D/P, I am not (even to a small degree) failing to explain the recent high P/Es on stocks; rather, one would have to explain the opposite, because according to the model, the May 1998 P/E of 27.8 is slightly *lower* than it should be.

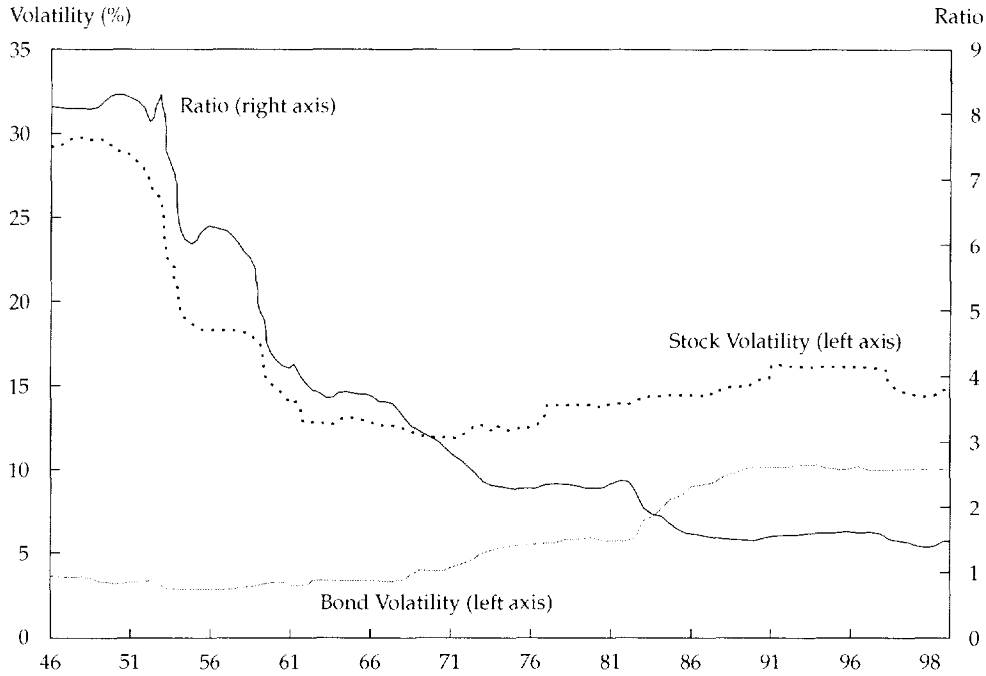
Again, these results are economically significant: The required earnings yield was moving virtually one-for-one with 10-year T-bond yields and increasing 245 bps for each 5 percent rise in stock market volatility (all else being equal). Examining Figure 2 and Table 1 shows that E/P and Y were strongly positively correlated only for the later period of the sample (in the earlier period, they were actually negatively correlated, and for the whole period, they were close to uncorrelated). When changing stock- and bond-market volatility is accounted for in Equation 10, however, the strong positive relationship between E/P and Y is extended to the full period.

Critique and Further Evidence

The regression results presented in the previous section fit intuition and the hypothesis as formalized in Equation 6, but they are certainly open to criticism. They are in-sample regression results and are thus particularly open to charges of data mining. They are level-on-level regressions, which renders the t-statistics invalid and makes the high R^2 figures potentially spurious.[13] Worse, they are level-on-level regressions that use 20-year rolling data and a highly autocorrelated dependent variable.[14] Because the inference is suspect, stock and bond volatility may have followed a pattern that explained a secular-level change in dividend and earnings yield merely by chance.

To examine this possibility, **Figure 5** shows the rolling 20-year volatilities of the stock and bond markets used in the preceding regressions and the ratio of stock to bond volatility. Aside from the very early and very late years of the period, the ratio of rolling 20-year stock volatility to bond volatility was dropping nearly monotonically from 1946 through mid-1998. Thus, a hypothesis that fits the regression results and Figure 5 is that stock yields and bond yields are positively related but, exogenous to this relationship, the level of stock yields has been declining over time.

Figure 5. Rolling 20-Year Volatilities of Stock and Bond Markets and Ratio of Stock to Bond Volatility, January 1946–May 1998



The issue is one of causality. Was the drop in the level of stock yields versus that of bond yields occurring because of changes in their relative experienced volatilities (as I hypothesize), or were other factors causing this drop through time and thus producing spurious regression results? A 50-year regression that uses 20-year rolling data makes answering this question difficult. So, the next subsections attempt to explore this critique.

Performance of the Model versus a Time Trend. If the drop in stock yields versus bond yields is coincidentally, not causally, related to volatility, then a time trend might do as well as volatility in the regression tests. For ease of comparison, recall the results for D/P regressed on bond yields and stock and bond volatility; Equation 9 was

$$\underset{(-0.05)}{D/P = 0.00\%} + \underset{(28.77)}{0.35Y} + \underset{(39.51)}{0.23\,\sigma(\text{Stocks})} - \underset{(-25.69)}{0.31\sigma(\text{Bonds})},$$

and the adjusted R^2 was 75.4 percent. The next equations report similar regressions in which, instead of stock and bond volatility, either a linear or loglinear time trend was used:

$$D/P = \underset{(51.44)}{6.18\%} + \underset{(14.69)}{0.25(Y)} - \underset{(-21.97)}{0.00(\text{Linear trend})} \tag{11}$$

(with an adjusted R^2 of 43.8 percent) and

$$D/P = \underset{(32.32)}{27.97\%} + \underset{(19.88)}{0.33(Y)} - \underset{(-27.61)}{0.04(\text{Loglinear trend})} \tag{12}$$

(with an adjusted R^2 of 55.1 percent).

The time-trend variables capture much of the effect being studied. That is, the relationship between D/P and Y goes from weakly negative (Equation 7) to strongly positive in the presence of the trend variable—meaning that the expected difference between stock and bond yields was declining through time and, after accounting for this trend, stock and bond yields were positively related. The volatility-based regression, however, is clearly the strongest: The adjusted R^2 is higher, and the coefficient on bond yields is larger and more significant.

Next, the loglinear time trend is added to Equation 9 to see how the volatility variables fare in head-on competition:

$$D/P = \underset{(-3.98)}{-10.00\%} + \underset{(28.50)}{0.35Y} + \underset{(19.63)}{0.28\sigma(\text{Stocks})} \tag{9a}$$
$$- \underset{(-11.87)}{0.46\sigma(\text{Bonds})} + \underset{(3.99)}{0.02(\text{Loglinear trend})}$$

(with an adjusted R^2 of 76.0 percent).

Clearly, the volatility variables drive out the time trend (analogous results held for the linear time trend) to the point at which the trend's coefficient is slightly positive (the wrong sign). Although the nearly monotonic fall in bond versus stock volatility makes it hard to distinguish between causality and coincidence for the 1946–98 period, the superiority of the volatility-based model over a time trend gives comfort. Analogous results favoring the volatility model were found for E/P.

Rolling Regression Forecasts. I formed rolling out-of-sample forecasts of D/P starting with January 1966. (I began in 1966 because I needed the 20 years from 1926 to 1946 to estimate volatility and the 20 years from 1946 to 1966 to formulate the first predictive regression.) The regressions used an "expanding window" that always started in January 1946 and went up to the month before the forecast.

For comparison purposes, I formed these forecasts based on five models. Model 1 attempted to forecast D/P by using only the average D/P (so the forecast of D/P on January 1966 was the average D/P from January 1946 through December 1965). Model 2 attempted to forecast D/P by using a rolling regression on bond yields only. Model 3 used a rolling version of the complete model from Equation 9 (a regression on bond yields, stock volatility, and bond volatility). Model 4 and Model 5 corresponded to rolling versions of, respectively, the linear trend model in Equation 11 and the log-linear trend model in Equation 12. **Table 2** presents the results of these out-of-sample forecasts.

The volatility-based Model 3 was nearly unbiased over the 1966–98 period, had the lowest absolute bias of any of the five models, and had the lowest standard deviation of forecast error. The out-of-sample rolling regressions thus support the superiority of the volatility model, although again, the time-trend models are somewhat effective when compared with the more naive Models 1 and 2.

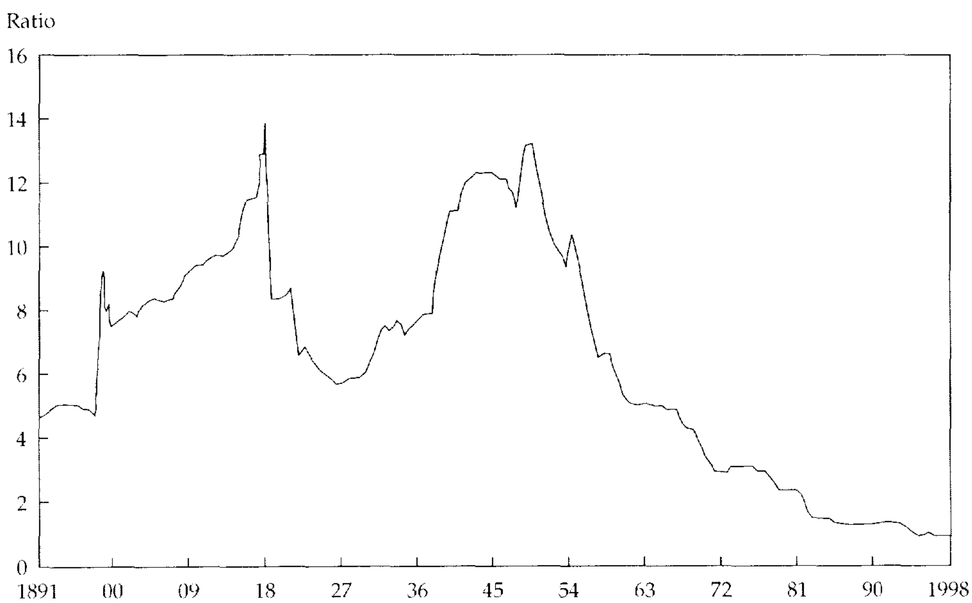
Earlier Data. The best response to many statistical problems is extensive out-of-sample testing—that is, tests with data for a previously unexamined period. All of the tests so far used monthly data for the commonly studied period commencing in 1926. For the tests reported in this section, I used earlier data. Although perhaps not as reliable as the modern data, annual data on the aggregate stock and bond markets are available for as early as 1871.[15]

In addition to simply using new data points, examining the older information provides an advantage that is specific to this study. In **Figure 6**, the new data are used to plot the ratio of rolling 20-year stock market volatility to rolling 20-year bond market volatility over the entire 1891–1998 period.[16]

Table 2. Out-of-Sample Forecasts, January 1966–May 1998

Model	Average Forecasting Error	σ(Forecasting error)
1. Using average D/P	–0.56%	0.97%
2. Using regression on Y	0.29	1.38
3. Using the full model	0.14	0.50
4. Using linear time trend	0.71	0.66
5. Using loglinear time trend	0.54	0.62

Figure 6. Ratio of Rolling 20-Year Stock Market Volatility to Bond Market Volatility, January 1891–May 1998



Recall that one problem with testing the hypothesis for 1946–1998 was that the volatility ratio declined nearly monotonically. Figure 6 shows that the new data preserve this property for this same time period but that the 1891–1945 period reflects no monotonic trend. Thus, if the model works for 1891–1945, or 1891–1998, a spurious time trend is not driving the results. I found that dividend yields also trended down strongly over the 1946–98 period but appear much more stationary when viewed over the entire 1891–1998 period (this figure is available upon request).

As a data check, before examining the pre-1946 data, I reexamined the 1946–98 period with the new annual data set. The following are *annual* regressions for the already-studied 1946–98 period:

$$D/P = \underset{(10.78)}{4.12\%} - \underset{(-0.65)}{0.04Y} \tag{13}$$

(with an adjusted R^2 of –1.1 percent);

$$D/P = \underset{(-1.64)}{-1.15\%} + \underset{(6.07)}{0.29Y} + \underset{(8.03)}{0.24\sigma(\text{Stocks})} - \underset{(-4.88)}{0.16\sigma(\text{Bonds})} \tag{14}$$

(with an adjusted R^2 of 66.0 percent;

$$E/P = \underset{(7.57)}{6.98\%} + \underset{(0.95)}{0.13Y} \tag{15}$$

(with an adjusted R^2 of –1.8 percent);

$$E/P = \underset{(-1.64)}{-3.12\%} + \underset{(6.07)}{0.85Y} + \underset{(8.03)}{0.46\sigma(\text{Stocks})} - \underset{(-4.88)}{0.40\sigma(\text{Bonds})} \tag{16}$$

(with an adjusted R^2 of 48.9 percent).

Although not precisely the same as the monthly regressions presented earlier, the annual regressions on the new data set are similar enough to be encouraging.

Now, consider the results for these same regressions for the earlier 1891–1945 data:

$$D/P = \underset{(2.70)}{2.60\%} + \underset{(2.72)}{0.77Y} \tag{17}$$

(with an adjusted R^2 of 10.6 percent);

$$D/P = \underset{(-1.18)}{-1.65\%} + \underset{(5.00)}{1.36Y} + \underset{(4.75)}{0.19\sigma(\text{Stocks})} - \underset{(-2.10)}{0.53\sigma(\text{Bonds})} \tag{18}$$

(with an adjusted R^2 of 35.7 percent);

$$E/P = \underset{(2.20)}{4.20\%} + \underset{(1.90)}{1.06Y} \tag{19}$$

(with an adjusted R^2 of 4.6 percent);

$$E/P = \underset{(1.05)}{2.90\%} + \underset{(3.13)}{1.68Y} + \underset{(3.15)}{0.25\sigma(\text{Stocks})} - \underset{(-4.50)}{2.23\sigma(\text{Bonds})} \tag{20}$$

(with an adjusted R^2 of 31.5 percent).

These regressions provide bad news and good news. The bad news is that some of the regression coefficients are very different for the 1891–1945 period from what they were for the 1946–98 period. Apparently, the (admittedly simple) model is not completely stable over time. Given changes in the world economy from 1871 to 1998, to think that the coefficients would be completely stable is perhaps wildly optimistic.[17] The good news is that, although over the 1891–1945 period the stock market's D/P and E/P were univariately weakly positively related to Y (see Equations 17 and 19), this relationship became much more strongly positive when I allowed for changing relative stock and bond market volatilities (as in the completely separate 1946–98 period). This relationship was, as my hypothesis forecasted, a strong positive function of the previous 20 years' relative stock versus bond volatility.

Finally, I present the regressions for D/P for the full 1891–1998 period. For comparison, I also present full-period tests of the time-trend variables (the E/P results were highly analogous for all regressions):[18]

$$D/P = \underset{(17.79)}{5.20\%} - \underset{(-2.53)}{0.14Y} \tag{21}$$

(with an adjusted R^2 of 4.8 percent);

$$D/P = \underset{(17.32)}{5.90\%} + \underset{(0.42)}{0.03Y} - \underset{(-3.54)}{0.00\text{Linear trend}} \tag{22}$$

(with an adjusted R^2 of 14.1 percent);

$$D/P = \underset{(6.09)}{7.75\%} - \underset{(-0.91)}{0.06Y} - \underset{(-2.06)}{0.07\text{Loglinear trend}} \tag{23}$$

(with an adjusted R^2 of 7.6 percent);

$$D/P = \underset{(2.96)}{1.98\%} + \underset{(3.52)}{0.26Y} + \underset{(4.95)}{0.14\sigma(\text{Stocks})} - \underset{(-5.65)}{0.29\sigma(\text{Bonds})} \tag{24}$$

(with an adjusted R^2 of 35.5 percent).

The earlier data and the full-period data strongly support the central tenet of the hypothesis: Without adjusting for volatility and with or without a time trend (Equations 21–23), either a negative or flat relationship appears between D/P and bond yields over the entire period. After adjustment for relative stock and bond volatility, this relationship is strongly positive (Equation 24). Unlike the 1946–98 results, these results are clearly present in the absence of a significant trend in the ratio of stock to bond market volatility and despite any changes in the world economy from 1871 to 1998. In fact, unlike the volatility-based model, the time trends utterly fail to resurrect the positive relationship between stock and bond yields over the full period. When I used the data for 1946–1998, I introduced the issue of distinguishing whether the volatility-based model was spuriously supported because the changes in relative volatility approximated a time trend. The earlier and full-period evidence powerfully indicates that it is the time trend whose efficacy is spurious for 1946–1998, not the volatility-based model.

Full-Period Scatter Plots. As a final and perhaps most compelling test, I examined nonoverlapping 20-year periods from 1878 until 1998. I report the results for the resulting six observations in **Figure 7**. Figure 7 plots the ratio of annualized monthly stock market volatility over corresponding monthly bond volatility for the 20 years ending before the labeled year against the excess of stock market earnings yields over bond yields for the year in question. I chose earnings yields for this investigation because the evidence is that they are directly close to being comparable to bond market yields whereas dividend yields move as a dampened function of bond yields (that is, the coefficient on *Y* in Equation 10 is nearly 1.0, which makes the simple difference relevant to examine).

Figure 7 clearly supports the model: The greater stock volatility is versus bond volatility, the higher E/P must be versus *Y*. In contrast to the earlier regression tests, which were admittedly an econometric nightmare, nonoverlapping observations were used for Figure 7, and the autocorrelation of both the dependent and independent series was close to zero.[19] Thus, any need for econometric corrections (e.g., first differencing) was avoided.

The problem now is that I have only six observations, so the tests might lack power, but this is not the case. The *t*-statistic of the regression line is +7.64, and the adjusted R^2 is 92.0 percent. With six observations, a *t*-statistic must exceed +2.45 to be significant at a *p* value of 2.5 percent in a one-tailed test. Clearly, the *t*-statistic for this test is well past this level of significance.

As a robustness check, I recreated Figure 7 but starting 10 years later (resulting in only five observations over this period). The results are in **Figure 8**. This figure is even more striking than Figure 7 (the *t*-statistic in Figure 8 is +12.46, and the adjusted R^2 is 97.5 percent). Note from Figure 6 (the graph of the rolling volatility ratio) that two peaks are visible in the ratio of stock to bond volatility. These peaks roughly correspond to the right side of, respectively, Figures 7 and 8. In both cases, the model fits these extreme observations exceptionally well (that is, the largest volatility ratio corresponded to the largest end-of-period gap of stock earnings yield over bond yield). Also note that these two periods (the 20 years ending in 1918 and the 20 years ending in 1948) share no overlapping observations, yet the model fits both perfectly.

Figure 7. Ratio of Annualized Monthly Stock Market Volatility to Corresponding Monthly Bond Volatility versus Excess of Stock Market Earnings Yield over Bond Yield, 1871–May 1998

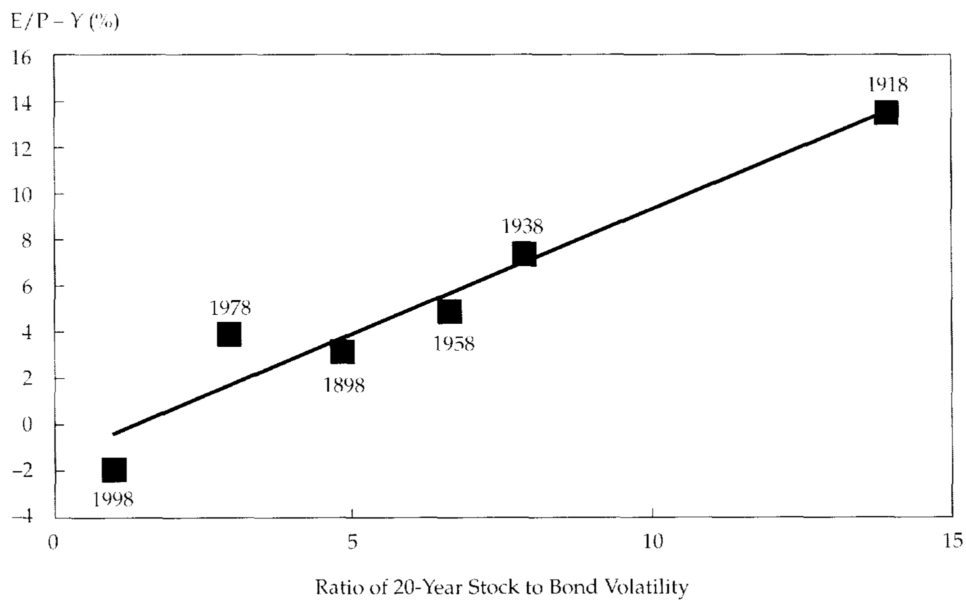
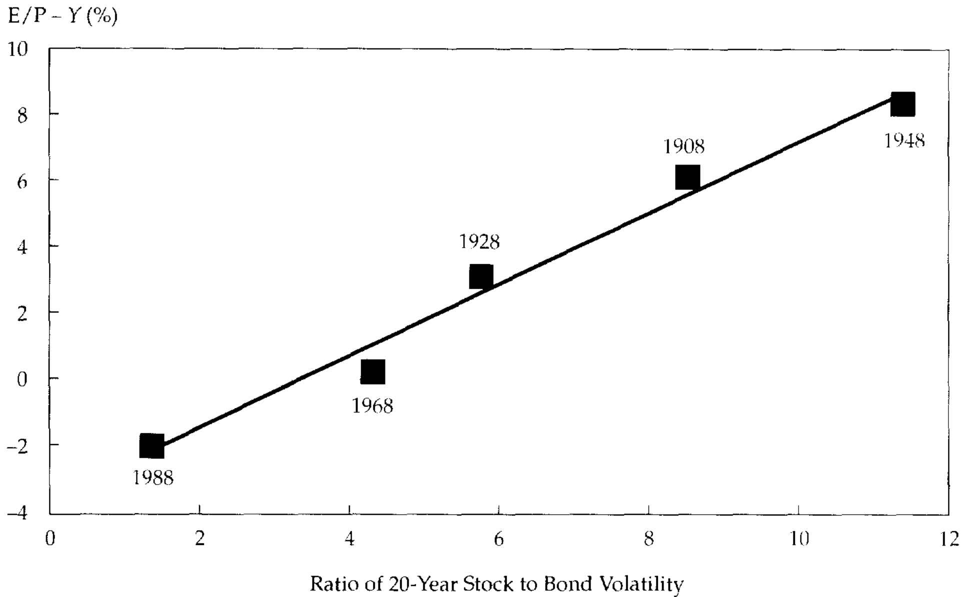


Figure 8. Ratio of Annualized Monthly Stock Market Volatility to Corresponding Monthly Bond Volatility versus Excess of Stock Market Earnings Yield over Bond Yield, 1881–May 1998



Finally, for completeness, I present in **Table 3** the adjusted R^2 and t-statistics for each of eight possible regressions on nonoverlapping periods for which I have six 20-year data points (each row in Table 3 presents the results of a regression that differs by one year in its starting and ending point from the prior/next row). Only one of these eight regressions produced results well below traditional levels of significance, and even in this case, the sign is correct.[20]

We believe these nonoverlapping tests are compelling evidence, irrespective of the econometric problems with our earlier tests, that following long-term periods of high (low) stock market volatility relative to bond market volatility, the required yield on stocks is relatively high (low) versus bonds.

Table 3. Statistics for Eight Regressions

Period	Adjusted R^2	t-Statistic
1891–1991	88.5%	+6.28
1892–1992	73.7	+3.87
1893–1993	81.0	+4.72
1894–1994	45.6	+2.28
1895–1995	9.9	+1.25
1896–1996	91.5	+7.42
1897–1997	78.3	+4.36
1898–1998	92.0	+7.64
Mean	70.1	+4.73
Median	79.7	+4.54

Note: Each row presents the results of a regression that differs by one year in its starting and ending point from the prior/next row.

Market Predictability

Researchers have found that variables D/P and E/P have power to forecast aggregate stock market returns. Moreover, this power appears to increase as time horizon lengthens (e.g., Fama and French 1988, 1989). I tested this finding for 1946–1998 using predictive regressions of excess monthly and annualized 5- and 10-year compound S&P 500 returns on aggregate D/P (t-statistics on all multiperiod regressions were adjusted for overlapping observations and heteroscedasticity). Here are the findings:

$$\underset{}{\text{S\&P monthly return}} = \underset{(-1.03)}{-0.56\%} + \underset{(2.38)}{0.32\text{D/P}} \tag{25}$$

(with an adjusted R^2 of 0.7 percent);

$$\text{S\&P 5-year return} = \underset{(-0.88)}{-4.13\%} + \underset{(4.77)}{4.09\text{D/P}} \tag{26}$$

(with an adjusted R^2 of 56.1 percent);

$$\text{S\&P 10-year return} = \underset{(-0.38)}{-1.443\%} + \underset{(4.34)}{3.22\text{D/P}} \tag{27}$$

(with an adjusted R^2 of 58.7percent).

Equations 25–27 verify the findings of other authors that D/P has weak, but statistically significant, power for forecasting monthly returns and strong statistically significant power for forecasting longer-horizon returns.

Now, a new predictive variable, D/P(Error), is introduced. It is the in-sample residual term from the regression of D/P on Y, σ(Stocks), and σ(Bonds) for the 1946–98 period (Equation 9). It represents the

D/P on the S&P 500 in excess or deficit of what I would have predicted had I been using this model to forecast D/P (i.e., the unexplained portion). The results of the same regression tests as done for Equations 25–27 on this new variable are as follows (all results of this section were analogous when tested on E/P):

$$\text{S\&P monthly return} = \underset{(4.29)}{0.67\%} + \underset{(6.74)}{1.75}\text{D/P(Error)} \quad (28)$$

(with an adjusted R^2 of 6.6 percent);

$$\text{S\&P 5-year return} = \underset{(6.50)}{12.60\%} + \underset{(3.00)}{4.65}\text{D/P(Error)} \quad (29)$$

(with an adjusted R^2 of 21.2 percent);

$$\text{S\&P 10-year return} = \underset{(5.64)}{12.08\%} + \underset{(1.35)}{2.01}\text{D/P(Error)} \quad (30)$$

(with an adjusted R^2 of 7.1 percent).

Comparing the results for D/P(Error) with D/P shows that D/P(Error) has far more predictive power than D/P at short (monthly) horizons but far less power at longer horizons.[21] The power of D/P(Error) to forecast short-horizon returns can be interpreted as picking up time-varying risk aversion or, alternatively, as market mispricing (I leave this decision to future work). In either case, when D/P(Error) is high, stocks are selling for lower prices than is usual in the same interest rate and volatility environment and those low prices indicate higher short-horizon expected returns (and vice versa).

Finally, I formed D/P(Fit) as the fitted values from regression Equation 9. D/P(Fit) can be interpreted as the normal dividend yield as forecasted by the model considering the level of bond yields and stock and bond market volatility. By construction, the following relationship holds:

$$\text{D/P} = \text{D/P(Fit)} + \text{D/P(Error)}. \quad (31)$$

By regressing stock returns on both D/P(Fit) and D/P(Error), I decomposed the forecasting power of D/P into a portion coming from fitted D/P and a portion coming from residual D/P. The following regressions were carried out for 1946–98 data:[22]

$$\text{S\&P monthly return} = \underset{(2.07)}{1.25\%} - \underset{(-0.99)}{0.15}\text{D/P(Fit)} + \underset{(6.74)}{1.75}\text{D/P(Error)} \quad (32)$$

(with an adjusted R^2 of 6.6 percent);

$$\text{S\&P 5-year return} = \underset{(-0.56)}{-2.80\%} + \underset{(3.93)}{3.77}\text{D/P(Fit)} + \underset{(4.97)}{4.96}\text{D/P(Error)} \quad (33)$$

(with an adjusted R^2 of 57.1 percent);

$$\text{S\&P 10-year return} = \underset{(-0.76)}{-3.00\%} + \underset{(4.81)}{3.61}\text{D/P(Fit)} + \underset{(2.00)}{2.29}\text{D/P(Error)} \quad (34)$$

(with an adjusted R^2 of 61.1 percent).

Clearly, the power of D/P for predicting short-run (monthly) S&P 500 returns is driven by D/P(Error). As horizon lengthens, D/P(Fit) becomes more and more important, and at the 10-year horizon, D/P(Fit) is considerably more important.

To examine even longer forecast horizons and over longer periods, I again used annual data back to 1871 and formed D/P(Fit) and D/P(Error) from Equation 24. Recall that the first 20 years are needed to estimate volatility, so the following regressions are for 1891–1998 (all returns are annualized compound returns):

$$\text{S\&P annual return} = \underset{(1.89)}{18.1\%} - \underset{(-0.71)}{1.46}\text{D/P(Fit)} + \underset{(1.91)}{2.89}\text{D/P(Error)} \quad (35)$$

(with an adjusted R^2 of 2.0 percent);

$$\text{S\&P 5-year return} = \underset{(0.59)}{5.32\%} + \underset{(0.51)}{0.99}\text{D/P(Fit)} + \underset{(3.67)}{2.32}\text{D/P(Error)} \quad (36)$$

(with an adjusted R^2 of 12.2 percent);

$$\text{S\&P 10-year return} = \underset{(-0.21)}{-1.78\%} + \underset{(1.43)}{2.43}\text{D/P(Fit)} + \underset{(1.89)}{0.81}\text{D/P(Error)} \quad (37)$$

(with an adjusted R^2 of 12.4 percent);

$$\text{S\&P 15-year return} = \underset{(-3.91)}{-10.89\%} + \underset{(9.72)}{4.24}\text{D/P(Fit)} + \underset{(0.43)}{0.18}\text{D/P(Error)} \quad (38)$$

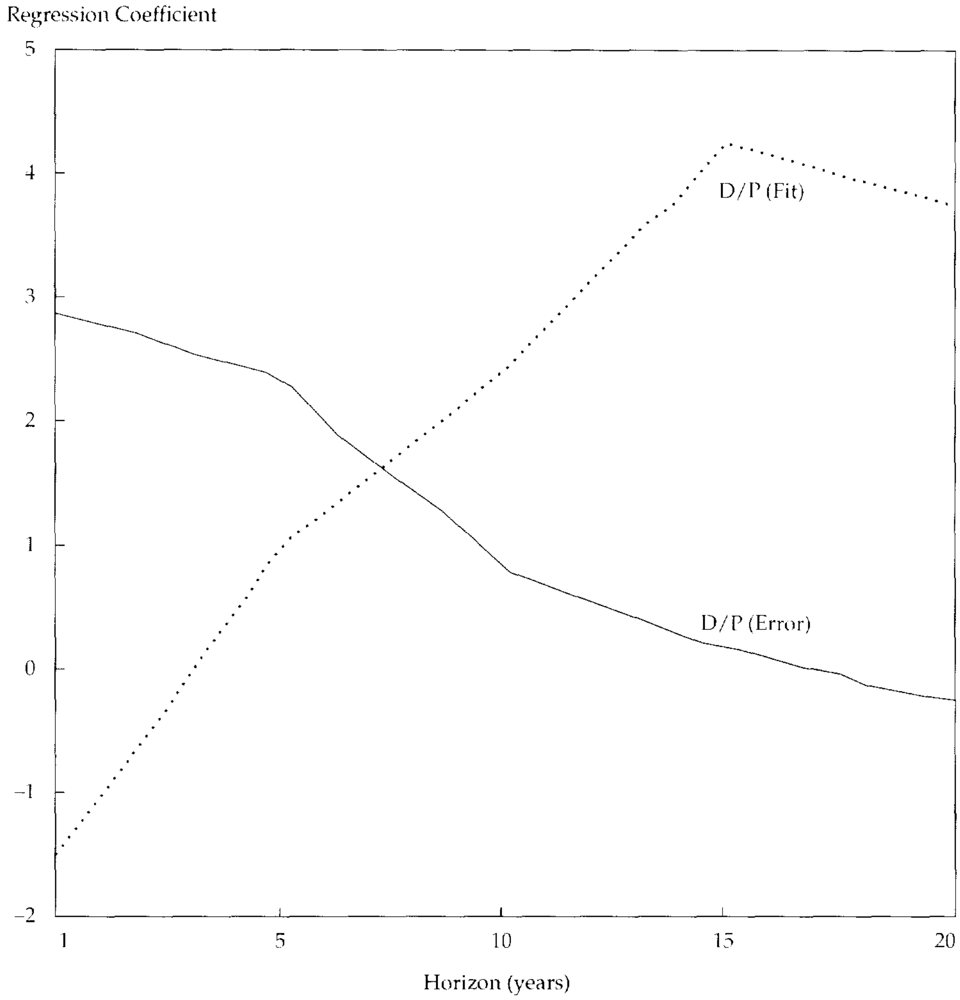
(with an adjusted R^2 of 33.7 percent);

$$\text{S\&P 20-year return} = \underset{(-2.36)}{-8.66\%} + \underset{(5.58)}{3.74}\text{D/P(Fit)} - \underset{(-2.08)}{0.29}\text{D/P(Error)} \quad (39)$$

(with an adjusted R^2 of 42.2 percent).

The estimated coefficients of D/P(Fit) and D/P(Error) for each of the forecast horizons (regression Equations 35–39) are plotted in **Figure 9**. Although annual predictability (Equation 35) is weak, the short-term predictability present is clearly driven by D/P(Error). The story changes dramatically as horizon increases, until at long

Figure 9. Estimated Coefficients of D/P(Fit) and D/P(Error) for Each Forecast Horizon, 1891–1998



Note: All returns are annualized compound returns.

horizons (15 years and 20 years), D/P(Fit) is clearly adding considerable predictive power whereas D/P(Error) is adding none. Figure 9 tells a clear story that at short horizons, D/P(Error) is what counts but at long horizons, what counts is D/P(Fit). (Analogous results held for E/P.)

To sum up, the forecasting power of D/P can be decomposed into the forecasting power of D/P(Fit) and D/P(Error). In the model, D/P(Fit) is the normal or expected dividend yield, and D/P(Error) is interpreted as the D/P in excess (or deficit) of normal. Evidence presented here indicates that D/P itself forecasts stock returns at both long and short horizons but for different reasons. D/P(Fit) forecasts long-horizon stock returns but has almost no power for the short term. D/P(Error) forecasts short-horizon stock returns but has little power for the long term.

Do Stock Yields Have Farther to Fall?

Many have wondered lately why the market is currently selling at such a historically low D/P and E/P (or high P/D and P/E). In particular, in the book *Dow 36,000*, Glassman and Hassett came to an extreme conclusion. They argued that the reason stock prices seem so high relative to measures such as dividends and earnings is that the expected (or required) return on the stock market is going down as investors realize that the stock market is less risky in relation to the bond market than previously thought. Furthermore, they reasoned that this fall in expected returns is not over yet and concluded that it will not stop until stock and bond market expected returns are equal (a point at which, by their calculations, the Dow will reach approximately 36,000). Part of their reasoning sounds much like the arguments advanced here. Well, part of it is, and part of it is not.

Their first conclusion is 100 percent consistent with this article: the conclusion that stocks have low yields now because they are perceived to be less risky versus bonds than historically normal. In fact, my central thesis is that the return required by investors to own stocks versus bonds varies directly with the perceived relative risk of the two assets (for which I used their respective rolling 20-year volatilities as proxies). I believe that my model, coupled with currently low bond market yields and a low perceived risk of stocks versus bonds, entirely explains, within the bounds of statistical error, today's low yields on stocks (and, according to the model, the low long-term expected returns that come with low yields). Thus, my work strongly supports one aspect of the argument in *Dow 36,000*, namely, that stock market expected returns versus bonds have come down as investor perceptions of the relative risk of stocks versus bonds have changed.

My conclusions differ, however, from the next conclusion of *Dow 36,000*. Glassman and Hassett extrapolated the trend in lowered return-premium expectations to continue, but my model offers them no support. The authors of *Dow 36,000* stated that the fall in stock expected returns is not over yet and will not be complete until the expected return on stocks is the same as bonds (presumably not yet the case) because the authors believe that stocks are no riskier than bonds in the long term. This hypothesis is quite provocative. If stocks are no riskier than bonds, then stock prices should rise as investors realize stocks are currently priced as if they are more risky. Now, much debate involves the long-run risk of stocks versus bonds, and to review or settle this matter is not the province of this paper.[23] However, much of the reason behind the current prominence of this debate in the first place is how different today appears from the past (i.e., today's historically high stock prices versus dividends or earnings). My conclusion is that, in fact, the structure of the world really is not much different today; only the inputs to the model have changed. In other words, stock yields (and required returns) have always moved with bond yields, and the relative difference between them has always been a function of their relative perceived volatility. In fact, when I directly estimated this relationship, I found that it fits well for the long term and fits well today.

The reason the study reported here is a problem for theories like those proposed in *Dow 36,000* is that I say the rise in stock prices today, rather than simply beginning as investors start to perceive how safe stocks really are, is actually proceeding much as it has throughout financial history. According to the model, investors have repriced stocks to reflect a lower perception of stock market risk, but any farther drop in the required return on stocks (and concurrent rise in stock prices) must come from a further reduction in actual stock volatility (versus bond volatility) or a reduction in bond yields. If investors have been all along implicitly using the relationship hypothesized here to price stocks (as the data strongly support they have since at least 1891), then they have acted consistently in recently raising the price of equities. But we can expect no more such rises unless either interest rates or realized relative volatility change.[24] The model discussed here suggests that unless the inputs to the model change, any repricing of equities is approximately complete.

Finally, if the model is accurate, a belief that a near-term windfall profit of about three times your money is currently available in the broad stock market, a belief held by Glassman and Hassett, is dangerous. First, investors who believe in the windfall possibility may overallocate to stocks.[25] Second, short-term pricing errors induced by believers in this argument (or "bubbles") can be dangerous to the real economy. Third, and perhaps most worrisome, if the model presented and tested in this paper is correct, the belief that stocks stand to receive a one-time enormous windfall profit is not simply wrong, it is backward. The low stock yields of today are fully explained by the model, meaning that the forecast of short-term stock returns is about average.[26] Moreover, if the conclusion here is true that the best forecasting variable for long-term stock returns is the absolute level of stock yields, then today's low yields (both D/P and E/P) point to a poor forecast for the long-term return on stocks.

Conclusion

Each of the puzzles stated at the beginning of this article can be resolved by using the model provided in Equation 6 for the required yield on stocks. Consider the first question: Why did the stock market strongly outyield bonds for so long only to now consistently underyield bonds? The model states that (1) the higher bond yields are and (2) the higher perceived stock market volatility versus bond market volatility is, then the higher stock yields must be. For a long time (before the 1950s), stocks outyielded bonds because the realized volatility of stocks versus bonds was much higher than in modern times.

Consider the second question: Why did stock and bond yields move relatively independently, or even perversely, in the 1927–98 period but strongly move together in the later 40 years of this period? Stock and bond yields appear to move independently or even perversely over long periods (e.g., 1926–1998), but this appearance is an artifact of missing a part of their structural relationship. If the impact of changing volatility is taken into account, stock and bond yields are strongly positively correlated over the entire period for which we have data, which many strategists and economists would have hypothesized.

Finally, consider the third question: Why are today's stock market yields so low and what does that fact mean for the future? Today's stock market yields are so low simply because bond yields are low and recent realized stock market volatility has been low when compared with bond market volatility. I do not need to resort to "the world has changed" types of arguments to explain today's low yields. The model fully explains them. And the model indicates that they will not go much lower unless realized stock versus bond volatility or interest rates fall farther.

Although testing a long-term, slowly changing relationship has statistical difficulties, the model easily survived every reasonable robustness check, including out-of-sample testing of a previously untouched period (1871–1945) and the formation of completely nonoverlapping, nonserially correlated independent and dependent variables for the entire 1871–1998 period.

This work has strong theoretical implications. A link between volatility and expected return is one of the strongest implications of modern finance.[27] Researchers have found compelling evidence of this phenomenon in comparing asset classes (i.e., stocks versus bonds), but evidence of a link *within* asset classes (e.g., testing the capital asset pricing model for stocks) or an intertemporal link within one asset class has been weak. This article addresses the intertemporal link. Past studies failed to convincingly link expected stock returns to *ex ante* volatility through realized stock returns.[28] However, realized stock returns are very noisy. I hypothesized that D/P (or E/P) is a proxy for expected stock returns and that Y is a proxy for expected bond returns and found strong confirmation that the difference between these proxies is a positive function of differences in experienced volatility. In other words, unlike many other studies, I have documented a strong positive intertemporal relationship between expected return and perceived risk.

This article demonstrated that the relative long-term volatility experienced by investors is a strong driver of the relative yields they require on stocks versus bonds; it did *not* show that these long-term realized volatility figures are accurate forecasts of future volatility. Thus, I have clearly identified a behavioral relationship that I believe is important, but I offer no verdict on market efficiency.[29]

The bottom line is that today's stock market (as of May 1998) has very low yields (D/P and E/P) for the simple reason that bond yields are low and stock volatility has been low as compared with bond volatility. These conditions historically lead investors to accept a low yield (and expected return) on stocks. If one is a short-term investor, knowing that these low yields are not abnormal may be comforting. A long-term investor, however, might be very nervous, because raw stock yields (D/P and E/P) are the best predictors of long-term stock market returns and these raw yields are currently at very low levels.

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Notes

1. A set of assumptions sufficient for this equality to hold for coupon-bearing bonds is that the yield curve be flat and unchanging.
2. The sources and/or construction of the data for this article are as follows: For stocks, return and earnings yield data on the S&P 500 came from Datastream and dividend yields from Ibbotson Associates. For bonds, return data for January 1980 to May 1998 are from the J.P. Morgan Government Bond Index levered to a constant duration of 7.0 (i.e., the monthly return used is the T-bill rate plus 7.0 divided by the beginning-of-the-month J.P. Morgan duration times the return on the J.P. Morgan index minus the T-bill return). I constructed a constant-duration bond in the hopes of making my bond return series more homoscedastic. The choice of a duration of 7.0 was arbitrary and had no effect on the results. I performed the regression of this excess return series on the excess monthly return of the Ibbotson Associates long- and intermediate-term bond series for January 1980 to May 1998. For January 1926 to December 1979, I used the fitted values on the Ibbotson return series to approximate the 7.0-year duration J.P. Morgan government bond series. For bond yields, I used the 10-year benchmark yield from Datastream from January 1980 to May 1998. For January 1926 to December 1979, I used the fitted multiple regression forecast (fitted from the regression over the January 1980–May 1998 period) of the 10-year yield on the Ibbotson

short-, intermediate-, and long-term government bond series. The results are not sensitive to precise definitions of the bond yield or return.

3. The earnings yield I used is prior year's earnings over current price. All the economic results in this article are robust to using either a 3- or 10-year moving average of real earnings in the numerator.
4. Equation 3 almost assuredly should be augmented with variables proxying time-varying expected dividend growth (see Fama and French 1988). I have tested such proxies and found them to be statistically significant, but I omitted them from this article because they affect none of the results or conclusions significantly.
5. Bernstein (1993, 1997) examined a related (although slightly different) model and came to some of the same conclusions.
6. The results presented here were insensitive to assuming other reasonable functional forms for this relationship (for example, assuming linearity in the log of the volatilities rather than the levels).
7. Kane, Marcus, and Noh (1996) examined a related model for the first difference of market P/Es (a somewhat different exercise) and came to some conclusions similar to mine.
8. These studies used forms similar to Equation 5.
9. Another logical extension of Equations 3, 4, and 5 is $Y = c + e\text{T-bill} + d\sigma(\text{Bonds})$. That is, the yield on bonds moves (possibly at a multiple) with the short-term interest rate, and this weighted difference between long-term and short-term yields is a positive function of perceived bond volatility. Although not the focus of this article (but the focus of a future paper), empirical tests of this equation strongly support this specification.
10. This work is not sensitive to the definition of generation as precisely 20 years.
11. Note that I am not attempting to use the best short-term conditional estimate of volatility. Short-term changes in volatility may be mostly transitory. If so, they would have little impact on stock prices and required stock yields (see, for instance, Poterba and Summers 1986).
12. All R^2 values were adjusted for degrees of freedom.
13. Granger and Newbold (1974) found that in regressions of one random walk on another, rejection of the null hypothesis is more the rule than the exception. Also see Kirby (1997) or Goetzmann and Jorion (1993).
14. As mentioned previously, the results of this article are not very sensitive to the choice of a 20-year window for volatility. For instance, using a 10-year window for volatility estimation greatly reduced (but did not eliminate) the degree of autocorrelation in the right-hand variables. When I reestimate Equation 9 using 10-year rolling volatility (which also added 10 more years, 1936–1945, to the regression), the t-statistics did not materially change; the t-statistics on Y, σ(Stocks), and σ(Bonds) were, respectively, +10.00, +14.45, and –14.75. Using a 7-year window (now adding data from 1933–1945 to the regression), the t-statistics were +5.21, +11.54, and –10.93. A later section addresses this issue more directly by using longer-term data and analyzing nonoverlapping 20-year periods.
15. The sources for these data are Robert J. Shiller's Web page (an update of the data in Chapter 26 of Shiller 1989) and the company Global Financial Data.
16. These ratios are somewhat higher than reported in Figure 5 because the duration of the bond used in these annual tests was, on average, somewhat shorter than the duration of 7.0 years used in the monthly tests. Thus, bond volatility is somewhat lower in these annual tests. This change is only a matter of scale and has no economic effect on the tests.
17. For instance, Fama and French (1988) found that the parameters of the Lintner (1956) model for explaining dividend changes changed radically during the 1927–86 period.
18. As a final check, I reestimated Equation 24 using the Cochrane–Orcutt procedure to adjust for first-order auto-

correlation in the residuals. Each coefficient was essentially the same and remained statistically significant, whereas the first-order annual residual autocorrelation was highly statistically significant at 0.55.

19. This low autocorrelation matches the results of Poterba and Summers, who found only very short-term persistence in market volatility. Interestingly, I found that long-term rolling estimates of volatility seem to be crucial in determining the required expected return on the market but do not forecast the next period of long-term volatility itself. Thus, although investor perceptions of volatility drive market expected returns, those perceptions have not necessarily been accurate. My model might correctly describe investor behavior, but reconciling this behavior with market efficiency may be difficult (although not necessarily impossible). I leave this endeavor to future work.
20. In fact, the failure of the one regression (1895–1995) was driven by the 1975 observation (without this observation, the regression had an R^2 of 89.5 percent and a t-statistic of +5.93). Furthermore, by the luck of the draw, this regression did not include values for either the x or y variable as extreme as in Figures 7 and 8, which lowered the power of this test.
21. These regression results should not be considered an accurate test of a short- or long-term trading strategy. First, the regressions used D/P, which because it has price in the denominator, is known to induce a small bias toward finding a positive coefficient. The regressions also used the full-period data to form D/P(Error), which would not have been known prior to the end of the period. Finally, of course, the regressions do not account for trading costs. These regressions are meant to be indicative of the forecasting power of the model versus traditional models. Formal tests of a trading strategy based on these methods are not available from the author; trying to profit from such strategies is what I do for a day job.
22. These tests were carried out on in-sample regression residuals to retain the full 1946–98 period. Analogous significant results (although a bit weaker) were found for 1966–1998 when rolling out-of-sample versions of D/P(Fit) and D/P(Error) were used.
23. Two good sources for a scholarly but readable review of these issues are Siegel (1994) and Cornell (1999).
24. Glassman and Hassett did offer some reasons why stock volatility might be lower in the future than in the past, but their central argument does not need this farther drop to happen because their argument is that stocks are no more risky than bonds right now.
25. In all fairness, the actual practical investment advice in the book *Dow 36,000* appears quite reasonable, although it is still easy to see how an investor who believes in the authors' premise will not act so reasonably.
26. When this article was written, May 1998 data were the latest used. As of November 1999, the model's short-term forecast for stocks had joined the long-term forecast of stocks as below average, although not nearly as severely below average as the long-term forecast. I would be happy to provide a more up-to-date forecast and can be contacted at cliff.asness@aqrcapital.com. Of course, trade on such a forecast at your own risk!
27. This link does not need to hold precisely for inefficient portfolios.
28. An exception is Kane, Marcus, and Noh, who correctly pointed out that this relationship is much clearer in *ex ante* measures than in *ex post* returns.
29. Unfortunately, I also could not determine the rationality of the predictive power of D/P(Error) over short horizons and D/P(Fit) over long horizons. Modigliani and Cohn (1979) argued that when inflation (and presumably bond yields) is low, investors mistakenly (i.e., irrationally or inefficiently) overprice equities (and vice versa). The empirical results of this study support their hypothesis in one way: When volatility is held constant, investors do price stocks at higher P/Es and P/Ds when interest rates are low (and vice versa). This empirical finding is an important contribution, because more-naive tests (which fail to account for relative volatility changes) do not pick up this relationship. However, distinguishing whether the short-term predictive power of D/P(Error) or the long-term predictive power of D/P(Fit) is coming from such mispricing or rational variance in expected return (perhaps caused by changing risk aversion) is beyond the scope of this article.

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Cash Flow Risk, Discounting Risk, and the Equity Premium Puzzle

Gurdip Bakshi and Zhiwu Chen*

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*Bakshi is at Department of Finance, Smith School of Business, University of Maryland, College Park, MD 20742, Tel: (301) 405-2261, email: gbakshi@rhsmith.umd.edu, and Website: www.rhsmith.umd.edu/finance/gbakshi/; and Chen at Yale School of Management, 135 Prospect Street, New Haven, CT 06520, Tel: (203) 432-5948, email: zhiwu.chen@yale.edu and www.som.yale.edu/faculty/zc25. The earnings data used in the paper are provided to us by I/B/E/S International Inc. We thank our colleagues Doron Avramov, Charles Cao, Steve Heston, Nengjiu Ju, Mark Loewenstein, Dilip Madan, and Harry Mamaysky for many constructive discussions on this topic. This article is being prepared for the *Handbook of Investments: Equity Premium*, edited by Rajnish Mehra. We are grateful to Rajnish Mehra for inviting us to contribute this chapter. The paper has improved from the feedback of Rajnish Mehra and two anonymous referees. We welcome comments, including references to related papers we have inadvertently overlooked. The computer codes used to implement the model are available from either of the authors.

Cash Flow Risk, Discounting Risk, and the Equity Premium Puzzle

Abstract

This article investigates the impact of cash flow risk and discounting risk on the aggregate equity premium. Our approach is based on the idea that consumption is hard to measure empirically, so if we substitute out an empirically difficult-to-estimate marginal utility by a pricing kernel of observables, we can evaluate the empirical performance of an equilibrium asset pricing model in a different way. Once the pricing-kernel process is specified, we can endogenously solve for the equity premium, the price of the market-portfolio and the term structure of interest rates within the same underlying equilibrium. Embedded in the closed-form solution are compensations for cash flow risk and discounting risk. With the solution for the risk premium explicitly given, we then calibrate the model to evaluate its empirical performance. This approach allows us to avoid the impact of the unobservable consumption or market portfolio on inferences regarding the model's performance. Our illustrative model is based on the assumption that aggregate dividend equals a fixed fraction of aggregate earnings plus noise, and the expected aggregate earnings growth follows a mean-reverting stochastic process. Moreover, the economy-wide pricing kernel is chosen to be consistent with (i) a constant market price of aggregate risk and (ii) a mean-reverting interest rate process with constant volatility. Estimation results show that the framework can mimic the observed market equity premium.

1 Introduction

In their seminal contribution, Mehra and Prescott (1985) show that the observed equity premium on the S&P 500 market index is far too high given the stochastic properties of aggregate consumption and under plausible assumptions about risk aversion. Furthermore, equity returns empirically covary little with aggregate consumption growth, implying also that the average equity premium can only be reconciled through an implausibly large coefficient of relative risk aversion. Table 1 in Mehra and Prescott (2003) documents that the average equity premium in the U.S. is 6.92%, while the real rate of interest is 1.14%, over the sample period of 1889-2000. Why have stocks delivered an average return of about 7% over risk-free bonds? Why is the observed real rate on Treasuries so low? Why is the systematic risk, as exemplified by the correlation between consumption growth and market-index return, so small?

Collectively known as the equity premium puzzle, this set of questions has consumed financial economists over the past two decades and generated competing explanations ranging from (i) generalizations to state-dependent utility functions (Constantanides (1990), Epstein and Zin (1991), Benartzi and Thaler (1995), Bakshi and Chen (1996), Campbell and Cochrane (1999), and Barberis, Huang, and Santos (2001)); (ii) the fear of catastrophic consumption drops (Reitz (1988)); (iii) the presence of uninsurable and idiosyncratic income risk (Heaton and Lucas (1996) and Mankiw (1986)); (iv) borrowing constraints (Constantinides, Donaldson, and Mehra (2002)); and (v) measurement errors and poor consumption growth proxies (Breeden, Gibbons, and Litzenberger (1989), Mankiw and Zeldes (1991), Ferson and Harvey (1992), and Aït-Sahalia, Parker, and Yogo (2004)). Despite the substantial research efforts, there is controversy whether these explanations can completely explain all aspects of the equity premium puzzle (Mehra and Prescott (2003)), and the original puzzle remains unsolved. That is, under plausible parameterizations, existing models can only generate a small equity premium.

This article expounds on a risk-based explanation without taking a stand on the precise parametric specification of the marginal utility function. Our approach is based on the idea that consumption is hard to measure empirically, so if we substitute out an empirically difficult-to-estimate marginal utility by a pricing-kernel function of observables we can evaluate the empirical performance of an equilibrium asset pricing model in a different way. That is, once the pricing-kernel process is specified, we can endogenously solve for the equity premium, the current price of the market portfolio and the term structure of interest rates within the same underlying equilibrium. Embedded in the closed-form solutions are compensations for cash flow risk and discounting risk. With these solutions for the risk premium, we can then calibrate the model to evaluate its empirical performance. This approach allows us to avoid the impact of unobservable consumption on inferences regarding an asset pricing model's performance.

We illustrate the potential of this modeling approach by using some simple assumptions. First, we posit that a fixed proportion of the market-portfolio earnings (plus some noise) will be paid out as dividends. This assumption allows us to directly link the stock price and the equity premium to the firm's earnings, instead of dividends. This modeling feature is important because dividend-based stock valuation models have not succeeded empirically, and investors are far more interested in the earnings of a stock rather than its dividends. Second, we assume some marginal utility function that is consistent with both a constant market price of aggregate risk and a single-factor Vasicek (1977) term structure of interest rates. It is further assumed that the market-portfolio earnings-per-share (EPS) obeys a proportional stochastic process, with its expected growth rate following a mean-reverting process (under the physical probability measure). Thus, in our equity valuation setting, there is an embedded stochastic term structure of interest rates, the expected EPS growth follows a stochastic process, the current market-index level depends on earnings (instead of dividends), and both cash flow risk and interest rate risk are priced. The rationale for our assumptions will be discussed in more details shortly.

It is shown that risk aversion implicit in the pricing kernel introduces a wedge between the physical process and the risk-neutralized process of variables in the economy. Specifically, the working of risk aversion makes the risk-neutral drift of the interest rate process higher than its physical counterpart and leads to a heavier discounting of stochastic cash flow streams. This mechanism generates lower market valuations and a higher equity premium (even though this effect also raises bond yields).

Risk aversion also affects the risk-neutralized cash flow process: the risk-neutral drifts for both the earnings and the expected earnings growth processes are lower than their counterpart under the physical probability measure. Such a mapping is suggestive of a positive compensation for both earnings risk and expected earnings-growth risk. Overall, the equity premium is a weighted sum of compensations for risks associated with interest rate, earnings, and expected earnings-growth shocks, with the weights dependent on the state-of-the economy and the structural parameters.

Our empirical implementation provides several insights on how discounting risk and cash flow risks are reflected and simultaneously priced in the S&P 500 index and default-free bonds. We find that the interest-rate risk premium is negative and it contributes to a 77.16 basis-point spread between the market-portfolio and the risk-free interest rate. Moreover, the compensation for expected earnings-growth risk is negligible, and the compensation for earnings risk is 6.53%. It is the risk premium for earnings uncertainty, and not expected earnings-growth uncertainty, that largely drives the equity premium. The total model-derived equity premium is 7.31% and quantitatively robust under perturbations to test design methods. Overall, our empirical exercise demonstrates that the signs of the risk premiums are consistent with economic theory and show promise in explaining the behavior of the average equity premium and the Treasury yield curve. We argue that replacing the marginal utility by a pricing-kernel function of observables, and sensibly parameterizing the discounting structure and cash flows, is crucial to achieving a reasonable equity premium and improved performance.

The purpose of this article is not to test whether a particularly parameterized economic model would be able to explain the observed equity premium under some reasonable set of parameter values. Rather, the goal is to show that given the unobservability of key economic variables (such as consumption and the market portfolio), an alternative approach to testing an economic model is to rely on its internal equilibrium relations to substitute out unobservable variables by functions of observable financial market variables. Then, a test on the resulting equilibrium relations amounts to a test on the economic model itself. Perhaps, another way to look at the results in this article is that it shows what basic properties an empirically successful pricing kernel must have in order to be consistent with the observed equity premium in the U.S. stock market.

In what follows, Section 2 outlines assumptions and develops analytical expressions for the price of the market portfolio and the equity premium. Section 3 describes the data on S&P 500 earnings, equity premium, interest rates, and the panel of bond prices. Section 4 estimates the valuation model and discusses its implication for the equity premium. Concluding statements are provided in Section 5. The mathematical derivations for the price of the market portfolio and the equity premium are provided in the Appendix.

2 Economic Determinants of Equity Premium

This section develops a framework to study the determinants of the time-t price of the market-portfolio, P_t, for each time $t \geq 0$, and the instantaneous market-index risk premium $\mu_t - r_t$, for short interest rate r_t.

Consider a continuous-time, infinite-horizon economy whose underlying valuation standard is represented by some pricing-kernel process, denoted by M_t. Assume that the market-portfolio entitles its holder to an infinite dividend stream $\{D_t : t \geq 0\}$. Asset pricing models under the perfect-markets assumption implies

$$P_t = \int_t^\infty E_t\left[\frac{M_u}{M_t} D_u\right] du, \qquad \text{and,} \tag{1}$$

$$\mu_t - r_t = -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, \frac{dP_t}{P_t}\right)/dt, \tag{2}$$

where $E_t[\cdot]$ is the time-t conditional expectation operator with respect to the objective probability measure. All variables in (1)-(2) are in nominal terms. In this framework, the instantaneous equity premium and the price of the market-portfolio are determined endogenously and jointly within the same underlying risk-return equilibrium. The basic model outlined below is adopted from Bakshi and Chen (2005).

2.1 Cash Flow Process

To explicitly solve (1)-(2), assume that the market-portfolio has a constant dividend-payout ratio (plus noise), α (with $1 \geq \alpha \geq 0$), that is,

$$D_t\, dt = \alpha\, Y_t\, dt + d\, Z_t, \tag{3}$$

where Y_t is the aggregate earnings-per-share (EPS) flow at t and hence $Y_t\, dt$ is the total EPS over the interval from t to $t + dt$, and $d\, Z_t$ is the increment to a martingale process with zero mean. The existence of $d\, Z_t$ allows the market-portfolio dividends to randomly deviate from the fixed proportion of its EPS, and it makes D_t and Y_t not perfectly substitutable. Although this temporary deviation could be correlated with recent earnings and past deviations, incorporating this feature, or the stochastic pay-out ratio feature, into the assumption would unnecessarily complicate the model (see Lintner (1956), Marsh and

Merton (1987), Barsky and Delong (1993), and Menzly, Santos, and Venonesi (2004)).

Under the objective probability measure, Y_t is assumed to follow a process given below:

$$\frac{dY_t}{Y_t} = G_t\,dt + \sigma_y\,dW_t^y, \tag{4}$$

$$d\,G_t = \kappa_g\left(\mu_g^* - G_t\right)\,dt + \sigma_g\,dW_t^g, \tag{5}$$

for constants σ_y, κ_g, μ_g^* and σ_g. The long-run mean for both G_t and actual EPS growth $\frac{dY_t}{Y_t}$ is μ_g^*, and the speed at which G_t adjusts to μ_g^* is reflected by κ_g. Further, $\frac{1}{\kappa_g}$ measures the duration of the firm's business growth cycle. Volatility for both earnings growth and changes in G_t is time-invariant.

The cash flow process parameterized in (4) offers enough flexibility to model the level of the market-portfolio and the instantaneous equity premium (see also Bakshi and Chen (1997) and Longstaff and Piazzesi (2004)). First, both actual and expected earnings growth can take either positive or negative values, reflecting business cycles. Second, expected EPS growth G_t is mean-reverting and has both a permanent component (reflected by μ_g^*) and a transitory component, so that G_t can be high or low relative to its long-run mean μ_g^*. Finally, since Y_t is observable and G_t can be obtained from analyst estimates, we can learn about the equity premium based on readily identifiable and observable state variables.

2.2 The Discounting Process

Turning to the pricing kernel, assume, as in Constantinides (1992), that M_t follows an Ito process satisfying

$$\frac{dM_t}{M_t} = -r_t\,dt - \sigma_m\,dW_t^m, \tag{6}$$

for a constant σ_m, where the instantaneous discounting rate, r_t, follows the Ornstein-Uhlenbeck mean-reverting process:

$$d\,r_t = \kappa_r\left(\mu_r^* - r_t\right)\,dt + \sigma_r\,dW_t^r, \tag{7}$$

for constants κ_r, μ_r^* and σ_r. The pricing kernel can be interpreted in the context of the consumption-based asset pricing model. Suppose $M_t = C_t^{-\gamma}$ for coefficient of relative risk aversion γ and aggregate consumption C_t, then Ito's lemma impies $\frac{dM_t}{M_t} = -\gamma\frac{dC_t}{C_t} + \frac{1}{2}\gamma(1+\gamma)\left(\frac{dC_t}{C_t}\right)^2$. Thus, we can write risk-return equation (2) as $\mu_t - r_t = \gamma\,\mathrm{Cov}_t\left(\frac{dC_t}{C_t}, \frac{dP_t}{P_t}\right)/dt$, and the equilibrium $r_t\, dt = \gamma\, E_t\left(\frac{dC_t}{C_t}\right) - \frac{1}{2}(\gamma)(1+\gamma)\, E_t\left(\frac{dC_t}{C_t}\right)^2$. Thus, unlike the traditional approaches in Mehra and Prescott (1985) and Weil (1989), we independently model the interest rate dynamics as specified in (7).

Parameter κ_r measures the speed at which r_t adjusts to its long-run mean μ_r^*. The pricing kernel (6) leads to a single-factor Vasicek (1977) term structure of interest rates, that is, the τ-period bond-price is: $B(t,\tau) = \exp\left(-\xi[\tau] - \varsigma[\tau] r_t\right)$, where $\varsigma[\tau] \equiv \frac{1-e^{-k_r \tau}}{k_r}$, and $\xi(\tau) \equiv -\frac{1}{2}\,\sigma_r^2 \int_0^\tau \varsigma^2[u]\, du + \left(\kappa_r\, \mu_r\, + \mathrm{Cov}_t\left(\frac{dM_t}{M_t}, dr_t\right)\right) \int_0^\tau \varsigma[u]\, du$. This approach provides interest rate parameters that can be separately calibrated to the observed Treasury yield curve.

Notice that shocks to expected growth, W^g, may be correlated with both systematic shocks W^m and interest rate shocks W^r, with their respective correlation coefficients denoted by $\rho_{g,m}$ and $\rho_{g,r}$. In addition, the correlations of W^y with W^g, W^m and W^r are respectively denoted by $\rho_{g,y}$, $\rho_{m,y}$ and $\rho_{r,y}$. Thus, both actual and expected EPS growth shocks are priced risk factors. The noise process dZ_t in (3) is however assumed to be uncorrelated with G_t, M_t, r_t and Y_t, and hence it is not a priced risk factor.

2.3 Dynamics of the Market-Portfolio

Substituting assumptions (3)-(7) into (1)-(2), we can see that the conditional expectations in P_t must be a function of G_t, r_t and Y_t. Applying Ito's lemma to P_t and substituting the resulting expression into risk-return equation (2), we have the partial differential equation (PDE) for P_t (the details are given in the Appendix):

$$\begin{aligned}
&\frac{1}{2}\,\sigma_y^2\, Y^2\, \frac{\partial^2 P}{\partial Y^2} + (G - \Pi_y)\, Y\, \frac{\partial P}{\partial Y} + \rho_{g,y}\sigma_y\sigma_g\, Y\, \frac{\partial^2 P}{\partial Y \partial G} + \rho_{r,y}\sigma_y\sigma_r\, Y\, \frac{\partial^2 P}{\partial Y \partial r} + \\
&\rho_{g,r}\sigma_g\sigma_r\, \frac{\partial^2 P}{\partial G \partial r} + \frac{1}{2}\sigma_r^2\, \frac{\partial^2 P}{\partial r^2} + \kappa_r\,(\mu_r - r)\, \frac{\partial P}{\partial r} + \frac{1}{2}\sigma_g^2 \frac{\partial^2 P}{\partial G^2} \\
&+\kappa_g\,(\mu_g - G)\, \frac{\partial P}{\partial G} - r\, P + \alpha\, Y = 0,
\end{aligned} \tag{8}$$

subject to the transversality condition $P_t < \infty$. The transversality condition states that the stock price stay bounded for all combinations of the parameters governing cash flows, discounting, and their risk premiums. In the valuation equation PDE (8) we set,

$$\mu_g \equiv \mu_g^* - \frac{\Pi_g}{\kappa_g}, \tag{9}$$

$$\mu_r \equiv \mu_r^* - \frac{\Pi_r}{\kappa_r}, \tag{10}$$

which are, respectively, the long-run means of G_t and r_t under the risk-neutral probability measure defined by the pricing kernel M_t. It can be shown that

$$\begin{aligned}
\Pi_y &\equiv -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, \frac{dY_t}{Y_t}\right)/dt, && (11)\\
\Pi_g &\equiv -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, dG_t\right)/dt, && (12)\\
\Pi_r &\equiv -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, dr_t\right)/dt, && (13)
\end{aligned}$$

are the risk premium for the earnings shocks, expected earnings growth, and interest rate, respectively. Conjecture that the solution to the PDE (8) is of the form:

$$P_t = \alpha\, Y_t \int_0^\infty \overline{p}[t,u;G,r]\, du, \tag{14}$$

where $\overline{p}[t,u;G,r]$ can be interpreted as the time-t price of a claim that pays \$1 at a future date $t+u$. Solving the resulting valuation equation and the associated Ricatti equations subject to the boundary condition that $\overline{p}[t+u,0]=1$ yields,

$$\overline{p}[t,u;G,r] = \exp\left(\,\varphi[u] - \varrho[u]\, r_t + \vartheta[u]\, G_t\,\right), \tag{15}$$

where

$$\begin{aligned}
\varphi[u] \;&\equiv\; -\Pi_y\, u + \frac{1}{2}\frac{\sigma_r^2}{\kappa_r^2}\left(u + \frac{1-e^{-2\kappa_r u}}{2\kappa_r} - \frac{2(1-e^{-\kappa_r u})}{\kappa_r}\right) - \frac{\kappa_r\mu_r + \sigma_y\sigma_r\rho_{r,y}}{\kappa_r}\left(u - \frac{1-e^{-\kappa_r u}}{\kappa_r}\right)\\
&\quad + \frac{1}{2}\frac{\sigma_g^2}{\kappa_g^2}\left(u + \frac{1-e^{-2\kappa_g u}}{2\kappa_g} - \frac{2}{\kappa_g}(1-e^{-\kappa_g u})\right) + \frac{\kappa_g\mu_g + \sigma_y\sigma_g\rho_{g,y}}{\kappa_g}\left(u - \frac{1-e^{-\kappa_g u}}{\kappa_g}\right)\\
&\quad - \frac{\sigma_r\sigma_g\rho_{g,r}}{\kappa_r\kappa_g}\left(u - \frac{1}{\kappa_r}(1-e^{-\kappa_r u}) - \frac{1}{\kappa_g}(1-e^{-\kappa_g u}) + \frac{1-e^{-(\kappa_r+\kappa_g)u}}{\kappa_r+\kappa_g}\right), && (16)\\
\varrho[u] \;&\equiv\; \frac{1-e^{-\kappa_r u}}{\kappa_r}, && (17)\\
\vartheta[u] \;&\equiv\; \frac{1-e^{-\kappa_g u}}{\kappa_g}, && (18)
\end{aligned}$$

subject to the transversality condition that

$$\mu_r - \mu_g > \frac{\sigma_r^2}{2\,\kappa_r^2} - \frac{\sigma_r \sigma_y \rho_{r,y}}{\kappa_r} - \frac{\sigma_g \sigma_r \rho_{g,r}}{\kappa_g \kappa_r} - \Pi_y + \frac{\sigma_g^2}{2\kappa_g^2} + \frac{\sigma_g \sigma_y \rho_{g,y}}{\kappa_g}. \tag{19}$$

Thus, the model price for the market-portfolio or a stock is the summed value of a continuum of claims that each pay at a future time an amount respectively determined by the earnings process. The presence of an integral in (14) should not hamper the applicability of the model as the integral can be computed numerically.

The valuation formula in (14) is not as simple to comprehend as the Gordon dividend growth model. Realize that the Gordon model is a special case in which both G_t and r_t are constant over time: $G_t = g$ and $r_t = r$, for constants g and r. Consequently, both M_t and Y_t follow a geometric Brownian motion. In this case, we obtain $P_t = \frac{\alpha Y_t}{r + \Pi_y - g}$ provided $r + \Pi_y - g > 0$. In our economic setting, valuation is more complex as both discounting and cash flow forecasts have to be simultaneously assessed at the same time.

2.4 Dynamics of the Equity Premium

In deriving the valuation formula, we relied on a CAPM-like risk-return relation to arrive at the PDE in (8). In this sense, our model is consistent with and built upon developments in the risk-return literature. But, as seen, a risk-return equation alone is not sufficient to determine P_t since assumptions on the cash flow processes are also needed. Based on (2) and the pricing solution (14), we can show that the equity premium is,

$$\begin{aligned}
\mu_t - r_t &\equiv E_t\left(\frac{dP_t}{P_t}\right)/dt + \frac{\alpha\, Y_t}{P_t} - r_t, \\
&= -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, \frac{dP_t}{P_t}\right)/dt, \\
&= \Pi_y \frac{Y_t}{P_t}\frac{\partial P_t}{\partial Y_t} + \Pi_g \frac{1}{P_t}\frac{\partial P_t}{\partial G_t} + \Pi_r \frac{1}{P_t}\frac{\partial P_t}{\partial r_t}, && (20) \\
&= \Pi_y + \Pi_g \left(\frac{\int_0^\infty \overline{p}[t,u;G,r] \times \vartheta[u]\,du}{\int_0^\infty \overline{p}[t,u;G,r]\,du}\right) - \Pi_r \left(\frac{\int_0^\infty \overline{p}[t,u;G,r] \times \varrho[u]\,du}{\int_0^\infty \overline{p}[t,u;G,r]\,du}\right), && (21)
\end{aligned}$$

where $\overline{p}[t,u;G,r]$ is displayed in (15). Equation (20) shows that the equity premium is a weighted sum of the risk premiums for shocks respectively due to earnings, expected earnings growth, and interest rate, with weights equal to the sensitivity of the price with respect to the respective state-variables.

Equation (21) follows from (20) since $\frac{Y_t}{P_t}\frac{\partial P_t}{\partial Y_t} = 1$, $\frac{\partial P_t}{\partial G_t} = \alpha\, Y_t \int_0^\infty \overline{p}[t,u;G,r] \times \vartheta[u]\, du$, and $\frac{\partial P_t}{\partial r_t} = -\alpha\, Y_t \int_0^\infty \overline{p}[t,u;G,r] \times \varrho[u]\, du$. Thus, the equilibrium equity premium is a function of the time-t interest rate, the expected EPS growth, the firm's required risk premiums, and the structural parameters governing the cash flow and interest rate processes. According to (21), $\mu_t - r_t$ is independent of the current level of cash flows and is mean-reverting with the state of r_t and G_t.

The dynamics of the state-variables under the equivalent martingale measure, Q, can facilitate our understanding of the nature of risk compensation in this economy. Based on (8), we may write the stock price as,

$$P_t \;=\; \alpha \int_t^\infty E_t^Q \left(e^{-\int_t^u r_s\, ds}\, Y_u \right) du, \tag{22}$$

where the processes for (Y_t, G_t, r_t) under the Q-measure are:

$$\frac{dY_t}{Y_t} \;=\; (G_t - \Pi_y)\; dt + \sigma_y\, d\widetilde{W}_t^y, \tag{23}$$

$$d\,G_t \;=\; \kappa_g \left([\mu_g^* - \Pi_g/\kappa_g] - G_t \right)\, dt + \sigma_g\, d\widetilde{W}_t^g, \tag{24}$$

$$d\,r_t \;=\; \kappa_r \left([\mu_r^* - \Pi_r/\kappa_r] - r_t \right)\, dt + \sigma_r\, d\widetilde{W}_t^r. \tag{25}$$

Economically, risk-averse investors seek to discount future cash flows more heavily under the equivalent martingale measure. For instance, we should expect $\Pi_r < 0$, which makes the drift of the risk-neutral discounting process higher. Consistent with this effect, a higher long-run mean $\mu_r = \mu_r - \Pi_r/\kappa_r$ will simultaneously reduce the discount bond price and raise all Treasury yields. Thus, our decomposition in (20) shows that $\Pi_r < 0$ can be expected to increase the overall equity premium, because $\frac{\partial P_t}{\partial r_t} < 0$. There is evidence from bond markets that the interest rate risk premium is non-zero (see, for example, Duffee (2002)).

A similar risk-aversion-based reasoning suggests that investors tend to be less optimistic about future cash flows under the equivalent martingale measure than under the physical probability measure. Intuitively, we have $\Pi_y > 0$ and $\Pi_g > 0$: the presence of both risk premiums decreases the drift of the (Y_t, G_t) process. The working of both of these forces reduces the present value of future cash flows and, thus, elevates the market risk premium. Thus, the earnings risk premium Π_y, the expected earnings growth risk premium Π_g, and the discounting risk premium receive positive compensation and contribute separately to the total equity premium.

To explore the properties of equity premium derived in (21), we turn to a comparative statics exercise and study how it responds to any structural parameter. In this example, $\kappa_r = 0.23$, $\mu_r^* = 7.8\%$, $\sigma_r = 0.012$, $\kappa_g = 1.44$, $\mu_g^* = 0.10$, $\sigma_g = 0.089$, σ_y=0.20, $\rho_{g,r}$= -0.05, $\rho_{g,y} = 1$, and $\alpha = 0.50$. We fix the interest rate risk premium $\Pi_r = -0.002$, the expected earnings growth risk premium $\Pi_g = 0.002$, and the earnings risk premium Π_y=0.06. In all calculations $r_t = 5.68\%$ and $G_t = 7.48\%$ which are market observed values as of July 1998 and correspond to S&P 500 index level of 1174.

Our numerical exercise shows that the equity premium is increasing in both G_t and μ_g^*, but decreasing in both r_t and μ_r^*. Therefore, as expected, positive shocks to expected EPS growth tend to raise the equity premium, whereas positive shocks to interest rates depress it. However, the equity premium is much more sensitive to μ_g^* (μ_r^*) than to G_t (r_t). Intuitively, these comparative static results hold because current expected EPS growth G_t may have a transitory component, whereas a change in μ_g is permanent. Lastly, the model equity premium increases with EPS growth volatility σ_y, the volatility of expected EPS growth σ_g, and the volatility of the interest rate σ_r. Risks as measured by these parameters raise the required compensation to shareholders. Modeling the EPS and the expected EPS processes explicitly indeed allows us to see how they affect the equity premium.

3 Time-Series Data on S&P 500 EPS, EPS Growth, and the Interest Rate

For the remainder of the paper we choose the S&P 500 index as the proxy for the market-portfolio. To explore whether the model equity premium derived in (21) is close to the sample equity premium requires three data inputs: expected EPS growth G_t, interest rate r_t, current EPS Y_t, and the model parameters. For the S&P 500 index, I/B/E/S did not start collecting analyst EPS estimates until January 1982. Thus, our focus is on the sample period from January 1982 to July 1998. Pastor and Stambaugh (2001) detect structural shifts in the equity premium especially over the past two decades. According to Lettau, Ludvigson, and Watcher (2004), the market price-to-earnings ratio rose sharply over this period and have argued in favor of the declining ex-ante equity risk premium explanation.

I/B/E/S US History File contains mid-month observations on reported actual earnings-per-share and consensus analyst forecasts of future S&P 500 earnings, plus the contemporaneous price. In implementation, I/B/E/S consensus analyst estimate for current-year S&P 500 EPS (i.e., FY1) is taken to be the proxy for Y_t. In any given month, the FY1 estimate may contain actual quarterly EPS numbers for the passed quarters of the fiscal year, with the EPS numbers for the remaining quarters being consensus analyst forecasts. Because firms' earnings typically exhibit seasonalities, the total EPS over a fiscal year is a natural proxy for Y_t.

Analyst-expected EPS growth from the current (FY1) to the next fiscal-year (FY2) is the measure for G_t. This choice is reasonable since the year-over-year EPS growth has been the conventional calculation method in the industry. For instance, quarter-over-quarter and month-over-month (if available) EPS growth rates would not be better proxies for G_t, as they would be subject to seasonal biases in earnings and revenue.

Valuation formulas for the market index and the equity premium also depend on interest rate r_t, for which there is no established benchmark. Empirically, movements in the 30-year Treasury yield are much more closely followed by stock market participants than the short-term rate, as the long-term yields often co-move strongly with S&P 500 earnings-yields. To be consistent with theory, however, we use the 3-month Treasury yield or those implied by the Kalman-filter as candidates for r_t in estimation and calibration. The 30-year Treasury yield is used in a robustness exercise. The source of monthly 3-month interest-rate is DataStream International, Inc.

To infer the interest rate risk premium independent of the price observations on the market portfolio, we rely on a panel of Treasury yields. We choose Treasury securities with constant maturity of 6 months, 2 years, 5 years, and 10 years. The Treasury yields are gathered from the Federal Reserve Board.

Table 1 reveals that the average equity premium over the sample period is 8.76% and volatile. Although the average equity premium is somewhat higher than the 7% reported by Mehra and Prescott (1985, 2003), it is nonetheless of a similar order of magnitude. That the equity index provides a higher return relative to bonds is also a stylized feature over our shorter sample.

Forward price-to-earnings ratio (the current price divided by FY1 earnings) has a sample average of 15.10, with a minimum price-to-earnings ratio of 7.28 and a maximum is 26.47. As seen, the average expected EPS growth for the S&P 500 index is 10.13% and varies between 0.09% and 26.13%. The average 3-month nominal interest rate is 6.28% with a standard deviation of 2.44%.

4 Implications of the Model for Equity Premium

The purpose of this section is two-fold. First, we pursue a traditional risk-based explanation of the equity premium puzzle and present an estimation strategy aimed at recovering each of the three components of the equity premium in (21). That is, we estimate Π_r, Π_g, Π_y, along with other model parameters, and judge empirical performance accordingly. Second, we quantitatively assess whether the risk premium parameterizations, interest rate dynamics, and cash flow dynamics embedded in the valuation model are capable of generating a reasonably large equity premium. We conduct these tasks while simultaneously fitting the Treasury yield curve as close as possible. Hence, our approach circumvents the risk-free rate puzzle outlined in Weil (1989).

4.1 How Large is the Interest Rate Risk Premium?

We first address the sign and magnitude of the interest rate risk premium by using the Kalman filtering approach and a panel of Treasury bond yields. This approach (i) enables the estimation of the interest rate risk premium jointly with the parameters of the interest rate dynamics in (7) (i.e., κ_r, μ_r^*, and σ_r), and (ii) allows us to test whether the interest rate model is able to generate realistic yield curve movements.

To implement this estimation procedure, we note that the transition equation for the instantaneous interest rate, r_t, can be expressed as (e.g., Bergstrom (1984)):

$$r_t \;=\; \mu_r^* \,(1 - e^{-\kappa_r \Delta t}) + e^{-\kappa_r \Delta t}\, r_{t-1} \,+\, \eta_t, \tag{26}$$

where $E_{t-1}[\eta_t] = 0$ and $E_{t-1}[\eta_t^2] = \sigma_r^2 \Delta t$, and η_t is a serially uncorrelated disturbance term that is distributed normal.

Next, let $\Psi_t = (\Psi_{j,t}, ..., \Psi_{J,t})'$ be the month-t observed Treasury yields where J denotes the number of yields employed in the estimation. As is standard from Babbs and Nowman (1999) and Chen and Scott (2003), the measurement equation describing observed Treasury yields is:

$$\Psi_t \;=\; \mathcal{U}_t + \mathcal{V}_t\, r_t + \upsilon_t, \qquad\qquad t = 1, ..., T, \tag{27}$$

where $\mathcal{U}_t$ is an $N \times 1$ vector with i-th element $\frac{\xi[\tau_i]}{\tau_i}$, $\mathcal{V}_t$ is an $N \times 1$ vector with i-th element $\frac{\varsigma[\tau_i]}{\tau_i}$, and $\upsilon_t \sim \mathcal{N}(0, \mathcal{H}_t)$. The normality of υ_t and η_t allows us to implement a Kalman filter recursion based on the maximum-likelihood approach described in Harvey (1991).

For this maximum-likelihood estimation, we select Treasury yields with maturity of 6 months, 2 years, 5 years, and 10 years and display the estimation results in Table 2. Panel A of this table shows that the interest rate parameters are reasonable and the interest-rate risk premium is in line with economic theory.

Let us discuss these parameter estimates in turn. First, the long-run interest rate, μ_r^*, is estimated at 7.28% and of an order of magnitude similar to that reported in Babbs and Nowman (1999) and Chen and Scott (2003). Second, the estimated $\kappa_r = 0.2313$ implies a half-life of 2.99 years, and indicates slow mean-reversion of the interest rate process. Third, the reported volatility of interest rate changes, $\sigma_r = 1.28\%$, suggests a relatively stable interest rate process. Finally, the maximized log-likelihood value for the estimation is 1804.93, and the estimated parameters are several times larger than their standard errors, suggesting statistical significance.

The estimated interest-rate risk premium, Π_r is, as we previously postulated, negative with a point estimate of -0.00201 (i.e., -20 basis points) and a standard error of 0.0005. Although the estimate appears quantitatively small, it can drive a substantial wedge between the risk-neutral and the physical interest rate processes. To see this point more clearly, we compute $\mu_r = \mu_r^* - \Pi_r/\kappa_r = 8.154\%$, which has the effect of raising the risk-neutral interest-rate drift by 86.9 basis points (hereafter, bp). Intuitively the risk factor $\Pi_r < 0$ causes a heavier discounting of future cash flows and theoretically supports the presence of a positive equity premium as the partial derivative of P_t with respect to the interest rate is negative in (21). Bonds provide a hedge during periods of stock market declines, which justifies a negative interest-rate risk premium. We refer the reader to the related work of Buraschi and Jitsov (2005) on the inflation risk premium and Bakshi and Chen (1996b) on a general model of inflation and interest rates in a monetary economy.

Goodness-of-fit statistics assessed in Panel B of Table 2 reveal that the interest rate model provides reasonable fitting-errors as measured by actual minus model-implied yield.

Across the Treasury yield curve the median absolute errors for 6-month, 2-year, 5-year, and 10-year yields are 37bp, 25bp, 35bp and 50bp, respectively. In sum, the time-series on the cross section of bond yields provide the desired flexibility in estimating the interest-rate risk premiums and the interest-rate parameters. Although there is scope for improvement, the pricing kernel process can realistically mimic both the short and the long end of the yield curve through time.

4.2 Maximum-Likelihood Estimation of the (Physical) G_t Process

The unavailability of contingent claims written directly on the G_t process precludes a joint estimation of the expected EPS growth processes in (5) and (24). We propose a two-step procedure to estimate Π_g. First, we exploit the transition density function to estimate the structural parameters, $\Theta_g \equiv \{\kappa_g, \mu_g^*, \sigma_g\}$, of the G_t process in (5). Second, taking Θ_g as given, we estimate Π_g, along with other unknown parameters, based on the time-series of S&P 500 index (the criterion function is specified in Section 4.3), and consequently recover the risk-neutral G_t process in (24).

Let $\{G_t : 1, \ldots, T\}$ be the monthly time-series on expected earnings growth rate. The discrete equation corresponding to the G_t process in (5), is:

$$G_t = \mu_g^* + e^{-\kappa_g} \left(G_{t-1} - \mu_g^*\right) + \zeta_t \tag{28}$$

where ζ_t is Gaussian mean-zero and satisfies the condition $E(\zeta_t \zeta_u) = 0$ for $t \neq u$, and

$$E(\zeta_t^2) = \frac{\sigma_g^2}{2\,\kappa_g} \left(1 - e^{-\kappa_g}\right). \tag{29}$$

Guided by Nowman (1997), we construct the likelihood function as minus twice the logarithmic of the Gaussian likelihood function

$$\max_{\kappa_g, \mu_g^*, \sigma_g} \quad \sum_{t=1}^{T} \left(\log \left\{ \frac{\sigma_g^2}{2\,\kappa_g} \left(1 - e^{-\kappa_g}\right) \right\} + \frac{\left\{G_t - \mu_g^* - e^{-\kappa_g} \left(G_{t-1} - \mu_g^*\right)\right\}^2}{\left\{\frac{\sigma_g^2}{2\,\kappa_g} \left(1 - e^{-\kappa_g}\right)\right\}^2} \right). \tag{30}$$

Maximizing the log-likelihood function in (30) by the choice of Θ_g, we report the maximum-likelihood parameter estimates below (the standard errors are shown in parenthesis):

$$\kappa_g = 1.4401 \ (0.4411) \tag{31}$$

$$\mu_g^* = 0.1024 \ (0.0153) \tag{32}$$

$$\sigma_g = 0.0894 \ (0.0047) \tag{33}$$

with an average log-likelihood value of 2.29575.

Several observations are relevant to our analysis. First, the point-estimate of long-run expected earnings growth rate, μ_g^*, is 10.04% and close to the sample average documented in Table 1. Thus, analysts have been optimistic about S&P 500 index earnings growth. Second, the volatility of changes in the expected earnings-per-share growth, σ_g, is 8.94%, which is considerably more volatile than the interest rate counterpart. Finally, according to the κ_g estimates, the S&P 500 expected earnings growth rate is mean-reverting with a half-life, $\log(2)/\kappa_g$, of 6 months. The duration of the expected earnings growth rate cycle is, thus, much shorter than the interest rate cycle and roughly consistent with stylized business cycle findings. Realizations of the physical G_t process are devoid of any information about the pricing measure, so the risk premium for expected earnings growth rate cannot be recovered through this estimation step.

4.3 Compensation for Cash Flow Risk and the Equity Premium

To estimate the risk premium for expected EPS growth risk, Π_g, and the risk premium for actual EPS growth, Π_y, and assess their implications for the equity premium, we make several choices. First, to reduce the estimation burden, we preset $\rho_{g,y} = 1$, and $\rho \equiv \rho_{g,r} = \rho_{r,y}$. This assumption implies that the actual and expected EPS growth rates are subject to a common random shock in (4) and (5). Second, we set Θ_g and $\{\kappa_r, \mu_r^*, \sigma_r, \Pi_r\}$ to the values estimated in Section 4.2 and Table 2, respectively. Thus, we treat these parameter inputs as representing the true values. Substituting Θ_g and $\{\kappa_r, \mu_r^*, \sigma_r, \Pi_r\}$ into (14)-(19), we can see that 5 parameters:

$$\Theta \equiv \{\Pi_g, \Pi_y, \alpha, \sigma_y, \rho\}, \tag{34}$$

are still required to determine the price of the market portfolio, P_t, in (14).

Observe that the valuation model for the market portfolio does not constitute a set of moment restrictions on asset prices; rather, it is an exact restriction on the price of the market portfolio in relation to the contemporaneous EPS, the expected EPS growth, and the interest rate. For this reason, the generalized method of moments and related econometric techniques may not be applicable.

Following the lead in fixed-income and option pricing, Θ is estimated using the time-series of market prices. We follow two estimation methods, one correcting, and the other not correcting, for the serial correlation of the model errors. Focusing on the first method, define from (14), the model price-to-earnings ratio as:

$$\mathrm{pe}_t \equiv \frac{P_t}{Y_t} = \alpha \int_0^\infty \overline{p}[t,u;G,r]\,du, \tag{35}$$

and let $\widetilde{\mathrm{pe}}_t$ be the month-t observed price-to-earnings ratio. Our estimation procedure tries to find a Θ to solve,

$$\mathrm{RMSE} \equiv \min_{\Theta} \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\alpha \int_0^\infty \overline{p}[t,u;G,r]\,du - \widetilde{\mathrm{pe}}_t\right)^2}, \tag{36}$$

subject to the transversality condition in (19). This estimation method seeks to minimize the sum of squared errors between each observed price-to-earnings ratio and the model-determined price-to-earnings ratio. The restriction in (19) ensures that P_t does not explode in each iteration of the minimization routine.

Fitting the price-to-earnings is desirable because P_t/Y_t serves as a normalized price that is comparable across time periods. If the purpose would be to fit the observed price levels as closely as possible, the estimation procedure would then favor the higher price observations. The criterion function in (36) fails to account for the serial correlation of the model pricing errors. However, when we assume a first-order autoregressive process for the model error, the resulting estimates are similar. Hence, we omit them and focus on the least-squares method in (36).

The optimized objective function value from (36), RMSE, is zero only if the obtained Θ estimate leads to a perfect fit of each market price-to-earnings by the model. In general, the average in-sample price-to-earnings pricing error will not be zero because the objective in (36) is to minimize the sum of squared errors, but not the average pricing errors.

In our estimation approach, the estimated risk premiums and parameters reflect the historical valuation standards applied to the S&P 500 index by the investors. Panel A of Table 3 reports the parameter estimates of Θ when the 3-month Treasury rate is used as the proxy for r_t. Consistent with how the market has priced the market-portfolio in the past, the market-implied ρ is negative with a ρ of -0.109. This mildly negative point estimate of ρ suggests that expected earnings growth rate is likely high when the interest rate is low, and vice-versa.

Another result worth emphasizing is that the dividend-payout ratio, α, is consistent with intuition: the estimated $\alpha = 0.41$ does not depart substantially from the historical average payout ratios of 44.29%. Table 3 also provides the estimate of $\sigma_y = 18.17\%$, with the conclusion that the cash flow process experiences high volatility.

One central observation from Table 3 is that the market-implied expected-EPS-growth risk premium, $\Pi_g = -0.145\%$, is surprisingly small relative to the market-implied earnings risk premium, $\Pi_y = 6.531\%$. For example, the reported Π_g, implies that the sample average of $\Pi_g \left(\frac{\int_0^\infty \overline{p}[t,u;G,r] \times \vartheta[u]\, du}{\int_0^\infty \overline{p}[t,u;G,r]\, du} \right)$ is only 1 bp. This finding indicates that accounting for the compensation for bearing expected-EPS-growth risk plays virtually no role in explaining the equity premium puzzle.

If we accept the premise that the market fairly prices the S&P 500 index and correctly reflects the market price of various risks, then our empirical findings have a straightforward interpretation: Risk-averse agents may deem it unnecessary to "double-penalize" the physical drift of (Y_t, G_t) process. This may occur since P_t is homogenous of degree 1 in Y_t and has a first-order impact on the stock price. Therefore, a large compensation in the form of Π_y may make it unnecessary to require compensation for G_t risk. To further explain our reasoning, define $\widetilde{G}_t \equiv G_t - \lambda_y$. Therefore, we may write (23) and (24) as: $\frac{dY_t}{Y_t} = \widetilde{G}_t\, dt + \sigma_y\, d\widetilde{W}_t^y$, where $d\,\widetilde{G}_t = \left(\kappa_g \mu_g^* - \Pi_g - \kappa_g \Pi_y - \kappa_g \widetilde{G}_t \right) dt + \sigma_g\, d\widetilde{W}_t^g$. Thus, the presence of Π_y reduces the level and drift of the $\widetilde{G}_t$ process.

With $\Pi_r = -0.002$, the sample average of $-\Pi_r \left(\frac{\int_0^\infty \overline{p}[t,u;G,r] \times \varrho[u]\, du}{\int_0^\infty \overline{p}[t,u;G,r]\, du} \right)$ is 77.16 bp. This suggests that accounting for discounting risk can help alleviate the equity premium puzzle.

Based on (21), the overall equity premium can, thus, be calculated as

$$\begin{aligned} \mu_t - r_t &= \Pi_y + \Pi_g \left(\frac{\int_0^\infty \overline{p}[t,u;G,r] \times \vartheta[u]\, du}{\int_0^\infty \overline{p}[t,u;G,r]\, du} \right) - \Pi_r \left(\frac{\int_0^\infty \overline{p}[t,u;G,r] \times \varrho[u]\, du}{\int_0^\infty \overline{p}[t,u;G,r]\, du} \right), \\ &= 6.53\% + 0.01\% + 0.7716\%, \end{aligned}$$

$$= \quad 7.31\%.$$

The ability of the model to generate an equity premium of 7.31% is in sharp contrast with the exercise in Mehra and Prescott (1985) that a standard representative agent model calibrated to the per-capita consumption data can generate at most a 0.40% equity premium. Thus, the proper parameterization of both the discounting structure and the cash flow process is key to improving performance by an asset pricing model and to achieving a reasonable equity premium. Our exercise in Panel B of Table 3 demonstrates that the equity premium is virtually insensitive to the choice of the interest rate in the estimation procedure in (36).

Another economic yardstick that can be applied is whether the estimated risk premiums and model parameters provide a "good enough" approximation of the market's implicit valuation process. In Table 3, we also present two percentage pricing-error measures, computed by dividing the market-to-model price difference by the market price: (i) the absolute percentage pricing error, and (ii) the mean percentage pricing error. The mean pricing error reflects the average pricing performance, while the absolute pricing error reflects the magnitude of the pricing errors as negative and positive errors do not cancel each other. According to the pricing-error measures, the model's fit is reasonable: the average mean pricing error is -7.22% with a standard deviation of 23.98%, and the absolute pricing error of the S&P 500's 18.30%. Given the negative sign of the average errors, the model price is on average higher than the market price.

In summary, the class of models examined here are not only consistent with the average equity premium and the term structure of interest rates, but also mimics the time-evolution of the S&P 500 index. The latter dimension imposes a stringent restriction on the validity of the pricing framework and differentiates this paper from other studies on the equity premium.

5 Concluding Remarks and Extensions

The equity premium puzzle advocated by Mehra and Prescott (1985) remains a fascinating problem awaiting new and novel answers. This paper investigated the impact of cash flow risk and discounting risk on the aggregate equity premium, the price of the market portfolio, and the default-free bond prices. Our theoretical approach is based on the observation that aggregate per-capita consumption is hard to measure empirically. Thus, if we can replace the empirically difficult-to-estimate marginal utility by a pricing-kernel function of observables and then specify both the primitive process for discounting and the exogenous cash flow stream, we will have an equilibrium asset pricing model based on observable state variables. Once this is done we can endogenously solve for the equity premium, the price of the market portfolio and the term structure of interest rates within the same underlying equilibrium.

Embedded in the closed-form solution for the market portfolio and the bond prices are compensations for cash flow risk and discounting risk. With the solution for the risk premium explicitly given, we can then estimate the model to evaluate its empirical performance. This approach allows us to avoid the impact of unobservable consumption on inferences regarding the model's performance. Our illustrative model is based on the assumption that aggregate dividend equals a fixed fraction of aggregate earnings plus noise, and the expected aggregate earnings growth follows a mean-reverting stochastic process. Moreover, the economy-wide pricing kernel is chosen to be consistent with (i) a constant market price of aggregate risk and (ii) a mean-reverting interest rate process with constant volatility.

S&P 500 index-based estimation results show that the framework is quantitatively useful in explaining the observed market equity premium. Specifically, we find that the interest rate risk premium is negative and the cash flow risk premium is positive. Overall, disentangling the equity premium into its cash flow and discounting components produces an economically meaningful equity premium of 7.31%.

Our empirical results suggest three possible avenues for theoretical research. First, one can introduce richer cash flow dynamics and interest rate dynamics that possess stochastic volatility. Having multi-dimensional structures for the state variables with priced volatility risks can lead to more realistic models for the market portfolio and the equity premium. Second, one can examine alternative risk premium specifications that allow for richer stochastic variation in the risk premiums. Third, the valuation model can be used to pin down the sources of market return predictability, as in Menzly, Santos, and Veronesi (2004).

The equity premium puzzle occupies a special place in the theory of finance and economics, and more progress is needed to understand the spread of equities over bonds. Determining the factors that drive the equity premium over time, and across countries, will likely remain an active research agenda.

Appendix

To derive the analytical solution to the market portfolio, we note from equations (1) and (3) that P_t solves,

$$P_t \;=\; \alpha \int_t^{\infty} E_t\left[\frac{M_u}{M_t}\,Y_u\right] du, \tag{37}$$

since dZ_t is uncorrelated with dM_t. We also require by the transversality condition that $P_t < \infty$ for all t, which is the condition that the price of the market portfolio remain bounded for all pricing kernel and cash flow processes.

Inserting the pricing kernel process (6) into (37) and using the earnings process (4)-(5), we note, by the Markov property, that P_t can only be a function of Y_t, r_t, and G_t. Write $P[Y_t, G_t, r_t]$, where the interest rate process is as specified in (7). Therefore, the dynamics of the market portfolio, by Ito's lemma, is given by:

$$\begin{aligned} dP_t \;=\; & \frac{1}{2}\frac{\partial^2 P}{\partial Y^2}(dY)^2 + \frac{\partial P}{\partial Y}\,dY + \frac{1}{2}\frac{\partial^2 P}{\partial G^2}(dG)^2 + \frac{\partial P}{\partial G}\,dG + \frac{1}{2}\frac{\partial^2 P}{\partial r^2}(dr)^2 + \frac{\partial P}{\partial r}\,dr \\ & + \frac{\partial^2 P}{\partial Y \partial G} dY\,dG + \frac{\partial^2 P}{\partial Y \partial r} dY\,dr + \frac{\partial^2 P}{\partial G \partial r} dr\,dG. \end{aligned} \tag{38}$$

Substituting (38) into (2) implies that the instantaneous equity premium is,

$$\begin{aligned} \mu_t - r_t \;&=\; -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, \frac{dP_t}{P_t}\right)/dt, \\ &=\; -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, \frac{1}{P_t}\frac{\partial P}{\partial Y}\,dY + \frac{1}{P_t}\frac{\partial P}{\partial G}\,dG + \frac{1}{P_t}\frac{\partial P}{\partial r}\,dr\right)/dt, \end{aligned} \tag{39}$$

where the instantaneous expected return is, $\mu_t = E_t\left[\frac{dP_t}{P_t}\right]/dt + \frac{\alpha Y_t}{P_t}$.

Relying on (38) and taking expectations, we may obtain,

$$\begin{aligned} E_t\left[\frac{dP_t}{P_t}\right] \;=\; & \frac{1}{2}\frac{1}{P_t}\frac{\partial^2 P}{\partial Y^2}\,E_t[dY^2] + \frac{1}{P_t}\frac{\partial P}{\partial Y}\,E_t[dY] + \frac{1}{2}\frac{1}{P_t}\frac{\partial^2 P}{\partial G^2}\,E_t[dG]^2 + \frac{1}{P_t}\frac{\partial P}{\partial G}\,E_t[dG] \\ & + \frac{1}{2}\frac{1}{P_t}\frac{\partial^2 P}{\partial r^2}\,E_t[dr^2] + \frac{1}{P_t}\frac{\partial P}{\partial r}\,E_t[dr] \\ & + \frac{1}{P_t}\frac{\partial^2 P}{\partial Y \partial G}E_t[dY\,dG] + \frac{1}{P_t}\frac{\partial^2 P}{\partial Y \partial r}E_t[dY\,dr] + \frac{1}{P_t}\frac{\partial^2 P}{\partial G \partial r}E_t[dr\,dG]. \end{aligned} \tag{40}$$

Combining the expressions in (39) and (40) and using the definition of the instantaneous expected rate of return, we have

$$\begin{aligned}
& \frac{1}{2}\frac{\partial^2 P}{\partial Y^2}E_t[dY^2] + \frac{\partial P}{\partial Y}E_t[dY] + \frac{1}{2}\frac{\partial^2 P}{\partial G^2}E_t[dG]^2 + \frac{\partial P}{\partial G}E_t[dG] + \frac{1}{2}\frac{\partial^2 P}{\partial r^2}E_t[dr^2] \\
& + \frac{\partial P}{\partial r}E_t[dr] + \frac{\partial^2 P}{\partial Y \partial G}E_t[dY\,dG] + \frac{\partial^2 P}{\partial Y \partial r}E_t[dY\,dr] + \frac{\partial^2 P}{\partial G \partial r}E_t[dr dG] \\
& - r\,P\,dt + \alpha\,Y\,dt \\
= \; & -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, \frac{\partial P}{\partial Y}dY + \frac{\partial P}{\partial G}dG + \frac{\partial P}{\partial r}dr\right). \qquad (41)
\end{aligned}$$

Based on (41), now define the risk premium for the earnings shocks, expected earnings growth, and interest rate, respectively, as:

$$\begin{aligned}
\Pi_y &\equiv -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, \frac{dY_t}{Y_t}\right)/dt, \\
\Pi_g &\equiv -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, dG_t\right)/dt, \\
\Pi_r &\equiv -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, dr_t\right)/dt.
\end{aligned}$$

This immediately implies that,

$$\begin{aligned}
& \frac{1}{2}\frac{\partial^2 P}{\partial Y^2}E_t[dY^2] + \frac{\partial P}{\partial Y}E_t[dY] + \frac{1}{2}\frac{\partial^2 P}{\partial G^2}E_t[dG]^2 + \frac{\partial P}{\partial G}E_t[dG] + \frac{1}{2}\frac{\partial^2 P}{\partial r^2}E_t[dr^2] \\
& + \frac{\partial P}{\partial r}E_t[dr] + \frac{\partial^2 P}{\partial Y \partial G}E_t[dY\,dG] + \frac{\partial^2 P}{\partial Y \partial r}E_t[dY\,dr] + \frac{\partial^2 P}{\partial G \partial r}E_t[dr dG] - r\,P\,dt + \alpha\,Y\,dt \\
= \; & \frac{\partial P}{\partial Y}Y\,\Pi_y\,dt + \frac{\partial P}{\partial G}\Pi_g\,dt + \frac{\partial P}{\partial r}\Pi_r\,dt. \qquad (42)
\end{aligned}$$

Simplifying this equation and using the dynamics for Y_t, G_t and r_t, leads to the following partial differential equation for P_t:

$$\begin{aligned}
& \frac{1}{2}\sigma_y^2 Y^2 \frac{\partial^2 P}{\partial Y^2} + (G - \Pi_y)\,Y\frac{\partial P}{\partial Y} + \rho_{g,y}\sigma_y\sigma_g\,Y\frac{\partial^2 P}{\partial Y \partial G} + \rho_{r,y}\sigma_y\sigma_r\,Y\frac{\partial^2 P}{\partial Y \partial r} + \\
& \rho_{g,r}\sigma_g\sigma_r\,\frac{\partial^2 P}{\partial G \partial r} + \frac{1}{2}\sigma_r^2\frac{\partial^2 P}{\partial r^2} + \kappa_r\,(\mu_r - r)\frac{\partial P}{\partial r} + \frac{1}{2}\sigma_g^2\frac{\partial^2 P}{\partial G^2} \\
& + \kappa_g\,(\mu_g - G)\frac{\partial P}{\partial G} - r\,P + \alpha\,Y = 0, \qquad (43)
\end{aligned}$$

and must be solved subject the restriction that $P_t < \infty$. In the valuation partial differential equation (43) we have set, $\mu_g = \mu_g^* - \frac{\Pi_g}{\kappa_g}$ and $\mu_r \equiv \mu_r^* - \frac{\Pi_r}{\kappa_r}$. Consider the following candidate solution,

$$P_t = \alpha \int_0^\infty \hat{p}[t, u; Y, G, r]\, du. \tag{44}$$

Clearly, $\hat{p}[t + u, 0; Y, G, r] = Y_{t+u}$. Thus, we have the partial differential equation for $\hat{p}[t, u; Y, G, r]$ as,

$$\begin{aligned}
&(G - \Pi_y)\, Y \frac{\partial \hat{p}}{\partial Y} + \rho_{g,y}\sigma_y\sigma_g\, Y \frac{\partial^2 \hat{p}}{\partial Y \partial G} + \rho_{r,y}\sigma_y\sigma_r\, Y \frac{\partial^2 \hat{p}}{\partial Y \partial r} + \\
&\rho_{g,r}\sigma_g\sigma_r \frac{\partial^2 \hat{p}}{\partial G \partial r} + \frac{1}{2}\sigma_r^2 \frac{\partial^2 \hat{p}}{\partial r^2} + \kappa_r\,(\mu_r - r)\frac{\partial \hat{p}}{\partial r} + \frac{1}{2}\sigma_g^2 \frac{\partial^2 \hat{p}}{\partial G^2} \\
&+ \kappa_g\,(\mu_g - G)\frac{\partial \hat{p}}{\partial G} - r\,\bar{p} - \frac{\partial \hat{p}}{\partial u} = 0.
\end{aligned} \tag{45}$$

Suppose $\hat{p}[t, u; G, r] = Y_t \exp\left(\varphi[u] - \varrho[u]\, r_t + \vartheta[u]\, G_t\right)$. Taking the required partial derivatives with respect to Y_t, G_t and r_t and solving the valuation equations lead to a set of ordinary differential equations. Solving the ordinary differential equations subject to the boundary conditions $\varphi[0] = 0$, $\varrho[0] = 0$ and $\vartheta[0] = 0$ yields (14)-(15). The transversality condition (19) ensures that the restriction $\varphi[0] = 0$ is satisfied. □

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Table 1: Equity Premium for S&P 500 Index (January 1982 to July 1998)

The sample period is January 1982 to July 1998 with 199 monthly observations. The expected earnings-per-share growth for S&P 500 index, G_t, is the consensus earnings-per-share forecast for FY2 divided by FY1, minus 1. The price-to-earnings ratio, P/E, is the current S&P 500 index level normalized by FY1 earnings-per-share. We report the average, the standard deviation, the maximum, and the minimum. The computation of the monthly equity premium is based on the 3-month interest rate. The earnings and price on S&P 500 is collected from I/B/E/S and the interest rates are from the Federal Reserve Board.

	Average	**Std.**	**Max.**	**Min.**
Price-to-Earnings Ratio	15.10	4.13	26.47	7.28
Expected Earnings Growth	10.13%	5.31%	26.13%	0.09%
Interest Rate	6.98%	2.13%	14.68%	5.68%
Monthly Equity Premium	0.0073	0.040	0.162	-0.200

Table 2: Interest Rate Risk Premium Based on Kalman Filtering Estimation

The reported parameters of the interest rate process and the interest rate risk premium are based on Kalman filtering. We specify the interest rate process under the physical probability measure as:

$$dr_t \quad = \quad (\kappa_r\,\mu_r - \kappa_r\,r_t\,)\,dt + \sigma_r\,dW_t^r,$$

and under the equivalent martingale measure as

$$dr_t \quad = \quad (\kappa_r\,\mu_r - \Pi_r - \kappa_r\,r_t\,)\,dt + \sigma_r\,d\widetilde{W}_t^r,$$

The estimation uses a monthly time-series of treasury yields with maturity of 6-months, 2-years, 5-years and 10-years. The asymptotic standard errors are in parenthesis, and based on the outer-product of the log-likelihood function. Maximized log-likelihood function is reported as Log-Lik. Panel B reports the median absolute pricing errors (in bp), and the root mean squared pricing errors (in bp).

Panel A: Parameter Estimates

Parameter	κ_r	σ_r	μ_r^*	Π_r	Log-Lik
r_t process	0.2313 (0.0135)	0.0128 (0.0008)	0.0728 (0.0022)	-0.0020 (0.0005)	1804.93

Panel B: Fitting Errors for Bonds

	6-months	**2-years**	**5-years**	**10-years**
Median Absolute Pricing Errors (bp)	37	25	35	50
Squared-root of Mean Squared Errors (bp)	48	33	44	59

Table 3: Estimation of Risk Premiums for Earnings Growth and Expected Earnings Growth Rate: Implications for Equity Premium

Estimation of the risk premiums is based on S&P 500 index observations from January 1982 to July 1998 (199 observations). We minimize the distance between the model price-to-earnings ratio and the market price-to-earnings ratio denoted by $\widetilde{\mathrm{pe}}_t$:

$$\mathrm{RMSE} \equiv \min_{\Theta} \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\alpha \int_0^\infty \overline{p}[t,u;G,r]\,du - \widetilde{\mathrm{pe}}_t\right)^2},$$

subject to the transversality condition $\mu_r - \mu_g > \frac{\sigma_r^2}{2\,\kappa_r^2} + \frac{\sigma_g^2}{2\kappa_g^2} + \frac{\sigma_g \sigma_y \rho_{g,y}}{\kappa_g} - \frac{\sigma_r \sigma_y \rho_{r,y}}{\kappa_r} - \frac{\sigma_g \sigma_r \rho_{g,r}}{\kappa_g \kappa_r} - \Pi_y$. In this estimation $\kappa_r = 0.2313$, $\sigma_r = 0.0128$, $\mu_r^* = 0.0728$ and $\lambda_r = -0.00201$ which are based on the results in Table 2, and $\rho_{g,y} = 1$, and $\rho \equiv \rho_{g,r} = \rho_{r,y}$. Parameters governing the dynamics of the expected earnings growth rate are fixed to $\kappa_g = 1.4401$, $\mu_g^* = 0.1024$, and $\sigma_g = 0.089$. We compute the model error $\epsilon_t \equiv Y_t\,\left(\alpha \int_0^\infty \overline{p}[t,u;G,r]\,du - \widetilde{\mathrm{pe}}_t\right)$, and report the average pricing errors and the average absolute pricing errors. The standard deviations are shown as Std(.). Each month we compute the model equity premium as $\mu_t - r_t = \Pi_y + \Pi_g \left(\frac{\int_0^\infty \overline{p}[t,u;G,r]\times\vartheta[u]\,du}{\int_0^\infty \overline{p}[t,u;G,r]\,du}\right) - \Pi_r \left(\frac{\int_0^\infty \overline{p}[t,u;G,r]\times\varrho[u]\,du}{\int_0^\infty \overline{p}[t,u;G,r]\,du}\right)$, and report the sample average as Mean$(\mu_t - r_t)$, All calculations in Panel A are done using the 3-month treasury rate as a proxy for the interest rate, and repeated in Panel B using the 30-year treasury rate.

Panel A: Estimation Based on 3-Month Treasury Rate

Π_g	Π_y	α	σ_y	ρ	RMSE	Mean(ϵ_t) {Std(ϵ_t)}	Mean$(\lvert\epsilon_t\rvert)$ {Std$(\lvert\epsilon_t\rvert)$}	Mean$(\mu_t - r_t)$
0.001450	0.06531	0.4100	0.1817	-0.109	3.2293	-7.22% {23.98%}	18.30% {17.63}	7.312%

Panel B: Estimation Based on 30-Year Treasury Yield

Π_g	Π_y	α	σ_y	ρ	RMSE	Mean(ϵ_t) {Std(ϵ_t)}	Mean$(\lvert\epsilon_t\rvert)$ {Std$(\lvert\epsilon_t\rvert)$}	Mean$(\mu_t - r_t)$
0.001145	0.06379	0.4744	0.1513	-0.074	3.1351	-7.62% {23.66%}	19.05% {15.92}	7.213%

Do Analysts Practice What They Preach and Should Investors Listen? Effects of Recent Regulations

Ran Barniv
College of Business Administration
Kent State University
rbarniv@kent.edu

Ole-Kristian Hope
Rotman School of Management
University of Toronto
okhope@rotman.utoronto.ca

Mark Myring
Miller College of Business
Ball State University
mmyring@bsu.edu

Wayne B. Thomas
Michael F. Price College of Business
University of Oklahoma
wthomas@ou.edu

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Do Analysts Practice What They Preach and Should Investors Listen?
Effects of Recent Regulations

ABSTRACT: From 1994 to 1998, Bradshaw (2004) finds that analysts' stock recommendations relate *negatively* to residual income valuation estimates but *positively* to valuation heuristics based on the price-to-earnings-to-growth ratio and long-term growth. These results are surprising, especially considering that future returns relate positively to residual income valuation estimates and negatively to heuristics. Using a large sample of analysts for the 1993-2005 period, we consider whether recent regulatory reforms affect this apparent inconsistent analyst behavior. Consistent with the intent of these reforms, we find that the negative relation between analysts' stock recommendations and residual income valuations is diminishing following regulations. We also show that residual income valuations, developed using analysts' earnings forecasts, relate more positively with future returns. However, we document that stock recommendations continue to relate negatively with future returns. We conclude that recent regulations have affected analysts' outputs – forecasted earnings and stock recommendations – but investors should be aware that factors other than identifying mispriced stocks continue to influence how analysts recommend stocks.

Keywords: Stock recommendations, residual income valuations, valuation heuristics, future returns, regulations.

Data Availability: All data are available from public sources.

I. INTRODUCTION

Using an extensive sample of sell-side financial analysts, we first examine how Regulation Fair Disclosure (Reg FD) and other recent regulatory reforms (e.g., NASD Rule 2711, NYSE Rule 472, and the Global Research Analysts Settlement) affect the relation between analysts' stock recommendations and (1) theoretically-derived residual income models versus (2) valuation heuristics based on the price-to-earnings to growth (PEG) ratios and long-term growth (LTG) forecasts. Our second set of tests involves one-year-ahead excess stock returns. We examine the impact of regulations on relation between future returns and (1) stock recommendations, (2) residual income models, and (3) valuation heuristics. Finally, we consider the extent to which residual income models and valuation heuristics are incremental to stock recommendations in explaining future returns after regulations are implemented.

This research is important because it speaks directly to an issue of great interest to investors and regulators: To what extent do regulations impact financial information provided by an important user group (i.e., financial analysts)? Given the widespread availability of financial analysts' earnings forecasts and stock recommendations, our results have practical importance to the investment community and regulators, as well as implications for academic research. While our first set of tests provides understanding of how analysts incorporate their own earnings forecasts into their stock recommendations, our tests of future returns have direct importance to investors. Furthermore, given the historical problems associated with stock recommendations, the extent to which valuation estimates (based on analysts' earnings forecasts) provide explanatory power beyond stock recommendations for future returns will be particularly important to investors.[1]

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[1] We do not suggest that all investors use both analysts' earnings forecasts and stock recommendations when making investment decisions. Sophisticated investors may use analysts' earnings forecasts and ignore their stock

Presumably, analysts use their own publicly issued earnings forecasts to derive intrinsic value estimates. In this case, one should expect these estimates to relate to analysts' stock recommendations (e.g., Schipper 1991). When earnings-based intrinsic value estimates are above (below) the current stock price, analysts would issue a buy (sell) recommendation. If instead, analysts' recommendations are based on other factors (beyond sophisticated earnings-based valuation estimates), then valuation estimates may provide incremental explanatory power beyond recommendations for future stock performance.

In an interesting recent study, Bradshaw (2004) uses a sample of U.S. firms from 1994 to 1998 and finds that residual income valuations, developed using analysts' earnings forecasts, do not relate as expected with analysts' recommendations. Analysts give more favorable recommendations to stocks with lower residual income valuations relative to current price.[2] Instead, analysts' recommendations align more closely with their LTG forecasts and the PEG ratio. These findings suggest that analysts give the highest recommendations to growth stocks, and among growth stocks, they give the highest recommendations to the firms for which the value of growth estimated by the PEG model exceeds the current stock price. Bradshaw (2004) concludes that analysts rely on simple heuristics rather than more sophisticated residual income valuations to recommend stocks.[3]

Bradshaw (2004) also finds that residual income valuations, developed using analysts' earnings forecasts, relate *positively* to future excess stock returns. In other words, analysts'

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recommendations. Unsophisticated investors may be more likely to rely on analysts' stock recommendations, which require minimal analytical processing. As an example, Bonner et al. (2003) find that sophisticated investors have greater knowledge of the analyst- and forecast-specific factors that predict forecast accuracy, and they use these factors to predict the relative accuracy of analysts' forecast revisions.

[2] In certain specifications, Bradshaw (2004) finds no relation between residual income valuations and stock recommendations.

[3] These results are consistent with those in Gleason et al. (2007) who conclude that analysts rely on simple heuristics rather than formal valuation models in setting price targets. Bradshaw and Brown (2005) conclude that analysts face greater incentives to provide accurate earnings forecasts than target prices.

earnings forecasts are useful inputs into residual income valuation models, yet they tend to relate negatively or insignificantly to analysts' stock recommendations. Furthermore, LTG forecasts, which most closely align with analysts recommendations, relate *negatively* to future returns. It seems that analysts recommend stocks with strong growth potential, even if such potential is already impounded into the stock price. Consistent with these results, Bradshaw (2004) shows that stock recommendations are not significantly associated with buy-and-hold one-year future returns.[4] Recommendations do not appear to capture stocks' intrinsic values relative to their current prices.

Why do analysts appear to avoid using their valuable earnings forecasts in a sophisticated manner in setting their recommendations (i.e., fail to practice what they preach)? This surprising result makes this area of research interesting and motivates further examination of the link between valuation estimates and recommendations, and their relations to future stock returns. It could be that analysts have incentives other than using their recommendations to signal mispriced stocks. In fact, analyst behavior has received wide-spread criticism in the financial press and several groups have called for reforms to the analyst industry.[5] We examine how recent regulations (e.g., Reg FD, NASD Rule 2711, NYSE Rule 472, and the Global Research Analysts Settlement) affect the way valuation estimates map into recommendations and subsequently relate to future stock returns. Specifically, we test for differences in these relations between the 1993-1999 and 2000-2005 periods to determine the impact of Reg FD. Then, we tests for differences between the 2000-2002 and 2003-2005 periods to test for effects of other regulations.

[4] Other recent studies find mixed results on the usefulness of stock recommendations (Womack 1996; Barber et al. 2001, 2003; Mikhail et al. 2004; Li 2005; Gleason et al. 2007).
[5] Boni and Womack (2002) provide a useful overview of these issues and list many references to both practitioner and research articles.

Our results show that several important relations change across the regulation periods, while some interesting relations seem unaffected by the regulations. Prior to Reg FD, we find results generally consistent with Bradshaw (2004), even though our sample is substantially larger than his. Following Reg FD, we show that the negative relation between recommendations and residual income valuations becomes significantly smaller and even turns positive for one of our models. However, this change appears to be attributable primarily to regulations other than Reg FD. LTG forecasts continue to have a positive relation with recommendations in the post-Reg FD period, but the relation is weaker. PEG valuations have an increasingly positive relation with stock recommendations over our regulatory period.

In our next set of tests, we examine how valuations and recommendations relate to future stock returns. Like Bradshaw (2004), we find that residual income valuations relate positively to future returns. This relation becomes more positive following Reg FD. Furthermore, the increasing positive relation appears attributable to Reg FD as we find no evidence of an impact of other regulations. We find that the relation between LTG forecasts and future stock returns is significantly negative in the pre-Reg FD period and immediately following Reg FD. After regulations subsequent to Reg FD, LTG and future stock returns become slightly less negatively related. Finally, and perhaps of greatest interest to investors, stock recommendations have a significantly *negative* relation with future stock returns. Even though analysts' earnings forecasts are useful (in residual income valuation models) for predicting stock performance, their recommendations seem to predict the opposite performance. We find that the negative relation between recommendations and future stock performance persists after Reg FD but subsequent regulations have significantly reduced this negative relation. Overall, we conclude that regulatory reforms seem to be adjusting analysts' outputs (i.e., earnings forecasts and stock recommendations) in the expected direction, but the adjustment may be incomplete. Reg FD has played a greater role in increasing the usefulness of earnings forecasts, whereas regulations subsequent to Reg FD have had a greater effect on stock recommendations.

In the next section we summarize the related literature and discuss our framework for analyzing the analyst/investor relation, highlight objectives of recent regulations (and discuss some research findings related to these regulations), and present our hypotheses. In Section III we briefly describe the valuation models, and in Section IV we discuss our sample selection and descriptive statistics. Section V provides our main empirical findings as well as results from additional analyses. Section VI concludes.

II. PRIOR RESEARCH AND HYPOTHESES

In this section, we first describe the framework in which we analyze the analyst/investor relation. Then we focus on identifying factors that can affect this relation when examining analysts before and after recent regulatory reforms. Finally, we present our hypotheses.

Analyst/Investor Relation

Schipper (1991) encourages research to help better understand how earnings forecasts relate to stock recommendations. She argues that forecasts should be viewed as an input into producing a final output (i.e., a recommendation) and not just a standalone final output. We expect the following relations between analysts and investors. First, analysts gather firm-specific, industry-specific, and economy-wide information to generate earnings forecasts. Next, analysts input these earnings forecasts into a valuation model to compute an intrinsic value of the firm. Then, analysts issue recommendations based on comparing estimates from these valuation models with current stock prices. When the model indicates an intrinsic value above (below) the current price, analysts will issue a buy (sell) recommendation. Investors then adjust prices for the analyst's recommendation. If the academic research correctly identifies the analyst's *unobservable* valuation model, then a positive relation between valuation estimates and *observable* stock recommendations is expected.

Bradshaw (2004) examines whether valuation estimates based on analysts' earnings forecasts are consistent with their stock recommendations. He considers two residual income models, the PEG model, and LTG forecasts.[6] All valuation estimates rely on analysts' earnings forecasts. Perhaps surprisingly, he finds that residual income valuations are either unrelated to or *negatively* related to recommendations. But, these valuations are *positively* associated with future stock performance.[7] In addition, he finds that recommendations are *unrelated* to future stock performance.[8] From this evidence, one concludes that analysts' earnings forecasts provide useful information to investors for predicting future stock performance but analysts' recommendations do not. In other words, analysts do not appear to practice (recommend) what they preach (forecast). Our primary objective is to investigate the effects of recent regulations affecting analysts' work environments on the above relations.

Mitigating Factors

Several factors provide possible explanations for Bradshaw's surprising results. For example, after issuing an earnings forecast, the analyst might not employ rigorous valuation

[6] Details on these four models appear in Section III.
[7] Frankel and Lee (1998) also find a positive relation between residual income valuations and future stock performance.
[8] Womack (1996) and Barber et al. (2001) find that recommendation changes are associated with future stock returns. Other recent studies find mixed results on the usefulness of stock recommendations (Barber et al. 2003; Mikhail, Walther, and Willis 2004; Li 2005; Gleason et al. 2007). The combined evidence suggests that analysts' earnings forecasts provide useful information for measuring intrinsic values but that analysts' recommendations do not. Barber et al. (2006) suggest that market prices react slowly to the information contained in recommendations.

models but instead rely on simple heuristics, whereas investors rely on more sophisticated residual income models. Bradshaw finds evidence consistent with LTG forecasts being the most important determinant of stock recommendations, regardless of the degree to which these expectations are already impounded in stock prices. These results suggest that analysts tend to rely on valuation heuristics to a greater extent than on more "theoretically driven" residual income models. These archival results are consistent with findings in broad surveys of analysts (e.g., Barker 1999; Block 1999) as well as detailed analyses of small samples of research reports (e.g., Bradshaw 2002). Bradshaw (2002) examines 103 U.S. analyst reports and finds that analysts frequently support their stock recommendations with a PEG model. Asquith et al. (2005) investigate *Institutional Investor* "All American" analysts, presumably the most sophisticated analysts, and find that only 13 percent of their reports refer to discounted cash flows in formulating price targets. Results in Gleason et al. (2007) are also consistent with analysts' use of simple heuristics rather than more rigorous residual income models.

In addition, in setting their recommendations, analysts may consider factors other than the intrinsic value estimates relative to current stock prices. Rather than maximizing gains to investors, analysts may be serving personal objectives, such as increasing their compensation, improving relations with management, garnering investment banking business for the brokerage firm, "hyping" the stock to garner brokerage trading volumes, and increasing the value of shares personally owned (e.g., Lin and McNichols 1998; Michaely and Womack 1999, 2005; Ertimur et al. 2007; Ke and Yu 2007). For example, Gimein (2002) claims that investment advice offered by analysts is "so dishonest and fraught with conflicts of interest that it has become worthless" (see also Heflin et al. 2003). As evidence of this, prior research demonstrates that affiliated analysts (i.e., those having direct investment banking business with the firm) issue more optimistic forecasts (Dugar and Nathan 1995; Lin and McNichols 1998; Dechow, Hutton, and Sloan 2000). Das, Levine, and Sivaramakrishnan (1998) and Lim (2001) suggest that forecast optimism is used to increase access to management, especially in cases where the information asymmetry between management and investors is high.[9]

If stock recommendations are set based on incentives other than (only) identifying mispriced stocks, then the relation between stock recommendations and future stock performance is expected to be low or even negative. This may further explain why Bradshaw (2004) finds no significant relation between the level of analyst recommendations and future annual excess returns during his 1994-1998 sample period.[10] These alternative motivations are certainly consistent with the well-documented optimistic bias in analysts' stock recommendations.[11]

Regulatory Reforms

In recent years several important developments in the regulatory environment have affected sell-side financial analysts, and these reforms have the potential to significantly change analysts' incentives or behavior and therefore their output (e.g., earnings forecasts and stock recommendations). Our study tests whether relations between recommendations and valuation

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[9] Francis et al. (2004) provide an in-depth review of the evidence on security analyst independence and conclude that there is strong evidence that U.S. analysts behave in a biased manner. Using the tests in Bradshaw (2004), Barniv et al. (2008) investigate common law versus code law countries and conclude that analyst bias is more pervasive in common law countries. This result is consistent with analysts' stock recommendations in common law countries being affected more by factors other than identifying mispriced stocks.

[10] Jegadeesh et al. (2004) find that recommendation levels are positively related to subsequent returns only for firms with favorable quantitative characteristics such as value stocks and positive momentum stocks. Womack (1996) and Barber et al. (2001) examine changes in analysts' recommendations and conclude that these are positively associated with future excess returns. In this paper, we choose to follow Bradshaw (2004) and Jegadeesh et al. (2004) and examine recommendation levels. First, we want to be able to compare our results with those in Bradshaw (2004). Second, we want to examine recommendations the way a non-computer generated trading investor would process recommendations. Such an investor would find a stock, check out the outstanding recommendations, and then buy/not buy/sell.

[11] For example, Jegadeesh et al. (2004) report that approximately 80 percent of the recommendations are Buy or Strong Buy, and only five percent are Sell or Strong Sell.

estimates are affected by changes in the regulatory environment over time and thus sheds light on whether potential changes in the relations are consistent with the objectives of the reforms.

Reg FD, issued by the Securities and Exchange Commission (SEC) in October 2000, prohibits firms from selectively disclosing management information to analysts. The purpose of the reform was to level the playing field by giving all equal access to material information released by management. Some contend that prior to Reg FD, analysts would purposely bias their earnings forecasts to gain favor with management, thereby allowing easier access to inside information or investment banking business. If Reg FD eliminates the ability to gain privileged information, then one motivation for providing purposely biased earnings forecasts has been eliminated, presumably leading to improved usefulness of earnings forecasts.

Herrmann et al. (2008) find evidence to support this notion.[12] They conclude that Reg FD reduces the incentive for analysts to provide optimistically biased forecasts of internationally diversified firms, potentially improving the quality of analyst forecasts and the decisions of investors based on those forecasts. Others may argue that Reg FD has not led to improved earnings forecasts. Some research suggests that forecast accuracy decreases and forecast dispersion increases following Reg FD (e.g., Bailey et al. 2003; Agrawal et al. 2006). Based on their findings, Agrawal et al. (2006) conclude that a reduction has occurred in both selective guidance and the quality of analyst forecasts after Reg FD. Thus, although the intent of Reg FD is clear and should indicate a strengthened association between analysts' earnings forecasts and their stock recommendations, there is mixed empirical evidence regarding the possible effects of Reg FD on analysts' work environment and their earnings forecasts.

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[12] Using the extent of a multinational firm's international operations to proxy for analysts' need to gather privileged information from management, Herrmann et al. (2008) show that the relation between forecast bias (optimism) and international diversification significantly declines (and even disappears) in the post-Reg FD period.

In addition to Reg FD, other recent regulatory reforms also potentially impact the output of financial analysts. Because of huge investor losses as a result of the crash of technology stocks between 2000 and 2002, regulators came under pressure to "fix" analysts' research reports. It was analysts' overly optimistic research reports that were often cited as a key factor leading to the run up of security prices in the late 1990's. For example, by the end of 1999, less than one percent of analysts provided "sell" recommendations (Bogle 2002). The investing public argued that analysts employed by brokerage firms that offered both investment banking business and research reports faced a conflict of interest. The conflict arose because in an attempt to maintain investment banking business for the brokerage firm, analysts faced pressure to provide favorable research reports (i.e., buy recommendations) instead of providing objective research to the investment community. As a result of these criticisms, regulators proposed NASD Rule 2711 (Research Analysts and Research Reports) and an amendment to NYSE Rule 472 (Communications with the Public) in 2002. In general, the proposed regulatory changes were directed at limiting interactions and flow of information between analysts who provide recommendation reports and the investment banking business of the brokerage firm.[13] These proposals were formally accepted by the SEC on July 29, 2003.[14]

In December, 2002, the SEC announced the Global Research Analyst Settlement which was enforced in April, 2003. Here, the SEC reached a legal settlement with the New York Attorney General, NASD, NYSE, state regulators, and ten of the top U.S. investment firms. The

[13] For a complete description of the rules see "www.nyse.com/pdfs/rule472.pdf" for NYSE Rule 472 (2002) and "finra.complinet.com/finra/display/display.html?rbid=1189&element_id=1159000466" for NASD Rule 2711 (2002).

[14] Rule 2711 covers restrictions on relationships between the investment banking and research departments, restrictions on review of a research report by the subject company, prohibition of certain forms of research analyst compensation, prohibition of promise of favorable research, restrictions on personal trading by research analysts, and disclosure requirements. This rule was introduced on May 10, 2002, but its implementation was subsequently delayed several times (SEC 2002). It seems likely that the mere "threat" of its implementation could have an effect on analyst behavior.

settlement describes how analysts from leading banks provided misleading information to investors, allegedly because of investment banking incentives.[15] In particular, the settlement discloses that analysts issued positive public information that conflicted with their negative views about the stock (De Franco et al. 2007). In other words, as discussed above, investment banking incentives can lead to misleading analyst behavior.[16]

There is some evidence that these regulations have impacted analysts' recommendations. Kadan et al. (2006) show that prior to these regulations, analysts were 40 percent more likely to issue an optimistic recommendation for stocks that had recently undergone an initial public offering or seasoned equity offering. This probability increased by an additional 12 percent when the recommendation was made by an affiliated analyst. These effects vanished after regulations. Barber et al. (2006) support this notion by documenting a decrease in the overall percentage of buys in broker ratings between January 2000 and June 2003, particularly among sanctioned investment banks. Consistent with these findings, Ertimur et al. (2007) and Ke and Yu (2007) show that the improvement is analysts' recommendations around recent regulations was greater for analysts that likely faced higher conflicts of interest.[17]

In summary, recent regulations have addressed bias in analysts' earnings forecasts and stock recommendations. If these regulations have had their intended effects, we should observe

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[15] The settlement also enforces the brokerage firms to make structural changes in the production and dissemination of analyst research.

[16] The SEC further issued several releases governing investment firms' disclosure practices in 2003 (e.g., Regulation Analyst Certification, AC, 2003). Regulation AC requires certifications by analysts that the views expressed in their research reports accurately reflect their personal views. Analysts are required to disclose whether they receive any direct or indirect compensation for their reports. Analysts who cannot certify that they have not received compensation for a specific report must disclose the magnitude and source of the compensation. Finally, the Sarbanes-Oxley Act came into effect in 2002, potentially affecting the quality of financial reporting and thus the work of financial analysts.

[17] Specifically, Ke and Yu (2007) provide an interesting study of how analyst ability, analyst independence, and investor sentiment affect the efficiency with which analysts incorporate their own earnings forecasts into stock recommendations around recent regulations.

an increase in the usefulness of analysts' output – earnings forecasts and stock recommendations. This leads us to the following set of hypotheses.

H1: Following recent regulations, the relation between analysts' stock recommendations and earnings forecast-based residual income (heuristic) valuations is expected to become more (less) positive.

H2: Following recent regulations, the relation between earnings forecast-based residual income valuations and future stock returns is expected to become more positive.

H3: Following recent regulations, the relation between analysts' stock recommendations and future stock returns is expected to become more positive.

III. A BRIEF DESCRIPTION OF VALUATION MODELS

In this section, we briefly describe the valuation models used in this paper.[18] Following prior literature (e.g., Ohlson 1995; Frankel and Lee 1998; Bradshaw 2004), we estimate the residual income model as the present value of expected residual income for the next five years plus a terminal value:

$$V_t = BVPS_t + \sum_{\tau=1}^{5} \frac{E_t[\,RI_{t+\tau}\,]}{(1+r)^{\tau}} + \frac{E_t[\,TV_{t+5}\,]}{(1+r)^{5}}. \tag{1}$$

To estimate (1), we require availability of book value per share (*BVPS*) in year *t* from Compustat and forecasted earnings per share for years $t+1$ and $t+2$ from I/B/E/S. If available, we use analysts' forecasts of years $t+3$ through $t+5$. If not available, we extrapolate earnings

[18] For more on these models, see Frankel and Lee (1998), Lee et al. (1999), Liu et al. (2002), Easton (2004), and Hope et al. (2008).

forecasts for these years using the earnings forecast for year *t+2* and the long-term growth forecast.[19] Residual income (*RI*) equals forecasted earnings, less the discount rate (*r*) times the prior year's book value. Future book values are extrapolated from book value in year t using the clean surplus assumption (i.e., $BVPS_{t+1} = BVPS_t + EPS_{t+1} - DPS_{t+1}$), where future earnings, EPS_{t+1}, are forecasted earnings, and future dividends, DPS_{t+1}, are measured using the assumption of a constant payout ratio based on year *t*.

Due to the importance of assumptions embedded in the terminal value (*TV*) computation, we estimate two versions of the residual income model (Bradshaw 2004). The first, V_{RI1}, assumes that abnormal profits are driven away over time due to competitive pressures. In practice we build in a fade rate (ω) that implies that residual income reverts to zero over ten years:

$$V_{RI1,t} = BVPS_t + \sum_{\tau=1}^{5} \frac{E_t[RI_{t+\tau}]}{(1+r)^{\tau}} + \frac{\omega E_t[RI_{t+5}]}{(1+r-\omega)(1+r)^5} \tag{2}$$

The second specification of the residual income valuation model (V_{RI2}) assumes that residual income in the terminal year persists in perpetuity, which is a more optimistic assumption than the fade-rate assumption used for V_{RI1}:

$$V_{RI2,t} = BVPS_t + \sum_{\tau=1}^{5} \frac{E_t[RI_{t+\tau}]}{(1+r)^{\tau}} + \frac{E_t[RI_{t+5}]}{r(1+r)^5}. \tag{3}$$

Barker (1999), Block (1999), Bradshaw (2002), and Chen et al. (2004) discuss how analysts use price-earnings based techniques in practice. Numerous articles in the financial press describe the pervasiveness of the use of the "PEG ratio" as a basis for stock recommendations. For example, Peter Lynch advocates the PEG ratio in his book *One Up on Wall Street* (Lynch 2000). The *PEG* ratio is defined as:

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[19] For example, if forecasted earnings for year t+2 equal \$1.00 and the long-term growth forecast is 10 percent, then forecasted earnings for year t+3 is \$1.10, forecasted earnings for year t+4 is \$1.21, and forecasted earnings for year t+5 is \$1.33. To provide this extrapolation, we require that forecasted earnings for year t+2 be positive.

$$PEG_t = \frac{P_t / E_t\left[EPS_{t+2}\right]}{LTG_t * 100}, \tag{4}$$

where P is stock price, $E_t[EPS_{t+2}]$ is forecasted earnings per share in year $t+2$, and LTG is the long-term growth forecast. Following Bradshaw (2004), we compute the PEG valuation as:

$$V_{PEG,t} = E_t\left[EPS_{t+2}\right] * LTG_t * 100 \tag{5}$$

V_{RI1}, V_{RI2}, and V_{PEG} are divided by current stock price. To the extent that the valuation estimate is greater (less) than current price, the valuation model suggests an under (over) priced stock and therefore higher (lower) future returns, on average.

Finally, although not a valuation estimate per se, we include *LTG* forecasts as our fourth metric. This is important since *LTG* forecasts seem to be the primary measure used by analysts in setting their recommendations prior to regulations (Bradshaw 2004), yet they have a strong *negative* relation with future stock returns. We are interested in the impact that recent regulations have on the use of heuristics by analysts. While an increase in the relation between residual income valuations and stock recommendations might provide indirect evidence of a reduced reliance on heuristics, this is not necessarily the case. We believe it is important to provide a direct test. Providing results for each of these contrasting relations (heuristics versus theoretically-driven residual income values) provides additional evidence for understanding the link between analysts' earnings forecasts and their recommendations.

IV. DATA, SAMPLE, AND DESCRIPTIVE STATISTICS

We obtain data on annual consensus earnings forecasts, projections of long-term earnings growth, and stock recommendations from I/B/E/S for the sample period January 1993 – May

2005 for an extensive sample of firms.[20] Our initial sample includes 425,158 observations that have stock recommendations and data necessary to create our four valuation estimates.[21] Next, we exclude observations for months without changes in stock recommendations.[22] Since recommendations can be fairly sticky across months, using only months that involve a change in recommendations provides a more realistic setting of when analysts are more likely to incorporate current information into their recommendations (as opposed to current recommendations reflecting stale information). The final sample of consists of 187,889 monthly observations representing 8,079 firms. We have 112,477 observations for our pre-Reg FD (1993-1999) sample and 75,412 observations for our post-Reg FD (2000-2005) sample. Note that our pre-Reg FD sample is substantially larger than the one employed by Bradshaw (2004) of 15,318 observations over the 1994-1998 period (with LTG available, which we require for all of our tests).[23] Within the post-Reg FD sample, we have 36,799 observations prior to other regulations (2000-2002) and 38,613 observations for 2003-2005 (after other regulations). We refer to the periods before and after other regulations as the pre-OtherReg and post-OtherReg periods.

Panel A of Table 1 presents descriptive statistics for the pre- and post-Reg FD periods. Consistent with our prediction that Reg FD should reduce analyst optimism, the mean recommendation (*REC*) is significantly lower (at the one percent level) in the post-Reg FD era (3.72) than in the pre-Reg FD era (3.96) (1 = Strong Sell to 5 = Strong Buy). The percentage of buy and strong buy recommendation decreases from 67.7 to 47.1, and the percentage of sell and

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[20] Bradshaw (2004) uses First Call as his source for analyst data. First Call and I/B/E/S differ in that First Call includes consensus data for a month only if the consensus was revised during the month. I/B/E/S is more comprehensive in that it includes all months, including those with no changes in the consensus. We base our main results on using change months only (consistent with Bradshaw), but we show later in the paper that results are robust to using the full sample of observations.

[21] Results are similar if we relax the requirement that *LTG* forecasts be available (and thus have larger sample sizes).

[22] As a sensitivity test near the end of the paper, we discuss results when all months are included. All conclusions are unaffected. In addition, we have estimated all models after excluding consensus recommendations based on just one recommendation and the results are similar to those reported.

[23] As discussed below, we find results similar to Bradshaw (2004) for the pre-Reg FD period with a few exceptions.

strong sell recommendations increases from 1.1 to 4.4 percent. The means of V_{RI1}/P and V_{RI2}/P significantly increase and V_{PEG}/P and *LTG* significantly decrease.[24] As expected, firm size (market value of equity) increases. In addition, the number of analysts per firm also increases.

[Place TABLE 1 here]

Consistent with their high recommendation levels, analysts estimate high long-term growth rates (*LTG*) for the companies they follow – 18.9 percent and 18.0 percent for the pre- and post-Reg FD periods, respectively (and the difference is significant at the one percent level). In untabulated analyses, we find that the mean actual annual earnings growth is 8.4 percent and 11.5 percent in these periods. These findings suggest that *LTG* projections are high and optimistically biased, but that this optimism has decreased somewhat in the post-Reg FD period.

Panel B presents the results for the pre-OtherReg period (2000-2002) and post-OtherReg period (2003-2005). The mean recommendation continues to significantly decline, going from 3.89 to 3.58.[25] The percentage of buy and strong buy recommendations decreases from 57.2 to 42.1, and the percentage of sell and strong sell recommendations increases from 2.6 to 5.2 percent, and. V_{RI1}/P, V_{RI2}/P, and V_{PEG}/P increase significantly, but *LTG* forecasts decrease significantly from 20.2 percent to 15.9 percent. These results suggest that the major decreases in analysts' recommendations and *LTG* projections appear following other regulations.

Panels C and D of Table 1 provide correlations between variables. Consistent with the intent of regulations, the correlations between residual income valuations and stock

[24] The fact that the mean recommendation *REC* is a buy and the mean residual income valuation estimates (V_{RI1}/P and V_{RI2}/P) are less than one suggests that analysts rely on more than just these valuations when deciding their stock recommendations (Bradshaw 2004). Unlike the residual income valuations, the *PEG* valuation is greater than the current price for the pre-Reg FD period (1.14) but is below current price for the post Reg FD (0.79).

[25] One potential alternative reason for the decline in recommendation levels over our sample period could be deteriorating economic conditions. We cannot exclude this possibility. However, it should be noted that recommendations are generally made with the explicit understanding that they represent whether a stock will underperform or outperform the market in general, and not necessarily whether the stock price is expected to decrease or increase. Thus, it is not necessarily the case that poorer economic conditions would lead to reduced recommendations in general.

recommendations increase over time. However, there is an increase in the positive correlation between V_{PEG}/P and recommendations, even though the correlation between V_{PEG}/P and future returns becomes insignificant post Reg FD and then becomes negative after other regulations. The correlation between residual income valuations and future returns is increasing, but that improvement occurs only around Reg FD. *LTG* forecasts and residual income valuations are negatively correlated, explaining why residual income valuations and future returns are positively correlated, while *LTG* forecasts and future returns are negatively correlated.

V. REGRESSION RESULTS

As in Bradshaw (2004), each coefficient reported in the tables represents the mean coefficient from 12 subsample regressions. The 12 subsamples are created by partitioning all observations based on one-year-ahead earnings forecast horizons (i.e., months t-1 to t-12). This controls for systematic differences in earnings forecast characteristics as the end of the period nears (Brown 2001; Bradshaw 2004). It is an empirical regularity that analysts walk down their forecasts as the year passes, and forecasts made near the end of the year are more accurate and less optimistic than those made near the beginning of the year. By running the regression for each fiscal month, we prevent mixing short-horizon earnings forecasts with long-horizon forecasts. In other words, we prevent mixing valuation estimates generated from more optimistic, less accurate forecasts (i.e., long-horizon forecasts) with those generated from less optimistic, more accurate forecasts (i.e., short-horizon forecasts).[26] Reported t-statistics are based on the

[26] As an example of this issue, we find that V_{RI1}/P uniformly decreases over the 12-month horizon. The mean of V_{RI1}/P is 12 percent lower in month t-1 compared to month t-12. The same decreasing pattern is observed for V_{RI2}/P (14 percent lower in month t-1) and V_{PEG}/P (24 percent lower in month t-1). Thus, Bradshaw's (2004) approach directly controls for this horizon effect in analysts' forecasts.

standard error of the monthly coefficients, using the adjustment for serial correlation across months.[27,28]

The adjusted R^2s presented are means across the 12 months. We estimate the regressions using quintile rankings of the independent variables. The quintile rankings are designated by allocating observations in equal numbers to quintiles within each month based on the distribution of the variable in that month. The quintile rankings are scaled to range between 0 and 1.[29]

Tests of Effects of Regulatory Reforms on Relations between Stock Recommendations and Valuation Estimates (Hypothesis 1)

To test the effect of Reg FD on the relation between valuation estimates and stock recommendations, we estimate the following model.

$$REC = \alpha_0 + \alpha_1 RegFD + \alpha_2 VALUATION + \alpha_3 VALUATION * RegFD + \varepsilon \tag{6}$$

where *VALUATION* is one of the four valuation estimates and *RegFD* is an indicator variable that takes the value of one following implementation of Reg FD, zero otherwise. α_2 provides an estimate of the relation between recommendations and valuations in the pre-Reg FD period. If α_3 is greater (less) than zero, then the relation between recommendations and valuations has increased (decreased) following Reg FD.

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27 Standard errors are multiplied by an adjustment factor, $\sqrt{\frac{(1+\Phi)}{(1-\Phi)} - \frac{2\Phi(1-\Phi^n)}{n(1-\Phi)^2}}$, where n is the number of months and Φ is the first-order autocorrelation of the monthly coefficient estimates (Abarbanell and Bernard 2000; Bradshaw 2004).

28 Since each of the fiscal month regressions contains multiple observations for the same firm, there is likely some residual dependence, understating the standard error in each of the monthly regressions. However, the monthly coefficients are unbiased. And since we base our reported t-statistics on the mean of the monthly coefficients (not the monthly standard errors), the reported significance levels are unaffected.

29 We have also estimated the models using five-group, three-group, and two-group (above/below median) ordered logit regressions. Untabulated results show that no inferences are affected with these alternative estimation techniques.

Table 2 presents regression results. Contrary to what one might expect but consistent with Bradshaw's (2004) 1994-1998 results, the table shows that analysts' recommendations are positively related to heuristic-based valuation estimates but are negatively related to more rigorous residual income valuations in the pre-Reg FD period. Directly related to H1, we find that the interactions of both V_{RI1}/P and V_{RI2}/P with *RegFD* are positive and significant at the one percent level. These findings support the first hypothesis that Reg FD will better align analysts' recommendations with residual income valuations, which were developed using analysts' earnings forecasts. Also consistent with H1, we find that recommendations are significantly less positively associated with *LTG* following Reg FD (i.e., the interaction term is negative and significant at the one percent level), suggesting a reduced reliance on *LTG*. However, in contrast to our prediction, the relation between stock recommendations and *PEG* valuation slightly increases following Reg FD.[30] In conclusion, for three of the four models the results provide support for the first hypothesis, suggesting significant effects of Reg FD on the association between analyst recommendations and valuation estimates.

[Place TABLE 2 here]

For our test of the effects of other regulations, we estimate a similar model but limit the sample period to the post-Reg FD era and repeat the above test after replacing *RegFD* with *OtherReg*, an indicator variable that takes the value of one for the 2003-2005 period (post-OtherReg) and zero for the 2000-2002 period (pre-OtherReg).

$$REC = \alpha_0 + \alpha_1 OtherReg + \alpha_2 VALUATION + \alpha_3 VALUATION * OtherReg + \varepsilon \qquad (7)$$

Table 3 presents regression results. The coefficients on V_{RI1}/P and V_{RI2}/P are significantly negative, indicating that residual income valuations remain significantly negatively related to

[30] Coefficient estimates in the post-Reg FD period are as follows (untabulated): V_{RI1}/P is significantly negative, V_{RI2}/P is not significantly different from zero, and V_{PEG}/P and *LTG* are significantly positive.

recommendations after Reg FD but before other regulations. The relation between residual income valuations and recommendations becomes significantly more positive after other regulations, as indicated by their interactions with *OtherReg*. These results are consistent with the first hypothesis. In fact, untabulated results show that the coefficient on V_{RI1}/P is indistinguishably different from zero in the post-OtherReg period and the coefficient on V_{RI2}/P becomes significantly positive. Thus, it appears that other regulations have played a greater role than has Reg FD in aligning residual income valuations and analysts' recommendations. At least with respect to V_{RI2}/P, the puzzling negative relation between residual income valuations and recommendations now appears to be positive, as one might expect prior to observing results in prior literature.

[Place TABLE 3 here]

Contrary to our first hypothesis, we do not detect a decline in the relation between *REC* and heuristics (*LTG* and V_{PEG}/P) after other regulations. The relation between *REC* and V_{PEG}/P continues to increase. The relation between *REC* and *LTG* also increases after having been reduced immediately following Reg FD.

To summarize, the results in Tables 2 and 3 suggest that recent regulations have had an effect on analyst behavior. Specifically, we document a greater reliance on residual income valuations in arriving at stock recommendations following recent regulations. These results are consistent with the objectives of Reg FD and the other regulations and provide support for H1. However, the results for the effects of regulations on heuristics-based valuation estimates (V_{PEG}/P and *LTG*) are mixed for Reg FD and contrary to expectations for other regulations.

Tests of Relations between Future Excess Returns and Valuation Estimates (Hypothesis 2) and Stock Recommendations (Hypothesis 3)

We now turn to testing the relation of future excess returns with both valuation estimates and stock recommendations. We compute one-year-ahead buy-and-hold size-adjusted returns (*SAR*) as:

$$SAR_i = \left[\prod_{\tau=1}^{12}\left(1+r_{i,t+\tau}\right)-\prod_{\tau=1}^{12}\left(1+r_{size,t+\tau}\right)\right], \tag{8}$$

where $r_{i,t+\tau}$ is the monthly raw stock return for firm i in month $t+\tau$, and $r_{size,t+\tau}$ is the month $t+\tau$ return of the size decile to which firm i belongs as of the beginning of the fiscal year. Using I/B/E/S price and dividend data (supplemented with Compustat data), we cumulate returns beginning in the month subsequent to the date of the consensus recommendation. We chose to use a one-year-ahead return horizon for two reasons. First, this is the horizon employed by Bradshaw (2004) so our results are directly comparable to his. Second, recommendations are generally provided by analysts with the intention of giving guidance over an extended period of time (e.g., 6 to 24 months).

To test the second hypothesis, we run the following regression to estimate the relation between future excess returns and the valuation estimates:

$$SAR = \beta_0 + \beta_1 RegFD + \beta_2 VALUATION + \beta_3 VALUATION * RegFD + \varepsilon \tag{9}$$

For the third hypothesis, we consider the relation between future returns and stock recommendations.

$$SAR = \beta_0 + \beta_1 RegFD + \beta_2 REC + \beta_3 REC * RegFD + \varepsilon \tag{10}$$

Panel A of Table 4 shows regression results for (9) and (10). Consistent with the findings of Frankel and Lee (1998) and Bradshaw (2004), we document that both V_{RI1}/P and V_{RI2}/P are positively and significantly related to future excess returns before Reg FD. In addition, we find that this positive relation increases following Reg FD (and in fact doubles). These results provide support for the second hypothesis. The coefficients on *LTG* and V_{PEG}/P are *negatively* related to future excess returns prior to Reg FD. The introduction of Reg FD did appear to make V_{PEG}/P significantly less negatively related to future returns (i.e., the interaction is positive and significant at the one percent level). For *LTG*, on the other hand, there is no significant effect of Reg FD. The final column of Panel A in Table 4 shows that recommendations are negatively related to future excess returns. After enactment of Reg FD, this negative relation persists. This suggests that Reg FD had no impact on the seemingly irrational relation between analyst recommendations and security returns.

[Place TABLE 4 here]

In Panel B, we examine whether valuations are incremental to stock recommendations. As discussed previously, to the extent that analysts' recommendations are not derived based on valuation models, the two can provide incremental effects. We first note that results for all four valuation estimates (reported in Panel A) and the effects of Reg FD are unaffected by adding recommendations to the regression. This provides further evidence that analysts' stock recommendations are influenced by many other factors. The biggest difference in the pre-Reg FD period is for *LTG*. Much of this variable's explanatory power is lost when testing for an incremental effect, which is consistent with our earlier result that recommendations appear most closely related to *LTG* (as opposed to residual income valuations). Results for the post-Reg FD are also very similar. Perhaps the most interesting result is that when controlling for V_{PEG}/P or *LTG*, the relation between stock recommendations and future excess returns becomes even more negative in the post-Reg FD period. This is not the case for residual income valuations. The ability of residual income valuations to explain future returns prevents the negative relation between recommendations and future returns from becoming increasingly negative.

Table 5 provides analyses of effects of other regulations (*OtherReg*) on the relations between future returns and valuation estimates and recommendations. The main findings reported in Panel A are as follows. First, the positive relation between residual income valuations and future returns remains the same before and after other regulations. Second, the other regulations do seem to have had an effect on the relation between stock recommendations and future returns, as the interaction effect is significantly positive. These results provide support for the third hypothesis. When we consider the incremental effects of valuations and stock recommendations for future returns (reported in Panel B), only one conclusion changes. The negative relation between stock recommendations and future returns does not become weaker when controlling for *LTG* (i.e., column 4 of Panel B). In general, the results in Table 5 further demonstrate that other regulations relate primarily to improvements in stock recommendations (as opposed to analysts' earnings forecasts) and this improvement is incremental to valuation estimates based on analysts' earnings forecasts.

[Place TABLE 5 here]

Sensitivity Analyses

Results for observations with no change in consensus

Recall that we base our results on using only monthly observations for which there has been a revision in the consensus recommendation. We use these observations to be consistent with Bradshaw (2004). However, as a sensitivity analysis, we repeat the tests using the full sample of observations from I/B/E/S data (i.e., including monthly observations with no change in consensus recommendation). This approach has the advantage of significantly increasing the sample size and thus the power of our tests. In fact, the sample size increases to 425,128. However, the results are quite similar to those reported previously, which provides some assurance that our findings are not unduly influenced by the use of a smaller sample.

Standard errors adjusted for clustering at the firm level

In Tables 2-5 we report coefficients using the mean coefficient from 12 fiscal month regressions. As an alternative, we consider estimating coefficients using a pooled model and use firm cluster adjusted standard errors. The pooled model has the disadvantage (as discussed previously) of mixing long-horizon and short-horizon earnings forecasts but the advantage of not relying on the average of only 12 monthly coefficients, which potentially reduces statistical power. Under this alternative approach, we find that coefficients are remarkably close to those reported in the tables. All conclusions reported from Tables 2 and 3 (i.e., the relations between stock recommendations and the four valuation estimates) are unaffected.

We do, however, notice some differences for results reported in Tables 4 and 5 (i.e., the relations with future returns). *LTG* is significantly more negatively related to future returns after Reg FD but significantly less negatively related to future returns after other regulations. These results are consistent with other regulations having their intended effect of reducing analysts' reliance on heuristics in setting stock recommendations. Furthermore, the conclusion that the increasing positive relation between residual income valuations and future returns is attributable primarily attributable to Reg FD (and not other regulations) is even more apparent. In summary, while we note some differences in results, overall conclusions regarding the effectiveness of regulations are unaffected.

Bear market and bull market effects

Our research period can be characterized by periods of primarily a bull market until March 2000, bear market from April 2000 through March 2003, and another bull market commencing in April of 2003. To test whether our inferences are affected by bull versus bear markets in addition to the effects of regulatory reforms, we re-estimate regressions using bull or bear monthly indicators.[31] The overall tenor of our results is the same. We do find that bull markets have positive effect on analysts' recommendations and excess returns in the pre-Reg FD.

VI. CONCLUSION

To date there has been surprisingly little research on analysts' recommendations and analysts' use of valuation models. A priori, the relation seems straightforward. Analysts input their earnings forecasts into the theoretically correct valuation model, such as a residual income model, to develop a valuation estimate. Analysts compare this valuation to current stock price. To the extent that the valuation estimate exceeds current stock price, analysts would issue a buy recommendation. Alternatively, if the valuation estimate is below the current stock price, analysts would issue a sell recommendation. Thus, it seems likely that residual income valuations and stock recommendations would have a positive relation and each would relate positively to future returns. Furthermore, if stock recommendations completely capture the information in valuation estimates, then valuation estimates would have no incremental explanatory power for future returns. However, while these arguments seem consistent with rational analyst behavior, prior research documents that these relations do not exist as expected

[31] For the entire 1993-2005 research period, we use a monthly indicator that equals one during bull markets and zero during the bear markets. We also use the monthly indicator for separate analysis during the post-Reg FD periods (2000-2005) and find no significant effects.

and in some cases exist in the opposite direction.

As an example, Bradshaw (2004) shows that residual income valuations, developed using analysts' earnings forecasts, relate negatively to analysts' recommendations yet relate positively to future returns. Why are analysts' earnings forecasts in residual income valuation models useful to investors (i.e., help in predicting future stock performance) yet analysts do not appear to use them in setting their recommendations? In other words, why do analysts not practice (recommend) what they preach (forecast)?

Because of these inconsistencies (along with the crash of technology stocks in the early 2000's), analyst activity has come under severe public scrutiny. Regulators were called upon to "fix" the analyst industry. The SEC enacted Regulation Fair Disclosure (Reg FD) in 2000, which prohibited management from disclosing material information to selected analysts. Some contend that analysts purposely biased their forecasts to gain favor with management, thereby allowing easier access to privileged information. Reg FD disallows the release of privileged information and therefore reduces at least one of the incentives for analysts to bias their forecasts.

Analysts were also criticized for the apparent conflict of interest that existed within brokerage firms. Analysts in the research department (i.e., those providing stock recommendations) felt pressure from those in the investment banking department to provide only favorable reports. Issuance of unfavorable reports could reduce investment banking business, a tremendous source of revenue for brokerage firms. Thus, analysts had incentives in issuing their recommendations beyond providing objective, reliable information to the investing public. In response, the SEC accepted NASD Rule 2711, NYSE Rule 472, and the Global Research Analyst Settlement in late 2002 and 2003. In general, these regulations address research analysts' conflicts of interest and limit interactions and flow of information between an analyst and the investment banking business of the brokerage firm.

We are interested in the extent to which these regulations had their intended effects. Using a large sample of stock recommendations over the 1993-2005 period, we first examine the relation between analysts' stock recommendations and (1) theoretically-derived residual income models versus (2) valuation heuristics (i.e., price-to-earnings to growth (PEG) ratio and long-term growth (LTG) forecast). We then examine the relation between future returns and (1) stock recommendations, (2) residual income models, and (3) valuation heuristics. Finally, we consider the extent to which residual income models and valuation heuristics are incremental to stock recommendations in explaining future returns. We examine changes in these relations in the pre-Reg FD period (1994-1999) versus the post-Reg FD period (2000-2005). Within the post-Reg FD period, we examine changes before (2000-2002) and after (2003-2005) other regulations (i.e., NASD 2711, NYSE Rule 472, and Global Research Analyst Settlement).

We report the following results. The documented negative relation between stock recommendations and residual income valuations diminishes in the post-Reg FD period and even becomes positive following other regulations. We also find evidence of a reduced analyst reliance on long-term growth forecasts in providing a stock recommendation in the post-Reg FD period. For our tests of a relation with future returns, we show that residual income valuations have an increasingly positive relation in the post-Reg FD period. This change is due primarily to Reg FD itself rather than other regulations. This finding implies that Reg FD had the effect of increasing the useful of earnings forecasts to investors. Also of interest to investors is our finding that the negative relation between stock recommendations and future returns still persists but is diminishing following regulations subsequent to Reg FD. Thus, it appears that in many ways regulations are having their intended effects but the effects on analysts' outputs may be incomplete.

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TABLE 1
Descriptive Statistics

Panel A: Descriptive Statistics for Pre- and Post-Reg FD Periods

	Pre Reg-FD (1993-1999) N = 112,477			Post Reg-FD (2000-2005) N = 75,412			Difference	
Variables	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**t-test**	**Wilcoxon Z**
REC	3.96	4.00	0.53	3.72	3.75	0.54	-92.5***	-89.7***
%Buy	67.7%			47.1%				
%Sell	1.1%			4.4%				
V_{RI1}/P	0.63	0.58	0.37	0.66	0.62	0.43	19.0***	24.2***
V_{RI2}/P	0.70	0.66	0.42	0.77	0.74	0.53	32.1***	45.0***
V_{PEG}/P	1.14	1.06	1.03	0.79	0.85	1.23	-65.7***	-81.0***
LTG	18.85	16.07	10.47	18.01	15.17	10.22	-17.4***	-20.8***
SAR	-0.027	-0.092	0.598	-0.038	-0.090	0.514	-3.41***	1.62
MV	5,127	821	18,215	7,471	1,249	24,248	22.6***	51.7***
NUM	9.42	7.00	7.02	10.56	9.00	7.13	34.2***	41.2***

Panel B: Descriptive Statistics for Pre- and Post-OtherReg Periods

	Pre-OtherReg (2000-2002) N = 36,799			Post-OtherReg (2003-2005) N = 38,613			Difference	
Variables	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**t-test**	**Wilcoxon Z**
REC	3.89	3.89	0.51	3.58	3.60	0.54	-74.7***	-74.1
%Buy	57.2%			42.1%				
%Sell	2.6%			5.2%				
V_{RI1}/P	0.62	0.55	0.49	0.71	0.66	0.36	28.9***	51.2***
V_{RI2}/P	0.65	0.62	0.57	0.89	0.85	0.46	62.3***	86.6***
V_{PEG}/P	0.74	0.87	1.54	0.83	0.82	0.84	10.9***	-13.6***
LTG	20.22	16.97	11.61	15.91	14.53	8.18	-58.6***	-48.8***
SAR	-0.041	-0.0982	0.513	-0.032	-0.104	0.515	1.95*	-0.69
MV	7,270	1,094	24,464	7,663	1,408	24,039	2.22**	20.6***
NUM	10.41	9.00	6.94	10.70	9.00	7.31	5.47***	3.42***

(Table 1 continued on next page)

TABLE 1 (continued)
Descriptive Statistics

Panel C: Pearson Correlations Before (1993-1999) and After (2000-2005) Reg FD[a]

	REC	*SAR*	V_{RI1}/P	V_{RI2}/P	V_{PEG}/P	*LTG*
REC	•	-0.119	-0.195	-0.129	0.228	0.339
SAR	-0.146	•	0.091	0.064	-0.163	-0.267
V_{RI1}/P	-0.127	0.197	•	0.935	0.460	-0.296
V_{RI2}/P	-0.075	0.170	0.888	•	0.543	-0.206
V_{PEG}/P	0.267	-0.017	0.466	0.545	•	0.407
LTG	0.283	-0.350	-0.307	-0.264	0.273	•

Panel D: Pearson Correlations Before (2000-2002) and After (2003-2005) OtherReg[b]

	REC	*SAR*	V_{RI1}/P	V_{RI2}/P	V_{PEG}/P	*LTG*
REC	•	-0.168	-0.170	-0.101	0.199	0.233
SAR	-0.115	•	0.209	0.188	-0.001	-0.411
V_{RI1}/P	-0.003	0.178	•	0.918	0.506	-0.305
V_{RI2}/P	0.113	0.148	0.860	•	0.603	-0.265
V_{PEG}/P	0.324	-0.053	0.460	0.584	•	0.136
LTG	0.269	-0.225	-0.267	-0.185	0.413	•

REC = mean consensus analyst recommendation, 1 = Strong Sell, 2 = Sell, 3 = Hold, 4 = Buy, 5 = Strong Buy.
%Buy = the percentage of recommendations rated Buy or Strong Buy.
%Sell = the percentage of recommendations rated Sell or Strong Sell.
V_{RI1} = residual income valuation with a five-year forecast horizon and a terminal value with a fade-rate assumption.
V_{RI2} = residual income valuation with a five-year forecast horizon and a terminal value with a perpetuity assumption.
V_{PEG} = forecasted earnings per share for a two-year forecast horizon times *LTG* (x 100).
LTG = consensus (median) projected long-term growth in earnings.
P = share price on the date of the consensus recommendation calculation.
SAR = annual size-adjusted return beginning the month following the recommendation.
MVE = market value of equity.
NUM = number of analysts following.
[a] Pearson correlations before (after) Reg FD are above (below) the diagonal.
[b] Pearson correlations before (after) other regulations are above (below) the diagonal.

TABLE 2
Relation between Recommendations and Valuation Estimates
Before (1993-1999) and After (2000-2005) Reg FD

Intercept	4.009 ***	3.954 ***	3.635***	3.536***
	(385.8)	(247.6)	(280.1)	(1891.9)
RegFD	-0.262 ***	-0.279 ***	-0.151***	-0.043*
	(-7.53)	(-7.58)	(-6.53)	(-1.89)
V_{RI1}/P	-0.304 ***			
	(-7.75)			
V_{RI2}/P		-0.186 ***		
		(-4.69)		
V_{PEG}			0.382***	
			(24.1)	
LTG				0.625***
				(103..2)
V_{RI1}/P*RegFD*	0.187 ***			
	(5.52)			
V_{RI2}/P*RegFD*		0.225 ***		
		(6.07)		
V_{PEG}/P*RegFD*			0.065**	
			(2.02)	
*LTG*RegFD*				-0.214***
				(-16.9)
Adjusted R^2	0.109	0.096	0.145	0.193

The table presents the results of regressions of consensus stock recommendations on valuation estimates. Regressions are estimated based on one-year-ahead earnings forecast horizon (i.e., months t-1 to t-12). The table presents mean coefficients for these 12 monthly regressions. t-statistics are based on the standard error of the coefficient estimates across the 12 months, adjusted for autocorrelation in the monthly coefficients based on as assumed AR(1) autocorrelation structure. Standard errors are multiplied by an adjustment factor, $\sqrt{\frac{(1+\Phi)}{(1-\Phi)} - \frac{2\Phi(1-\Phi^n)}{n(1-\Phi)^2}}$, where n is the number of months and Φ is the first-order autocorrelation of the monthly coefficient estimates. Adjusted R^2s presented are means across the 12 months. The regressions are estimated using quintile rankings of the independent variables. The quintile rankings are designated by allocating observations in equal numbers to quintiles within each month. The quintile rankings are scaled to range between 0 and 1 (e.g., (QUINTLE-1)/4)). *RegFD* equals 1 if an observation is in the post-Reg FD period (2000-2005) and zero otherwise (1993-1999). Other variables are defined in Table 1.
*, **, *** reflect significance at the 0.10, 0.05, and 0.01 level, respectively, based on two-tailed t-tests.

TABLE 3
Relation between Recommendations and Valuation Estimates
Before (2000-2002) and After (2003-2005) Other Regulations (OtherReg)

Intercept	4.022***	3.982***	3.805***	3.733***
	(760.5)	(661.5)	(537.3)	(437.1)
OtherReg	-0.346***	-0.412***	-0.378***	-0.283***
	(-9.15)	(-8.46)	(-9.48)	(-24.6)
V_{RI1}/P	-0.206***			
	(-8.90)			
V_{RI2}/P		-0.093***		
		(-4.33)		
V_{PEG}/P			0.309***	
			(40.1)	
LTG				0.347***
				(15.8)
V_{RI1}/P*OtherReg*	0.206***			
	(12.3)			
V_{RI2}/P*OtherReg*		0.293***		
		(24.2)		
V_{PEG}/P*OtherReg*			0.298***	
			(20.5)	
*LTG*OtherReg*				0.110***
				(8.08)
Adjusted R^2	0.102	0.292	0.165	0.150

The table presents the results of regressions of consensus stock recommendations on valuation estimates. Regressions are estimated based on one-year-ahead earnings forecast horizon (i.e., months t-1 to t-12). The table presents mean coefficients for these 12 monthly regressions. t-statistics are based on the standard error of the coefficient estimates across the 12 months, adjusted for autocorrelation in the monthly coefficients based on as assumed AR(1) autocorrelation structure. Standard errors are multiplied by an adjustment factor, $\sqrt{\frac{(1+\Phi)}{(1-\Phi)} - \frac{2\Phi(1-\Phi^n)}{n(1-\Phi)^2}}$, where n is the number of months and Φ is the first-order autocorrelation of the monthly coefficient estimates. Adjusted R^2s presented are means across the 12 months. The regressions are estimated using quintile rankings of the independent variables. The quintile rankings are designated by allocating observations in equal numbers to quintiles within each month. The quintile rankings are scaled to range between 0 and 1 (e.g., (QUINTLE-1)/4)). *OtherReg* equals 1 if an observation is in the post-other regulation period (2003-2005) and zero otherwise (2000-2002). Other variables are defined in Table 1.
*, **, *** reflect significance at the 0.10, 0.05, and 0.01 level, respectively, based on two-tailed t-tests.

TABLE 4
Relation between Annual Size-adjusted Returns and Stock Recommendations and Valuation Estimates Before (1993-1999) and After (2000-2005) Reg FD

Panel A: Individual Effects

Intercept	-0.095 ***	-0.073 ***	0.173 ***	0.246***	0.531***
	(-13.5)	(-7.91)	(18.2)	(29.2)	(29.9)
RegFD	-0.051	-0.055	-0.161	-0.005	0.067***
	(-1.64)	(-1.68)	(-5.17)	(-0.10)	(0.69)
V_{RI1}/P	0.176 ***				
	(12.4)				
V_{RI2}/P		0.124 ***			
		(7.69)			
V_{PEG}/P			-0.310 ***		
			(-11.2)		
LTG				-0.501***	
				(-30.4)	
REC					-0.139***
					(-33.6)
V_{RI1}/P*RegFD*	0.148 ***				
	(3.36)				
V_{RI2}/P*RegFD*		0.175 ***			
		(3.50)			
V_{PEG}/P*RegFD*			0.280 ***		
			(7.35)		
*LTG*RegFD*				-0.061	
				(-1.34)	
*REC*RegFD*					-0.019
					(-0.89)
Adjusted R^2	0.019	0.014	0.022	0.088	0.018

(Table 4 continued on next page)

TABLE 4 (continued)
Relation between Annual Size-adjusted Returns and Stock Recommendations and Valuation Estimates Before (1993-1999) and After (2000-2005) Reg FD

Panel B: Incremental Effects

Intercept	0.401 ***	0.452 ***	0.526 ***	0.306***
	(34.5)	(37.0)	(24.4)	(22.9)
RegFD	-0.009	0.020	0.084	0.208
	(-0.16)	(0.33)	(0.75)	(2.60)**
V_{RI1}/P	0.137 ***			
	(10.7)			
V_{RI2}/P		0.098 ***		
		(6.70)		
V_{PEG}			-0.271 ***	
			(-9.15)	
LTG				-0.490***
				(-28.2)
REC	-0.123 ***	-0.132 ***	-0.097 ***	-0.017***
	(-39.1)	(-38.2)	(-13.1)	(-4.44)
$V_{RI1}/P*RegFD$	0.166 ***			
	(4.49)			
$V_{RI2}/P*RegFD$		0.199 ***		
		(4.69)		
$V_{PEG}/P*RegFD$			0.304 ***	
			(6.54)	
*LTG*RegFD*				-0.043
				(-1.02)
*REC*RegFD*	-0.014	-0.023	-0.065 **	-0.056***
	(-1.08)	(-1.56)	(-2.26)	(-5.90)
Adjusted R^2	0.032	0.029	0.033	0.089

The table presents the results of regressions of buy-and-hold annual size-adjusted returns on valuation estimates and consensus stock recommendations. Regressions are estimated based on one-year-ahead earnings forecast horizon (i.e., months t-1 to t-12). The table presents mean coefficients for these 12 monthly regressions. t-statistics are based on the standard error of the coefficient estimates across the 12 months, adjusted for autocorrelation in the monthly coefficients based on as assumed AR(1) autocorrelation structure. Standard errors are multiplied by an adjustment factor, $\sqrt{\frac{(1+\Phi)}{(1-\Phi)} - \frac{2\Phi(1-\Phi^n)}{n(1-\Phi)^2}}$, where n is the number of months and Φ is the first-order autocorrelation of the monthly coefficient estimates. Adjusted R^2s presented are means across the 12 months. The regressions are estimated using quintile rankings of the independent variables. The quintile rankings are designated by allocating observations in equal numbers to quintiles within each month. The quintile rankings are scaled to range between 0 and 1 (e.g., (QUINTLE-1)/4)). *RegFD* equals 1 if an observation is from the post-Reg FD period (2000-2005) and zero otherwise (1993-1999). Other independent variables are defined in Table 1. *, **, *** reflect significance at the 0.10, 0.05, and 0.01 level, respectively, based on two-tailed t-tests.

TABLE 5
Relation between Annual Size-adjusted Returns and Stock Recommendations and Valuation Estimates Before (2000-2002) and After (2003-2005) Other Regulations (OtherReg)

Panel A: Individual Effects

Intercept	-0.160 ***	-0.145 ***	-0.051 ***	0.349***	0.674***
	(-18.6)	(-14.7)	(-7.2)	(7.8)	(7.2)
OtherReg	0.121 ***	0.143 ***	0.147 ***	-0.128	-0.190***
	(6.12)	(4.43)	(7.47)	(-1.40)	(-3.61)
V_{RI1}/P	0.344 ***				
	(7.47)				
V_{RI2}/P		0.329 ***			
		(6.19)			
V_{PEG}/P			0.005		
			(0.24)		
LTG				-0.652***	
				(-9.72)	
REC					-0.182***
					(-9.20)
V_{RI1}/P*OtherReg*	-0.054				
	(-0.65)				
V_{RI2}/P*OtherReg*		-0.083			
		(-0.76)			
V_{PEG}/P*OtherReg*			-0.102 **		
			(-2.63)		
*LTG*OtherReg*				0.283*	
				(1.93)	
*REC*OtherReg*					0.074***
					(3.67)
Adjusted R^2	0.045	0.038	0.004	0.135	0.027

(Table 5 continued on next page)

TABLE 5 (continued)
Relation between Annual Size-adjusted Returns and Stock Recommendations and Valuation Estimates Before (2000-2002) and After (2003-2005) Other Regulations (OtherReg)

Panel B: Incremental Effects

Intercept	0.449 ***	0.527 ***	0.680 ***	0.620***
	(8.03)	(8.75)	(6.97)	(7.11)
OtherReg	-0.069	-0.057	-0.197 ***	-0.169
	(-0.90)	(-0.76)	(-3.68)	(-2.10)**
V_{RI1}/P	0.310 ***			
	(7.36)			
V_{RI2}/P		0.310 ***		
		(6.28)		
V_{PEG}/P			0.063 **	
			(1.96)	
LTG				-0.626***
				(-8.61)
REC	-0.151 ***	-0.168 ***	-0.191 ***	-0.072***
	(-11.6)	(-11.9)	(-7.77)	(-2.79)
$V_{RI1}/P*OtherReg$	-0.017			
	(-0.20)			
$V_{RI2}/P*OtherReg$		-0.037		
		(-0.37)		
$V_{PEG}/P*OtherReg$			-0.100 **	
			(-2.31)	
*LTG*OtherReg*				0.281
				(1.62)
*REC*OtherReg*	0.042 *	0.042 ***	0.090 ***	0.010
	(2.02)	(2.70)	(3.96)	(0.17)
Adjusted R^2	0.063	0.061	0.029	0.142

The table presents the results of regressions of buy-and-hold annual size-adjusted returns on valuation estimates and consensus stock recommendations. Regressions are estimated based on one-year-ahead earnings forecast horizon (i.e., months t-1 to t-12). The table presents mean coefficients for these 12 monthly regressions. t-statistics are based on the standard error of the coefficient estimates across the 12 months, adjusted for autocorrelation in the monthly coefficients based on as assumed AR(1) autocorrelation structure. Standard errors are multiplied by an adjustment factor, $\sqrt{\frac{(1+\Phi)}{(1-\Phi)}-\frac{2\Phi(1-\Phi^n)}{n(1-\Phi)^2}}$, where n is the number of months and Φ is the first-order autocorrelation of the monthly coefficient estimates. Adjusted R^2s presented are means across the 12 months. The regressions are estimated using quintile rankings of the independent variables. The quintile rankings are designated by allocating observations in equal numbers to quintiles within each month. The quintile rankings are scaled to range between 0 and 1 (e.g., (QUINTLE-1)/4)). OtherReg equals 1 if an observation is in the post-other regulation period (2003-2005) and zero otherwise (2000-2002). Other variables are defined in Table 1. *, **, *** reflect significance at the 0.10, 0.05, and 0.01 level, respectively, based on two-tailed t-tests.

ABN·AMRO

February 2008

Global Investment Returns Yearbook 2008: Synopsis

A message from Rob Bate, ABN AMRO's Head of European Research:

We are proud to present the latest – the ninth – edition of the annual *Global Investment Returns Yearbook* (*GIRY*). Again, we present an updated global returns database with its unmatched breadth and historical perspective.

This year's thematic studies are about momentum, a subject of importance to all investors, whether their investment style favours it or not. We show that momentum profits in equities have been large and pervasive across time and markets, and present findings from the longest momentum study ever undertaken. We also discuss how supply and demand as well as financing mechanisms can work as important multipliers of momentum for real estate and for commodity prices. Our focus throughout is on the practical implications for investors. In short, as always with *GIRY*, we hope to stimulate an interesting and productive debate.

The Global Investment Returns Yearbook was launched in 2000. It is produced for ABN AMRO by London Business School experts Elroy Dimson, Paul Marsh and Mike Staunton, with a contributed chapter by Rolf Elgeti, ABN AMRO's former Head of Equity Strategy. This synopsis outlines the contents of the 2008 *Yearbook* and highlights some of its key findings.

The core of the *Yearbook* is provided by a long-run study covering 108 years of investment since 1900 in all the main asset categories in Australia, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, the Netherlands, Norway, South Africa, Spain, Sweden, Switzerland, the United Kingdom, and the United States. These markets today make up some 85% of world equity market capitalisation. *GIRY* also reviews recent performance in a wider set of 29 markets comprising 98% of world capitalisation. With the unrivalled quality and breadth of its database, the *Yearbook* is the global authority on long-run stock, bond, bill and foreign exchange performance.

In the 2008 *Yearbook*, the authors address some of the most important questions in investment.

- **Chapter 1** analyses the performance of global markets over 2007 and over the first eight years of the current decade, highlighting what happened and why.
- **Chapter 2** provides a comprehensive update on the long-term record of stocks, bonds, bills, inflation, currencies and risk premia around the world.
- **Chapter 3** focuses on momentum in equity markets, and shows that momentum profits have been large and pervasive across time and markets, drawing on findings from the longest momentum study ever undertaken.
- **Chapter 4,** by Rolf Elgeti, develops this theme by discussing how supply and demand as well as financing mechanisms can work as important multipliers of momentum for real estate and for commodity prices.
- **Chapters 5–24** cover each of the 17 countries, plus the combined world and world ex-US indices, providing in-depth analysis for each of five asset classes spanned by the authors' 108-year history of asset returns.
- **Chapter 25** provides a bibliography.

ABN AMRO distributes the *Global Investment Returns Yearbook* to its institutional investment clients, journalists and the media. Institutional clients should contact abnamroresearch@abnamro.com. Journalists should contact Aoife Cliodhna Reynolds (aoife.cliodhna.reynolds@uk.abnamro.com).

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250 Bishopsgate, London EC2M 4AA, United Kingdom

Overview of Chapter 1: Recent Investment Returns

The *Global Investment Returns Yearbook* starts by providing detailed statistics on, and analysing the recent performance of, equities and bonds in all the major world markets. Chapter 1 focuses on 2007 and the first eight years of this decade.

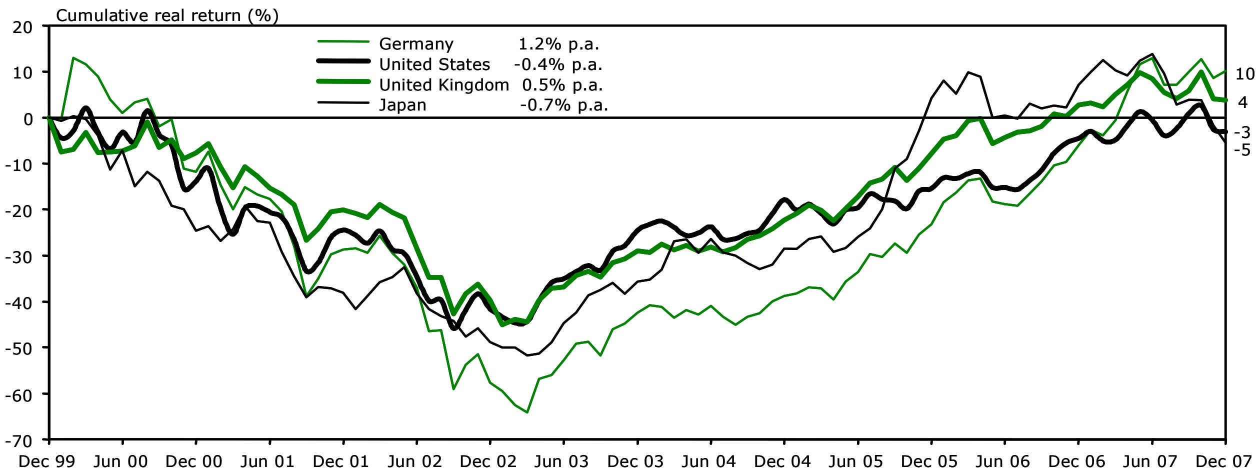
Key findings for 2007:

- Despite the turmoil in the credit markets, stock markets performed reasonably well in most countries. Emerging markets did best.
- Volatility accelerated from a low base at the start of 2007.
- Sector exposures had a larger impact than in recent years, with resource stocks doing particularly well, and financials suffering.
- The tide turned for small-caps, which suffered a reversal after four years of outperformance. Value stocks also disappointed, and they underperformed growth stocks.
- While the US (and world) bond indices did well, most government bond markets gave a negative real return.
- Commodities, notably oil, generally performed well.
- The second half of 2007 witnessed a real estate slowdown in many countries, and a sharp collapse in the US.
- Currency mattered. The US dollar was again weak, and nearly all currencies were performance enhancing. Most countries had satisfactory USD returns, but their Euro returns were markedly lower.

As Figure 1 shows, by end-2007 stock markets had largely eliminated the losses from the savage, start-of-century bear market. This is remarkable since, at the trough in March 2003, US stocks had fallen 45%, UK equity prices had halved, and German stocks had fallen by two-thirds. The *Yearbook* shows that:

- Annualised real equity returns over 2000-07 remain negative in only three of the 17 *Yearbook* countries, the US (-0.4%), Japan (-0.7%) and The Netherlands (-1.3%). However, returns remain low in several other markets, including the UK (0.5%), Germany (1.4%), France (1.2%), Italy (0.9%) and Sweden (1.4%).
- The annualised USD real return on the *GIRY* world index over 2000–07 is just 1.3%. Over this period, bonds beat equities (and bills) in 10 out of 17 countries, including all the largest markets. Realised equity risk premia over this period remain low by historical standards.

Figure 1: Equity performance in selected world markets in real, local-currency terms



Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, chart3, Dow Jones Wilshire and Thomson Financial Datastream

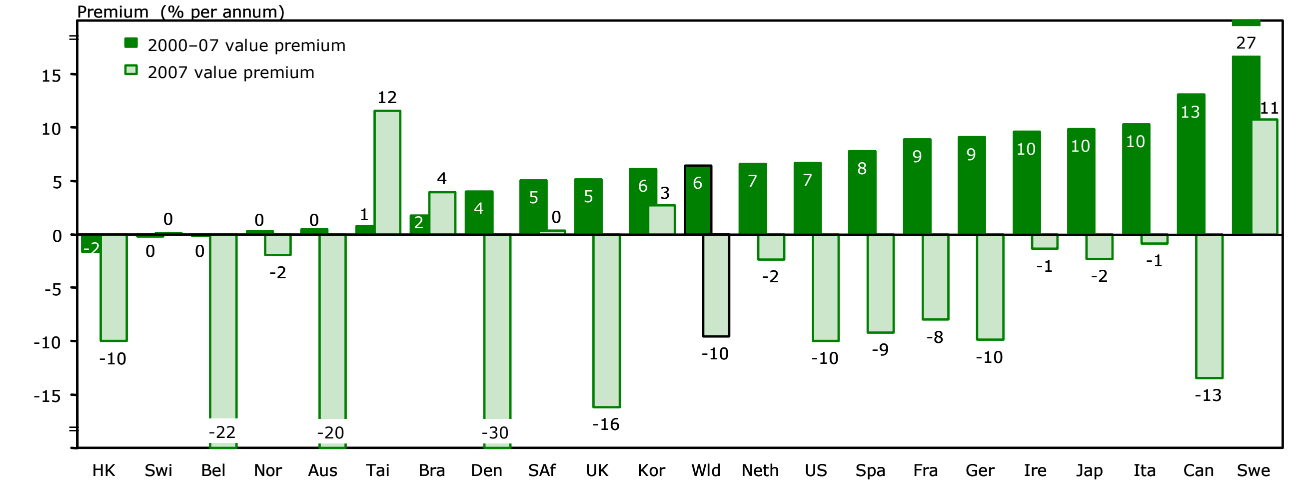
In recent years, there have been remarkable shifts worldwide in relative performance according to size, style and sector. The *Yearbook* documents and analyses these factors to shed light on the underlying causes of performance.

Findings over 2000-07 include:

- Despite 2007 being generally disappointing for small-caps, over 2000–07 they nevertheless beat large-caps in every *Yearbook* country except Norway (and, marginally, Taiwan). In most countries, those who invested in 2000 in small-caps are more than 50% richer than large-cap investors.

- The poor return in 2007 from value stocks did not eliminate the 2000-07 value premium. Figure 2 reports the value premium: the performance of value stocks relative to growth stocks. It shows that, over 2000-07, value stocks beat growth stocks in every *Yearbook* country except Hong Kong (and, marginally, Switzerland). In most markets, those who invested in 2000 in value stocks are more than 50% richer than growth-stock investors.

Figure 2: Value-growth premia around the world during 2007 and 2000–08



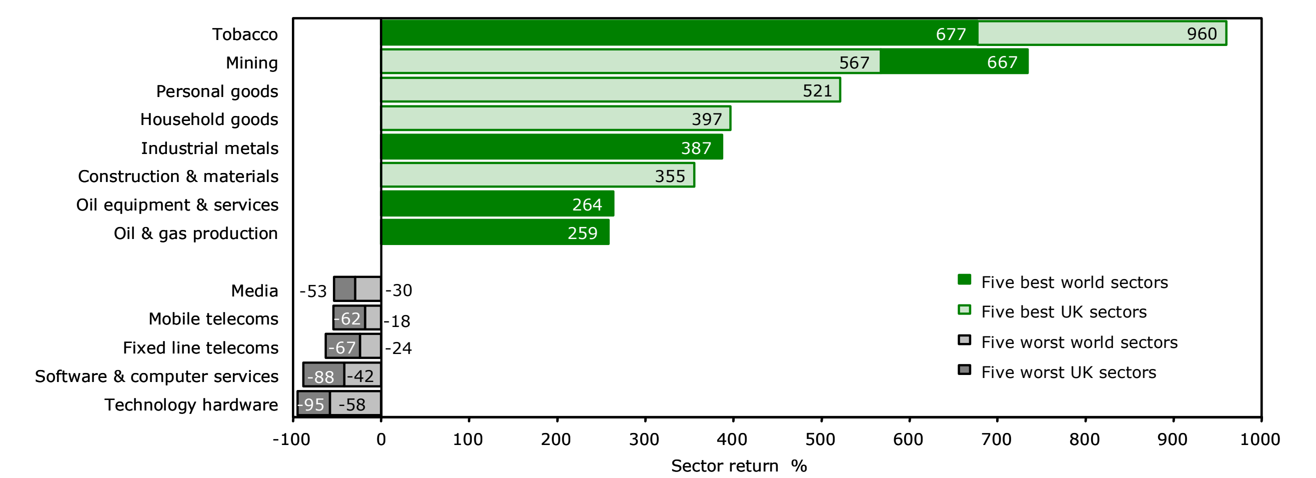
Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, chart7 and MSCI style-based indices

- Momentum trading has provided large potential profits in virtually every equity market. A strategy of buying stock market winners, while avoiding (or taking a short position in) stocks that have performed poorly, has provided a large premium since 2000-07. We also analyse momentum investing, in detail, in Chapter 3.

- A major factor is the investor's choice of reference currency. Over the eight years since 2000, the US dollar has fallen against all *Yearbook* currencies except two (the South African Rand and the Yen). Since 2002, the dollar has fallen against every *Yearbook* currency—by 39% in the case of the Euro.

- A huge gap has now opened up in sector performance since the tech-bubble burst in March 2000. Figure 3 highlights the best and worst performing sectors, showing that an investment in the top performing UK sector—tobacco—would now be worth 212 times more than an equivalent amount invested in the worst performing sector—technology hardware.

Figure 3: Returns on best and worst performing sectors from mid-March 2000 until end-2007



Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, Chart 5 and Nomura/FTSE International All-World Review

Chapter 1 delves into what happened in 2007 and over 2000-07, and why. The authors dissect the sources of global returns, revealing whether performance reflects skill, luck, or a combination of the two. While *GIRY* may inadvertently serve the "market for excuses", its main aim is to help investors diagnose the market exposures that can enhance or hinder performance.

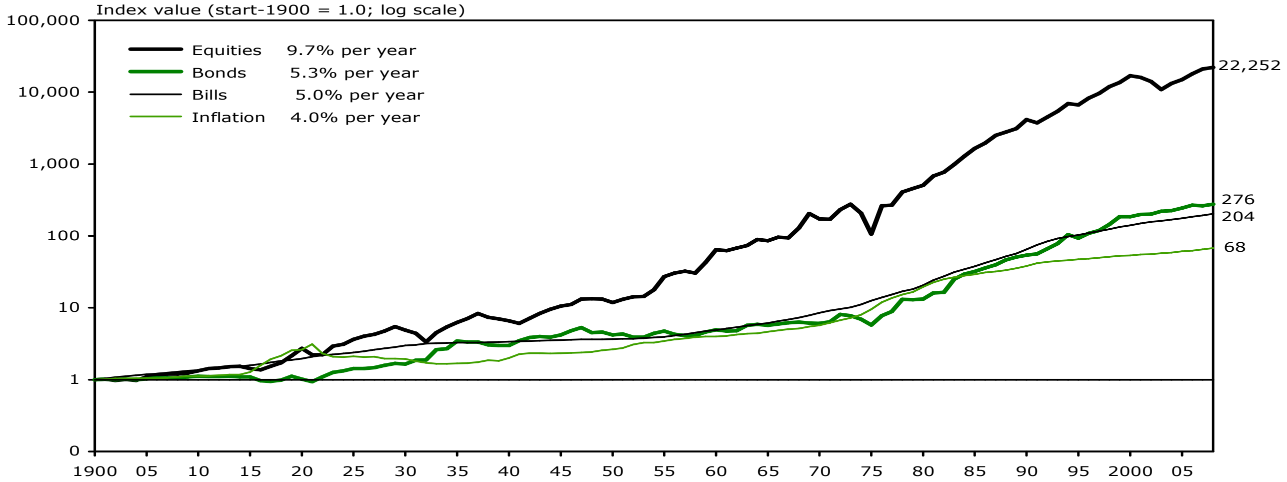
One—or even eight—years is a brief interval in investment. To form a meaningful judgement about the future we need to look not only at the recent past, but also at the long run. That is the subject of Chapter 2, which provides a comprehensive global analysis of the long-term record of stocks, bonds, bills, inflation, currency and risk premia.

Overview of Chapter 2: The Long-Run Perspective

Chapter 2 presents long-run evidence on asset returns over 108 years, and on stock market anomalies such as the size effect and the performance of value investing. Key findings are that:

- An investment in UK equities of £100 at the start of 1900 would, with dividends reinvested, have grown to over £2.2 million by the end of 2007, a return of 9.7% p.a. (see Figure 4). Long bonds and treasury bills gave lower annualised returns of 5.3% and 5.0%, respectively, although they beat inflation (4.0%).

Figure 4: Cumulative returns on UK asset classes in nominal terms, 1900—2007

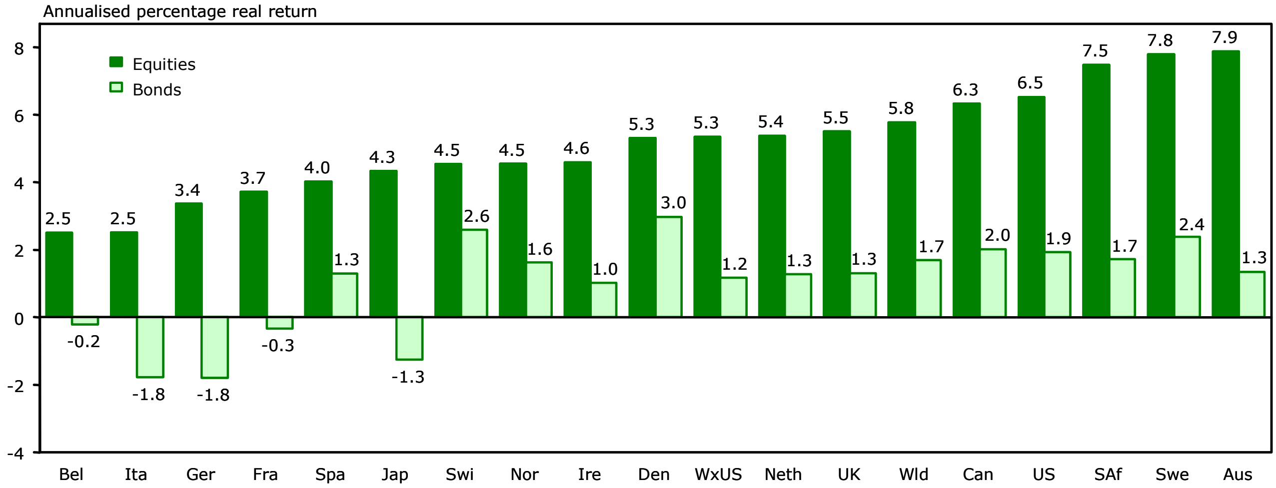


Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, chart 12

- The *Yearbook* provides charts similar to Figure 4, in both nominal and real terms, for all 17 countries plus the world and world ex-US indices (see the summary of chapters 5–24 below). They show that since 1900, equities are the best-performing asset class in every country, while bonds beat bills everywhere except Germany.

- Figure 5 shows that the best performing equity markets over the very long term are Australia and Sweden, with annualised real returns since 1900 of 7.9% and 7.8%, respectively, compared to a world average of 5.8%.

Figure 5: Real returns on equities versus bonds internationally, 1900—2007



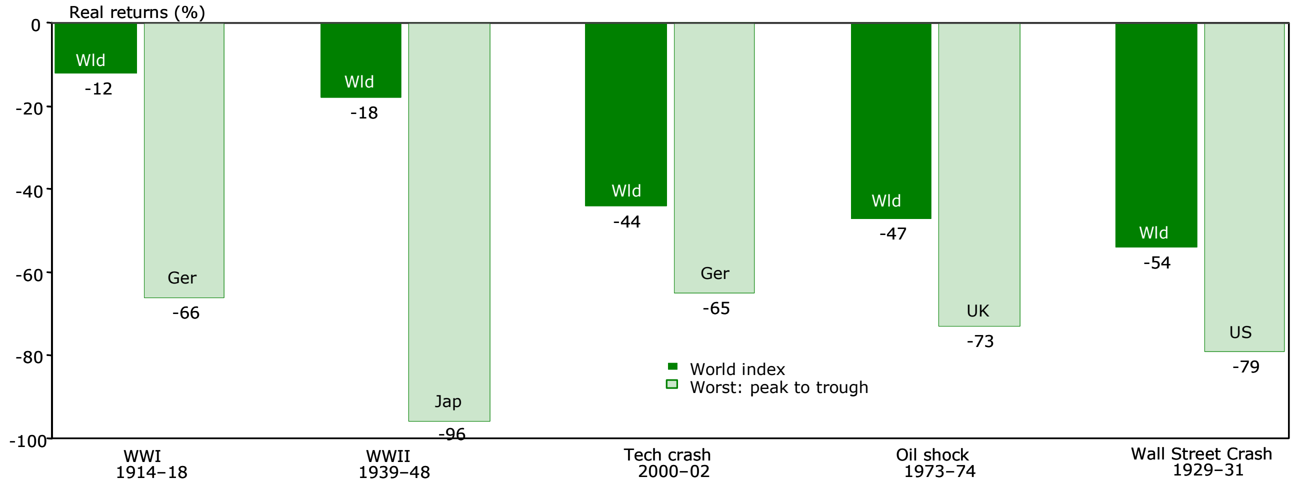
Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, chart 14

- Equity returns were subject to considerable volatility. The UK's standard deviation of 19.8% places it alongside the US (20.0%) at the lower end of the risk spectrum. The highest volatility markets were Germany (32.3%), Japan (29.8%), and Italy (28.9%), reflecting the impact of wars and inflation.

- In contrast to the volatility levels of individual markets, the *GIRY* world portfolio has a standard deviation of just 17.1%, showing the risk reduction obtained from international diversification.

- History has witnessed several episodes of extreme losses for equities. Figure 6 shows that the three great bear markets inflicted far more damage on world equities than the world wars. Note that in each episode of turbulence, the losses experienced in the worst affected market were very large indeed.

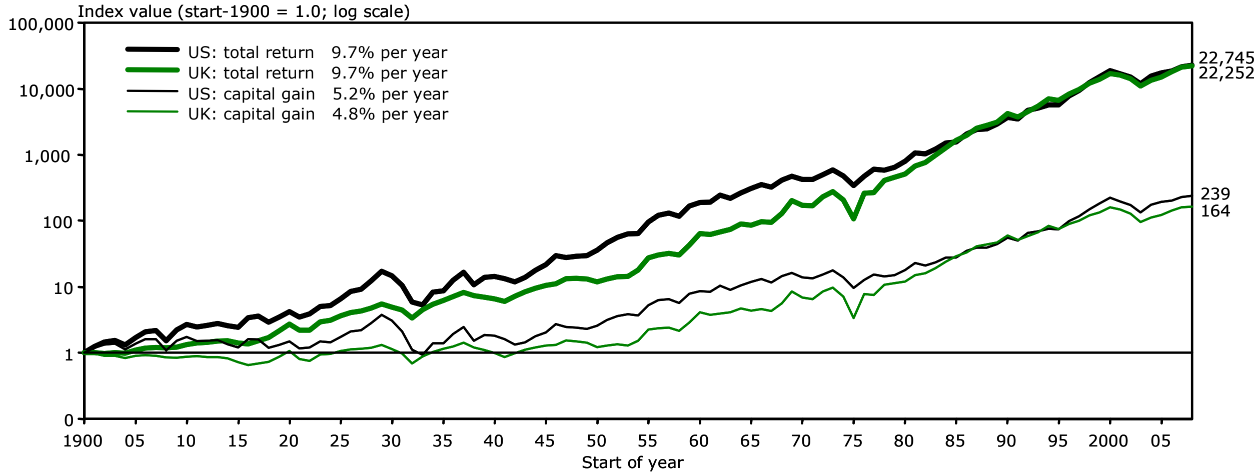
Figure 6: Extremes of equity market history, 1900-2007



Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, Table 6

- Chapter 2 shows that over the long run, small-caps have outperformed in most countries. Similarly, value stocks have beaten growth stocks. When these factors are analysed together, small-value did best of all.
- Long-run returns are heavily influenced by reinvested dividends. After 108 years, $1 invested in US equities in 2000 would have grown to $22,745 with dividends reinvested, but to just $239 on a capital gains only basis.

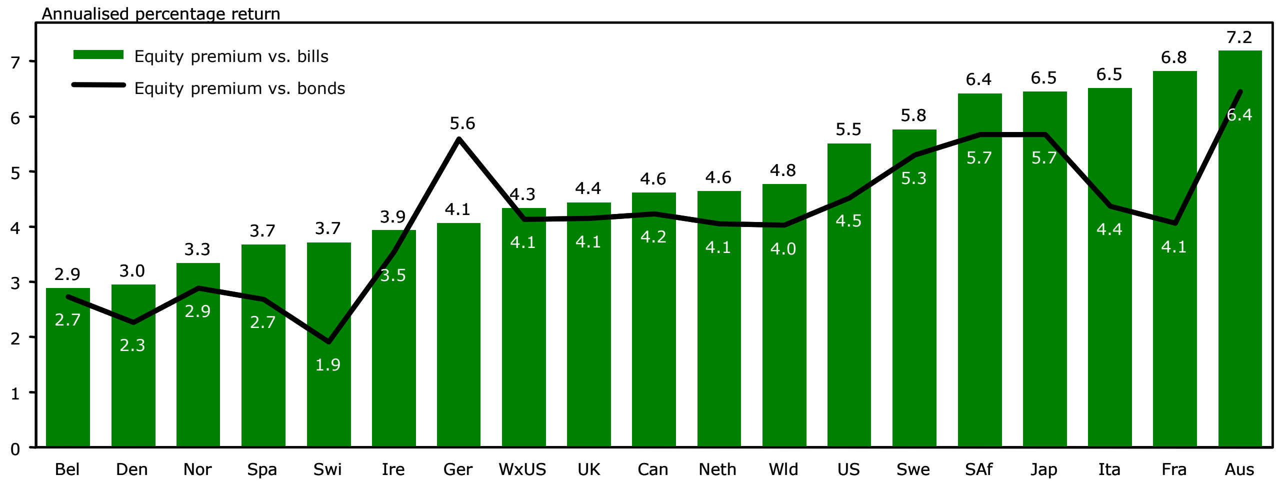
Figure 7: Impact of reinvested dividends on cumulative UK & US equity local-currency returns, 1900—2007



Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, chart 18

- Figure 8 shows the annualised (geometric) equity risk premia realised over the last 108 years.

Figure 8: Worldwide annualised equity risk premia relative to bonds and bills, 1900—2007



Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, chart 20

- The equity risk premium is the difference in performance between equities and bills (or bonds). As can be seen in Figure 8, from 1900–2007 the annualised equity risk premium relative to bills was 5.5% for the US, 4.4% for the UK, and 4.8% for the world index—somewhat lower than was previously believed.
- The authors' latest research, just published in 2008, decomposes historical returns into four components. They are the historical dividend yield, dividend growth, re-rating, and real currency movements. Chapter 2 of the *Yearbook* provides a breakdown of these components for all 17 countries and the world index.
- Drawing on their analysis, the London Business School team estimate that a plausible, forward-looking risk premium for the world's major markets would be around 3–3½% relative to bills on a geometric mean basis. The corresponding arithmetic mean risk premium is around 5% (references are at the end of this synopsis).

Overview of Chapter 3: Momentum in the Stock Market

Momentum, or the tendency for stock returns to trend in the same direction, is a major puzzle. In well-functioning markets, it should not be possible to make money from simply buying past winners and selling past losers. Yet Chapter 3 provides extensive evidence, across time and markets, that momentum profits have been large and pervasive. This evidence comes both from previous studies and from unique new London Business School research.

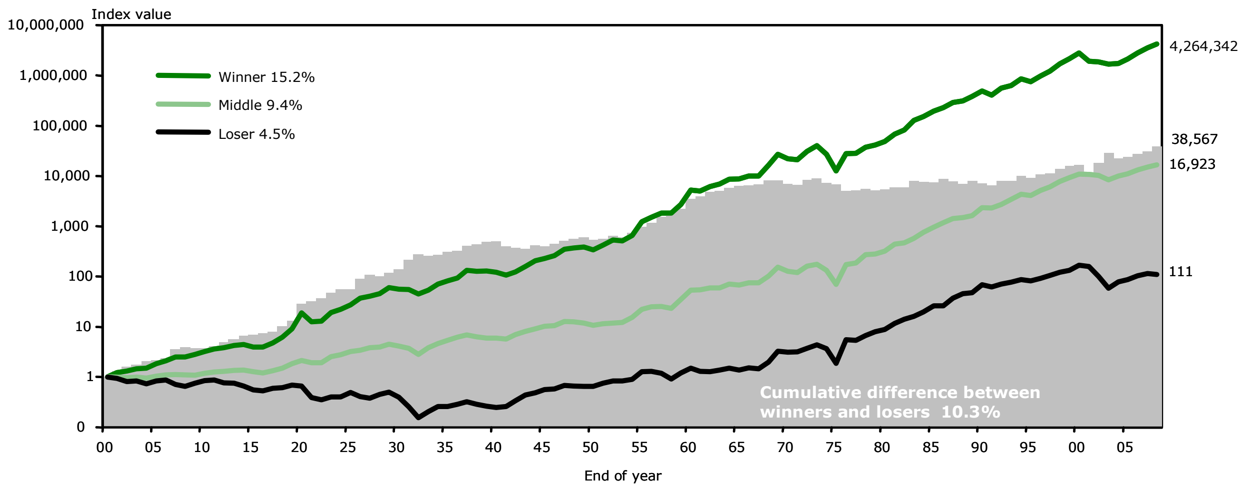
Momentum matters because most investors have styles that favour, or conflict, with momentum. Those "following" momentum include many hedge funds, quant strategies and growth investors. Practices like letting winners run or cutting losses also implicitly play to momentum. However, value investors, small-cap funds and contrarians tend to suffer from momentum. Whatever their style, momentum is highly relevant to all investors.

Pure momentum strategies involve ranking stocks into winners and losers based on past returns over a *ranking period*. One then buys the winners and short-sells the losers, over a *holding period*. To ensure implementability, there is usually a *wait period* before investing. Strategies are thus described as "**r**/**w**/**h**". For example, a 12/1/1 strategy **r**anks returns over the past 12 months, **w**aits 1 month, and then **h**olds for 1 month until rebalancing.

Key findings of Chapter 3 include:

- Winners (defined as the top 20% past returns) beat losers (bottom 20%) by 10.8% per year across the entire UK equity market from 1956–2007 (the period for which comprehensive data is available).
- With equal, rather than capitalisation, weights, the difference was even greater at 12.0%. And with winners/losers defined as the top/bottom 10% (rather than 20%), the gap was greater still.
- The winner-minus-loser (WML) gap was smaller at 7.0% p.a. when investment was limited to just the Top 100 UK stocks. However, within this group of highly liquid stocks, the strategy was much easier to implement.
- In the longest momentum study ever conducted, covering the Top 100 stocks over 108 years, Figure 9 shows that winners beat losers by 10.3% per year. £1 invested at start-1900 in the winner portfolio would have grown to more than £4¼ million (15.2% p.a.). £1 invested in the losers would have grown to only £111 (4.5% p.a.).

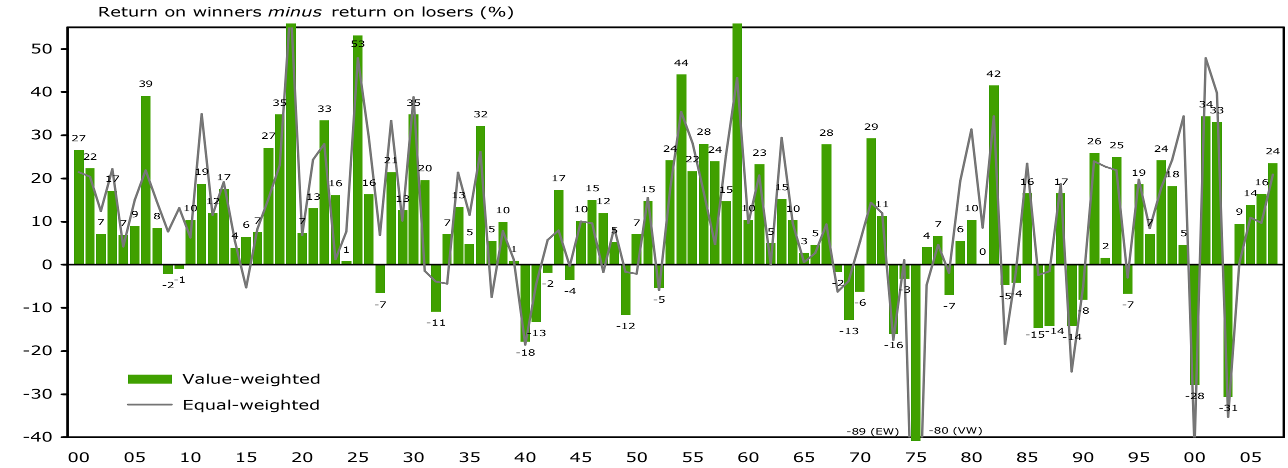
Figure 9: Annual value-weighted momentum portfolio returns for the Top 100 UK equities 1900-2007



This chart shows value-weighted returns for winner and loser portfolios among the Top 100 equities, defined with breakpoints at the 20th and 80th percentiles. The shaded area is the cumulative difference between winners and losers, and measures the value of a long-short WML portfolio. The momentum process followed here is a 12/1/1 strategy.
Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, chart 26

- Stock market research always needs a holdout period—to check whether the effect persists over a period other than the one used to "discover" it. The 108-year study uses the longest holdout period ever—56 years of virgin data from 1900–55, collected especially for *GIRY*. Momentum proved even stronger over this holdout period.
- Momentum returns were remarkably robust to the choice of ranking period, holding period, weighting scheme, definition of winners, and choice of sample. All strategies achieved a high level of statistical significance.
- However, there are important caveats. First, as Figure 10 shows, there are numerous periods when winners underperform losers, sometimes by a dramatic margin. Pure momentum plays are not for the faint hearted.

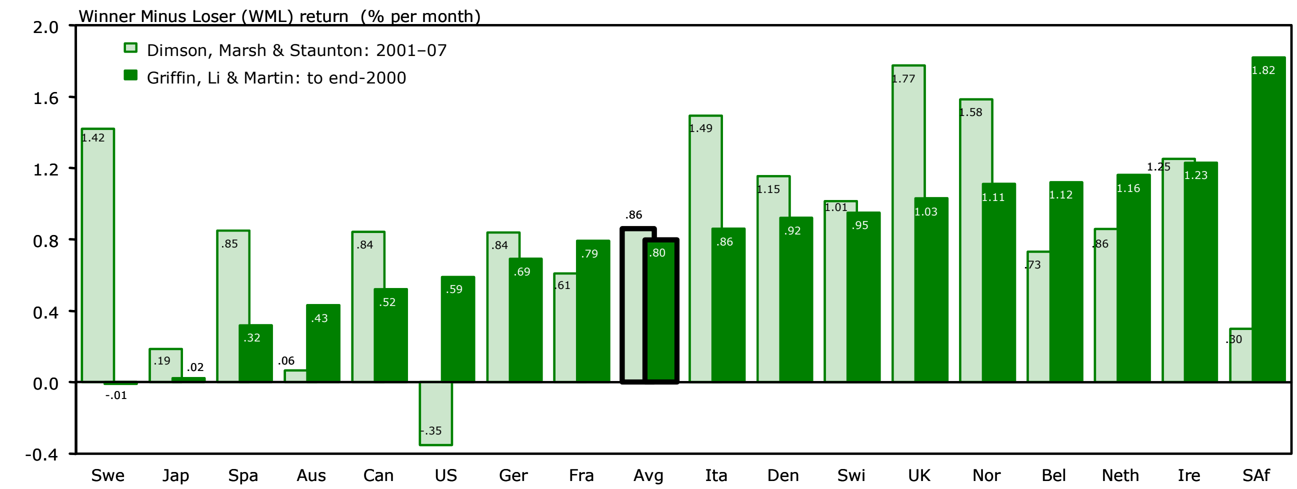
Figure 10: Return on winners minus losers for Top 100 UK equities, annually 1900-2007



This chart shows value-weighted WML returns based on portfolios with momentum breakpoints at the 20th and 80th percentiles. The momentum process followed here is a 12/1/1 strategy. Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, chart 27

- Second, turnover can be very high, especially with monthly rebalancing. For the 12/1/1 strategy, winner and loser turnover averages 31% and 33% per month. Transactions costs can seriously dent performance.
- Chapter 3 also presents up-to-date evidence on worldwide momentum covering 33 years for most *GIRY* markets. The dark bars in Figure 11 show that the average WML return in the 17 *GIRY* countries was 0.80% per month up to end-2000, as estimated by Griffin, Ji, and Martin (*Journal of Finance*, 2003).
- The light bars in Figure 11 show the equivalent returns from 2001–07. Over this "holdout" period, the average monthly return was even higher at 0.86%. The US was the only market for which WML returns were negative.

Figure 11: Monthly momentum returns in 17 stock markets, up to 2000 and 2001–2007



This chart shows the winner-minus-loser (WML) return from a 6/1/6 momentum strategy, following the methodology described in Griffin, Ji and Martin (2003). The breakpoints are the 20th and 80th percentiles. The Griffin, Ji and Martin sample period begins in 1975 (or, for a few countries, a different year) and ends in 2000. The subsequent period runs from start-2001 to end-2007. Data is from the LSPD (for the UK) and Datastream (other countries). Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, chart 29, Griffin, Ji and Martin (2003) and Thomson Financial Datastream.

The authors, Elroy Dimson, Paul Marsh and Mike Staunton of London Business School, conclude: "The momentum effect, both in the UK and globally, has been pervasive and persistent. Though costly to implement on a stand-alone basis, all investors need to be acutely aware of momentum. Even if they do not set out to exploit it, momentum is likely to be an important determinant of their investment performance."

Overview of Chapter 4: Momentum in Real Estate

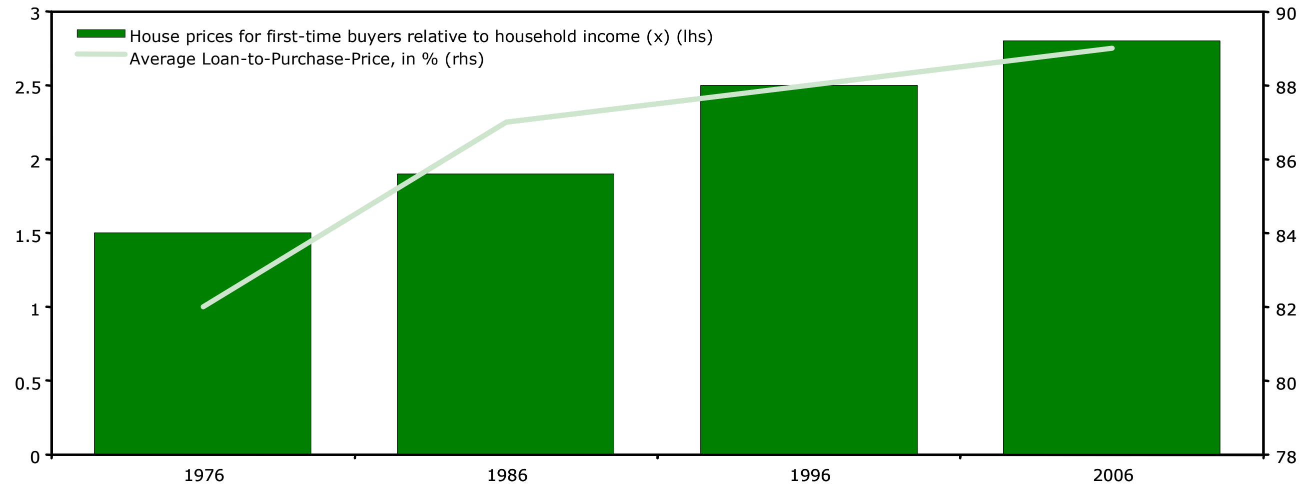
Momentum has become an important factor in many markets. In addition to equities, the *Yearbook* looks at other asset classes. An illiquid asset, like real estate, is more vulnerable to price momentum because of the time delays between transactions. In Chapter 4, Rolf Elgeti discusses momentum in real estate.

Elgeti's starting point is that investors are drawn to assets that go up in price, and that momentum is driven not only by buyers and sellers, but also by third parties who intervene in the market and affect supply and demand. This includes:

- Mortgage banks, which behave pro-cyclically, strengthening momentum in real estate – in either direction.
- First-time buyers, the number of whom rises in a buoyant market, even though affordability may actually worsen. Again, this reinforces momentum, creating a gradual structural change in the demand-pull of the market.
- House builders, who might be expected to increase the housing supply when prices rise and to stop when prices fall, but whose response can be untimely and with considerable regional differences.

In Figure 12, Elgeti examines the US market, noting how a small change in banking policy can influence what people pay for their first house. Over the past 30 years, US mortgage banks increased lending to first-time buyers from an average 82% (in 1976) to 89% (in 2006). The 7 percentage points of increased leverage resulted in first-time buyers paying much more: about 2.75x their income in 2006, versus about 1.5x their annual income in 1976.

Figure 12: Affordability and LTVs for first-time buyers in the US



Source: Federal Reserve Bank of Chicago

If banks were acting counter-cyclically, they would argue, "When houses cost about 1.5 times income we lent 82%; now they cost nearly 3 times their income risk is higher, so we should lend less." But the opposite has been the case, and banks raised their loan-to-purchase-price ratios, despite houses becoming not only more expensive but less affordable. Banks' behaviour thereby accentuates momentum in real estate prices.

Elgeti also offers evidence to support his claims in relation to first-time buyers and house-builders, drawing evidence from a number of countries. He notes similar momentum effects that may be found in other markets, such as commodities.

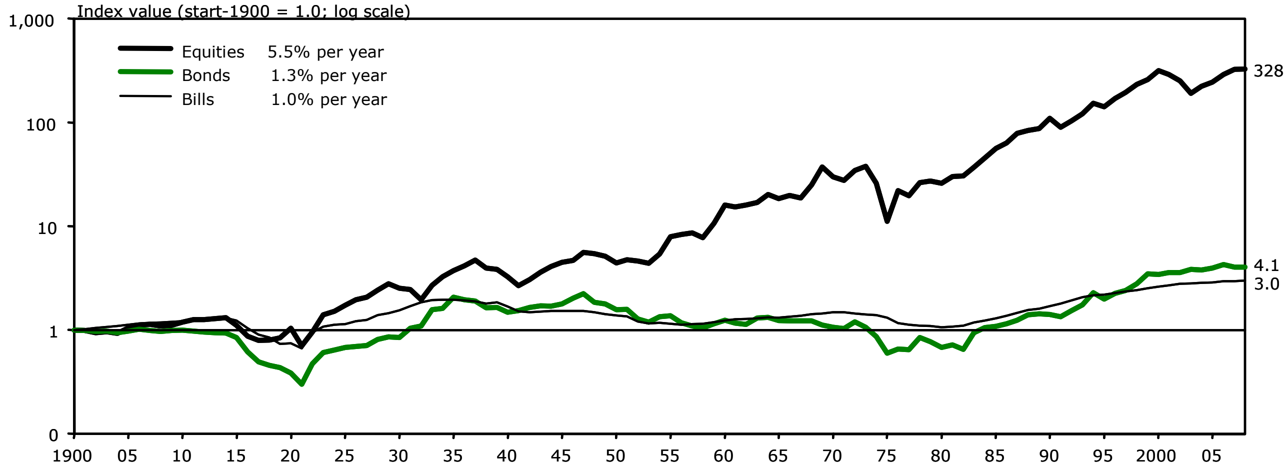
Overview of Chapters 5–24: Individual Markets

These chapters present detailed in-depth statistical analysis of the performance of each of five asset classes in each of the 17 *GIRY* countries over the full 108-year history from 1900–2007. Chapter 5 provides an introduction to the country Chapters. Chapters 6–22 then cover each country in turn, while Chapters 23 and 24 provide equivalent statistics for the combined world ex-US and world indices. Each country chapter contains:

- An introductory section describing the authors' data sources.
- A summary table, providing an overview of asset returns and risk premia for that country.

- Charts portraying both the cumulative returns, and the year-to-year returns for each country in both nominal terms (Figure 4 above) and real terms (Figure 13).

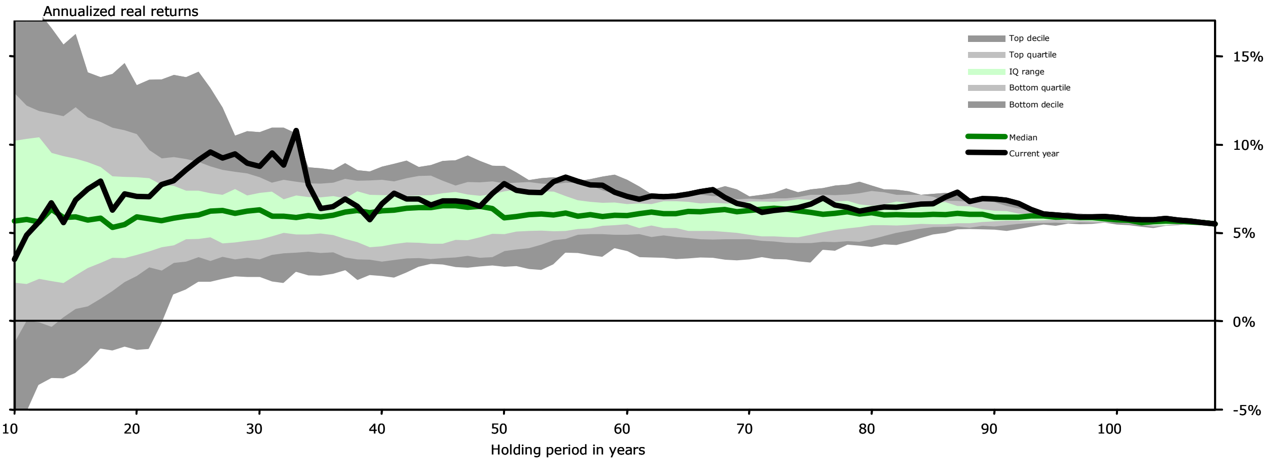
Figure 13: Cumulative returns on UK asset classes in real terms, 1900—2007



Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, charts 13 and 117

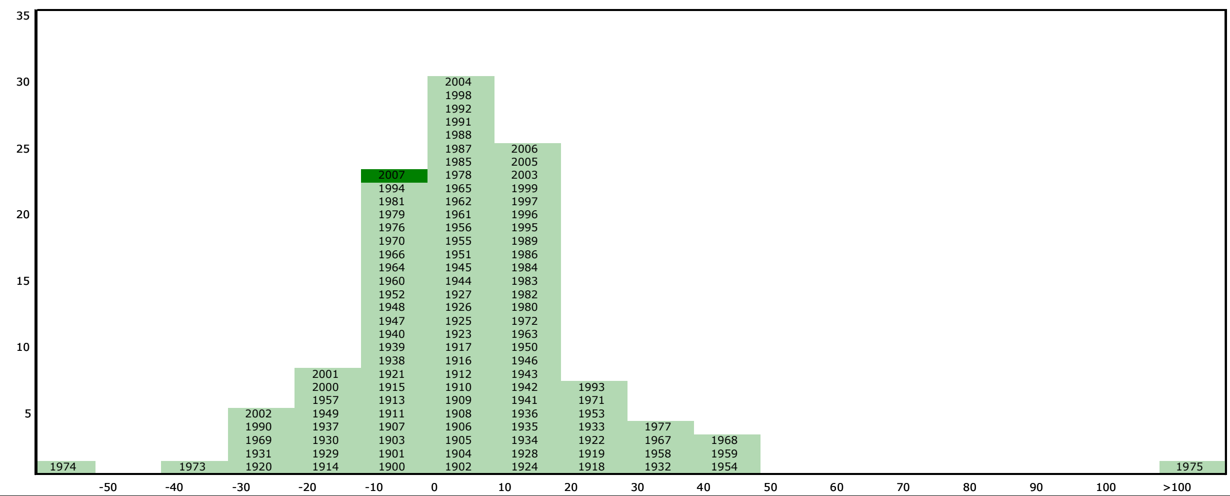
- Charts depicting the dispersion of returns over investment horizons of between 10 and 108 years (Figure 14).
- Histograms showing the distribution of annual risk premia (Figure 15)

Figure 14: Dispersion of real returns on UK equities over periods of 10-108 years



Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, charts 119

Figure 15: UK equity risk premium relative to bills



Source: ABN AMRO/LBS Global Investment Returns Yearbook 2008, charts 121

- Tables of annualised return "triangles". The tables present returns over individual and multiple decades, and returns to date from an initial investment made at the start of 1900, 1910, and so on to the start of 2000. They cover each of the four asset categories in real terms (as well as real equity capital gains); the three risk premia relating to equities, bonds and bills; the real and nominal exchange rates against the dollar; and the annualised inflation rate, over all periods of 1, 2,...,10 decades.
- Tables listing index levels and returns for all the asset series in nominal and real terms, with index values provided at intervals of one decade from 1900 to 2000, and thereafter on an annual basis.

Further information

Further information on long run rates of return is provided in Elroy Dimson, Paul Marsh and Mike Staunton's book, *Triumph of the Optimists* (published by Princeton University Press, 2002). The authors have also analysed the equity risk premium, the long-run risks of equity investment, international diversification and many other strategic issues in investment.

Their most recent research, exploring more aspects of the Yearbook data, is published in *Financial Analysts Journal*, *Journal of Portfolio Management*, and *Journal of Applied Corporate Finance*. Their latest paper, The Worldwide Equity Premium: A Smaller Puzzle, is in Rajnish Mehra (Ed.) *Handbook of the Equity Risk Premium* (Elsevier, 2008). It is available at http://papers.ssrn.com/id=891620 (free download).

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Earnings Growth: The Two Percent Dilution

William J. Bernstein and Robert D. Arnott

Two important concepts played a key role in the bull market of the 1990s. Both represent fundamental flaws in logic. Both are demonstrably untrue. First, many investors believed that earnings could grow faster than the macroeconomy. In fact, earnings must grow slower than GDP because the growth of existing enterprises contributes only part of GDP growth; the role of entrepreneurial capitalism, the creation of new enterprises, is a key driver of GDP growth, and it does not contribute to the growth in earnings and dividends of existing enterprises. During the 20th century, growth in stock prices and dividends was 2 percent less than underlying macroeconomic growth. Second, many investors believed that stock buybacks would permit earnings to grow faster than GDP. The important metric is not the volume of buybacks, however, but net buybacks—stock buybacks less new share issuance, whether in existing enterprises or through IPOs. We demonstrate, using two methodologies, that during the 20th century, new share issuance in many nations almost always exceeded stock buybacks by an average of 2 percent or more a year.

The bull market of the 1990s was largely built on a foundation of two immense misconceptions. Whether their originators were knaves or fools is immaterial; the errors themselves were, and still are, important. Investors were told the following:

1. With a technology revolution and a "new paradigm" of low payout ratios and internal reinvestment, earnings will grow faster than ever before. Real growth of 5 percent will be easy to achieve.

Like the myth of Santa Claus, this story is highly agreeable but is supported by neither observable current evidence nor history.

2. When earnings are not distributed as dividends and not reinvested into stellar growth opportunities, they are distributed back to shareholders in the form of stock buybacks, which are a vastly preferable way of distributing company resources to the shareholders from a tax perspective.

William J. Bernstein is principal at Efficient Frontier Advisors, LLC, Eastford, Connecticut. Robert D. Arnott is chairman of First Quadrant, LP, and Research Affiliates, LLC, Pasadena, California.

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True, except that over the long term, net buybacks (that is, buybacks minus new issuance and options) have been reliably negative.

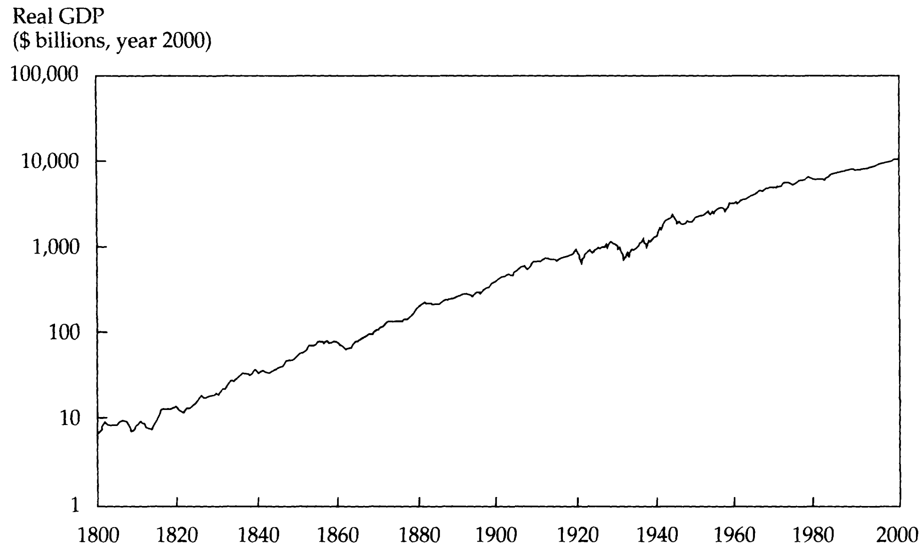
The vast majority of the institutional investing community has believed these untruths and has acted accordingly. Whether these tales are lies or merely errors, our implied indictment of these misconceptions is a serious one—demanding data. This article examines some of the data.

Big Lie #1: Rapid Earnings Growth

In the past two centuries, common stocks have provided a sizable risk premium to U.S. investors: For the 200 years from 1802 through 2001 (inclusive), the returns for stocks, bonds, and bills were, respectively, 8.42 percent, 4.88 percent, and 4.21 percent. In the most simplistic terms, the reason is obvious: A bill or a bond is a promise to pay interest and principal, and as such, its upside is sharply limited. Shares of common stock, however, are a claim on the future dividend stream of the nation's businesses. While the investor in fixed-income securities is receiving a modest fixed trickle from low-risk securities, the shareholder is the beneficiary of the ever-increasing fruits of innovation-driven economic growth.

Viewed over the decades, the powerful U.S. economic engine has produced remarkably steady growth. **Figure 1** plots the real GDP of the United States since 1800 as reported by the U.S. Department

Figure 1. Real U.S. GDP Growth, 1800–2000



of Commerce. From that year to 2000, the economy as measured by real GDP, averaging about 3.7 percent growth a year, has grown a thousandfold. The long-term uniformity of economic growth demonstrated in Figure 1 is both a blessing and a curse. To know that real U.S. GDP doubles every 20 years is reassuring. But it is also a dire warning to those predicting a rapid acceleration of economic growth from the computer and Internet revolutions. Such extrapolations of technology-driven increased growth are painfully oblivious to the broad sweep of scientific and financial history, in which innovation and change are constant and are neither new to the current generation nor unique.

The impact of recent advances in computer science pales in comparison with the technological explosion that occurred between 1820 and 1855. This earlier era saw the deepest and most far reaching technology-driven changes in everyday existence ever seen in human history. The changes profoundly affected the lives of those from the top to the bottom of the social fabric in ways that can scarcely be imagined today. At a stroke, the speed of transportation increased tenfold. Before 1820, people, goods, and information could not move faster than the speed of the horse. Within a generation, journeys that had previously taken weeks and months involved an order of magnitude less time, expense, danger, and discomfort. Moreover, important information that previously required the same long journeys could now be transmitted instantaneously.

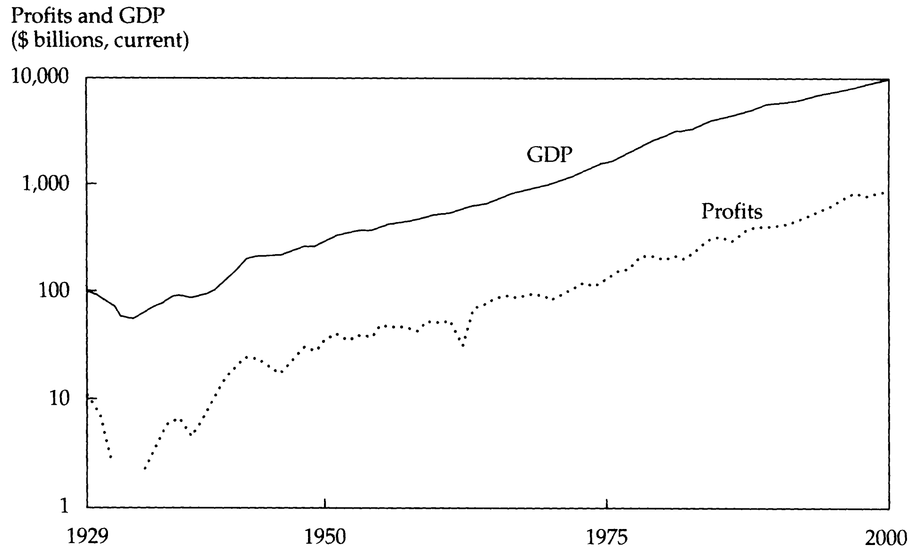
The average inhabitant of 1820 would have found the world 35 years later incomprehensible, whereas a person transported from 1967 to 2002 would have little trouble understanding the intervening changes in everyday life. From 1820 to 1855, the U.S. economy grew sixfold, four times the growth seen in the "tech revolution" of the past 35 years. More importantly, a close look at the right edge of Figure 1—the last decade of the 20th century—shows that the acceleration in growth during the "new paradigm" of the tech revolution of the 1990s was negligible when measured against the broad sweep of history.

The relatively uniform increase in GDP shown in Figure 1 suggests that corporate profits experienced a similar uniformity in growth. And, indeed, **Figure 2** demonstrates that, except for the Great Depression, during which overall corporate profits briefly disappeared, nominal aggregate corporate earnings growth has tracked nominal GDP growth, with corporate earnings remaining constant at 8–10 percent of GDP since 1929. The trend growth in corporate profits shown in Figure 2 is nearly identical, within a remarkable 20 bps, to the trend growth in GDP.[1]

Cannot stock prices also, then, be assumed to grow at the same rate as GDP? After all, a direct relationship between aggregate corporate profits and GDP has existed since at least 1929. The problem with this assumption is that per share earnings and dividends keep up with GDP *only if* no new shares are created. Entrepreneurial capitalism, however, creates a "dilution effect" through new enterprises and new stock in existing enterprises. So, per share earnings and dividends grow considerably slower than the economy.

In fact, since 1871, real stock prices have grown at 2.48 percent a year—versus 3.45 percent a year for GDP. Despite rising price–earnings ratios, we observe a "slippage" of 97 bps a year between stock

Figure 2. Nominal U.S. Corporate Profits and GDP, 1929–2000



prices and GDP. The true degree of slippage is much higher because almost half of the 2.48 percent rise in real stock prices after 1871 came from a substantial upward revaluation. The highly illiquid industrial stocks of the post–Civil War period rarely sold at more than 10 times earnings; often, they sold for multiples as low as 3 or 4 times earnings. These closely held industrial stocks gave way to instantly and cheaply tradable common shares, which today are priced nearly an order of magnitude more dearly.

Until the bull market of 1982–1999, the average stock was valued at 12–16 times earnings and 20–25 years' worth of dividends. By the peak of the bull market, both figures had tripled. Although the bull market was compressed into 18 years of the total period under discussion, this tripling of valuation levels was worth almost 100 bps a year—even when amortized over the full 130-year span. Thus, per share earnings and dividends grew 2 percent a year slower than the macroeconomy. If aggregate earnings and dividends grew as quickly as the economy while per share earnings and dividends were growing at an average of 2 percent a year slower, then shareholders have seen a slippage or dilution of 2 percent a year in the per share growth of earnings and dividends.

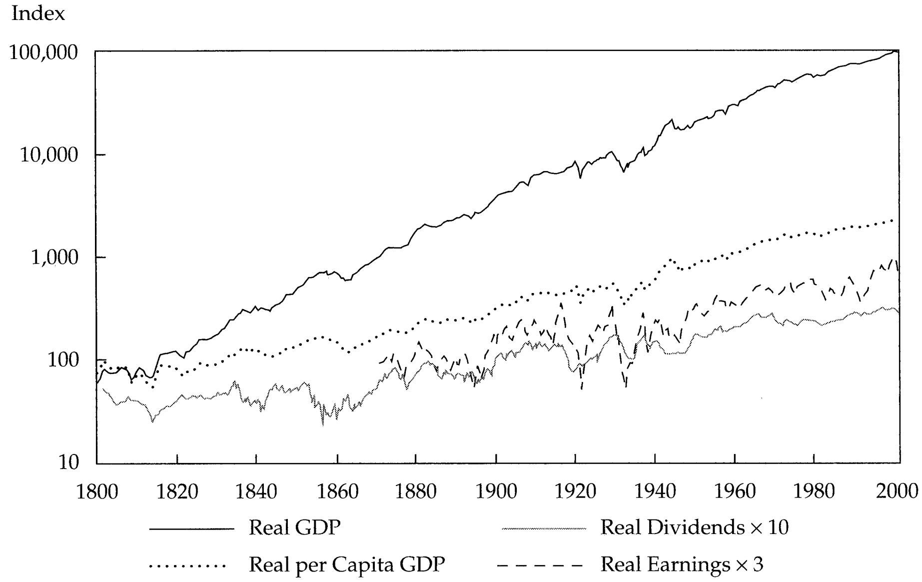
The dilution is the result of the net creation of shares as existing and new companies capitalize their businesses with equity. An often overlooked, but unsurprising, fact is that more than half of aggregate economic growth comes from new ideas and the creation of new enterprises, not from the growth of established enterprises. Stock investments can participate only in the growth of established businesses; venture capital participates only in the new businesses. The same investment capital cannot be simultaneously invested in both.

"Intrapreneurial capitalism," or the creation of new enterprises within existing companies, is a sound engine for economic growth, but it does not supplant the creation of new enterprises. Nor does it reduce the 2 percent gap between economic growth and earnings and dividend growth.

Note also that earnings and dividends grow at a pace very similar to that of per capita GDP (with some slippage associated with the "entrepreneurial" stock rewards to management). Consider that per capita GDP is a measure of productivity (with slight differences for changes in the work force) and aggregate economic wealth per capita can grow only in close alignment with productivity growth. Productivity growth is also the key driver of per capita income and of per share earnings and dividends. Accordingly, no one should be surprised that *per capita GDP, per capita income, per share earnings, and per share dividends—all grow in reasonably close proportion to productivity growth.*

If earnings and dividends grow faster than productivity, the result is a migration from return on labor to return on capital; if earnings and dividends grow more slowly, by a margin larger than the stock awards to management, then the economy migrates from rewarding capital to rewarding labor. Either way, such a change in the orientation of the economy cannot continue indefinitely. **Figure 3** demonstrates the close link between the growth of real corporate earnings and dividends and the growth of real per capita GDP; note that all of these measures exhibit growth far below the growth of real GDP.

Figure 3. Link of U.S. Earnings and Dividends to Economic Growth, 1802–2001



Note: Real GDP, real per capita GDP, and real stock prices were all constructed so that the series are on a common basis of January 1802 = 100.

A Global Laboratory

Is the United States unique? For an answer, we compared dividend growth, price growth, and total return with data on GDP growth and per capita GDP growth for the 16 countries covered by Dimson, Marsh, and Staunton (2002) spanning the 20th century.[2] The GDP data came from Maddison's (1995, 2001) world GDP survey for 1900–1998 and International Finance Corporation data for 1998–2000. The interrelationships of the data shown in **Table 1** are complex:

- The first column contains the real return (in U.S. dollars) of each national stock market.
- The second is real per share dividend growth.
- The third is real aggregate GDP growth for each nation (measured in U.S. dollars).
- The fifth is growth of real per capita GDP (measured in U.S. dollars).
- Thus, the fourth column measures the gap between growth in per share dividends and aggregate GDP—an excellent measure of the leakage that occurs between macroeconomic growth and the growth of stock prices.
- The last column represents the gap between the growth in per share dividends and per capita GDP.

For the full 16-nation sample in Table 1, the average gap between dividend growth and the growth in aggregate GDP is a startling 3.3 percent. The annual shortfall between dividend growth and per capita GDP growth is still 2.4 percent.

The 20th century was not without turmoil. Therefore, we divided the 16 nations into two groups according to the degree of devastation visited upon them by the era's calamities. The first group suffered substantial destruction of the countries' productive physical capital at least once during the century; the second group did not.

The nine nations in Group 1—Belgium, Denmark, France, Germany, Italy, Japan, the Netherlands, Spain, and the United Kingdom—were devastated by one or both of the two world wars or by civil war. The remaining seven—Australia, Canada, Ireland, South Africa, Sweden, Switzerland, and the United States—suffered relatively little direct damage. Even in this fortunate group, Table 1 shows dividend growth that is 2.3 percent less than GDP growth and 1.1 percent less than per capita GDP growth, on average. These gaps are close to the 2.7 percent and 1.4 percent figures observed in the United States during the 20th century.

The data for nations that were devastated during World Wars I and II and the Spanish Civil War are even more striking: The good news is that the economies in Group 1 repaired the devastations wrought by the 20th century; they enjoyed overall GDP growth and per capita GDP growth that rivaled the growth of the less-scarred Group 2 nations. The bad news is that the same cannot be said for per share equity performance; a 4.1 percent slippage occurred between the growth of their economies and per share corporate payouts. The

Table 1. Dilution of GDP Growth as It Flows Through to Dividend Growth: 16 Countries, 1900–2000

Country	Constituents of Real Stock Returns: Real Return	Constituents of Real Stock Returns: Dividend Growth	Real GDP Growth	Dilution in Dividend Growth (vis-à-vis GDP growth)	Real per Capita GDP Growth	Dilution in Dividend Growth (vis-à-vis per capita GDP growth)
Australia	7.5%	0.9%	3.3%	–2.4%	1.6%	–0.7%
Belgium	2.5	–1.7	2.2	–3.9	1.8	–3.5
Canada	6.4	0.3	4.0	–3.7	2.2	–1.9
Denmark	4.6	–1.9	2.7	–4.6	2.0	–3.9
France	3.6	–1.1	2.2	–3.3	1.8	–2.9
Germany	3.6	–1.3	2.6	–3.9	1.6	–2.9
Ireland	4.8	–0.8	2.3	–3.1	2.1	–2.9
Italy	2.7	–2.2	2.8	–5.0	2.2	–4.4
Japan	4.2	–3.3	4.2	–7.5	3.1	–6.4
Netherlands	5.8	–0.5	2.8	–3.3	1.7	–2.2
South Africa	6.8	1.5	3.4	–1.9	1.2	0.3
Spain	3.6	–0.8	2.7	–3.5	1.9	–2.7
Sweden	7.6	2.3	2.5	–0.2	2.0	0.3
Switzerland	5.0	0.1	2.5	–2.4	1.7	–1.6
United Kingdom	5.8	0.4	1.9	–1.5	1.4	–1.0
United States	6.7	0.6	3.3	–2.7	2.0	–1.4
Full-sample average	5.1	–0.5	2.8	–3.3	1.9	–2.4
War-torn Group 1 average	4.0	–1.4	2.7	–4.1	1.9	–3.3
Non-war-torn Group 2 average	6.4	0.7	3.0	–2.3	1.8	–1.1

creation of new enterprises in the wake of war was an even more important engine for economic recovery than in the Group 2 nations.

Thus, in Group 2 "normal nations" (i.e., those untroubled by war, political instability, and government confiscation of wealth), the natural ongoing capitalization of new technologies apparently produces a net dilution of outstanding shares of slightly more than 2 percent a year. The Group 1 nations scarred badly by war represent a more fascinating phenomenon; they can be thought of as experiments of nature in which physical capital is devastated and must be rebuilt. Fortunately, destroying a nation's intellectual, cultural, and human capital is much harder than destroying its economy; within little more than a generation, the GDP and per capita GDP of war-torn nations catch up with, and in some cases surpass, those of the undamaged nations. Unfortunately, the effort requires a high rate of equity recapitalization, which is reflected in the substantial dilution seen in Table 1 for the war-torn countries. This recapitalization savages existing shareholders.

In short, the U.S. experience was not unique. Around the world, every one of these countries except Sweden experienced dividend growth sharply slower than GDP growth, and only two countries experienced dividend growth even slightly faster than per capita GDP growth. The U.S. experience was better than most and was similar to that of the other nations that were not devastated by war.

The data for the individual countries in Table 1 show that the average real growth in dividends was negative for most countries. It also shows that dilution of GDP growth (the fourth column) was substantial for all the countries studied and that dilution of per capita GDP growth (the last column) was substantial for most countries but fit dividend growth with much less "noise" than did the dilution of overall GDP growth.

This analysis has disturbing implications for "paradigmistas" convinced of the revolutionary nature of biotechnology, Internet, and telecommunications/broadband companies. A rapid rate of technological change may, in effect, turn "normal" Group 2 nations into strife-torn Group 1 nations: An increased rate of obsolescence effectively destroys the economic value of plant and equipment as surely as bombs and bullets, with the resultant dilution of per share payouts happening much faster than the technology-driven acceleration of economic growth—if such acceleration exists. How many of the paradigmistas truly believe that the tech revolution will benefit the shareholders of existing enterprises remotely as much as it can benefit the entrepreneurs creating the new enterprises that make up the vanguard of this revolution?

Whatever the true nature of the interaction of technological progress and per share earnings, dividends, and prices, it will come as an unpleasant surprise to many that even in the Group 2 nations, average real per share dividend growth was only 0.66 percent a year (rounded in Table 1 to 0.7 percent); for the war-torn Group 1 nations, it was disturbingly negative.

In short, the equity investor in a nation blessed by prolonged peace cannot expect a real return greatly in excess of the much-maligned dividend yield; the investor cannot expect to be rescued by more rapid economic growth. Not only is outsized economic growth unlikely to occur, but even if it does, its benefits will be more than offset by the dilution of the existing investor's ownership interest by technology-driven increased capital needs.

Big Lie #2: Stock Buybacks

Stock buybacks are attractive to companies and beneficial to investors. They are a tax-advantaged means of providing a return on shareholder capital and preferable to dividends, which are taxed twice. Buybacks have enormous appeal. But contrary to popular belief, they did not occur in any meaningful way in the 1990s.

To support this contention, we begin with a remarkably simple measure of slippage in per share earnings and dividend growth: the ratio of the proportionate increase in market capitalization to the proportionate increase in stock price. For example, if over a given period, the market cap increases by a factor of 10 and the cap-weighted price index increases by a factor of 5, a 100 percent net share issuance has taken place in the interim. Formally,

$$\text{Net dilution} = \left(\frac{1+c}{1+r}\right) - 1,$$

where c is capitalization increase and r is price return. This relationship has the advantage of factoring out valuation changes, which are embedded in both the numerator and denominator, and neutralizing the impact of stock splits. Furthermore, it holds only for universal market indexes, such as the CRSP 1–10 or the Wilshire 5000, because less inclusive indexes can vary the ratio simply by adding or dropping securities. **Figure 4** contains plots of the total market cap and price indexes of the CRSP 1–10 beginning at the end of 1925.

The CRSP data contained NYSE-listed stocks until 1962. Even the CRSP data, however, can involve adding securities: CRSP added the Amex stocks in July 1962 and the Nasdaq stocks in July 1972, which created artificial discontinuities on those dates. The adjustment for these shifts is evident in **Figure 5**, for which we held the dilution ratio constant during the two months in question.[3] Note how market cap slowly and gradually pulls away from market price. The gap does not look large in Figure 4, but by the end of 2001, the cap index had grown 5.49 times larger than the price index, suggesting that for every share of stock extant in 1926, 5.49 shares existed in late 2001. The implication is that net new share issuance occurred at an annualized rate of 2.3 percent a year. Note that this rate is identical to the average dilution for non-war-torn countries during the 20th century given in Table 1. To give a better idea of how this dilution has proceeded over the past 75 years, Figure 5 provides a dilution index, defined as the ratio of capitalization growth to price index growth.

Figure 4. CRSP 1–10 Market Cap and Price Indexes, 31 December 1925–June 2002

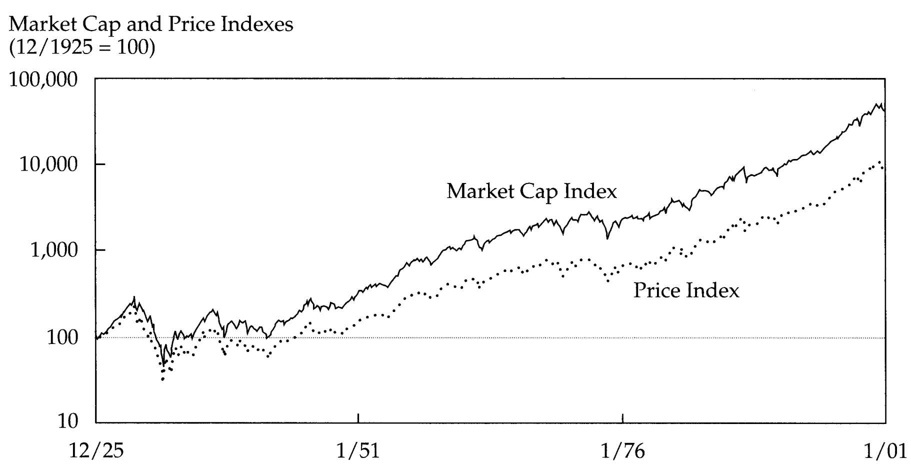


Figure 5. Cumulative Excess Growth of Market Cap Relative to Price Index, 31 December 1925 through June 2002

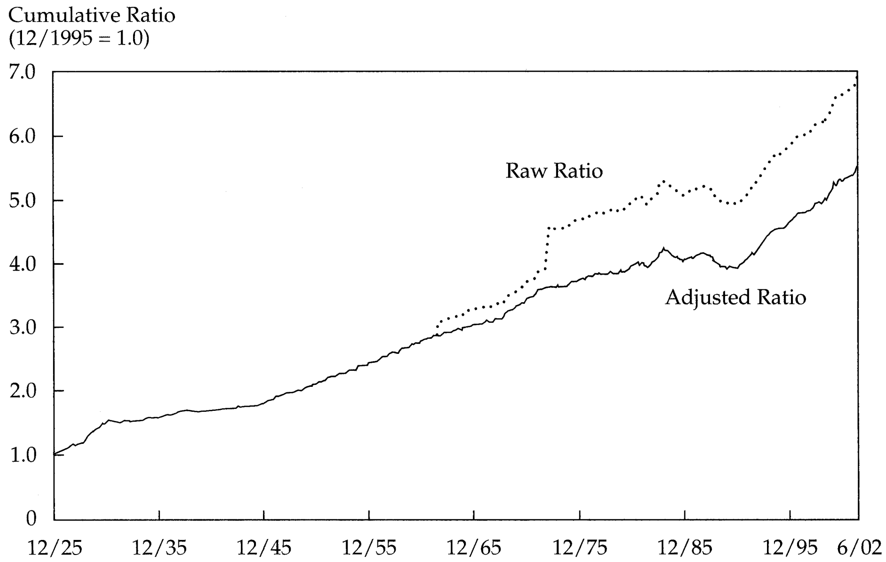
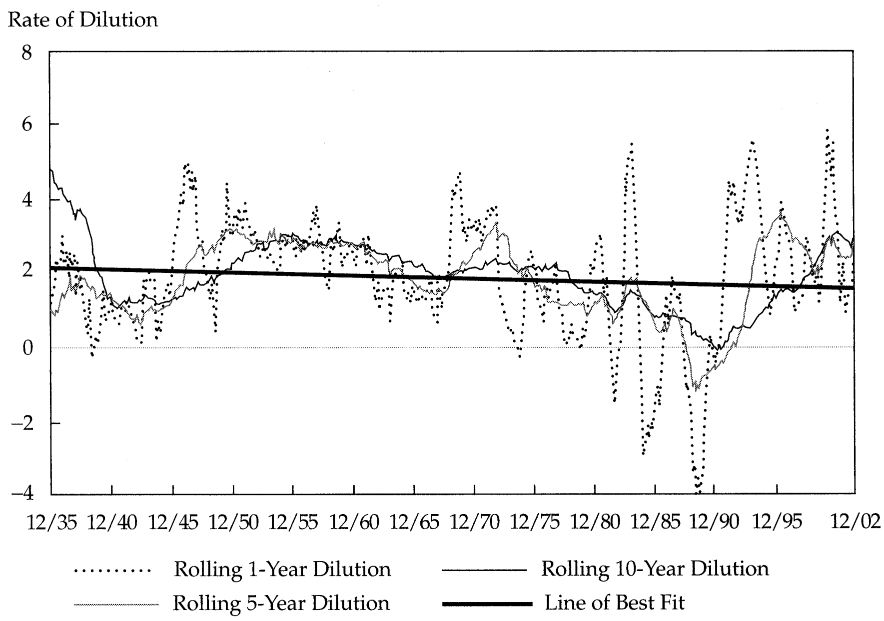


Figure 5 traces the growth in the ratio of the capitalization of the CRSP 1–10 Index as compared with the market-value-weighted price appreciation of these same stocks. The fact that this line rises nearly monotonically shows clearly that new-share issuance almost always sharply exceeds stock buybacks. The notable exception occurred in the late 1980s, when buybacks modestly outpaced new share issuance (evident from the fact that the line falls slightly during these "Milken years"). This development probably played a key role in precipitating the popular illusion that buybacks were replacing dividends. For a time, they did. But that stock buybacks were an important force in the 1990s is simply a myth. And belief in the myth may have been an important force in the bull market of the 1990s.

Figure 6 shows the rolling 1-year, 5-year, and 10-year dilution effect on existing equity shareholders as a consequence of a growth in the aggregate

Figure 6. Annualized Rate of Shareholder Dilution, 31 December 1935 through June 2002



supply of equity shares. Keep in mind that every 1 percent rise in equity capital is a 1 percent rise in market cap in which existing shareholders did not (could not) participate. Aside from the 1980s, this dilution effect on shareholders was essentially never negative—not even on a one-year basis. One can see how the myth of stock buybacks gained traction after the 1980s; even the 10-year average rate of dilution briefly dipped negative in the late 1980s. But then, during the late 1990s, stock buybacks were outstripped by new share issuance at a pace that was only exceeded in the IPO binge of 1926–1930. These conclusions hold true whether one is looking at net new share issuance on a 1-year, 5-year, or 10-year basis.

Those who argue that stock buybacks will allow future earnings growth to exceed GDP growth can draw scant support from history. Investors did see enormous earnings growth, far faster than real economic growth, from 1990 to 2000. But Figure 3 shows how tiny that surge of growth was in the context of 130 years of earnings history. Much of the earnings surge of the 1990s was dubious, at best.

The Eye of the Storm?

The big question today is whether the markets are likely to rebound into a new bull market or have merely been in the eye of the storm. We think the markets are in the eye.

The rapid earnings growth of the 1990s, which many pointed to as "proof" of a new paradigm, had several interesting characteristics:

1. A trough in earnings in the 1990 recession transformed into a peak in earnings in the 2000 bubble. Measuring growth from trough to peak is an obvious error; extrapolating that growth is even worse. This decade covered a large chunk of the careers of most people on Wall Street, many of whom have come to believe that earnings can grow very fast for a very long time. Part of conventional wisdom now is that earnings growth can outstrip macroeconomic growth.
2. Influenced by the new paradigm, analysts frequently ignored write-offs to focus increasingly on operating earnings. This practice is acceptable if write-offs are truly "extraordinary items," but it is not acceptable if write-offs become a recurring annual or biannual event, as was commonplace in the 1990s. Furthermore, what are extraordinary items for a single company are entirely ordinary for the economy as a whole. In some companies and some sectors, write-offs are commonplace. The focus on operating earnings for the broad market averages is misguided at best and deceptive at worst.
3. Those peak earnings of 1999–2000 consisted of three dubious components. The first is an underrecognition of the impact of stock options, which various Wall Street strategists estimated at 10–15 percent of earnings. The second is pension expense (or pension "earnings") based on assumptions of a 9.5 percent return, which were realistic then but are no longer; this factor pumped up earnings by approximately 15 percent at the peak and 20–30 percent from current depressed levels. The third component is Enron-style "earnings management," which various observers have estimated to be 5–10 percent of the peak earnings. (We suspect this percentage will turn out to be conservative.)

If these three sources of earnings overstatement (aggressive pension accounting, failure to expense management stock options, and outright fraud) are removed, the $54 peak earnings per share for the S&P 500 Index in 2000 turn out to be closer to $36. This figure implies normalized earnings a notch lower still. If the normalized earnings for the S&P 500 are in the $30–$36 range, as we suspect is the case, then the market at mid-year 2003 was still at a relatively rich 27–32 times normalized earnings. Using Shiller's (2000) valuation model (real S&P 500 level divided by 10-year average of real reported earnings) confirms this analysis. Shiller's model pegs the current multiple at nearly 30 times normalized earnings in mid-2003.

In principle, several conditions could allow earnings growth to exceed GDP growth. Massive stock buybacks are one. But we have demonstrated that buybacks in the 20th century were far more smoke than fire. Buybacks have been much touted as the basis for sustained earnings growth at unprecedented rates, but they simply do not show up in the data on market capitalization relative to market index price levels. Cross-holdings could also offer an interesting complication. But again, their impact does not show up in the objective shareholder dilution data. We have demonstrated that buybacks and cross-holdings do not yet show any signs of offsetting the historical 2 percent dilution, but the exploration of the possible impact of buybacks and cross-holdings is beyond the scope of this study.

Conclusion

Expected stock returns would be agreeable if dividend growth, and thus price growth, proceeded at the same rate as, or a higher rate than, aggregate economic growth. Unfortunately, dividends do not grow at such a rate: When we compared the Dimson et al. 20th century dividend growth series with aggregate GDP growth, we found that even in nations that were not savaged by the century's tragedies, dividends grew 2.3 percent more slowly, on average, than GDP. Similarly, by measuring the gap between the growth of market cap and share prices in the CRSP database, we found that between 1926 and the present, a 2.3 percent net annual dilution has occurred in the outstanding number of shares in the United States.

Two independent analytical methods point to the same conclusion: In stable nations, a roughly 2 percent net annual creation of new shares—the Two Percent Dilution—leads to a separation between long-term economic growth and long-term growth in dividends per share, earnings per share, and share price.

The markets are probably in the eye of a storm and can expect further turmoil as the rest of the storm passes over. If normalized S&P 500 earnings are \$30–\$36 per share, if payout ratios on those normalized earnings are at the low end of the historical range (implying lower-than-normal future earnings growth), if normal earnings growth is really only about 1 percent a year above inflation, if stock buybacks have been little more than an appealing fairy tale, if the credibility of earnings is at an all-time low, and if demographics suggest Baby Boomer dis-saving in the next 20 years, then we have a problem.

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Notes

1. In calculating "trend growth," we used a loglinear line of best fit to minimize the impact of distortions from an unusually high or low starting or ending date. The loss years of 1932 and 1933 were excluded because of loglinear calculation.
2. The Dimson et al. book is a masterwork. If you do not have a copy, you should.
3. We assumed the dilution factor to be zero in those two months. If a massive stock buyback or a massive new IPO occurred during one of these two months, we may have missed it. But net buybacks or net new share issuance during months in which the "index" saw a major reconstitution would be difficult to measure.

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Measuring the equity risk premium

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Peter Best*

is a senior portfolio manager at Old Mutual Asset Managers in London, where he manages international equities using quantitative models.

Alistair Byrne

is Head of Investment Strategy at AEGON Asset Management in Edinburgh and is also responsible for the firm's quantitative research team. Peter and Alistair have been working on risk premium analysis since 1995, when they were both at Scottish Equitable.

*Old Mutual Asset Managers Limited, 80 Cheapside, London EC2V 6EE, UK.
Tel: +44 20 7332 7558; e-mail: peter.best@omam.co.uk

Abstract We use surveys of economic forecasts to derive a forward-looking estimate of the US equity risk premium (ERP) relative to government bonds. Our ERP measure helps predict short-term relative returns between stocks and bonds. Over the period we studied, low readings of the ERP tended to adjust back to the mean via a rally in the bond market rather than a fall in stock prices. We do not generalise from this result, however, as our sample period is characterised by strong trends of falling inflation and rising stock prices. Our estimate of the expected ERP — averaging just over 2 per cent — is markedly lower than the premium that historical studies show has been realised. Data from the UK paint a similar picture to the US experience.

Keywords: *equity risk premium; survey data; asset allocation*

Introduction

In this paper, we use surveys of consensus economic forecasts to produce a forward-looking estimate of the equity risk premium (ERP) relative to government bonds for the US market. Using this novel data source, our model provides a more realistic estimate of the *ex ante* ERP than assuming that realised returns accurately indicate what investors expected. Furthermore, the ERP offers the potential to be used as the basis of a tactical asset allocation strategy by active investment managers.

We find that our ERP measure shows a tendency to mean revert and helps predict relative returns between US stocks and bonds; high values of the risk premium are associated with above-average short-term equity–bond return spreads. Also, when the ERP is low, the correction typically takes place via a rally in the bond market rather than a fall in stock prices. We need to be cautious in generalising this result, however, as the period we investigate is characterised by strong trends of falling inflation and rising stock prices.

In the sections that follow, we outline our measure of the ERP and describe the underlying data. We then test the power of the measure in predicting relative returns between stocks and bonds and look in detail at what contributes to this. In particular, we look at the process by which extreme values of the series adjust back towards the mean. We also look briefly at UK data to assess the similarity with the US experience.

The equity risk premium

Finance theory holds that stocks are more 'risky' than government bonds — meaning that equity prices are more volatile than bond prices. Investors require higher expected returns in order to invest in the (volatile) stock market than they do to invest in (more stable) bonds. In simple terms, equity returns must offer a 'risk premium' compared with the returns available on bonds and treasury bills. Welch (1999) notes that this equity risk premium 'is perhaps the single most important number in financial economics', with implications for asset allocation decisions and providing a key input into calculations of the appropriate discount rate for evaluating investments.

It is well documented that US stocks have delivered higher returns, on average, than US Treasury bonds. Returns on the stock market have also been more volatile than those earned from bonds. Figures for the period 1900–1999 are shown in Table 1.

Table 1 US stock and bond returns, 1900–1999 (%)

	Stocks	Government bonds
Arithmetic average annual return	12.2	5.0
Standard deviation	20.0	8.1

Source: Dimson *et al*. (2000).

Welch describes the approach of extrapolating the historically realised equity premium as 'the most popular' method of obtaining an estimate of the required ERP. His survey of the views of 226 financial economists yields an average estimate for the ERP relative to treasury bills of about 7 per cent, not far below the figure derived from historical information. Mehra and Prescott (1985) noted that the realised ERP in the US from 1889 to 1978 (6 per cent) was much larger than could be explained by standard models of risk aversion. Implicitly, they make the assumption that the realised figure they measured is a fair estimate of what investors had required. Their paper sparked a search for a solution to the 'equity premium puzzle'.[1]

The view that the realised ERP is a fair estimate of what investors *required*, or expected, however, needs some quite strong assumptions. We must assume the investors hold 'rational expectations' and that the required risk premium is constant. The growing literature on behavioural finance contains many illustrations of investors making decisions that are inconsistent with the traditional notions of rationality used in finance.[2] Furthermore, Fama and French (1989) present plausible arguments and evidence to suggest risk premiums are not constant, but rather vary through the business cycle. It is also possible to argue that structural factors, such as changing demographics, can cause longer-term shifts in the level of required risk premiums.

Relaxing the rational expectations and constant risk premium assumptions breaks the link between what actually happened — the realised risk premium — and the premium expected by investors when they made their investment. Bernstein (1997), in particular, argues that realised returns on stocks and bonds — and risk premium estimates derived from them — are dominated by unexpected changes in valuations. Siegel (1999) notes the high realised ERP appears to be due more to low returns on bonds than to high returns on stocks. The average real return on fixed income assets this century looks unduly low, and he suggests this may be the result of investors' failure to anticipate higher inflation.[3] If the high realised ERP was not expected by investors, there may not be an 'equity premium puzzle', at least not in the sense used by Mehra and Prescott.

Overall, we think the evidence weighs against the realised ERP being a good measure of the premium investors actually expected. A key motivation of our work is to find a better way of estimating the risk premium expected by investors than the 'extrapolation' approach. As active investors, we also want to assess whether the estimate is a useful predictor of short-term relative returns. The following section outlines the model we use.

Our model

The *ex ante* ERP is simply the difference in expected return between stocks and bonds.

In notation form:

$$ERP = r - y \tag{1}$$

where ERP is the *ex ante* equity risk premium, r is the expected return on the stock market, and y is the expected return on long-term government bonds.

The expected return on the stock market can in turn be expressed in terms of the constant growth dividend discount model developed by Gordon (1962).[4] The model is represented as follows:

$$r = (d/p) + g \tag{2}$$

where d is the expected value of dividends payable in the coming year, p is the price of the stock market index, and g is the expected long-term growth rate of dividends.

Substituting Equation (2) into Equation (1) yields the following expression for the ERP:

$$ERP = (d/p) + g - y \tag{3}$$

The obvious problem with Equation (3) is that only one of the right-hand-side variables, p, the value of the stock market index, is observable. The other variables relate to investors' expectations and are not directly observable. To make our model operational, we need to find proxies for these expectations.

Variable y, the expected return on government bonds, can be dealt with relatively easily. The current redemption yield on a government bond is a reasonable approximation of its longer-term expected return, and this can be observed in the market.[5]

Survey data can be used to provide estimates of d and g. Analysts' forecasts for corporate earnings are readily available through services such as IBES.[6] Each month IBES collate analysts' earnings estimates for each stock and calculate a 'consensus' in the form of the mean forecast. It is then possible to aggregate these forecasts to derive an earnings figure for the market as a whole. By applying a payout ratio to the forecasts of the following year's earnings, we can arrive at an estimate of d, the next period dividends expected by investors. The calculation of the payout ratio is discussed in the next section.

We also need an estimate of expectations of the long-term rate of dividend growth. Over the longer term, we assume that profits, and by implication dividends, will grow at the same pace as nominal gross domestic product. For this assumption to be true, a number of conditions must hold, namely that the stock market index is representative of the economy as a whole, the profit share of GDP is steady, the overseas earnings of US listed companies grow at the same pace as their domestic profits, and the payout ratio is steady. While these conditions may not hold exactly, our analysis will show whether our approach represents a valid proxy for long-term dividend growth expectations.

Long-term 'consensus' forecasts of GDP growth are available from a publication called *Blue Chip Economic Indicators* (various editions). Each month since August 1976, Blue Chip has published a survey of economists' forecasts of key variables for the US economy looking one to two years ahead. The survey takes forecasts from about 50 economists at major financial institutions, industrial corporations and consulting firms. Twice a year since 1979, the survey has been extended to cover the economists' ten-year forecasts. We use the Blue Chip ten-year forecast of nominal GDP growth as our proxy for g — the expected long-term rate of dividend growth.

We are now in a position to estimate the ERP from Equation (3) using observable proxies for the unobservable expectation variables. In the next section, we examine whether our estimate of the ERP is useful as a measure of valuation — specifically, whether it helps predict the short-term return spread between stocks and bonds.

Our measure is closely related to the practice common among market participants of estimating the ERP by comparing the nominal yields available on stocks and bonds — either in ratio form or as a difference. In difference form, this comparison is equivalent to our model with the long-term growth parameter, g, missing. The risk in excluding this parameter is that we may confuse yield shifts that are an appropriate response to changing profit growth expectations with shifts driven by other factors, possibly including 'irrational' misvaluation. In the following section, we test these alternative specifications of the risk premium model. We also test specifications of our model using actual rather than forecast dividends.

Predicting relative returns

In this section, we test whether our estimate of the ERP is useful for predicting the short-term return spread between stocks and bonds. If investors require a risk premium for investing in (volatile) stocks rather than (more stable) bonds, this implies stocks should outperform bonds on average over the long run. However, the degree of outperformance we observe is volatile and, in some shorter periods, bonds return more than stocks. Our ERP measure may offer a more reliable prediction of the return spread in any single period than simply assuming the historical average will hold.

We make the assumption that the equilibrium level of the ERP is relatively stable over time.[7] Our hypothesis is then that unusually high observations of the ERP should be associated with subsequent periods when stocks outperform bonds by more than average and the risk premium reverts towards its mean level. In contrast, unusually low observations should be associated with low, and possibly negative, return spreads between stocks and bonds as the risk premium reverts to the mean.

It is possible for our risk premium series to mean revert without being a useful predictor of relative returns between stocks and bonds. It may be that the expectation variables in our model change in such a way as to generate mean reversion in the risk premium series independent of moves in relative prices. Our tests deal with this

Table 2 Equity risk premium and relative returns, March 1979–March 1999 (%)

	ERP	Subsequent stock return	Subsequent bond return	Stock–bond return spread
Mean	2.06	8.60	4.37	4.23
Standard deviation	1.33	11.68	7.08	12.81
Minimum	0.11	−18.02	−11.03	−33.54
Maximum	6.25	38.85	23.52	39.03

All returns are expressed as semi-annual rates.

by looking directly at whether the ERP predicts relative returns.

The data we require to estimate Equation (3) are obtained from a number of sources. The forecasts of long-run nominal GDP we use to proxy dividend growth are available from the Blue Chip publication in March and October each year from 1979, with the survey being published on the 10th of the month.[8] We match these data with the corresponding level of the S&P500 index and the ten-year Treasury note yield obtained from Datastream. In the latter case, we use the Datastream Ten Year Benchmark index.

IBES data are used to estimate the forward dividend yield on the S&P500 index. We apply an estimated payout ratio of 0.4 to the IBES consensus forecast of the next 12 months' earnings. We estimate the payout ratio by calculating the relationship between IBES earnings forecasts and subsequent dividends over the period for which we have data. On average, subsequent dividends amount to about 40 per cent of the earnings forecast. Varying the payout ratio between 30 per cent and 50 per cent shows the results of our analysis are largely insensitive to the figure used.

We also use Datastream to source total return data for the S&P500 index and the ten-year benchmark bond index. We match each calculation of the risk premium with the total returns on stocks and bonds in the following period, eg we calculate the risk premium on 10th March and match this with returns from 10th March to 10th October. Since the Blue Chip data are published in March and October, our time series consists of five-month and seven-month periods rather than actual half years. We transform the five-month and seven-month returns into the corresponding semi-annual rates. The return spread series is calculated in ratio form rather than as differences.

Descriptive statistics for the estimated ERP and the relative return series are shown in Table 2. The ERP measure is graphed in Figure 1. While the sample period is short by comparison with those used in many academic studies, it has to be noted that we are constrained by the availability of the survey data. We have used all of the available data.[9]

Figure 1 shows the ERP started the sample period at a high level of over 5 per cent, perhaps reflecting the uncertain economic environment following the second OPEC oil price 'shock'. The premium declined sharply over the following two years and the range 1–3 per cent is much more typical for the rest of the sample period, with the mean level just over 2 per cent. Most deviations outside this range look to have 'corrected' quite quickly. Interestingly, the range is consistent with the theoretical estimates produced by Mehra and Prescott (1985) using standard models of risk aversion. The low of the series occurs in October 1987, just before the 'crash'. It is notable that the

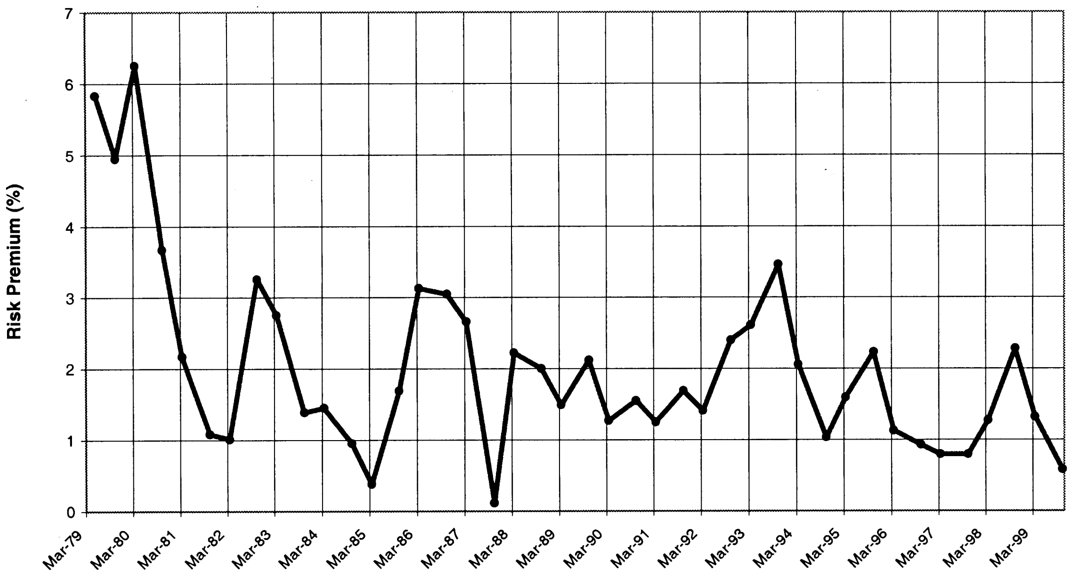

Figure 1 US equity risk premium

last data point from October 1999 is the third-lowest reading in the series, lending support to some commentators' concerns about high valuation levels in the US equity market.

To test whether our ERP measure is a useful predictor of the return spread between stocks and bonds, we estimate an ordinary least squares regression, where the level of the ERP at the end of one period is used to explain the return spread in the following period.

In notation terms:

$$SVB_t = a + b\ ERP_{t-1} + e_t \tag{4}$$

where SVB_t is the log total return on stocks in period t relative to the total return on bonds [=(1 + total return on S&P500 index)/(1 + total return on Datastream 10-Year Treasury Index)], ERP_{t-1} is the estimated ERP at the end of period $t-1$, and e_t is the error term. The results of the regression are shown in Table 3.

The regression equation reveals a positive relationship between our ERP measure and the subsequent return spread between stocks and bonds. The t-statistic of 3.3 indicates the relationship is statistically significant at a 99 per cent confidence level. Our ERP measure explains almost 20 per cent of the variation in relative returns between stocks and bonds over the sample period. Diagnostic tests show no significant econometric problems, although the sample size is relatively small.

Putting our results into more obvious economic terms, on average, stocks outperformed bonds by 4.2 per cent in each semi-annual period in our sample. The average ERP measure over the sample period was 2.1 per cent. For every percentage point increase (decrease) in the ERP, the subsequent semi-annual relative return was increased (decreased) by 4.5 percentage points. Figure 2 shows a scatter diagram of the ERP

Table 3 **Regression results, March 1979–March 1999**

	$SVB_t = -5.00 + 4.47\ ERP_{t-1}$	
t-statistics	(−1.50) (3.27)	
Adjusted	$R^2 = 19.5\%$	$n = 41$

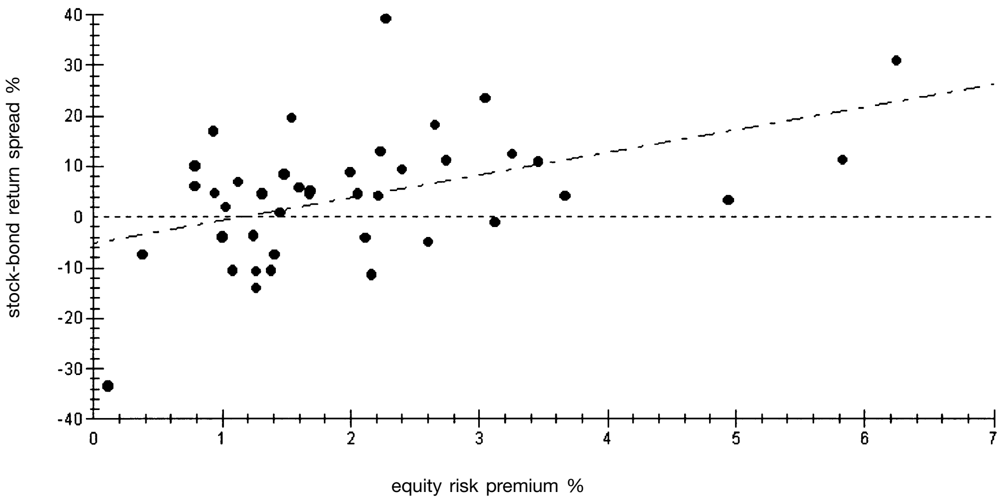

Figure 2 Stocks and bonds return spread against equity risk premium

observations against the subsequent equity–bond return spread. The positive relationship can be seen in the data.

In order to test the robustness of our results, we also tested a number of alternative specifications of the ERP. Using actual dividends rather than the IBES forecasts produces results that are similar, but slightly weaker, than our initial specification. Using the difference between the nominal earnings yield on stocks and the bond yield, ie omitting the long-term growth term, also produces similar results for predicting relative returns. This measure does not show significant mean reversion, however, raising questions about its reliability. Using the ratio between the forecast earnings yield on the stock market and the bond yield produces results similar to but slightly stronger than our chosen specification. Our main concern about this specification is that it is unlikely to be robust to significant changes in long-term dividend growth expectations. Using the Blue Chip forecasts for growth in the national income definition of profits rather than nominal GDP produces similar, but slightly weaker results.

In short, the alternative specifications produce similar, though generally slightly weaker, results. We would argue that the more complete specification of our measure makes it more robust to changes in the environment, especially revised long-term growth expectations.

What really happened

We have established that our risk premium measure is a reliable predictor of the return spread between stocks and bonds. An unusually high risk premium implies stocks will outperform bonds by a wider-than-average margin in the following period. Similarly, a low-risk premium implies the short-term return margin between stocks and bonds will be narrow or even negative.

To investigate what is driving these results, we rank the 41 observations according to the level of the ERP. We then split the data into quartiles — missing out the median observation[10] — and examine the return characteristics of each quartile. The results are shown in Table 4. Note all returns shown are expressed on a semi-annual basis.

Table 4 reveals that in quartiles one

Table 4 Equity risk premium and returns by quartile (%)

	Average ERP	Average relative return	Average stock return	Average bond return
Quartile One	3.90	12.38	11.29	−1.09
Quartile Two	2.18	6.29	8.17	1.88
Quartile Three	1.40	−0.81	4.75	5.56
Quartile Four	0.82	−0.97	8.24	9.21

All returns are expressed as semi-annual rates.

and two, bond returns are below average, while stock returns are higher than average. It is apparent that the above-average relative returns observed in these quartiles are driven both by below-average bond returns and by above-average stock returns. In quartiles three and four, bonds perform better than stocks on average, which is unsurprising given the econometric results in the previous section. The mechanism for this result is interesting, however. The 'overvaluation' of stocks is usually corrected by a rally in the bond market rather than by stocks falling in price — stock returns are below average, but not generally negative. The most notable exception is the October 1987 data point. The forecast ERP registered just 0.1 per cent on 10th October 1987. Over the following five months, bonds delivered a 15.5 per cent semi-annual return, helping to restore a more normal ERP. Stocks dropped sharply, however, registering a return of −18.0 per cent for the period. As we know, the 22.0 per cent 'crash' on Black Monday, 19th October, caused most of the damage to investors' portfolios.

Our measure appears to have some predictive power over both stocks and bonds individually as well as over relative returns. To confirm these results in econometric terms, Table 5 shows regression equations where we use the ERP measure to predict the return on stocks S_t and the return on bonds B_t.

As expected given the quartile analysis above, there is a negative relationship between the ERP measure and the return on bonds, ie bonds tend to perform poorly in the period following a high ERP. Stocks tend to perform strongly following a high ERP, as shown by the positive regression coefficient. The main caveat is that the regression coefficient for stocks is not statistically significant at conventional confidence levels.

Our results show that over the period for which we have data, overvaluation of the stock market relative to bonds has tended to be corrected by a rally in the bond market, ie a fall in yields. In only seven of the 41 periods was the return on the stock market negative. It would be wrong to generalise from this result, however. Over the period we studied, the average level of inflation dropped sharply, providing a beneficial environment for financial assets. Consumer price inflation averaged 7.9 per cent in the five years leading up to

Table 5 Regression results, March 1979–March 1999

Stocks			
	$S_t = 5.32 + 1.59\ \text{ERP}_{t-1}$		
t-statistics	(1.57) (1.15)		
Adjusted	$R^2 = 0.8\%$		$n = 41$
Bonds			
	$B_t = 10.33 - 2.89\ \text{ERP}_{t-1}$		
t-statistics	(5.89) (−4.03)		
Adjusted	$R^2 = 27.5\%$		$n = 41$

Table 6 UK equity risk premium and relative returns, April 1982–April 1999 (%)

	ERP	Subsequent stock return	Subsequent bond return	Stock–bond return spread
Mean	2.07	8.40	5.88	2.52
Standard deviation	1.22	12.01	6.20	11.96
Minimum	0.35	−26.75	−6.66	−38.26
Maximum	5.34	30.00	24.53	24.41

All returns are expressed as semi-annual rates.

our first data point in March 1979. For the five years to October 1999, the comparable figure is 2.4 per cent. The ten-year bond yield has fallen in tandem with the drop in inflation, moving from 9.1 per cent in March 1979 to 6.0 per cent in October 1999. Without this beneficial environment of falling inflation, and rising stock prices, investors buying stocks when the risk premium was low may have faced a harsher experience than they have had.

While many investors and media commentators have been talking about the overvaluation of the US stock market for several years, there has been significant variation in the level of the ERP measure over the recent period. During the third quarter of 1998, stocks fell sharply as investors undertook a 'flight to safety' in the aftermath of the Russian government's decision to introduce a moratorium on debt repayments. Treasury bond yields fell as investors sought secure and liquid instruments in which to hold their capital. The result was to drive the ERP to an above-average level of 2.3 per cent in October 1998. In contrast, the March 1998 reading was only 1.3 per cent. The October 1998 data point stands out as the 'best' buying signal for equities in our series, with the S&P500 index outperforming bonds by 39.0 per cent on a semi-annual basis over the following five months, as fears of deflation and recession abated.

The international evidence

We have focused on the US market due to the ready availability of the survey data we use to proxy expectations. Some data, however, are also available for international markets. In particular, we have been able to assemble a series of ERP estimates for the UK market from April 1982 to April 1999 using IBES earnings forecasts and long-run nominal GDP from Consensus Economics Inc.'s *Consensus Forecasts* (various editions), an international equivalent to *Blue Chip Economic Indicators*.[11] We use the FTSE 100 as our equity index and the Datastream ten-year benchmark gilt index for our bond series. With the exception of the sources of the forecasts, the methodology and data sources are the same as outlined for the US in the section on 'Our model'. Table 6 gives descriptive statistics for our UK ERP measure and the corresponding returns. Figure 3 plots the ERP series.

It is notable that the UK series shares many similarities with our US data. The mean level of the ERP, at 2.1 per cent, is almost identical to the US average. The highs and lows are also broadly similar, and both series typically occupy a range from about 1 per cent to 3 per cent. Unlike the US, October 1987 did not represent the low for the UK, which in fact occurred in April 1991. The last data point in the sample, 1.7 per cent in October 1999, is much closer to the mean than the comparable US observation.

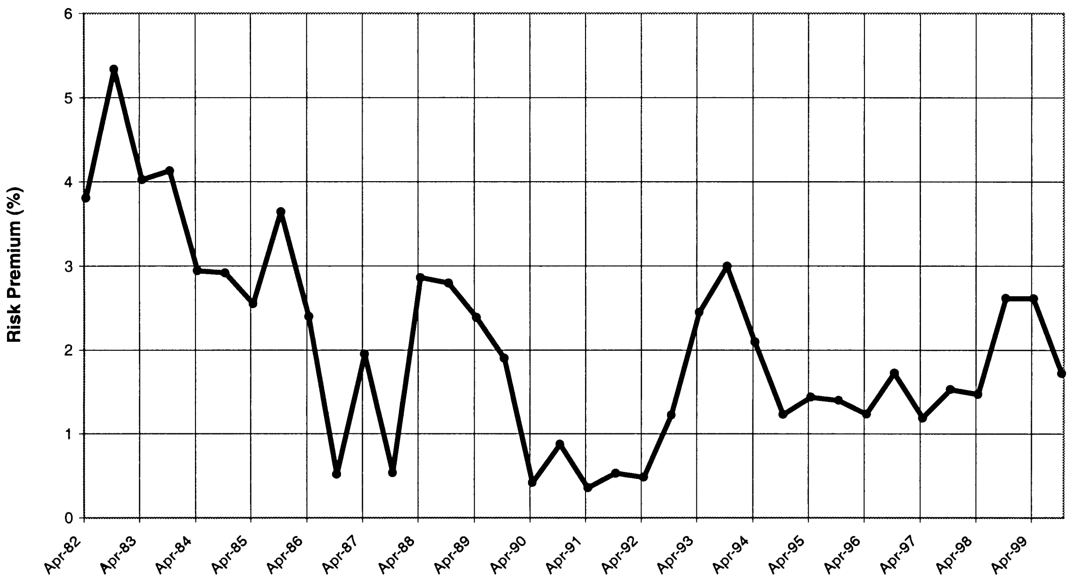

Figure 3 UK equity risk premium

Following the US analysis, we also test whether the UK ERP series helps predict the short-term stock–bond return spread. The regression yields a slope coefficient of 3.72 with a *t*-statistic of 2.35 — similar to the US equation. The adjusted *R*-square statistic at 12 per cent is lower than in the US model. Overall, the results are qualitatively similar.

Regression of the ERP series on stock and bond returns separately produces a contrast to the US results. In our results (not shown), we find the ERP series is more predictive of stock returns than bond returns. The slope coefficient of the bond equation is statistically insignificant, though it has the expected negative sign.

In general, the UK results and their similarity to the US experience give us confidence in the validity of our approach. The techniques are also applicable for other international markets, but data availability is a problem. For many European and Asian markets, comprehensive surveys of economic forecasts have only become available in the past decade. This will, however, provide a useful 'out-of-sample' test of our analysis once the data histories are longer.

Table 7 Regression results, April 1982–April 1999

Stocks
$SVB_t = -5.19 + 3.72\ \mathrm{ERP}_{t-1}$
t-statistics (−1.37) (2.35)
Adjusted $R^2 = 11.7\%$ $n = 35$

Conclusions

Our work represents an attempt to produce a well-specified *ex ante* measure of the ERP expected by investors. We use surveys of economic forecasts as a novel way to solve the problem that many of the variables in the risk premium calculation are unobservable. We focus on the US experience, but also present results for the UK which are similar.

The results show that the ERP measure helps predict the short-term relative return between stocks and bonds. When the premium is higher than average, the stock–bond return spread in the coming period also tends to be above average. When the risk premium measure is below average, the subsequent return spread tends to be low or even negative. The measure therefore offers scope to be the basis of a tactical asset allocation strategy.[12]

It is not clear why our measure, which uses widely available data, should offer potential for generating excess returns. It may be the model captures inefficiency in the relative pricing of stocks and bonds, but other, more 'rational', explanations are possible. Fama and French (1989) find that US stock and bond returns between 1926 and 1987 were predictable using the market dividend yield; the 'default' spread between the average corporate bond yield and the yield on AAA-rated bonds; and the term premium of AAA-rated corporate bonds over Treasury bills. They argue the explanatory variables are related to the business cycle and that predictable variation in expected returns reflects a rational response to economic conditions. For example, when business conditions are poor, income is low and expected returns from bonds and stocks must be high to induce substitution from consumption to investment. In the case of our analysis, it may be that the business cycle leads to short-term fluctuations in the compensation investors require for equity risk. Similarly, the actual or perceived level of risk in stocks and bonds may vary through the business cycle, leading to variations in expected returns that have rational foundations. Our tests do not offer any way to decide between these different explanations.

Our analysis also suggests, in recent years at least, the risk premium expected by equity investors has been significantly less than the levels (7 per cent or so) that historical studies show have been realised. The most recent US data we have show stocks priced to deliver only about 1 per cent more than bonds over the longer term, if our model specification is correct. Our concluding message has to be to caution against using a measure of the realised ERP as an indication of what can be expected in future.

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Notes

1 A review of some of the initial solutions proposed can be found in Kocherlakota (1996).
2 See Shefrin (1999) for a comprehensive review of this field.
3 Best *et al*. (1998) show that investors in the US bond market in recent years appear to have made large and persistent errors in forecasting inflation. As a result the realised real returns earned by these investors seem to have been very different from what they expected at the outset. It is not apparent in the data that these forecast errors average out to zero over time.
4 The Gordon model is a simple valuation model, which necessarily rests on a number of strong assumptions. The firm is assumed to be debt free and to finance its investments through retaining a constant portion of its earnings. The investments have infinite lives and earn a constant return on capital. A full critique of the model and the assumptions is outwith the scope of our paper.
5 This approximation involves a number of assumptions, such as a flat and unchanging yield curve and the ability to reinvest coupon payments at the same rate as the yield. The effect of these assumptions is likely to be small.
6 IBES is a data vendor specialising in the systematic collection of earnings estimates from 'sell-side' investment analysts.
7 It is possible to argue the risk premium will shift over time, eg as a result of changing demographics. Such changes by their nature, however, are likely to be very gradual. Tests on the ERP series indicate it is stationary over the sample period. The augmented Dickey–Fuller statistic for the series is −5.99, which is significant at a 95% confidence level.
8 Prior to 1983, some of the data points relate to May and November. After 1983, the series becomes more regular.
9 To avoid the need for survey data, some analysts assume investors have had perfect (or at least unbiased) foresight. They argue that what happened, for example in terms of dividend growth, was what

investors had expected and thus historical out-turn data can proxy for prior expectations. While this can yield longer data histories, to us the assumption is too strong.

10 The median observation is from October 1985 and is characterised by: $ERP = 1.69$ per cent; stock return = 28.01 per cent; bond return = 23.52 per cent; relative return = 4.49 per cent.

11 UK data from IBES and Consensus Economics is only available from 1987 and 1989 respectively. We create our own comparable series for the early periods by combining the relevant forecasts of leading economic forecasting institutions.

12 Best and Byrne (1997) present the results of a simulated tactical asset allocation strategy based on this measure.

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Bloomberg

One Hundred Years of Bond History Means Bears Fated to Lose

By Daniel Kruger and Liz Capo McCormick - Dec 8, 2014

If you're convinced the plummet in yields of U.S. government bonds is an aberration, it may be because you haven't been in the business long enough.

With the longest-dated Treasuries now yielding less than half the 6.8 percent average over the past five decades, it's not hard to see why forecasters say they're bound to rise as the Federal Reserve prepares to raise interest rates following the most aggressive stimulus measures in its 100-year history. Yet compared with levels that prevailed in the half-century before that, yields are in line with the norm.

For David Jones, the former vice chairman at Aubrey G. Lanston & Co. and a 51-year bond veteran, the notion that Treasury yields are too low is being shaped by traders, money managers and economists who began their careers in the wake of runaway inflation surpassing 10 percent in the 1970s and 1980s. With U.S. consumer prices rising at the slowest pace in five decades and economic growth weakening around the world, today's bond market may now be reverting back to form, he said.

"We have come full circle," Jones, 76, said by telephone on Dec. 1 from Denver. "Rather than decrying how low interest rates are and expecting them to shoot higher, it may be that we're in more normal territory than we thought we were."

Since the financial crisis, yields on Treasuries of all maturities have fallen as the Fed attempted to restore demand in the U.S. by dropping its overnight target rate close to zero and buying bonds to suppress long-term borrowing costs.

Bull Case

The 5.1 percent rally in U.S. government debt this year has pushed down yields even further, surprising everyone on Wall Street who anticipated the central bank's unprecedented stimulus would lead to stronger economic growth, faster inflation and ultimately higher borrowing costs.

Yields on 30-year bonds, the longest-term debt securities issued by the Treasury Department, have fallen a full percentage point this year to 2.95 percent as of 9:25 a.m. in New York today. At the start of 2014, forecasters said they would rise 0.28 percentage point to 4.25 percent.

Economists and strategists in a Bloomberg survey are sticking to their calls that yields will rise and predicting those on long-term Treasuries will reach 3.88 percent next year.

Lacy Hunt, the 72-year-old chief economist at Hoisington Investment Management, says lackluster demand and inflation will likely keep yields low for years to come as the U.S. contends with record debt levels.

Even though the Fed inundated the U.S. economy with almost $4 trillion of cheap cash with its bond buying, growth has averaged 1.8 percent a year since 2009. In the seven expansions dating back to the 1960s, growth averaged almost 4 percent.

History Lesson

Inflation, which erodes the value of fixed-income payments, has failed to reach the Fed's 2 percent target for 30 straight months based on its preferred measure. The U.S. consumer price index has risen an average 1.62 percent over the past five years, the least since the five-year period ended in 1965.

"Over time, what drives the bond yield is the inflationary expectations," Hunt said by telephone on Dec. 2. "If you wring all the inflationary expectations out, you are going down to 2 percent on the long bond over the next several years. That is the path that we are on."

Based on bond yields, inflation expectations over the next 30 years have fallen below 2 percent and reached a three-year low of 1.96 percent at the end of last month.

Those levels are more akin to inflation rates that were prevalent in the five decades after the Fed was established in 1913. Living costs rose an average 2.45 percent annually during that span, versus 4.3 percent in the half-century since, according to data compiled by the Labor Department.

Great Society

Long-term U.S. bond yields were also lower in the earlier period, averaging about 3.1 percent, according to more than 100 years of data provided by Austin, Texas-based Hoisington.

Forecasters have continued to anticipate higher borrowing costs partly because recent history has been marked by periods of elevated inflation, said Ray Stone, a Princeton, New Jersey-based managing director at Stone & McCarthy Research Associates.

"Those of us that grew up in the 1970s and when there were very high interest rates in the early 1980s might think that that is the norm," Stone, who began his career at the New York Fed in 1973, said by telephone Dec. 3. "But it's not. What prevailed before then is probably more indicative of the norm."

Yields on the longest-term U.S. government bonds started to rise to unprecedented levels in the 1960s as government spending increased with the Vietnam War and the social welfare programs of the Great Society under President Lyndon B. Johnson.

Oil Shock

In the 1970s, oil shocks stemming from the 1973 embargo by the Organization of Petroleum Exporting Countries and the Iranian revolution in 1979, as well as the easy-money policies by the Fed during the Nixon administration, caused annual consumer prices to soar as much as 14.8 percent in March 1980.

Yields on 30-year Treasuries followed, surging to a record 15 percent in October 1981.

While former Fed Chairman Paul Volcker was credited with finally breaking the inflationary cycle by raising interest rates to 20 percent that year, at least one bond veteran says the three-decade bull market in bonds that ensued may finally be over as the central bank tightens policy. His name? Bill Gross.

"Prepare for at least a halt of asset appreciation engineered upon a false central bank premise of artificial yields," Gross, 70, who left Pacific Investment Management Co. in September to join Janus Capital Group Inc., wrote in his investment outlook for December.

Less than two months earlier, billionaire hedge-fund manager Paul Tudor Jones said there's a bubble in debt globally that will burst and that "the piper will be paid one day."

Secular Bear

Signs that the trillions of dollars of stimulus by the Fed will lead to a pickup in inflation may already be emerging. Last month, the economy created more jobs than at any time in almost three years, helping trigger a 0.4 percent jump in average hourly wages that was the biggest in 17 months.

Before November, earnings remained flat or rose just 0.1 percent in five of the prior eight months. Economists also anticipate that 3 percent economic growth in the U.S. next year, which would be the fastest in a decade, will compel the Fed to raise rates in the second quarter of 2015.

"We're in a transition period between secular bull and bear markets in bonds," Stewart Taylor, a money manager at Boston-based Eaton Vance Management, which oversees $294 billion, said by telephone on Dec. 4.

Even as the U.S. economy gains momentum, a slowdown abroad may help keep Treasuries in demand as central banks in Europe and Japan step up their own stimulus measures.

No Return

With the inflation rate for the 18-nation euro area matching a five-year low in November and Japan falling into a recession, JPMorgan Chase & Co. estimates their central banks will buy $1.1 trillion of debt in 2015 to support demand.

That's already made Treasuries more attractive on a relative basis, with 10-year German bunds yielding 1.58 percentage points less than similar-maturity Treasuries today, the widest since 1999. The gap between the U.S. and Japan is even greater at 1.88 percentage points.

"It's more of a structural shift related to globally low yields," Jennifer Vail, the head of fixed income at U.S. Bank Wealth Management, which oversees $115 billion, said by telephone. "It's driving a lot of money into our market."

A price war between OPEC and U.S. shale oil drillers is also likely to keep inflationary pressures tied to energy from building. The price of the U.S. benchmark grade has plummeted 33 percent this year and reached a five-year low of $63.72 a barrel on Dec. 1. Since soaring to a record of $147.27 in July 2008, prices fallen by about half. During the oil shock in the late 1970s and early 1980s, crude prices more than tripled.

"Inflation is a non-story, and as long as inflation is a non-story, we're not going back to those elevated yield levels," David Robin, an interest-rate strategist at Newedge, an institutional brokerage firm, said in a Dec. 3 telephone interview in New York. "We're not going back there."

To contact the reporters on this story: Daniel Kruger in New York at dkruger1@bloomberg.net; Liz Capo McCormick in New York at emccormick7@bloomberg.net

To contact the editors responsible for this story: Michael Tsang at mtsang1@bloomberg.net; Dave Liedtka at dliedtka@bloomberg.net Dave Liedtka

Bloomberg

Unstoppable $100 Trillion Bond Market Renders Models Useless

By Susanne Walker and Liz Capo McCormick - Jun 2, 2014

If the insatiable demand for bonds has upended the models you use to value them, you're not alone.

Just last month, researchers at the Federal Reserve Bank of New York retooled a gauge of relative yields on Treasuries, casting aside three decades of data that incorporated estimates for market rates from professional forecasters. Priya Misra, the head of U.S. rates strategy at Bank of America Corp., says a risk metric she's relied on hasn't worked since March.

After unprecedented stimulus by the Fed and other central banks made many traditional models useless, investors and analysts alike are having to reshape their understanding of cheap and expensive as the global market for bonds balloons to $100 trillion. With the world's biggest economies struggling to grow and inflation nowhere in sight, catchphrases such as "new neutral" and "no normal" are gaining currency to describe a reality where bonds are rallying the most in a decade.

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- You're All Whales in the Bond Market Now
- **Opinion:** Adam Smith vs. Keynes and Minsky

"The world's gotten more complicated and it's a little different," James Evans, a New York-based money manager at Brown Brothers Harriman & Co., which oversees $30 billion, said in a telephone interview on May 30. "As far as predicting direction up and down, I don't think they have much value," referring to bond-market models used by forecasters.

Flawed Consensus

With the Fed paring its $85 billion-a-month bond buying program this year and economists calling for the five-year-long U.S. expansion to finally take off, Wall Street prognosticators said at the start of the year that yields were bound to rise as central banks began employing tighter monetary policies.

Instead, investors poured into bonds of all types as global growth weakened, disinflation emerged in Europe and tensions between Ukraine and Russia intensified.

Globally, bonds have returned an average 3.89 percent this year for the biggest year-to-date gain since 2003, index data compiled by Bank of America Merrill Lynch show. The advance decreased yields on 10-year Treasuries by more than a half percentage point to 2.48 percent, the fastest pace over the same span since 1995, while borrowing costs for the riskiest U.S. companies tumbled to a record 5.94 percent last week.

Benchmark Treasury 10-year note yields rose six basis points, or 0.06 percentage point, to 2.53 percent as of 3:36 p.m. in New York.

In developed countries, benchmark yields in 24 of 25 nations tracked by Bloomberg have fallen this year, with those in Italy and Spain closing below 3 percent for the first time.

'How Wrong'

"I don't expect the consensus to be right, I'm just surprised by how wrong it has been," Jim Bianco, president of Chicago-based Bianco Research LLC, said by telephone on May 28.

The seemingly unstoppable rally has caused bond-market professionals to reassess whether they're using the right tools.

At the New York Fed, researchers Tobias Adrian, Richard Crump, Benjamin Mills and Emanuel Moench on May 12 released an updated methodology for a metric known as the term premium, which can be used to determine whether 10-year Treasuries are cheap or expensive relative to short-term rates.

After stripping out all human predictions and using only market prices to calculate future expectations, the researchers found the extra yield longer-term Treasuries offered has been "considerably higher since the onset of the financial crisis" than previous models, according to their blog post that included the data. That may be because the metric now suggests the Fed's short-term interest rate may not rise as high as survey-based results predicted, wrote the economists.

Old Model

Based on the old model, last updated on March 31, the term premium on 10-year notes was 0.25 percentage point, versus 0.96 percentage point on the same day using the current methodology. The reading was at 0.67 percentage point last week.

The researchers declined to comment beyond the blog post, according to Eric Pajonk, a spokesman at the New York Fed.

Bank of America's Misra says she stopped looking at the gap between the rate on 10-year interest-rate swaps and yields on benchmark government debt as a measure of risk.

The gauge, which usually widens as investors seek out haven assets in times of stress, is being distorted as those betting on losses in Treasuries have unwound their trades, she said.

Hedge funds and other large speculators cut their net short positions in 10-year note futures by the most since February as of May 27, according to data from the U.S. Commodity Futures Trading Commission. Primary dealers, which had net short positions in March for the first time since 2011, have since reversed those wagers, data compiled by Bloomberg show.

Forced Buying

"Everyone is short and they are forced to cover," Misra said by telephone on May 28.

While economists and strategists have reduced their yield forecasts, they're still sticking to the view borrowing costs will end the year higher as the economy gains momentum.

They now see yields on 10-year Treasuries rising to 3.25 percent by year-end as the economy accelerates 3.1 percent in 2015, estimates compiled by Bloomberg show. At the start of the year, the median yield forecast was 3.44 percent.

Investors risk becoming lulled into complacency by six years of near-zero U.S. interest rates at a time when yields are so low, according to Zach Pandl, the Minneapolis-based senior interest-rate strategist at Columbia Management Investment Advisers, which oversees $340 billion.

Pandl, who developed his own version of the term premium, maintains that U.S. government bonds are too expensive.

"The Treasury market is overvalued," he said by telephone on May 28. "The funds rate has been at zero for so long so it becomes difficult to envision it being higher at all. Monetary policy is closer to exit."

Biggest Mistake

Traditional models are failing to explain the resilience of fixed-income assets as central banks led by the Fed pump trillions of dollars into their economies and suppress short-term rates at historical lows, according to Bianco.

The Fed, Bank of Japan and Bank of England all have quantitative-easing programs in place, while at least two dozen nations have dropped benchmark rates to 1 percent or less.

"The biggest mistake for people is they think interest rates are merely a projection of where the economy is supposed to go," Bianco said. "It's the Fed and the way they have changed the marketplace." He foresees that yields on 10-year notes will end the year at 2 percent to 2.5 percent.

Fed Chair Janet Yellen said on May 7 there will be "considerable time" before the central bank raises its benchmark rate as slack in the jobs market keeps inflation below its 2 percent target.

Household spending declined in April, while the world's largest economy contracted in the first quarter for the first time since 2011, government reports showed last week.

"Given the outlook for the global economy and inflation, bonds are not a bad place to be," Gary Pollack, the New York-based head of fixed-income trading at Deutsche Bank AG's private-wealth management unit, which oversees $12 billion, said in a telephone interview on May 28.

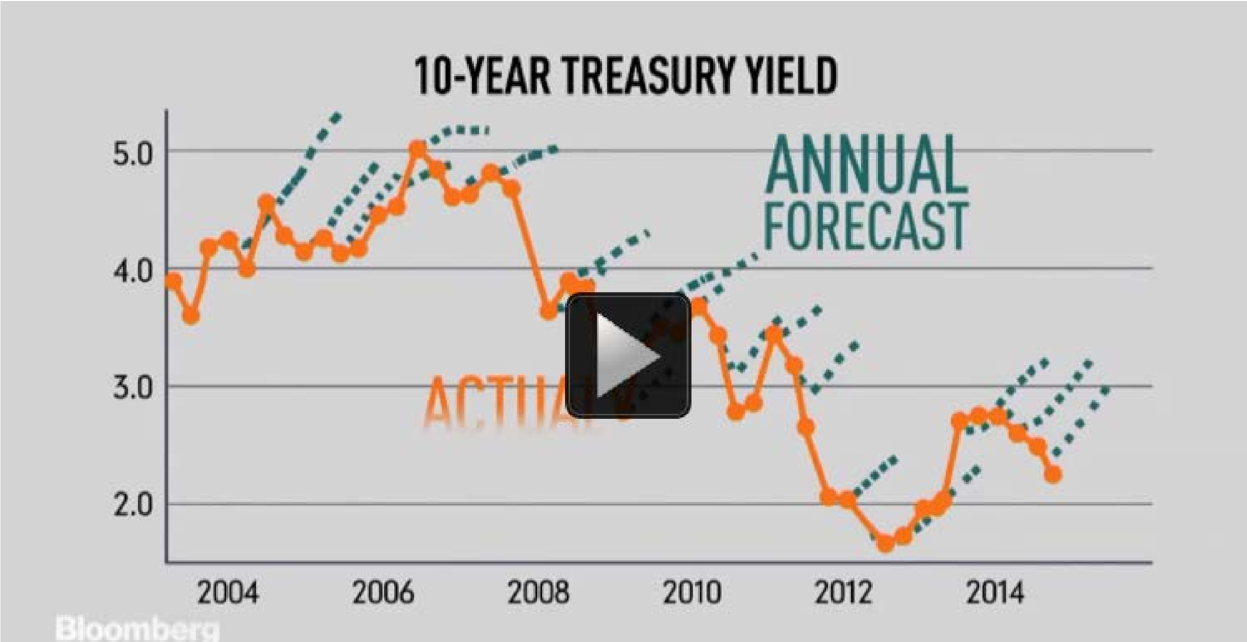
To contact the reporters on this story: Susanne Walker in New York at swalker33@bloomberg.net; Liz Capo McCormick in New York at emccormick7@bloomberg.net

To contact the editors responsible for this story: Dave Liedtka at dliedtka@bloomberg.net Michael Tsang

http://www.bloomberg.com/news/articles/2015-03-16/how-interest-rates-keep-making-people-on-wall-street-look-like-fools

How Interest Rates Keep Making People on Wall Street Look Like Fools

Will this be the year they get it right?



If there's one call that investors and economists almost always seem to get wrong, it's the direction of long-term interest rates. For years economists have been predicting that rates would rise, yet rates have been on a downtrend for ages.

Over the years, a variety of reasons have been given for the forecasted rise. Inflation and the amount of government spending have often been cited. You also frequently hear that "rates have nowhere to go but up," yet it turns out that yes, they can keep getting lower.

The ongoing decline in interest rates isn't just a U.S. phenomenon, either. In Europe, many government bonds now carry negative interest rates—a decline some wouldn't have thought possible. In Japan, the term "the widowmaker" has been used to describe the perpetually losing trade of betting on higher government rates.

So why have rates declined so intensely over the years? Inflation has been on a steady downtrend in most places. And as societies get older, the demand for ultra-safe assets, such as government bonds, gets bigger.

And yes, in 2015, analysts are once again predicting higher rates.

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NEWS RELEASE

Transmission of material in this release is embargoed until
8:30 a.m. (EST) Friday, January 16, 2015

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Technical information: (202) 691-7000 • Reed.Steve@bls.gov • www.bls.gov/cpi
Media Contact: (202) 691-5902 • PressOffice@bls.gov

CONSUMER PRICE INDEX – DECEMBER 2014

The Consumer Price Index for All Urban Consumers (CPI-U) declined 0.4 percent in December on a seasonally adjusted basis, the U.S. Bureau of Labor Statistics reported today. Over the last 12 months, the all items index increased 0.8 percent before seasonal adjustment.

The gasoline index continued to fall sharply, declining 9.4 percent and leading to the decrease in the seasonally adjusted all items index. The fuel oil index also fell sharply, and the energy index posted its largest one-month decline since December 2008, although the indexes for natural gas and for electricity both increased. The food index, in contrast, rose 0.3 percent, its largest increase since September.

The index for all items less food and energy was unchanged in December, following a 0.2 percent increase in October and a 0.1 percent rise in November. This was only the second time since 2010 that it did not increase. The shelter index continued to rise, and the index for medical care posted its largest increase since August 2013. However, these increases were offset by declines in a broad array of indexes including apparel, airline fares, used cars and trucks, household furnishings and operations, and new vehicles.

The all items index increased 0.8 percent over the last 12 months. This is notably lower than the 1.3 percent change for the 12 months ending November. The energy index has declined 10.6 percent over the span. In contrast, the 3.4 percent increase in the food index is its largest 12-month increase since February 2012. The index for all items less food and energy has increased 1.6 percent over the last 12 months, its smallest 12-month change since the 12 months ending February 2014.

Chart 1. One-month percent change in CPI for All Urban Consumers (CPI-U), seasonally adjusted, Dec. 2013 - Dec. 2014
Percent change

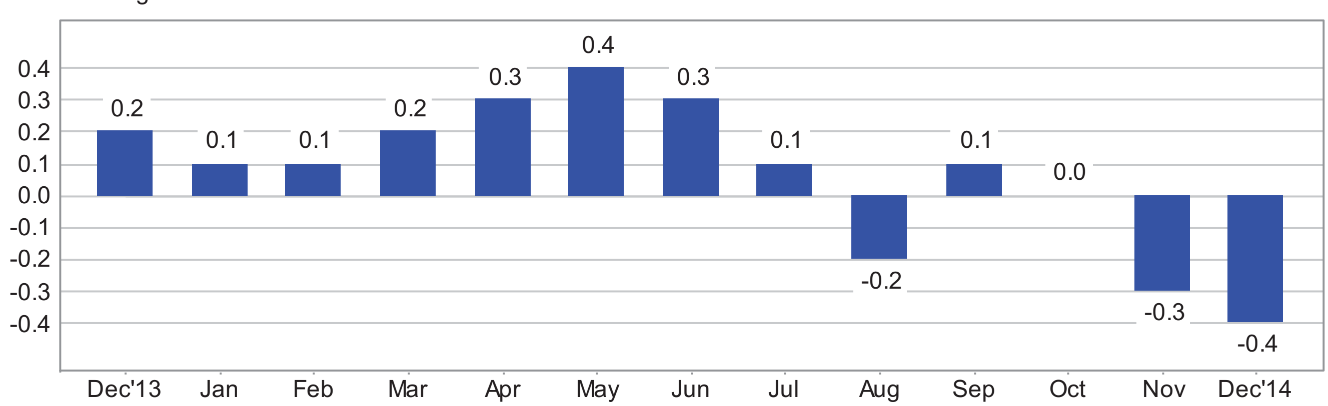

Chart 2. 12-month percent change in CPI for All Urban Consumers (CPI-U), not seasonally adjusted, Dec. 2013 - Dec. 2014

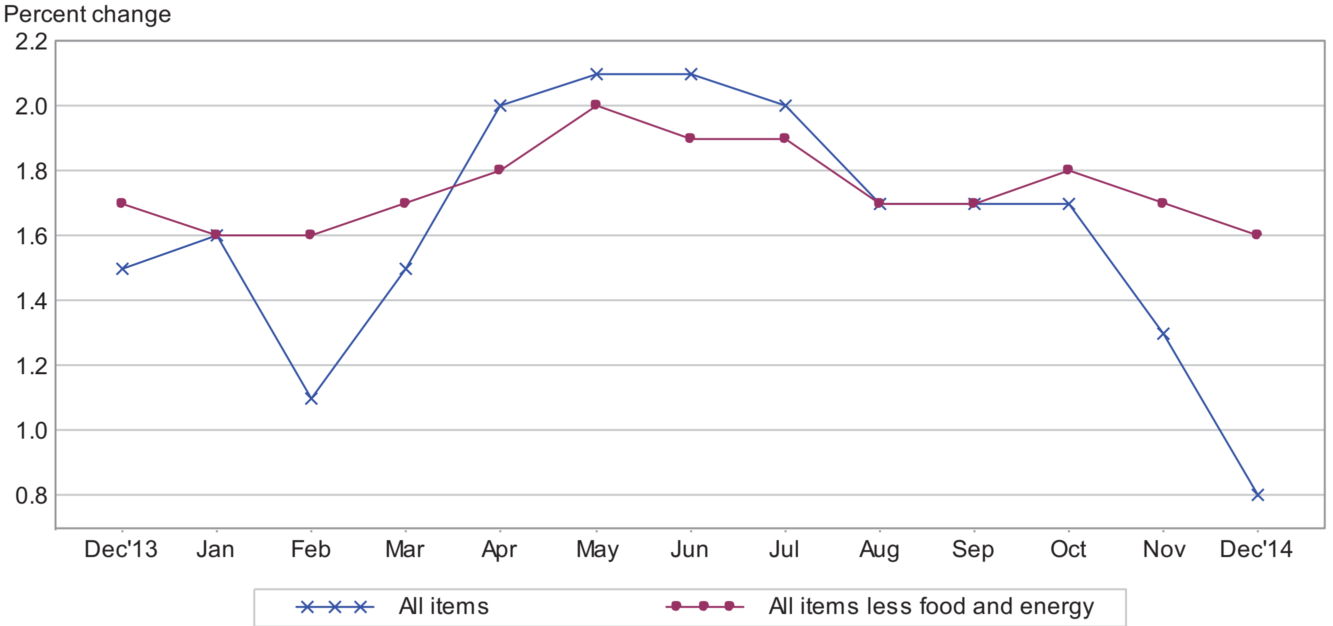

Table A. Percent changes in CPI for All Urban Consumers (CPI-U): U.S. city average

	Seasonally adjusted changes from preceding month							Un-adjusted 12-mos. ended Dec. 2014
	June 2014	July 2014	Aug. 2014	Sep. 2014	Oct. 2014	Nov. 2014	Dec. 2014	
All items	.3	.1	-.2	.1	.0	-.3	-.4	.8
Food	.1	.4	.2	.3	.1	.2	.3	3.4
Food at home	.0	.4	.2	.3	.1	.1	.3	3.7
Food away from home [1]	.2	.3	.2	.3	.2	.4	.3	3.0
Energy	1.6	-.3	-2.6	-.7	-1.9	-3.8	-4.7	-10.6
Energy commodities	3.0	-.3	-3.9	-1.1	-3.0	-6.4	-9.1	-20.5
Gasoline (all types)	3.3	-.3	-4.1	-1.0	-3.0	-6.6	-9.4	-21.0
Fuel oil [1]	-1.7	-.7	-1.2	-2.1	-4.0	-3.5	-7.8	-19.1
Energy services	-.4	-.4	-.6	-.2	-.2	-.3	1.0	3.7
Electricity	.2	-.3	.1	-.7	.5	.1	.8	3.1
Utility (piped) gas service	-2.6	-.4	-2.8	1.6	-2.7	-1.7	1.5	5.8
All items less food and energy	.1	.1	.0	.1	.2	.1	.0	1.6
Commodities less food and energy commodities	.1	.0	-.1	.0	.0	-.4	-.3	-.8
New vehicles	-.3	.3	.2	.0	.2	-.1	-.1	.5
Used cars and trucks	-.4	-.3	-.3	-.1	-.9	-1.2	-1.2	-4.2
Apparel	.5	.2	-.2	.0	-.2	-1.1	-1.2	-2.0
Medical care commodities	.7	.3	-.1	.5	.0	.6	1.0	4.8
Services less energy services	.1	.1	.0	.2	.3	.2	.1	2.4
Shelter	.2	.3	.2	.3	.2	.3	.2	2.9
Transportation services	.1	-.7	-.6	.1	.8	.3	-.5	1.7
Medical care services	.0	.1	.0	.1	.2	.4	.3	2.4

[1] Not seasonally adjusted.

Consumer Price Index Data for December 2014

Food

The food index rose 0.3 percent in December after a 0.2 percent increase in November. The index for food at home rose 0.3 percent with five of the six major grocery store food groups increasing. The index for dairy and related products posted the largest increase, rising 0.6 percent after declining in November. The fruits and vegetables index rose 0.4 percent, with the fresh vegetables index rising 2.4 percent but the index for fresh fruits declining 1.3 percent. The index for meats, poultry, fish, and eggs increased 0.3 percent as the index for beef and veal continued to rise, advancing 0.7 percent. The index for other food at home increased 0.3 percent, and the cereals and bakery products index advanced 0.2 percent. The nonalcoholic beverages index, in contrast, declined in December, falling 0.4 percent after rising in each of the previous three months. The food at home index has risen 3.7 percent over the last 12 months, with all six groups rising over the span. The index for food away from home rose 0.3 percent in December after a 0.4 percent increase in November, and has risen 3.0 percent over the last year.

Energy

The energy index continued to decline, falling 4.7 percent in December after a 3.8 percent decrease in November. This was its sixth decline in a row, and the index has fallen 13.3 percent over the six month span. The gasoline index fell 9.4 percent in December and has declined 22.4 percent since June. (Before seasonal adjustment, gasoline prices fell 11.1 percent in December.) The fuel oil index also continued to decline, falling 7.8 percent, its largest decline since June 2012. However, the index for natural gas turned up in December, rising 1.5 percent after falling in October and November. The electricity index also increased in December, rising 0.8 percent.

All items less food and energy

The index for all items less food and energy was unchanged in December. The shelter index increased, advancing 0.2 percent, with the indexes for rent, owners' equivalent rent, and lodging away from home all rising 0.2 percent. The medical care index rose 0.5 percent in December. The index for prescription drugs rose 0.9 percent, and the hospital services index increased 0.5 percent. The tobacco index advanced in December, increasing 0.8 percent, and the personal care index rose 0.1 percent. A wide array of declines offset these increases. The apparel index fell 1.2 percent in December following a 1.1 percent decline the prior month. The index for airline fares, which rose in October and November, fell sharply in December, declining 5.0 percent. The index for used cars and trucks fell 1.2 percent, the same decline as last month. The index for household furnishings and operations fell 0.3 percent, as did the alcoholic beverages index. The index for new vehicles declined 0.1 percent, the same decrease as in November.

Not seasonally adjusted CPI measures

The Consumer Price Index for All Urban Consumers (CPI-U) increased 0.8 percent over the last 12 months to an index level of 234.812 (1982-84=100). For the month, the index fell 0.6 percent prior to seasonal adjustment.

The Consumer Price Index for Urban Wage Earners and Clerical Workers (CPI-W) increased 0.3 percent over the last 12 months to an index level of 229.909 (1982-84=100). For the month, the index fell 0.7 percent prior to seasonal adjustment.

The Chained Consumer Price Index for All Urban Consumers (C-CPI-U) increased 0.3 percent over the last 12 months. For the month, the index fell 0.8 percent on a not seasonally adjusted basis. Please note that the indexes for the post-2012 period are subject to revision.

Year in Review

The CPI rose 0.8 percent in 2014 after a 1.5 percent increase in 2013. This is the second-smallest December-December increase in the last 50 years, trailing only the 0.1 percent increase in 2008. It is considerably lower than the 2.1 percent average annual increase over the last ten years.

The energy index, which rose slightly in both 2012 and 2013, declined sharply in 2014, falling 10.6 percent, the largest decline since 2008. The gasoline index was the main cause of the decline, falling 21.0 percent, with most of the decrease over the last few months of the year. This followed a 1.0 percent decline in 2013. The fuel oil index declined as well, falling 19.1 percent in 2014 after a 1.8 percent decline in 2013. In contrast, the energy services index accelerated in 2014, rising 3.7 percent after a 2.4 percent advance in 2013. The electricity index rose 3.1 percent in 2014, similar to its 3.2 percent advance in 2013. The index for natural gas, which fell slightly in 2013, rose 5.8 percent in 2014, ending a streak of five years of declines. Despite the decline in 2014, the energy index has risen at a 3.2 percent annual rate over the past 10 years.

The index for food rose 3.4 percent in 2014, a substantial acceleration from its 2013 increase of 1.1 percent. The index for food at home rose 3.7 percent in 2014 after rising only 0.4 percent in 2013. All six major grocery store food group indexes increased in 2014. The index for meats, poultry, fish, and eggs, which rose 2.9 percent in 2013, increased 9.2 percent, its largest December-December increase since 2003. The index for beef and veal rose 18.7 percent in 2014. The index for dairy and related products rose 5.3 percent in 2014, while the index for fruits and vegetables advanced 3.2 percent; both had declined in 2013. Also turning up after declining in 2013 was the index for other food at home (up 1.5 percent) and the index for nonalcoholic beverages (up 0.7 percent). The only major grocery store food group index not to accelerate was cereals and bakery products, which repeated its 2013 increase of 0.5 percent. The index for food away from home rose 3.0 percent in 2014 after increasing 2.1 percent in 2013. Over the last ten years, the food index has risen at an average annual rate of 2.7 percent.

The index for all items less food and energy rose 1.6 percent in 2014, a slight deceleration from its 1.7 percent increase in 2013, and below its 1.9 percent annual rate over the past ten years. The shelter index accelerated in 2014, increasing 2.9 percent after advancing 2.5 percent in 2013. This was its largest increase since 2007. The rent index rose 3.4 percent and the index for owners' equivalent rent increased 2.6 percent. The medical care index also accelerated, rising 3.0 percent after a 2.0 percent increase in 2013. The new vehicles index accelerated slightly, rising 0.5 percent in 2014 after a 0.4 percent advance the previous year. The personal care index decelerated slightly, rising 1.3 percent in 2014 following a 1.4 percent increase in 2013. The recreation index was unchanged in 2014 after rising slightly in 2013. The index for used cars and trucks turned down in 2014, falling 4.2 percent after rising 2.0 percent in 2013. Similarly, the apparel index, which rose 0.6 percent in 2013, fell 2.0 percent in 2014. The index for household furnishings and operations continued to decline in 2014, falling 0.9 percent after a 1.4

percent decrease the previous year. The index for airline fares also continued to fall, declining 4.7 percent after a 1.4 percent decrease the prior year.

The Consumer Price Index for January 2015 is scheduled to be released on Thursday, February 26, 2015, at 8:30 a.m. (EST).

Chained Consumer Price Index to be Revised Quarterly

Effective with the release of CPI data for January 2015 on February 26, 2015, the Bureau of Labor Statistics will begin quarterly revisions of the Chained Consumer Price Index for All Urban Consumers (C-CPI-U). In addition, a Constant Elasticity of Substitution (CES) formula will replace the geometric mean formula for the calculation of Initial and Interim C-CPI-U indexes.

More frequent weight updates and index revisions. Whereas CPI-U and CPI-W indexes are considered final when released, the final C-CPI-U index is published with a lag for administration and processing of Consumer Expenditure Survey household data, the source of the final C-CPI-U monthly expenditure weights. Under the traditional annual revision process, the final C-CPI-U index was published 13 to 24 months after the CPI-U. The CPI program is implementing a new estimation system that calculates monthly expenditure weights and revised C-CPI-U indexes on a quarterly basis. Under the new quarterly process, the final C-CPI-U index will lag the CPI-U index by 10 to 12 months.

Final C-CPI-U indexes for 2014 will be published on the following quarterly schedule:

Index Month	Release Month
January 2013 – March 2014	February 2015
April – June 2014	May 2015
July – September 2014	August 2015
October – December 2014	November 2015

Initial C-CPI-U indexes will continue to be released concurrent with the CPI-U release, and will be updated as interim C-CPI-U indexes with every quarterly revision until the final version is published.

New formula for initial and interim C-CPI-U Indexes. The CES formula will replace the geometric mean formula for initial and interim C-CPI-U indexes effective with the February 26, 2015 release. The CES formula is an improvement over the geometric mean formula because the CES formula more closely models consumer substitution behavior.

With the use of the geometric mean formula, consumers are assumed to consistently substitute within item classification to goods whose prices are falling relative to others. Using a fixed quantity formula, such as a Laspeyres formula, consumers are assumed to make no substitutions between goods when faced with relative price change. In reality, consumers respond to relative price changes differently than either model implies. The CES formula attempts to capture the amount of substitution occurring in the marketplace as consumers respond to changing relative prices.

For further details on the implementation of the CES formula and the frequency of weight updates for the C-CPI-U, please contact the CPI Information and Analysis section at (202) 691-6966.

New Estimation System

Effective with the release of the January 2015 CPI on February 26, 2015, the Bureau of Labor Statistics will utilize a new estimation system for the Consumer Price Index. The new estimation system, the first major improvement to the existing system in over 25 years, is a redesigned, state-of-the-art system with improved flexibility and review capabilities. For more information on this new system, please see http://www.bls.gov/cpi/cpinewest.htm.

Facilities for Sensory Impaired

Information from this release will be made available to sensory impaired individuals upon request. Voice phone: 202-691-5200, Federal Relay Services: 1-800-877-8339.

Brief Explanation of the CPI

The Consumer Price Index (CPI) is a measure of the average change in prices over time of goods and services purchased by households. The Bureau of Labor Statistics publishes CPIs for two population groups: (1) the CPI for Urban Wage Earners and Clerical Workers (CPI-W), which covers households of wage earners and clerical workers that comprise approximately 28 percent of the total population and (2) the CPI for All Urban Consumers (CPI-U) and the Chained CPI for All Urban Consumers (C-CPI-U), which covers approximately 89 percent of the total population and includes, in addition to wage earners and clerical worker households, groups such as professional, managerial, and technical workers, the self-employed, short-term workers, the unemployed, and retirees and others not in the labor force.

The CPIs are based on prices of food, clothing, shelter, and fuels, transportation fares, charges for doctors' and dentists' services, drugs, and other goods and services that people buy for day-to-day living. Prices are collected each month in 87 urban areas across the country from about 4,000 housing units and approximately 26,000 retail establishments-department stores, supermarkets, hospitals, filling stations, and other types of stores and service establishments. All taxes directly associated with the purchase and use of items are included in the index. Prices of fuels and a few other items are obtained every month in all 87 locations. Prices of most other commodities and services are collected every month in the three largest geographic areas and every other month in other areas. Prices of most goods and services are obtained by personal visits or telephone calls of the Bureau's trained representatives.

In calculating the index, price changes for the various items in each location are averaged together with weights, which represent their importance in the spending of the appropriate population group. Local data are then combined to obtain a U.S. city average. For the CPI-U and CPI-W separate indexes are also published by size of city, by region of the country, for cross-classifications of regions and population-size classes, and for 27 local areas. Area indexes do not measure differences in the level of prices among cities; they only measure the average change in prices for each area since the base period. For the C-CPI-U data are issued only at the national level. It is important to note that the CPI-U and CPI-W are considered final when released, but the C-CPI-U is issued in preliminary form and subject to two annual revisions.

The index measures price change from a designed reference date. For the CPI-U and the CPI-W the reference base is 1982-84 equals 100. The reference base for the C-CPI-U is December 1999 equals 100. An increase of 16.5 percent from the reference base, for example, is shown as 116.500. This change can also be expressed in dollars as follows: the price of a base period market basket of goods and services in the CPI has risen from $10 in 1982-84 to $11.65.

For further details visit the CPI home page on the Internet at http://www.bls.gov/cpi/ or contact our CPI Information and Analysis Section on (202) 691-7000.

Note on Sampling Error in the Consumer Price Index

The CPI is a statistical estimate that is subject to sampling error because it is based upon a sample of retail prices and not the complete universe of all prices. BLS calculates and publishes estimates of the 1-month, 2-month, 6-month and 12-month percent change standard errors annually, for the CPI-U. These standard error estimates can be used to construct confidence intervals for hypothesis testing. For example, the estimated standard error of the 1 month percent change is 0.04 percent for the U.S. All Items Consumer Price Index. This means that if we repeatedly sample from the universe of all retail prices using the same methodology, and estimate a percentage change for each sample, then 95% of these estimates would be within 0.08 percent of the 1 month percentage change based on all retail prices. For example, for a 1-month change of 0.2 percent in the All Items CPI for All Urban Consumers, we are 95 percent confident that the actual percent change based on all retail prices would fall between 0.12 and 0.28 percent. For the latest data, including information on how to use the estimates of standard error, see “Variance Estimates for Price Changes in the Consumer Price Index, January-December 2013”. These data are available on the CPI home page (http://www.bls.gov/cpi), or by using the following link: http://www.bls.gov/cpi/cpivar2013.pdf

Calculating Index Changes

Movements of the indexes from one month to another are usually expressed as percent changes rather than changes in index points, because index point changes are affected by the level of the index in relation to its base period while percent changes are not. The example below illustrates the computation of index point and percent changes.

Percent changes for 3-month and 6-month periods are expressed as annual rates and are computed according to the standard formula for compound growth rates. These data indicate what the percent change would be if the current rate were maintained for a 12-month period.

<u>Index Point Change</u>

CPI	202.416
Less previous index	201.800
Equals index point change	.616

<u>Percent Change</u>

Index point difference	.616
Divided by the previous index	201.800
Equals	0.003
Results multiplied by one hundred	0.003x100
Equals percent change	0.3

A Note on Seasonally Adjusted and Unadjusted Data

Because price data are used for different purposes by different groups, the Bureau of Labor Statistics publishes seasonally adjusted as well as unadjusted changes each month.

For analyzing general price trends in the economy, seasonally adjusted changes are usually preferred, since they eliminate the effect of changes that normally occur at the same time and in about the same magnitude every year--such as price movements resulting from changing climatic conditions, production cycles, model changeovers, holidays, and sales.

The unadjusted data are of primary interest to consumers concerned about the prices they actually pay. Unadjusted data also are used extensively for escalation purposes. Many collective bargaining contract agreements and pension plans, for example, tie compensation changes to the Consumer Price Index before adjustment for seasonal variation.

Seasonal factors used in computing the seasonally adjusted indexes are derived by the X-13ARIMA-SEATS Seasonal Adjustment Method. Seasonally adjusted indexes and seasonal factors are computed annually. Each year, the last five years of seasonally adjusted data are revised. Data from January 2009 through December 2013 were replaced in January 2014. Exceptions to the usual revision schedule were: the updated seasonal data at the end of 1977 replaced data from 1967 through 1977; and, in January 2002, dependently seasonally adjusted series were revised for January 1987-December 2001 as a result of a change in the aggregation weights for dependently adjusted series. For further information, please see "Aggregation of Dependently Adjusted Seasonally Adjusted Series," in the October 2001 issue of the CPI Detailed Report.

Effective with the publication of data from January 2006 through December 2010 in January 2011, the Video and audio series and the Information technology, hardware and services series were changed from independently adjusted to dependently adjusted. This resulted in an increase in the number of seasonal components used in deriving seasonal movement of the All items and 64 other lower level aggregations, from 73 for the publication of January 1998 through December 2005 data to 82 for the publication of seasonally adjusted data for January 2006 and later. Each year the seasonal status of every series is reevaluated based upon certain statistical criteria. If any of the 82 components change their seasonal adjustment status from seasonally adjusted to not seasonally adjusted, not seasonally adjusted data will be used in the aggregation of the dependent series for the last five years, but the seasonally adjusted indexes before that period will not be changed. Note: 35 of the 82 components are not seasonally adjusted for 2014.

Seasonally adjusted data, including the all items index levels, are subject to revision for up to five years after their original release. For this reason, BLS advises against the use of these data in escalation agreements.

Effective with the calculation of the seasonal factors for 1990, the Bureau of Labor Statistics has used an enhanced seasonal adjustment procedure called Intervention Analysis Seasonal Adjustment for some CPI series. Intervention Analysis Seasonal Adjustment allows for better estimates of seasonally adjusted data. Extreme values and/or sharp movements which might distort the seasonal pattern are estimated and removed from the data prior to calculation of seasonal factors. Beginning with the calculation of seasonal factors for 1996, X-12-ARIMA software was used for Intervention Analysis Seasonal Adjustment. In 2014, for the 2009-2013 revisions, the Bureau of Labor Statistics began using X-

13ARIMA-SEATS to perform the seasonal adjustment of CPI series, including Intervention Analysis Seasonal Adjustment for certain series.

For the seasonal factors introduced in January 2014, BLS adjusted 31 series using Intervention Analysis Seasonal Adjustment, including selected food and beverage items, motor fuels, electricity and vehicles. For example, this procedure was used for the Motor fuel series to offset the effects of events such as the response in crude oil markets to the worldwide economic downturn in 2008.

For a complete list of Intervention Analysis Seasonal Adjustment series and explanations, please refer to the article “Intervention Analysis Seasonal Adjustment”, located on our website at http://www.bls.gov/cpi/cpisapage.htm.

For additional information on seasonal adjustment in the CPI, please write to the Bureau of Labor Statistics, Division of Consumer Prices and Price Indexes, Washington, DC 20212 or contact Chris Graci at (202) 691-5826, or by e-mail at graci.christopher@bls.gov, or contact Carlyle Jackson at (202) 691-6984, or by e-mail at jackson.carlyle@bls.gov . If you have general questions about the CPI, please call our information staff at (202) 691-7000.

Recalculated Seasonally Adjusted Indexes to be Available on February 20, 2015

Each year with the release of the January CPI, seasonal adjustment factors are recalculated to reflect price movements from the just-completed calendar year. This routine annual recalculation may result in revisions to seasonally adjusted indexes for the previous 5 years. BLS will make available recalculated seasonally adjusted indexes, as well as recalculated seasonal adjustment factors, for the period January 2010 through December 2014, on Friday, February 20, 2015. This date is before the scheduled release of the January 2015 CPI on Thursday, February 26, 2015.

The revised indexes and seasonal factors will be available on the internet. The address is http://www.bls.gov/cpi/cpisapage.htm. Look under Seasonal Adjustment in the CPI and select Revised Seasonally Adjusted Indexes and Factors, 2010-2014.

For further information please contact Christopher Graci by electronic mail at Graci.Christopher@bls.gov or by telephone at (202) 691-5826 or Carlyle Jackson by electronic mail at Jackson.Carlyle@bls.gov or by telephone at (202) 691-6984.

Table 1. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Unadjusted indexes			Unadjusted percent change		Seasonally adjusted percent change		
		Dec. 2013	Nov. 2014	Dec. 2014	Dec. 2013-Dec. 2014	Nov. 2014-Dec. 2014	Sep. 2014-Oct. 2014	Oct. 2014-Nov. 2014	Nov. 2014-Dec. 2014
All items	100.000	233.049	236.151	234.812	0.8	-0.6	0.0	-0.3	-0.4
Food	14.131	237.869	245.192	245.976	3.4	0.3	0.1	0.2	0.3
Food at home	8.348	233.802	241.576	242.457	3.7	0.4	0.1	0.1	0.3
Cereals and bakery products	1.130	269.267	270.344	270.635	0.5	0.1	0.3	-0.2	0.2
Meats, poultry, fish, and eggs	1.998	239.102	260.457	261.055	9.2	0.2	-0.4	0.6	0.3
Dairy and related products[1]	0.888	218.376	228.412	229.870	5.3	0.6	0.5	-0.2	0.6
Fruits and vegetables	1.355	288.136	293.978	297.429	3.2	1.2	0.9	-0.7	0.4
Nonalcoholic beverages and beverage materials	0.953	165.767	167.511	166.978	0.7	-0.3	0.6	0.5	-0.4
Other food at home	2.025	203.720	206.210	206.831	1.5	0.3	-0.4	0.4	0.3
Food away from home[1]	5.783	245.300	251.987	252.628	3.0	0.3	0.2	0.4	0.3
Energy	8.443	234.542	221.844	209.785	-10.6	-5.4	-1.9	-3.8	-4.7
Energy commodities	4.691	289.461	257.629	230.195	-20.5	-10.6	-3.0	-6.4	-9.1
Fuel oil[1]	0.150	375.607	329.681	303.844	-19.1	-7.8	-4.0	-3.5	-7.8
Motor fuel	4.444	284.445	252.897	225.165	-20.8	-11.0	-3.1	-6.6	-9.3
Gasoline (all types)	4.364	282.773	251.172	223.404	-21.0	-11.1	-3.0	-6.6	-9.4
Energy services[2]	3.753	192.394	197.459	199.592	3.7	1.1	-0.2	-0.3	1.0
Electricity[2]	2.903	198.043	202.889	204.275	3.1	0.7	0.5	0.1	0.8
Utility (piped) gas service[2]	0.850	172.898	178.558	182.908	5.8	2.4	-2.7	-1.7	1.5
All items less food and energy	77.426	235.000	239.248	238.775	1.6	-0.2	0.2	0.1	0.0
Commodities less food and energy commodities	19.473	146.277	146.439	145.127	-0.8	-0.9	0.0	-0.4	-0.3
Apparel	3.461	126.461	129.023	123.942	-2.0	-3.9	-0.2	-1.1	-1.2
New vehicles	3.529	145.766	146.481	146.524	0.5	0.0	0.2	-0.1	-0.1
Used cars and trucks	1.606	148.183	144.151	141.957	-4.2	-1.5	-0.9	-1.2	-1.2
Medical care commodities	1.751	333.801	347.616	349.750	4.8	0.6	0.0	0.6	1.0
Alcoholic beverages	1.012	235.804	239.551	238.856	1.3	-0.3	0.1	0.8	-0.3
Tobacco and smoking products[1]	0.708	890.438	909.610	916.707	3.0	0.8	0.6	0.0	0.8
Services less energy services	57.953	289.001	295.911	296.021	2.4	0.0	0.3	0.2	0.1
Shelter	32.482	265.881	273.233	273.598	2.9	0.1	0.2	0.3	0.2
Rent of primary residence[2]	7.099	271.688	280.123	280.874	3.4	0.3	0.2	0.3	0.2
Owners' equivalent rent of residences[2, 3]	24.163	274.135	280.840	281.288	2.6	0.2	0.2	0.2	0.2
Medical care services	5.899	457.296	467.482	468.393	2.4	0.2	0.2	0.4	0.3
Physicians' services[2]	1.578	356.469	361.001	361.659	1.5	0.2	0.1	0.5	0.3
Hospital services[2, 4]	1.835	269.365	281.491	282.547	4.9	0.4	0.2	0.2	0.5
Transportation services	5.624	281.680	288.174	286.585	1.7	-0.6	0.8	0.3	-0.5
Motor vehicle maintenance and repair[1]	1.161	263.081	268.389	268.588	2.1	0.1	0.3	0.1	0.1
Motor vehicle insurance	2.279	428.640	447.271	448.933	4.7	0.4	0.6	0.2	0.3
Airline fare	0.743	301.357	305.885	287.175	-4.7	-6.1	2.4	1.4	-5.0

[1] Not seasonally adjusted.

[2] This index series was calculated using a Laspeyres estimator. All other item stratum index series were calculated using a geometric means estimator.

[3] Indexes on a December 1982=100 base.

[4] Indexes on a December 1996=100 base.

NOTE: Index applies to a month as a whole, not to any specific date.

Table 2. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by detailed expenditure category, December 2014

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Unadjusted percent change		Seasonally adjusted percent change		
		Dec. 2013-Dec. 2014	Nov. 2014-Dec. 2014	Sep. 2014-Oct. 2014	Oct. 2014-Nov. 2014	Nov. 2014-Dec. 2014
All items	100.000	0.8	-0.6	0.0	-0.3	-0.4
Food	14.131	3.4	0.3	0.1	0.2	0.3
Food at home	8.348	3.7	0.4	0.1	0.1	0.3
Cereals and bakery products	1.130	0.5	0.1	0.3	-0.2	0.2
Cereals and cereal products	0.370	-0.3	-0.5	1.0	-1.0	-0.4
Flour and prepared flour mixes	0.048	-1.9	-0.6	0.0	0.2	-1.6
Breakfast cereal[1]	0.196	1.3	-0.1	1.5	0.7	-0.1
Rice, pasta, cornmeal[1]	0.127	-2.1	-1.1	0.0	-1.7	-1.1
Rice[1, 2, 3]		-2.8	-1.0	0.4	-1.1	-1.0
Bakery products	0.760	0.9	0.4	-0.2	0.3	0.5
Bread[2]	0.225	1.2	1.5	-1.3	0.7	1.2
White bread[1, 3]		0.9	1.4	-0.4	-0.2	1.4
Bread other than white[1, 3]		0.8	1.6	-1.3	0.2	1.6
Fresh biscuits, rolls, muffins[1, 2]	0.115	1.9	0.3	0.4	0.4	0.2
Cakes, cupcakes, and cookies	0.189	0.6	-0.5	-0.3	-0.2	0.2
Cookies[1, 3]		-0.2	-1.0	-0.3	0.1	-0.3
Fresh cakes and cupcakes[1, 3]		1.5	0.1	0.6	-0.7	0.1
Other bakery products	0.231	0.4	0.2	0.7	0.3	0.2
Fresh sweetrolls, coffeecakes, doughnuts[1, 3]		0.6	1.8	0.0	-0.5	1.8
Crackers, bread, and cracker products[3]		1.0	0.3	0.8	0.3	0.1
Frozen and refrigerated bakery products, pies, tarts, turnovers[3]		-0.5	-0.4	-0.8	1.4	-0.9
Meats, poultry, fish, and eggs	1.998	9.2	0.2	-0.4	0.6	0.3
Meats, poultry, and fish	1.874	9.1	-0.3	-0.4	0.6	0.0
Meats	1.223	12.7	-0.1	-0.2	0.3	0.2
Beef and veal[1]	0.575	18.7	0.7	0.3	0.8	0.7
Uncooked ground beef[1]	0.236	19.2	0.2	1.0	1.4	0.2
Uncooked beef roasts[1, 2]	0.083	20.6	1.4	-0.4	2.0	1.4
Uncooked beef steaks[1, 2]	0.204	16.0	0.9	-0.2	-0.9	0.9
Uncooked other beef and veal[1, 2]	0.052	24.0	1.2	0.7	2.7	1.2
Pork	0.376	8.2	-1.7	-0.7	-0.3	-0.7
Bacon, breakfast sausage, and related products[2]	0.141	2.4	-0.8	-1.4	-0.5	-0.2
Bacon and related products[3]		-1.0	-1.6	-2.5	-0.9	-0.4
Breakfast sausage and related products[2, 3]		7.3	-0.1	0.1	0.6	0.4
Ham	0.080	13.1	-4.0	0.8	1.3	-1.2
Ham, excluding canned[3]		14.4	-4.9	0.3	1.2	-1.7
Pork chops	0.064	10.1	-0.3	2.0	-1.1	0.0
Other pork including roasts and picnics[2]	0.091	12.5	-2.1	-1.2	-1.6	-1.3
Other meats	0.272	7.4	0.5	-0.3	0.4	0.4
Frankfurters[3]		12.1	3.6	-1.7	1.6	4.1
Lunchmeats[1, 2, 3]		5.8	0.0	0.5	0.2	0.0
Lamb and organ meats[1, 3]		8.8	-0.5	0.8	1.6	-0.5
Lamb and mutton[1, 2, 3]		3.2	-1.1	-1.2	1.4	-1.1
Poultry	0.360	1.6	-0.5	-1.2	1.7	-0.7
Chicken[2]	0.293	2.1	-0.3	-1.3	1.6	-0.5
Fresh whole chicken[1, 3]		3.0	0.5	-1.8	0.7	0.5
Fresh and frozen chicken parts[1, 3]		1.6	-0.5	-0.4	1.6	-0.5
Other poultry including turkey[2]	0.067	-0.5	-1.4	-1.1	1.8	-1.8
Fish and seafood[1]	0.291	4.3	-0.8	-0.8	0.3	-0.3
Fresh fish and seafood[1, 2]	0.149	5.6	-0.7	-1.9	0.0	-0.7
Processed fish and seafood[2]	0.143	3.0	-0.8	-0.2	0.6	-0.9
Shelf stable fish and seafood[1, 3]		1.3	-1.0	1.1	0.9	-1.0

See footnotes at end of table.

Table 2. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by detailed expenditure category, December 2014 — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Unadjusted percent change		Seasonally adjusted percent change		
		Dec. 2013-Dec. 2014	Nov. 2014-Dec. 2014	Sep. 2014-Oct. 2014	Oct. 2014-Nov. 2014	Nov. 2014-Dec. 2014
Frozen fish and seafood[3]		5.2	-0.7	-1.0	0.9	-0.5
Eggs	0.124	10.7	7.7	-0.4	1.1	5.5
Dairy and related products[1]	0.888	5.3	0.6	0.5	-0.2	0.6
Milk[1, 2]	0.279	4.3	0.8	-0.5	-0.4	0.8
Fresh whole milk[1, 3]		5.2	-0.1	-0.6	0.1	-0.1
Fresh milk other than whole[1, 2, 3]		4.1	1.5	-0.6	-0.6	1.5
Cheese and related products[1]	0.285	8.2	-0.2	0.7	0.5	0.2
Ice cream and related products	0.122	3.5	2.4	-0.9	0.4	2.3
Other dairy and related products[2]	0.202	3.7	0.5	1.3	-0.2	0.0
Fruits and vegetables	1.355	3.2	1.2	0.9	-0.7	0.4
Fresh fruits and vegetables	1.057	4.1	1.2	1.1	-0.8	0.4
Fresh fruits	0.573	3.6	-0.1	0.9	-2.9	-1.3
Apples	0.084	-2.3	-2.1	-0.1	-0.4	-0.9
Bananas	0.088	-0.7	-1.3	-0.1	1.5	-1.9
Citrus fruits[2]	0.155	5.4	-5.9	3.0	-2.1	-1.6
Oranges, including tangerines[3]		3.7	-7.8	3.8	-0.1	-1.8
Other fresh fruits[2]	0.247	6.2	4.6	1.0	-4.0	-0.2
Fresh vegetables	0.484	4.6	2.8	1.4	1.8	2.4
Potatoes	0.075	-1.8	-0.6	3.4	-1.8	1.4
Lettuce	0.074	4.4	-3.4	-0.3	5.5	-4.3
Tomatoes[1]	0.093	16.5	9.3	4.6	10.4	9.3
Other fresh vegetables	0.242	2.3	3.2	0.8	-0.6	3.0
Processed fruits and vegetables[2]	0.298	0.4	1.1	0.5	-0.7	0.8
Canned fruits and vegetables[2]	0.154	-0.2	1.2	1.6	-1.3	0.8
Canned fruits[2, 3]		0.5	2.2	0.5	-0.3	1.0
Canned vegetables[2, 3]		0.0	1.1	1.8	-1.8	1.1
Frozen fruits and vegetables[2]	0.087	1.5	1.0	-1.1	-0.8	1.3
Frozen vegetables[3]		0.9	1.4	-1.1	-1.8	2.0
Other processed fruits and vegetables including dried[2]	0.057	0.2	0.9	0.8	-0.4	0.7
Dried beans, peas, and lentils[1, 2, 3]		4.6	1.1	-0.5	1.0	1.1
Nonalcoholic beverages and beverage materials	0.953	0.7	-0.3	0.6	0.5	-0.4
Juices and nonalcoholic drinks[2]	0.696	0.1	-0.2	0.7	0.6	-0.5
Carbonated drinks	0.283	1.4	0.1	0.5	-0.3	0.7
Frozen noncarbonated juices and drinks[1, 2]	0.014	2.3	0.0	2.6	0.6	0.0
Nonfrozen noncarbonated juices and drinks[1, 2]	0.399	-1.0	-0.5	1.1	1.3	-0.5
Beverage materials including coffee and tea[2]	0.256	2.6	-0.5	-0.3	0.3	-0.4
Coffee	0.158	3.6	-0.5	-0.5	-0.1	-0.2
Roasted coffee[3]		4.2	-0.9	-0.1	0.2	0.5
Instant and freeze dried coffee[1, 3]		0.2	1.9	-0.9	-0.8	1.9
Other beverage materials including tea[2]	0.099	1.0	-0.5	0.4	1.0	-0.7
Other food at home	2.025	1.5	0.3	-0.4	0.4	0.3
Sugar and sweets[1]	0.295	1.1	0.5	-1.0	-0.2	0.5
Sugar and artificial sweeteners	0.053	0.2	0.9	-2.2	0.6	1.3
Candy and chewing gum[1, 2]	0.183	1.8	0.6	-0.2	0.1	0.6
Other sweets[2]	0.060	-0.2	-0.1	-1.9	1.0	-0.4
Fats and oils	0.245	1.0	-0.4	0.3	-0.9	-0.5
Butter and margarine[2]	0.077	11.6	-1.6	2.8	-0.2	-1.8
Butter[3]		22.5	-2.8	5.1	-1.7	-1.6
Margarine[3]		2.6	0.4	1.5	0.1	0.2
Salad dressing[1, 2]	0.061	-4.3	0.5	0.4	-1.8	0.5
Other fats and oils including peanut butter[2]	0.107	-2.5	0.0	-1.0	-0.7	-0.4
Peanut butter[1, 2, 3]		-3.6	-0.3	-0.1	-0.6	-0.3
Other foods	1.485	1.7	0.4	-0.4	0.7	0.4

See footnotes at end of table.

Table 2. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by detailed expenditure category, December 2014 — Continued
[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Unadjusted percent change		Seasonally adjusted percent change		
		Dec. 2013-Dec. 2014	Nov. 2014-Dec. 2014	Sep. 2014-Oct. 2014	Oct. 2014-Nov. 2014	Nov. 2014-Dec. 2014
Soups	0.094	-0.6	-1.6	-1.6	1.2	-1.1
Frozen and freeze dried prepared foods[1]	0.282	1.9	0.3	-1.2	1.2	0.3
Snacks[1]	0.327	1.8	0.4	0.4	0.1	0.4
Spices, seasonings, condiments, sauces	0.288	2.2	1.1	-1.2	0.5	1.6
Salt and other seasonings and spices[2, 3]		4.8	-0.1	-1.5	2.3	0.1
Olives, pickles, relishes[1, 2, 3]		0.2	1.0	-1.5	-2.2	1.0
Sauces and gravies[2, 3]		1.7	2.0	-0.2	-0.8	1.8
Other condiments[3]		1.8	0.0	-0.3	1.0	3.1
Baby food[1, 2]	0.055	2.1	-0.1	0.5	0.0	-0.1
Other miscellaneous foods[1, 2]	0.439	1.6	0.5	0.4	1.0	0.5
Prepared salads[1, 3, 4]		3.9	1.0	-0.9	0.9	1.0
Food away from home[1]	5.783	3.0	0.3	0.2	0.4	0.3
Full service meals and snacks[1, 2]	2.800	3.1	0.2	0.2	0.3	0.2
Limited service meals and snacks[1, 2]	2.392	3.2	0.3	0.3	0.5	0.3
Food at employee sites and schools[2]	0.211	1.8	0.0	0.9	0.2	0.1
Food at elementary and secondary schools[3, 5]		2.3	-0.1	1.4	0.2	0.0
Food from vending machines and mobile vendors[1, 2]	0.063	0.5	0.6	-0.1	0.7	0.6
Other food away from home[1, 2]	0.317	2.0	0.2	-0.1	0.2	0.2
Energy	8.443	-10.6	-5.4	-1.9	-3.8	-4.7
Energy commodities	4.691	-20.5	-10.6	-3.0	-6.4	-9.1
Fuel oil and other fuels[1]	0.246	-13.7	-4.9	-2.3	-2.0	-4.9
Fuel oil[1]	0.150	-19.1	-7.8	-4.0	-3.5	-7.8
Propane, kerosene, and firewood[1, 6]	0.096	-4.6	-0.4	-0.5	-1.8	-1.4
Motor fuel	4.444	-20.8	-11.0	-3.1	-6.6	-9.3
Gasoline (all types)	4.364	-21.0	-11.1	-3.0	-6.6	-9.4
Gasoline, unleaded regular[3]		-21.6	-11.3	-3.2	-6.8	-9.6
Gasoline, unleaded midgrade[3, 7]		-19.6	-11.5	-3.0	-5.7	-9.8
Gasoline, unleaded premium[3]		-18.3	-9.7	-2.5	-5.9	-8.0
Other motor fuels[2]	0.080	-11.9	-6.0	-1.9	-1.6	-5.2
Energy services[8]	3.753	3.7	1.1	-0.2	-0.3	1.0
Electricity[8]	2.903	3.1	0.7	0.5	0.1	0.8
Utility (piped) gas service[8]	0.850	5.8	2.4	-2.7	-1.7	1.5
All items less food and energy	77.426	1.6	-0.2	0.2	0.1	0.0
Commodities less food and energy commodities	19.473	-0.8	-0.9	0.0	-0.4	-0.3
Household furnishings and supplies[1, 9]	3.336	-1.9	-0.4	0.4	-0.5	-0.4
Window and floor coverings and other linens[1, 2]	0.271	-3.6	-2.5	-0.3	-0.6	-2.5
Floor coverings[1, 2]	0.047	0.8	-0.2	-1.2	-0.7	-0.2
Window coverings[1, 2]	0.055	-2.3	-3.3	-0.1	3.4	-3.3
Other linens[1, 2]	0.170	-5.2	-2.8	-0.1	-1.9	-2.8
Furniture and bedding[1]	0.762	-1.6	0.3	0.7	0.1	0.3
Bedroom furniture[1]	0.267	-2.4	-0.3	0.0	-0.2	-0.3
Living room, kitchen, and dining room furniture[1, 2]	0.359	-1.9	0.7	1.4	0.3	0.7
Other furniture[2]	0.127	0.8	0.4	-0.1	-1.1	0.0
Infants' furniture[1, 3, 5]						
Appliances[2]	0.271	-5.2	-0.8	0.2	-1.3	-0.6
Major appliances[2]	0.146	-6.9	0.2	-0.2	-2.5	0.3
Laundry equipment[3]		-7.4	0.7	-0.7	-4.4	1.3
Other appliances[1, 2]	0.122	-3.1	-2.1	0.4	-0.1	-2.1
Other household equipment and furnishings[2]	0.482	-3.9	-1.2	0.3	-1.1	-0.9
Clocks, lamps, and decorator items[1]	0.260	-5.8	-1.6	0.8	-1.8	-1.6
Indoor plants and flowers[10]	0.106	1.9	0.7	0.0	0.9	0.3
Dishes and flatware[1, 2]	0.043	-6.7	-3.6	-0.5	-3.8	-3.6
Nonelectric cookware and tableware[2]	0.074	-3.7	-0.9	0.8	-1.2	-0.5

See footnotes at end of table.

Table 2. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by detailed expenditure category, December 2014 — Continued
[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Unadjusted percent change		Seasonally adjusted percent change		
		Dec. 2013-Dec. 2014	Nov. 2014-Dec. 2014	Sep. 2014-Oct. 2014	Oct. 2014-Nov. 2014	Nov. 2014-Dec. 2014
Tools, hardware, outdoor equipment and supplies[2]	0.706	0.1	0.0	0.5	-0.1	0.0
Tools, hardware and supplies[1, 2]	0.188	0.8	0.4	0.2	-0.5	0.4
Outdoor equipment and supplies[2]	0.366	-0.3	-0.1	0.9	0.1	-0.3
Housekeeping supplies[1]	0.844	-0.8	-0.1	0.6	-0.3	-0.1
Household cleaning products[1, 2]	0.334	-0.9	0.2	0.7	0.4	0.2
Household paper products[1, 2]	0.247	-0.7	-0.3	0.2	-0.6	-0.3
Miscellaneous household products[1, 2]	0.263	-0.7	-0.4	0.8	-0.8	-0.4
Apparel	3.461	-2.0	-3.9	-0.2	-1.1	-1.2
Men's and boys' apparel	0.864	-3.0	-4.1	-1.1	-0.1	-1.1
Men's apparel	0.680	-3.0	-4.6	-1.6	-0.1	-1.2
Men's suits, sport coats, and outerwear	0.110	-7.1	-6.1	-4.0	-1.2	-2.1
Men's furnishings	0.192	-2.4	-3.9	-1.5	-0.5	-1.6
Men's shirts and sweaters[2]	0.207	-4.5	-5.9	-0.5	-0.8	-1.8
Men's pants and shorts	0.164	1.1	-2.8	-0.9	1.7	-0.9
Boys' apparel	0.184	-2.7	-2.2	1.6	-1.5	0.2
Women's and girls' apparel	1.514	-3.6	-5.5	0.4	-1.9	-2.2
Women's apparel	1.273	-3.5	-5.5	0.3	-1.7	-1.9
Women's outerwear	0.123	3.6	-5.0	-1.8	-3.7	-0.3
Women's dresses	0.167	1.6	-7.8	4.3	0.4	-0.7
Women's suits and separates[2]	0.588	-8.2	-6.9	-0.7	-2.4	-1.9
Women's underwear, nightwear, sportswear and accessories[2]	0.385	-0.3	-2.4	0.6	-1.9	-0.9
Girls' apparel	0.242	-4.0	-5.8	0.6	-3.4	-3.8
Footwear	0.732	2.8	-1.5	0.0	-0.9	0.4
Men's footwear[1]	0.219	1.8	-1.0	-1.1	-0.6	-1.0
Boys' and girls' footwear	0.178	6.1	-0.7	2.8	-1.7	-0.1
Women's footwear	0.335	1.7	-2.3	-0.2	-0.8	0.6
Infants' and toddlers' apparel	0.136	0.4	-1.0	0.5	-0.5	0.0
Jewelry and watches[6]	0.214	-4.3	-2.3	-1.9	-0.7	-0.8
Watches[1, 6]	0.046	-1.0	-1.3	-0.7	-2.5	-1.3
Jewelry[6]	0.168	-5.1	-2.6	-2.2	-0.6	-0.4
Transportation commodities less motor fuel[9]	5.674	-0.9	-0.4	-0.1	-0.4	-0.4
New vehicles	3.529	0.5	0.0	0.2	-0.1	-0.1
New cars and trucks[2, 3]		0.6	0.0	0.2	-0.1	-0.1
New cars[3]		-0.1	-0.1	0.2	0.0	-0.2
New trucks[3, 11]		1.3	0.2	0.1	-0.1	-0.1
Used cars and trucks	1.606	-4.2	-1.5	-0.9	-1.2	-1.2
Motor vehicle parts and equipment[1]	0.430	-0.7	0.4	-0.1	-0.2	0.4
Tires[1]	0.282	-1.9	0.5	-0.2	-0.4	0.5
Vehicle accessories other than tires[1, 2]	0.149	1.7	0.3	0.1	0.1	0.3
Vehicle parts and equipment other than tires[1, 3]		1.5	0.2	-0.1	0.3	0.2
Motor oil, coolant, and fluids[1, 3]		2.4	0.8	0.7	-0.5	0.8
Medical care commodities	1.751	4.8	0.6	0.0	0.6	1.0
Medicinal drugs[1, 9]	1.675	5.0	0.6	0.0	0.4	0.6
Prescription drugs	1.328	6.4	0.7	0.7	0.6	0.9
Nonprescription drugs[1, 9]	0.348	-0.2	0.4	-2.1	0.2	0.4
Medical equipment and supplies[1, 9]	0.076	0.9	-0.1	0.5	0.0	-0.1
Recreation commodities[9]	2.004	-2.6	-0.4	0.0	-0.6	-0.3
Video and audio products[9]	0.291	-10.5	-1.4	-0.6	-2.1	-1.4
Televisions	0.135	-16.7	-1.9	-1.2	-3.2	-2.1
Other video equipment[1, 2]	0.030	-0.8	-4.5	-0.2	-2.7	-4.5
Audio equipment	0.067	-7.3	-0.7	0.3	-1.3	0.1
Audio discs, tapes and other media[1, 2]	0.043	-3.6	0.7	-1.0	-0.1	0.7

See footnotes at end of table.

Table 2. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by detailed expenditure category, December 2014 — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Unadjusted percent change Dec. 2013-Dec. 2014	Unadjusted percent change Nov. 2014-Dec. 2014	Seasonally adjusted percent change Sep. 2014-Oct. 2014	Seasonally adjusted percent change Oct. 2014-Nov. 2014	Seasonally adjusted percent change Nov. 2014-Dec. 2014
Pets and pet products[1]	0.655	0.3	0.1	0.2	0.1	0.1
Pet food[1, 2, 3]		0.4	0.1	0.0	0.0	0.1
Purchase of pets, pet supplies, accessories[1, 2, 3]		0.4	0.1	0.7	0.3	0.1
Sporting goods[1]	0.401	-2.2	-0.8	-0.1	-0.8	-0.8
Sports vehicles including bicycles[1]	0.181	-1.1	-0.4	-0.2	-0.6	-0.4
Sports equipment	0.215	-3.1	-1.2	-0.2	-0.5	-0.5
Photographic equipment and supplies	0.059	-2.2	-3.4	-1.2	-0.5	-1.5
Film and photographic supplies[1, 2, 3]		23.4	-1.2	-0.1	0.9	-1.2
Photographic equipment[2, 3]		-6.1	-4.0	-1.1	-0.9	-1.5
Recreational reading materials[1]	0.218	2.2	0.1	1.4	-0.3	0.1
Newspapers and magazines[1, 2]	0.122	4.8	0.9	1.8	-0.4	0.9
Recreational books[1, 2]	0.095	-0.9	-0.8	0.8	-0.1	-0.8
Other recreational goods[2]	0.379	-3.8	-0.1	-0.2	-0.7	0.2
Toys	0.275	-5.4	0.3	-0.2	-0.9	0.7
Toys, games, hobbies and playground equipment[2, 3]		-2.9	-0.1	0.4	0.0	0.6
Sewing machines, fabric and supplies[1, 2]	0.051	0.1	-2.0	-1.1	0.0	-2.0
Music instruments and accessories[2]	0.042	2.4	-0.1	0.8	0.1	-0.1
Education and communication commodities[9]	0.613	-4.9	-1.0	-0.1	-0.9	-0.8
Educational books and supplies	0.200	4.6	0.6	0.8	0.2	1.1
College textbooks[1, 3, 12]		5.0	0.7	0.7	-0.1	0.7
Information technology commodities[9]	0.413	-9.0	-1.8	-0.5	-1.4	-1.6
Personal computers and peripheral equipment[4]	0.276	-10.5	-2.2	-0.6	-1.5	-2.1
Computer software and accessories[1, 2]	0.068	-1.2	-1.3	0.5	0.4	-1.3
Telephone hardware, calculators, and other consumer information items[1, 2]	0.068	-9.9	-0.3	-1.1	-2.9	-0.3
Alcoholic beverages	1.012	1.3	-0.3	0.1	0.8	-0.3
Alcoholic beverages at home	0.596	0.7	-0.5	-0.2	1.0	-0.4
Beer, ale, and other malt beverages at home	0.273	0.7	-0.3	-0.1	0.7	-0.3
Distilled spirits at home[1]	0.073	0.9	-0.4	0.3	0.5	0.0
Whiskey at home[3]		1.5	0.1	0.2	-0.2	0.1
Distilled spirits, excluding whiskey, at home[1, 3]		0.8	-0.3	0.1	0.0	-0.3
Wine at home	0.250	0.6	-0.7	-0.6	1.5	-0.4
Alcoholic beverages away from home[1]	0.416	2.2	0.0	0.5	0.5	0.0
Beer, ale, and other malt beverages away from home[1, 2, 3]		2.1	-0.1	0.2	0.6	-0.1
Wine away from home[1, 2, 3]		2.0	0.0	0.1	0.7	0.0
Distilled spirits away from home[1, 2, 3]		2.2	0.0	0.7	0.4	0.0
Other goods[9]	1.621	1.3	0.2	0.2	-0.6	0.3
Tobacco and smoking products[1]	0.708	3.0	0.8	0.6	0.0	0.8
Cigarettes[1, 2]	0.652	3.1	0.8	0.6	-0.1	0.8
Tobacco products other than cigarettes[1, 2]	0.050	1.4	0.5	0.7	0.4	0.5
Personal care products[1]	0.721	0.3	-0.2	0.0	-0.8	-0.2
Hair, dental, shaving, and miscellaneous personal care products[1, 2]	0.367	-0.3	-0.2	-0.5	-0.6	-0.2
Cosmetics, perfume, bath, nail preparations and implements[1]	0.346	1.0	-0.2	0.4	-1.0	-0.2
Miscellaneous personal goods[2]	0.192	-0.6	-0.1	-0.1	-1.7	0.0
Stationery, stationery supplies, gift wrap[3]		0.0	-0.1	0.0	-1.4	-0.1
Infants' equipment[1, 3, 5]		-0.7	0.5	-0.4	-0.6	0.5
Services less energy services	57.953	2.4	0.0	0.3	0.2	0.1
Shelter	32.482	2.9	0.1	0.2	0.3	0.2
Rent of shelter[13]	32.113	2.9	0.1	0.3	0.2	0.2
Rent of primary residence[8]	7.099	3.4	0.3	0.2	0.3	0.2

See footnotes at end of table.

Table 2. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by detailed expenditure category, December 2014 — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Unadjusted percent change		Seasonally adjusted percent change		
		Dec. 2013-Dec. 2014	Nov. 2014-Dec. 2014	Sep. 2014-Oct. 2014	Oct. 2014-Nov. 2014	Nov. 2014-Dec. 2014
Lodging away from home[2]	0.851	6.3	-2.1	0.7	0.0	0.2
Housing at school, excluding board[8, 13]	0.171	2.7	0.0	0.4	0.2	0.3
Other lodging away from home including hotels and motels	0.680	7.3	-2.6	0.8	-0.1	0.2
Owners' equivalent rent of residences[8, 13]	24.163	2.6	0.2	0.2	0.2	0.2
Owners' equivalent rent of primary residence[8, 13]	22.752	2.6	0.2	0.2	0.2	0.2
Tenants' and household insurance[1, 2]	0.369	5.6	0.9	-0.1	0.1	0.9
Water and sewer and trash collection services[2]	1.210	4.6	0.4	0.6	0.7	0.6
Water and sewerage maintenance[8]	0.935	5.6	0.5	0.8	0.9	0.7
Garbage and trash collection[1, 11]	0.275	1.4	0.1	0.2	0.0	0.1
Household operations[1, 2]	0.845	2.8	-0.3	0.8	0.0	-0.3
Domestic services[1, 2]	0.277	1.2	0.1	0.4	0.2	0.1
Gardening and lawncare services[1, 2]	0.278	4.4	0.0	1.6	0.0	0.0
Moving, storage, freight expense[2]	0.119	2.1	-2.4	0.4	-0.7	-1.8
Repair of household items[1, 2]	0.066	4.0	0.8	0.4	0.1	0.8
Medical care services	5.899	2.4	0.2	0.2	0.4	0.3
Professional services	3.011	1.7	0.1	0.2	0.5	0.2
Physicians' services[8]	1.578	1.5	0.2	0.1	0.5	0.3
Dental services[8]	0.799	1.8	0.0	0.1	0.2	-0.1
Eyeglasses and eye care[1, 6]	0.282	2.6	0.1	-0.1	0.6	0.1
Services by other medical professionals[8, 6]	0.352	2.0	0.0	0.6	0.9	0.1
Hospital and related services	2.139	4.5	0.3	0.3	0.2	0.6
Hospital services[8, 14]	1.835	4.9	0.4	0.2	0.2	0.5
Inpatient hospital services[8, 14, 3]		5.5	0.4	0.2	0.1	0.5
Outpatient hospital services[8, 3, 6]		4.5	0.3	0.3	0.0	0.6
Nursing homes and adult day services[8, 14]	0.173	2.9	0.0	0.2	0.4	0.1
Care of invalids and elderly at home[1, 5]	0.131	1.8	0.4	-0.1	0.1	0.4
Health insurance[1, 5]	0.748	-0.5	0.1	0.0	0.1	0.1
Transportation services	5.624	1.7	-0.6	0.8	0.3	-0.5
Leased cars and trucks[12]	0.394	-0.1	0.3	1.0	-0.4	0.8
Car and truck rental[2]	0.071	0.0	1.4	2.9	2.8	-0.9
Motor vehicle maintenance and repair[1]	1.161	2.1	0.1	0.3	0.1	0.1
Motor vehicle body work[1]	0.056	2.1	0.3	0.0	0.1	0.3
Motor vehicle maintenance and servicing[1]	0.490	2.2	0.0	0.1	0.7	0.0
Motor vehicle repair[1, 2]	0.583	2.0	0.1	0.5	-0.4	0.1
Motor vehicle insurance	2.279	4.7	0.4	0.6	0.2	0.3
Motor vehicle fees[1, 2]	0.561	0.3	0.1	0.5	0.1	0.1
State motor vehicle registration and license fees[1, 8, 2]	0.311	-1.0	0.0	0.2	-0.2	0.0
Parking and other fees[2]	0.232	2.2	0.3	0.9	0.6	0.3
Parking fees and tolls[1, 2, 3]		2.7	0.7	0.1	0.3	0.7
Automobile service clubs[1, 2, 3]		-0.4	-0.1	1.1	-0.1	-0.1
Public transportation	1.159	-2.9	-3.7	1.7	1.1	-3.1
Airline fare	0.743	-4.7	-6.1	2.4	1.4	-5.0
Other intercity transportation	0.153	-0.7	1.5	1.1	1.8	-0.2
Intercity bus fare[1, 3, 4]						
Intercity train fare[3, 4]		3.8	5.6	2.6	3.1	1.6
Ship fare[1, 2, 3]		-1.9	0.3	0.3	2.2	0.3
Intracity transportation[1]	0.258	1.1	0.0	0.1	0.0	0.0
Intracity mass transit[1, 3, 9]		1.1	0.0	0.1	0.0	0.0
Recreation services[9]	3.721	1.5	0.0	0.4	0.0	0.2
Video and audio services[9]	1.550	1.8	0.0	0.9	-0.2	0.3

See footnotes at end of table.

Table 2. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by detailed expenditure category, December 2014 — Continued
[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Unadjusted percent change		Seasonally adjusted percent change		
		Dec. 2013-Dec. 2014	Nov. 2014-Dec. 2014	Sep. 2014-Oct. 2014	Oct. 2014-Nov. 2014	Nov. 2014-Dec. 2014
Cable and satellite television and radio service[11]	1.459	2.2	0.1	0.8	-0.2	0.4
Video discs and other media, including rental of video and audio[1, 2]	0.090	-3.0	-1.2	1.5	-0.9	-1.2
Video discs and other media[1, 2, 3]		-6.3	-2.7	2.0	-2.4	-2.7
Rental of video or audio discs and other media[1, 2, 3]		1.4	1.2	0.2	0.1	1.2
Pet services including veterinary[2]	0.396	2.7	0.2	0.2	0.4	0.2
Pet services[1, 2, 3]		1.8	0.0	0.0	0.2	0.0
Veterinarian services[2, 3]		2.9	0.1	0.2	0.4	0.3
Photographers and film processing[1, 2]	0.061	2.2	0.2	-0.1	-0.1	0.2
Photographer fees[1, 2, 3]		1.1	0.1	0.6	-1.3	0.1
Film processing[1, 2, 3]		3.8	0.4	-0.1	0.0	0.4
Other recreation services[2]	1.714	0.8	0.0	0.0	0.0	0.0
Club dues and fees for participant sports and group exercises[2]	0.602	0.4	-0.6	0.1	0.0	-0.6
Admissions[1]	0.632	0.7	0.7	-0.4	0.0	0.7
Admission to movies, theaters, and concerts[1, 2, 3]		0.4	0.6	-0.4	-0.4	0.6
Admission to sporting events[1, 2, 3]		2.7	1.2	0.6	0.0	1.2
Fees for lessons or instructions[1, 6]	0.210	2.0	0.0	0.4	0.0	0.0
Education and communication services[9]	6.425	0.9	-0.1	-0.2	0.0	0.0
Tuition, other school fees, and childcare	3.106	3.2	-0.1	0.5	0.4	0.3
College tuition and fees	1.844	3.4	0.0	0.7	0.4	0.4
Elementary and high school tuition and fees	0.375	4.0	0.0	0.3	0.4	0.3
Child care and nursery school[10]	0.722	2.2	-0.2	0.1	0.3	0.0
Technical and business school tuition and fees[2]	0.039	1.8	0.0	0.5	0.4	0.2
Postage and delivery services[2]	0.144	3.8	-0.1	0.4	0.4	0.4
Postage[1]	0.129	4.1	0.0	0.5	0.5	0.5
Delivery services[1, 2]	0.014	1.1	-0.8	-0.1	-0.4	-0.8
Telephone services[1, 2]	2.454	-2.1	-0.2	-1.3	-0.4	-0.2
Wireless telephone services[1, 2]	1.623	-4.0	-0.5	-1.9	-0.6	-0.5
Land-line telephone services[1, 9]	0.830	1.8	0.3	0.0	-0.1	0.3
Internet services and electronic information providers[1, 2]	0.709	1.6	-0.2	0.3	-0.2	-0.2
Other personal services[1, 9]	1.747	1.9	0.2	0.3	0.1	0.2
Personal care services[1]	0.631	1.5	0.5	0.4	0.1	0.5
Haircuts and other personal care services[1, 2]	0.631	1.5	0.5	0.4	0.1	0.5
Miscellaneous personal services	1.116	2.1	0.0	0.3	0.2	0.3
Legal services[6]	0.315	1.4	-0.2	0.1	0.0	-0.2
Funeral expenses[6]	0.172	1.2	0.0	0.4	-0.1	0.0
Laundry and dry cleaning services[1, 2]	0.275	2.2	0.0	0.3	0.2	0.0
Apparel services other than laundry and dry cleaning[1, 2]	0.033	1.8	-0.2	0.7	0.1	-0.2
Financial services[1, 6]	0.226	3.5	0.3	0.3	0.5	0.3
Checking account and other bank services[1, 2, 3]		0.1	0.2	0.0	0.0	0.2
Tax return preparation and other accounting fees[2, 3]		6.1	0.2	0.7	0.6	0.2

[1] Not seasonally adjusted.
[2] Indexes on a December 1997=100 base.
[3] Special index based on a substantially smaller sample.
[4] Indexes on a December 2007=100 base.
[5] Indexes on a December 2005=100 base.
[6] Indexes on a December 1986=100 base.
[7] Indexes on a December 1993=100 base.

[8] This index series was calculated using a Laspeyres estimator. All other item stratum index series were calculated using a geometric means estimator.

[9] Indexes on a December 2009=100 base.

[10] Indexes on a December 1990=100 base.

[11] Indexes on a December 1983=100 base.

[12] Indexes on a December 2001=100 base.

[13] Indexes on a December 1982=100 base.

[14] Indexes on a December 1996=100 base.

NOTE: Index applies to a month as a whole, not to any specific date.

Table 3. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, special aggregate indexes, December 2014

[1982-84=100, unless otherwise noted]

Special aggregate indexes	Relative importance Nov. 2014	Unadjusted indexes			Unadjusted percent change		Seasonally adjusted percent change		
		Dec. 2013	Nov. 2014	Dec. 2014	Dec. 2013-Dec. 2014	Nov. 2014-Dec. 2014	Sep. 2014-Oct. 2014	Oct. 2014-Nov. 2014	Nov. 2014-Dec. 2014
All items less food	85.869	232.314	234.751	233.079	0.3	-0.7	0.0	-0.3	-0.5
All items less shelter	67.518	222.834	224.294	222.267	-0.3	-0.9	-0.1	-0.5	-0.6
All items less food and shelter	53.387	218.723	218.795	216.110	-1.2	-1.2	-0.2	-0.7	-0.9
All items less food, shelter, and energy	44.943	218.037	220.494	219.531	0.7	-0.4	0.2	-0.1	-0.1
All items less food, shelter, energy, and used cars and trucks	43.337	222.241	225.075	224.183	0.9	-0.4	0.2	0.0	-0.1
All items less medical care	92.350	223.631	226.365	224.921	0.6	-0.6	0.0	-0.3	-0.4
All items less energy	91.557	234.768	239.467	239.186	1.9	-0.1	0.2	0.1	0.0
Commodities	38.294	185.620	184.964	181.926	-2.0	-1.6	-0.4	-1.0	-1.2
Commodities less food, energy, and used cars and trucks	17.866	146.798	147.346	146.109	-0.5	-0.8	0.1	-0.3	-0.3
Commodities less food	24.163	161.014	157.379	152.990	-5.0	-2.8	-0.6	-1.7	-2.1
Commodities less food and beverages	23.151	158.269	154.441	149.965	-5.2	-2.9	-0.7	-1.8	-2.2
Services	61.706	280.102	286.840	287.129	2.5	0.1	0.2	0.2	0.2
Services less rent of shelter[1]	29.593	305.482	311.716	311.948	2.1	0.1	0.2	0.1	0.2
Services less medical care services	55.807	266.629	273.094	273.341	2.5	0.1	0.2	0.1	0.2
Durables[2]	8.942	110.704	109.016	108.500	-2.0	-0.5	-0.2	-0.7	-0.5
Nondurables	29.352	222.790	222.810	218.358	-2.0	-2.0	-0.4	-1.0	-1.3
Nondurables less food	15.221	208.623	203.028	194.603	-6.7	-4.1	-0.9	-2.3	-2.9
Nondurables less food and beverages	14.209	206.868	200.718	191.838	-7.3	-4.4	-1.0	-2.5	-3.1
Nondurables less food, beverages, and apparel	10.749	261.666	249.944	238.493	-8.9	-4.6	-1.3	-2.9	-3.7
Nondurables less food and apparel	11.761	258.079	247.792	237.355	-8.0	-4.2	-1.1	-2.6	-3.4
Housing	41.873	228.892	234.315	234.658	2.5	0.1	0.2	0.2	0.2
Education and communication[3]	7.037	136.857	137.708	137.410	0.4	-0.2	-0.2	-0.1	-0.1
Education[3]	3.306	228.578	236.098	236.066	3.3	0.0	0.5	0.3	0.3
Communication[3]	3.731	82.344	81.002	80.681	-2.0	-0.4	-0.8	-0.5	-0.4
Information and information processing[3]	3.588	78.607	77.161	76.846	-2.2	-0.4	-0.9	-0.5	-0.4
Information technology, hardware and services[4]	1.134	8.392	8.247	8.182	-2.5	-0.8	0.0	-0.6	-0.7
Recreation[3]	5.725	114.855	115.026	114.875	0.0	-0.1	0.2	-0.2	0.0
Video and audio[3]	1.841	99.010	98.945	98.702	-0.3	-0.2	0.6	-0.5	0.1
Pets, pet products and services[3]	1.050	164.992	166.686	166.919	1.2	0.1	0.2	0.2	0.2
Photography[3]	0.122	76.067	77.255	76.047	0.0	-1.6	-0.6	-0.3	-0.6
Food and beverages	15.143	237.820	244.902	245.585	3.3	0.3	0.1	0.3	0.2
Domestically produced farm food	7.017	241.358	250.058	251.370	4.1	0.5	0.2	0.1	0.5
Other services	11.893	331.067	335.308	335.162	1.2	0.0	0.0	0.0	0.1
Apparel less footwear	2.729	120.472	122.172	116.574	-3.2	-4.6	-0.3	-1.2	-1.6
Fuels and utilities	5.209	224.407	229.680	231.150	3.0	0.6	-0.1	-0.1	0.6
Household energy	3.999	192.224	195.703	197.092	2.5	0.7	-0.4	-0.4	0.6
Medical care	7.650	427.089	438.445	439.720	3.0	0.3	0.2	0.4	0.5
Transportation	15.743	212.911	206.874	199.777	-6.2	-3.4	-0.7	-2.0	-3.0
Private transportation	14.584	207.997	201.505	194.641	-6.4	-3.4	-0.9	-2.3	-3.0
New and used motor vehicles[3]	5.709	100.440	99.918	99.544	-0.9	-0.4	0.0	-0.4	-0.3
Utilities and public transportation	10.034	211.039	213.984	213.925	1.4	0.0	-0.1	-0.1	0.1
Household furnishings and operations	4.181	123.409	122.694	122.237	-0.9	-0.4	0.4	-0.2	-0.3
Other goods and services	3.368	404.097	409.825	410.642	1.6	0.2	0.3	-0.2	0.3
Personal care	2.660	216.109	218.752	218.850	1.3	0.0	0.3	-0.2	0.1

[1] Indexes on a December 1982=100 base.
[2] Not seasonally adjusted.
[3] Indexes on a December 1997=100 base.
[4] Indexes on a December 1988=100 base.
NOTE: Index applies to a month as a whole, not to any specific date.

Table 4. Consumer Price Index for All Urban Consumers (CPI-U): Selected areas, all items index, December 2014

[1982-84=100, unless otherwise noted]

Area	Pricing Schedule[1]	Percent change to Dec. 2014 from:			Percent change to Nov. 2014 from:		
		Dec. 2013	Oct. 2014	Nov. 2014	Nov. 2013	Sep. 2014	Oct. 2014
U.S. city average	M	0.8	-1.1	-0.6	1.3	-0.8	-0.5
Region and area size[2]							
Northeast urban	M	0.4	-0.9	-0.5	0.9	-0.5	-0.4
Size A - More than 1,500,000	M	0.6	-0.7	-0.5	1.1	-0.4	-0.2
Size B/C - 50,000 to 1,500,000[3]	M	-0.1	-1.4	-0.6	0.5	-0.9	-0.8
Midwest urban	M	0.7	-1.3	-0.7	1.2	-1.1	-0.6
Size A - More than 1,500,000	M	0.7	-1.3	-0.7	1.2	-1.0	-0.6
Size B/C - 50,000 to 1,500,000[3]	M	0.9	-1.3	-0.7	1.4	-1.2	-0.6
Size D - Nonmetropolitan (less than 50,000)	M	0.0	-1.5	-0.8	0.8	-1.3	-0.7
South urban	M	0.6	-1.2	-0.6	1.3	-0.8	-0.6
Size A - More than 1,500,000	M	0.7	-0.9	-0.5	1.5	-0.7	-0.4
Size B/C - 50,000 to 1,500,000[3]	M	0.4	-1.3	-0.7	1.1	-0.9	-0.6
Size D - Nonmetropolitan (less than 50,000)	M	1.3	-1.3	-0.6	2.0	-1.2	-0.8
West urban	M	1.3	-1.1	-0.5	1.7	-0.7	-0.6
Size A - More than 1,500,000	M	1.4	-1.0	-0.5	1.8	-0.7	-0.6
Size B/C - 50,000 to 1,500,000[3]	M	0.6	-1.1	-0.5	1.2	-0.8	-0.6
Size classes							
A[4]	M	0.9	-1.0	-0.5	1.4	-0.7	-0.5
B/C[3]	M	0.5	-1.3	-0.7	1.1	-0.9	-0.6
D	M	1.2	-1.3	-0.6	1.8	-1.1	-0.7
Selected local areas[5]							
Chicago-Gary-Kenosha, IL-IN-WI	M	1.5	-1.2	-0.4	1.6	-1.2	-0.8
Los Angeles-Riverside-Orange County, CA	M	0.7	-1.2	-0.5	1.3	-0.8	-0.7
New York-Northern N.J.-Long Island, NY-NJ-CT-PA	M	0.3	-0.9	-0.5	0.8	-0.6	-0.4
Boston-Brockton-Nashua, MA-NH-ME-CT	1				1.6	0.2	
Cleveland-Akron, OH	1				1.5	-0.6	
Dallas-Fort Worth, TX	1				0.8	-1.0	
Washington-Baltimore, DC-MD-VA-WV[6]	1				1.2	-0.4	
Atlanta, GA	2	0.9	-1.5				
Detroit-Ann Arbor-Flint, MI	2	-0.1	-1.8				
Houston-Galveston-Brazoria, TX	2	1.1	-1.2				
Miami-Fort Lauderdale, FL	2	1.4	-0.6				
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD	2	0.6	-0.8				
San Francisco-Oakland-San Jose, CA	2	2.7	-0.9				
Seattle-Tacoma-Bremerton, WA	2	1.7	-1.1				

[1] Foods, fuels, and several other items are priced every month in all areas. Most other goods and services are priced as indicated: M - Every month. 1 - January, March, May, July, September, and November. 2 - February, April, June, August, October, and December.

[2] Regions defined as the four Census regions.

[3] Indexes on a December 1996=100 base.

[4] Indexes on a December 1986=100 base.

[5] In addition, the following metropolitan areas are published semiannually and appear in Tables 34 and 39 of the January and July issues of the CPI Detailed Report: Anchorage, AK; Cincinnati-Hamilton, OH-KY-IN; Denver-Boulder-Greeley, CO; Honolulu, HI; Kansas City, MO-KS; Milwaukee-Racine, WI; Minneapolis-St. Paul, MN-WI; Phoenix-Mesa, AZ; Pittsburgh, PA; Portland-Salem, OR-WA; St. Louis, MO-IL; San Diego, CA; Tampa-St. Petersburg-Clearwater, FL.

[6] Indexes on a November 1996=100 base.

NOTE: Local area indexes are byproducts of the national CPI program. Each local index has a smaller sample size than the national index and is, therefore, subject to substantially more sampling and other measurement error. As a result, local area indexes show greater volatility than the national index, although their long-term trends are similar. Therefore, the Bureau of Labor Statistics strongly urges users to consider adopting the national average CPI for use in their escalator clauses.

NOTE: Index applies to a month as a whole, not to any specific date.

Table 5. Chained Consumer Price Index for All Urban Consumers (C-CPI-U) and the Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, all items index, December 2014

[Percent changes]

Month Year	Unadjusted 1-month percent change		Unadjusted 12-month percent change	
	C-CPI-U[1]	CPI-U	C-CPI-U[1]	CPI-U
December 2000			2.6	3.4
December 2001			1.3	1.6
December 2002			2.0	2.4
December 2003			1.7	1.9
December 2004			3.2	3.3
December 2005			2.9	3.4
December 2006			2.3	2.5
December 2007			3.7	4.1
December 2008			0.2	0.1
December 2009			2.5	2.7
December 2010			1.3	1.5
December 2011			2.9	3.0
January 2012	0.5	0.4	2.9	2.9
February 2012	0.4	0.4	2.8	2.9
March 2012	0.7	0.8	2.6	2.7
April 2012	0.3	0.3	2.2	2.3
May 2012	-0.1	-0.1	1.7	1.7
June 2012	-0.1	-0.1	1.6	1.7
July 2012	-0.2	-0.2	1.3	1.4
August 2012	0.5	0.6	1.6	1.7
September 2012	0.4	0.4	1.8	2.0
October 2012	-0.1	0.0	1.9	2.2
November 2012	-0.5	-0.5	1.5	1.8
December 2012	-0.3	-0.3	1.5	1.7
January 2013	0.3	0.3	1.3	1.6
February 2013	0.8	0.8	1.7	2.0
March 2013	0.3	0.3	1.3	1.5
April 2013	-0.1	-0.1	0.9	1.1
May 2013	0.2	0.2	1.1	1.4
June 2013	0.2	0.2	1.5	1.8
July 2013	0.0	0.0	1.7	2.0
August 2013	0.1	0.1	1.3	1.5
September 2013	0.1	0.1	1.0	1.2
October 2013	-0.3	-0.3	0.8	1.0
November 2013	-0.2	-0.2	1.1	1.2
December 2013	0.0	0.0	1.3	1.5
January 2014	0.4	0.4	1.4	1.6
February 2014	0.4	0.4	1.0	1.1
March 2014	0.6	0.6	1.4	1.5
April 2014	0.3	0.3	1.8	2.0
May 2014	0.3	0.3	2.0	2.1
June 2014	0.2	0.2	2.0	2.1
July 2014	-0.1	0.0	1.9	2.0
August 2014	-0.2	-0.2	1.5	1.7
September 2014	0.1	0.1	1.5	1.7
October 2014	-0.3	-0.3	1.5	1.7
November 2014	-0.7	-0.5	1.0	1.3
December 2014	-0.8	-0.6	0.3	0.8

[1] The C-CPI-U is designed to be a closer approximation to a cost-of-living index in that it, in its final form, accounts for any substitution that consumers make across item categories in response to changes in relative prices. Since the expenditure data required for the calculation of the C-CPI-U are available only with a time lag, the C-CPI-U is being issued first in preliminary form using the latest available expenditure data at that time and is subject to two revisions.

NOTE: Indexes for 2014 are intial estimates. Indexes for 2013 are interim adjustments. Data prior to 2013 are final.

NOTE: Index applies to a month as a whole, not to any specific date.

Table 6. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 1-month analysis table
[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	One Month: Seasonally adjusted percent change Nov. 2014-Dec. 2014	One Month: Seasonally adjusted effect on All Items Nov. 2014-Dec. 2014[1]	One Month: Standard error, median price change[2]	Largest (L) or Smallest (S) seasonally adjusted change since:[3] Date	Largest (L) or Smallest (S) seasonally adjusted change since:[3] Percent change
All items	100.000	-0.4		0.03	S-Dec.2008	-0.8
Food	14.131	0.3	0.037	0.07	L-Sep.2014	0.3
Food at home	8.348	0.3	0.022	0.12	L-Sep.2014	0.3
Cereals and bakery products	1.130	0.2	0.002	0.30	L-Oct.2014	0.3
Cereals and cereal products	0.370	-0.4	-0.001	0.50	L-Oct.2014	1.0
Flour and prepared flour mixes	0.048	-1.6	-0.001	0.71	S-Apr.2014	-1.6
Breakfast cereal[4]	0.196	-0.1	0.000	0.71	S-Sep.2014	-1.2
Rice, pasta, cornmeal[4]	0.127	-1.1	-0.001	0.70	L-Oct.2014	0.0
Rice[4, 5, 6]		-1.0		0.57	L-Oct.2014	0.4
Bakery products	0.760	0.5	0.004	0.39	L-Jul.2014	0.5
Bread[5]	0.225	1.2	0.003	0.59	L-Apr.2014	1.3
White bread[4, 6]		1.4		0.85	L-Apr.2014	2.2
Bread other than white[4, 6]		1.6		0.86	L-Nov.2013	2.3
Fresh biscuits, rolls, muffins[4, 5]	0.115	0.2	0.000	0.76	S-Sep.2014	-0.2
Cakes, cupcakes, and cookies	0.189	0.2	0.000	0.70	L-Aug.2014	0.4
Cookies[4, 6]		-0.3		1.12	S-Oct.2014	-0.3
Fresh cakes and cupcakes[4, 6]		0.1		0.75	L-Oct.2014	0.6
Other bakery products	0.231	0.2	0.000	0.76	S-Sep.2014	-0.3
Fresh sweetrolls, coffeecakes, doughnuts[4, 6]		1.8		0.97	L-Aug.2014	2.1
Crackers, bread, and cracker products[6]		0.1		1.51	S-Sep.2014	-0.8
Frozen and refrigerated bakery products, pies, tarts, turnovers[6]		-0.9		0.91	S-Aug.2014	-2.0
Meats, poultry, fish, and eggs	1.998	0.3	0.006	0.24	S-Oct.2014	-0.4
Meats, poultry, and fish	1.874	0.0	-0.001	0.25	S-Oct.2014	-0.4
Meats	1.223	0.2	0.003	0.31	S-Oct.2014	-0.2
Beef and veal[4]	0.575	0.7	0.004	0.44	S-Oct.2014	0.3
Uncooked ground beef[4]	0.236	0.2	0.000	0.62	S-Jul.2014	-0.4
Uncooked beef roasts[4, 5]	0.083	1.4	0.001	1.04	S-Oct.2014	-0.4
Uncooked beef steaks[4, 5]	0.204	0.9	0.002	0.83	L-Sep.2014	1.0
Uncooked other beef and veal[4, 5]	0.052	1.2	0.001	0.70	S-Oct.2014	0.7
Pork	0.376	-0.7	-0.002	0.50	S-Oct.2014	-0.7
Bacon, breakfast sausage, and related products[5]	0.141	-0.2	0.000	0.72	L-Aug.2014	0.0
Bacon and related products[6]		-0.4		0.81	L-Aug.2014	-0.3
Breakfast sausage and related products[5, 6]		0.4		1.04	S-Oct.2014	0.1
Ham	0.080	-1.2	-0.001	1.16	S-May 2012	-1.5
Ham, excluding canned[6]		-1.7		1.09	S-Sep.2009	-3.2
Pork chops	0.064	0.0	0.000	1.18	L-Oct.2014	2.0
Other pork including roasts and picnics[5]	0.091	-1.3	-0.001	1.07	L-Oct.2014	-1.2
Other meats	0.272	0.4	0.001	0.54	–	–
Frankfurters[6]		4.1		1.56	L-Apr.2014	4.5
Lunchmeats[4, 5, 6]		0.0		0.62	S-Feb.2014	-0.9
Lamb and organ meats[4, 6]		-0.5		1.55	S-Jun.2014	-2.1
Lamb and mutton[4, 5, 6]		-1.1		1.95	S-Oct.2014	-1.2
Poultry	0.360	-0.7	-0.002	0.54	S-Oct.2014	-1.2
Chicken[5]	0.293	-0.5	-0.001	0.67	S-Oct.2014	-1.3
Fresh whole chicken[4, 6]		0.5		1.51	S-Oct.2014	-1.8
Fresh and frozen chicken parts[4, 6]		-0.5		0.88	S-Apr.2014	-0.9
Other poultry including turkey[5]	0.067	-1.8	-0.001	0.72	S-Nov.2010	-1.8
Fish and seafood[4]	0.291	-0.3	-0.001	0.52	S-Oct.2014	-0.8
Fresh fish and seafood[4, 5]	0.149	-0.7	-0.001	0.82	S-Oct.2014	-1.9
Processed fish and seafood[5]	0.143	-0.9	-0.001	0.64	S-Feb.2014	-0.9

See footnotes at end of table.

Table 6. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 1-month analysis table — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	One Month				
		Seasonally adjusted percent change Nov. 2014-Dec. 2014	Seasonally adjusted effect on All Items Nov. 2014-Dec. 2014[1]	Standard error, median price change[2]	Largest (L) or Smallest (S) seasonally adjusted change since:[3] Date	Percent change
Shelf stable fish and seafood[4, 6]		-1.0		0.82	S-Aug.2014	-1.3
Frozen fish and seafood[6]		-0.5		0.79	S-Oct.2014	-1.0
Eggs	0.124	5.5	0.007	0.76	L-Nov.2010	8.0
Dairy and related products[4]	0.888	0.6	0.006	0.25	L-Aug.2014	0.6
Milk[4, 5]	0.279	0.8	0.002	0.37	L-Mar.2014	1.8
Fresh whole milk[4, 6]		-0.1		0.56	S-Oct.2014	-0.6
Fresh milk other than whole[4, 5, 6]		1.5		0.46	L-Mar.2014	1.7
Cheese and related products[4]	0.285	0.2	0.001	0.47	S-Sep.2014	-0.7
Ice cream and related products	0.122	2.3	0.003	0.89	L-Jan.2013	2.4
Other dairy and related products[5]	0.202	0.0	0.000	0.51	L-Oct.2014	1.3
Fruits and vegetables	1.355	0.4	0.006	0.37	L-Oct.2014	0.9
Fresh fruits and vegetables	1.057	0.4	0.004	0.44	L-Oct.2014	1.1
Fresh fruits	0.573	-1.3	-0.008	0.60	L-Oct.2014	0.9
Apples	0.084	-0.9	-0.001	0.94	S-Sep.2014	-3.2
Bananas	0.088	-1.9	-0.002	0.73	S-Oct.2013	-1.9
Citrus fruits[5]	0.155	-1.6	-0.003	1.31	L-Oct.2014	3.0
Oranges, including tangerines[6]		-1.8		1.43	S-Aug.2014	-3.1
Other fresh fruits[5]	0.247	-0.2	0.000	1.10	L-Oct.2014	1.0
Fresh vegetables	0.484	2.4	0.011	0.70	L-May 2014	2.6
Potatoes	0.075	1.4	0.001	1.29	L-Oct.2014	3.4
Lettuce	0.074	-4.3	-0.003	2.10	S-Dec.2013	-4.6
Tomatoes[4]	0.093	9.3	0.009	1.48	S-Oct.2014	4.6
Other fresh vegetables	0.242	3.0	0.007	0.80	L-Apr.2010	3.4
Processed fruits and vegetables[5]	0.298	0.8	0.002	0.47	L-Nov.2012	0.9
Canned fruits and vegetables[5]	0.154	0.8	0.001	0.77	L-Oct.2014	1.6
Canned fruits[5, 6]		1.0		0.91	L-Mar.2014	1.7
Canned vegetables[5, 6]		1.1		0.88	L-Oct.2014	1.8
Frozen fruits and vegetables[5]	0.087	1.3	0.001	0.86	L-Sep.2014	2.2
Frozen vegetables[6]		2.0		1.01	L-Sep.2014	2.8
Other processed fruits and vegetables including dried[5]	0.057	0.7	0.000	0.80	L-Oct.2014	0.8
Dried beans, peas, and lentils[4, 5, 6]		1.1		1.05	L-May 2014	1.6
Nonalcoholic beverages and beverage materials	0.953	-0.4	-0.004	0.35	S-Jul.2013	-0.4
Juices and nonalcoholic drinks[5]	0.696	-0.5	-0.003	0.45	S-Mar.2014	-0.5
Carbonated drinks	0.283	0.7	0.002	0.65	L-Apr.2013	1.1
Frozen noncarbonated juices and drinks[4, 5]	0.014	0.0	0.000	0.67	S-Aug.2014	-0.1
Nonfrozen noncarbonated juices and drinks[4, 5]	0.399	-0.5	-0.002	0.69	S-May 2014	-0.8
Beverage materials including coffee and tea[5]	0.256	-0.4	-0.001	0.46	S-Feb.2014	-0.4
Coffee	0.158	-0.2	0.000	0.65	S-Oct.2014	-0.5
Roasted coffee[6]		0.5		0.69	L-Sep.2014	0.5
Instant and freeze dried coffee[4, 6]		1.9		0.98	L-Jun.2014	2.6
Other beverage materials including tea[5]	0.099	-0.7	-0.001	0.57	S-Aug.2014	-1.2
Other food at home	2.025	0.3	0.007	0.25	S-Oct.2014	-0.4
Sugar and sweets[4]	0.295	0.5	0.002	0.52	L-Sep.2014	1.6
Sugar and artificial sweeteners	0.053	1.3	0.001	0.65	L-Jun.2014	1.7
Candy and chewing gum[4, 5]	0.183	0.6	0.001	0.85	L-Sep.2014	2.1
Other sweets[5]	0.060	-0.4	0.000	0.58	S-Oct.2014	-1.9
Fats and oils	0.245	-0.5	-0.001	0.42	L-Oct.2014	0.3
Butter and margarine[5]	0.077	-1.8	-0.001	0.67	S-Dec.2010	-1.8
Butter[6]		-1.6		0.88	L-Oct.2014	5.1
Margarine[6]		0.2		0.99	L-Oct.2014	1.5
Salad dressing[4, 5]	0.061	0.5	0.000	0.83	L-Sep.2014	0.6
Other fats and oils including peanut butter[5]	0.107	-0.4	0.000	0.69	L-Sep.2014	0.0

See footnotes at end of table.

Table 6. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 1-month analysis table — Continued
[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	One Month: Seasonally adjusted percent change Nov. 2014-Dec. 2014	One Month: Seasonally adjusted effect on All Items Nov. 2014-Dec. 2014[1]	One Month: Standard error, median price change[2]	Largest (L) or Smallest (S) seasonally adjusted change since:[3] Date	Largest (L) or Smallest (S) seasonally adjusted change since:[3] Percent change
Peanut butter[4, 5, 6]		-0.3		0.88	L-Oct.2014	-0.1
Other foods	1.485	0.4	0.006	0.30	S-Oct.2014	-0.4
Soups	0.094	-1.1	-0.001	1.07	S-Oct.2014	-1.6
Frozen and freeze dried prepared foods[4]	0.282	0.3	0.001	0.64	S-Oct.2014	-1.2
Snacks[4]	0.327	0.4	0.001	0.78	L-Oct.2014	0.4
Spices, seasonings, condiments, sauces	0.288	1.6	0.005	0.69	L-Nov.2013	1.7
Salt and other seasonings and spices[5, 6]		0.1		1.28	S-Oct.2014	-1.5
Olives, pickles, relishes[4, 5, 6]		1.0		1.84	L-Sep.2014	5.6
Sauces and gravies[5, 6]		1.8		1.16	L-May 2014	3.1
Other condiments[6]		3.1		0.73	L-Aug.2014	3.9
Baby food[4, 5]	0.055	-0.1	0.000	0.47	S-Sep.2014	-0.2
Other miscellaneous foods[4, 5]	0.439	0.5	0.002	0.57	S-Oct.2014	0.4
Prepared salads[4, 7, 6]		1.0		0.70	L-Sep.2014	1.4
Food away from home[4]	5.783	0.3	0.015	0.05	S-Oct.2014	0.2
Full service meals and snacks[4, 5]	2.800	0.2	0.007	0.07	S-Oct.2014	0.2
Limited service meals and snacks[4, 5]	2.392	0.3	0.007	0.09	S-Oct.2014	0.3
Food at employee sites and schools[5]	0.211	0.1	0.000	0.13	S-Aug.2014	-1.9
Food at elementary and secondary schools[8, 6]		0.0		0.09	S-Aug.2014	-2.3
Food from vending machines and mobile vendors[4, 5]	0.063	0.6	0.000	0.17	S-Oct.2014	-0.1
Other food away from home[4, 5]	0.317	0.2	0.001	0.11	–	–
Energy	8.443	-4.7	-0.412	0.14	S-Dec.2008	-9.5
Energy commodities	4.691	-9.1	-0.449	0.15	S-Dec.2008	-18.5
Fuel oil and other fuels[4]	0.246	-4.9	-0.012	0.34	S-Apr.2014	-5.4
Fuel oil[4]	0.150	-7.8	-0.012	0.34	S-Jun.2012	-7.9
Propane, kerosene, and firewood[4, 9]	0.096	-1.4	-0.001	0.68	L-Oct.2014	-0.5
Motor fuel	4.444	-9.3	-0.437	0.16	S-Dec.2008	-19.2
Gasoline (all types)	4.364	-9.4	-0.432	0.16	S-Dec.2008	-19.5
Gasoline, unleaded regular[6]		-9.6		0.39	S-Dec.2008	-19.9
Gasoline, unleaded midgrade[10, 6]		-9.8		0.40	S-Dec.2008	-18.6
Gasoline, unleaded premium[6]		-8.0		0.37	S-Dec.2008	-18.3
Other motor fuels[5]	0.080	-5.2	-0.004	0.14	S-Mar.2009	-11.1
Energy services[11]	3.753	1.0	0.037	0.25	L-May 2014	1.4
Electricity[11]	2.903	0.8	0.025	0.33	L-May 2014	2.3
Utility (piped) gas service[11]	0.850	1.5	0.012	0.19	L-Sep.2014	1.6
All items less food and energy	77.426	0.0	0.002	0.04	S-Aug.2014	0.0
Commodities less food and energy commodities	19.473	-0.3	-0.065	0.10	L-Oct.2014	0.0
Household furnishings and supplies[4, 12]	3.336	-0.4	-0.013	0.13	L-Oct.2014	0.4
Window and floor coverings and other linens[4, 5]	0.271	-2.5	-0.007	0.53	S-EVER	–
Floor coverings[4, 5]	0.047	-0.2	0.000	0.45	L-Sep.2014	0.3
Window coverings[4, 5]	0.055	-3.3	-0.002	0.54	S-Feb.2006	-3.4
Other linens[4, 5]	0.170	-2.8	-0.005	0.87	S-Dec.2010	-2.8
Furniture and bedding[4]	0.762	0.3	0.002	0.27	L-Oct.2014	0.7
Bedroom furniture[4]	0.267	-0.3	-0.001	0.39	S-Sep.2014	-0.5
Living room, kitchen, and dining room furniture[4, 5]	0.359	0.7	0.003	0.39	L-Oct.2014	1.4
Other furniture[5]	0.127	0.0	0.000	0.77	L-Sep.2014	0.0
Infants' furniture[4, 8, 6]						
Appliances[5]	0.271	-0.6	-0.002	0.46	L-Oct.2014	0.2
Major appliances[5]	0.146	0.3	0.000	0.68	L-Sep.2014	0.4
Laundry equipment[6]		1.3		0.84	L-Sep.2014	2.0
Other appliances[4, 5]	0.122	-2.1	-0.002	0.52	S-May 2014	-2.1
Other household equipment and furnishings[5]	0.482	-0.9	-0.004	0.38	L-Oct.2014	0.3
Clocks, lamps, and decorator items[4]	0.260	-1.6	-0.004	0.61	L-Oct.2014	0.8

See footnotes at end of table.

Table 6. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 1-month analysis table — Continued
[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	One Month: Seasonally adjusted percent change Nov. 2014-Dec. 2014	Seasonally adjusted effect on All Items Nov. 2014-Dec. 2014[1]	Standard error, median price change[2]	Largest (L) or Smallest (S) seasonally adjusted change since:[3] Date	Percent change
Indoor plants and flowers[13]	0.106	0.3	0.000	0.72	S-Oct.2014	0.0
Dishes and flatware[4, 5]	0.043	-3.6	-0.002	1.00	L-Oct.2014	-0.5
Nonelectric cookware and tableware[5]	0.074	-0.5	0.000	0.52	L-Oct.2014	0.8
Tools, hardware, outdoor equipment and supplies[5]	0.706	0.0	0.000	0.25	L-Oct.2014	0.5
Tools, hardware and supplies[4, 5]	0.188	0.4	0.001	0.42	L-Sep.2014	1.0
Outdoor equipment and supplies[5]	0.366	-0.3	-0.001	0.32	S-Jul.2014	-0.3
Housekeeping supplies[4]	0.844	-0.1	-0.001	0.20	L-Oct.2014	0.6
Household cleaning products[4, 5]	0.334	0.2	0.001	0.35	S-Sep.2014	0.2
Household paper products[4, 5]	0.247	-0.3	-0.001	0.38	L-Oct.2014	0.2
Miscellaneous household products[4, 5]	0.263	-0.4	-0.001	0.38	L-Oct.2014	0.8
Apparel	3.461	-1.2	-0.040	0.47	S-Sep.1998	-1.5
Men's and boys' apparel	0.864	-1.1	-0.009	0.90	S-Oct.2014	-1.1
Men's apparel	0.680	-1.2	-0.008	1.08	S-Oct.2014	-1.6
Men's suits, sport coats, and outerwear	0.110	-2.1	-0.002	2.92	S-Oct.2014	-4.0
Men's furnishings	0.192	-1.6	-0.003	1.13	S-Mar.2013	-2.0
Men's shirts and sweaters[5]	0.207	-1.8	-0.003	1.68	S-Aug.2014	-4.0
Men's pants and shorts	0.164	-0.9	-0.001	1.75	S-Oct.2014	-0.9
Boys' apparel	0.184	0.2	0.000	1.33	L-Oct.2014	1.6
Women's and girls' apparel	1.514	-2.2	-0.032	0.87	S-Dec.2004	-2.3
Women's apparel	1.273	-1.9	-0.023	0.87	S-Sep.2011	-2.0
Women's outerwear	0.123	-0.3	0.000	2.44	L-Aug.2014	4.6
Women's dresses	0.167	-0.7	-0.001	2.82	S-Aug.2014	-0.8
Women's suits and separates[5]	0.588	-1.9	-0.011	1.14	L-Oct.2014	-0.7
Women's underwear, nightwear, sportswear and accessories[5]	0.385	-0.9	-0.003	0.97	L-Oct.2014	0.6
Girls' apparel	0.242	-3.8	-0.009	2.02	S-Feb.2013	-5.2
Footwear	0.732	0.4	0.003	0.71	L-Sep.2014	0.6
Men's footwear[4]	0.219	-1.0	-0.002	1.16	S-Oct.2014	-1.1
Boys' and girls' footwear	0.178	-0.1	0.000	1.16	L-Oct.2014	2.8
Women's footwear	0.335	0.6	0.002	0.92	L-Sep.2014	0.8
Infants' and toddlers' apparel	0.136	0.0	0.000	0.88	L-Oct.2014	0.5
Jewelry and watches[9]	0.214	-0.8	-0.002	0.91	S-Oct.2014	-1.9
Watches[4, 9]	0.046	-1.3	-0.001	1.24	L-Oct.2014	-0.7
Jewelry[9]	0.168	-0.4	-0.001	1.13	L-Sep.2014	0.3
Transportation commodities less motor fuel[12]	5.674	-0.4	-0.020	0.08	–	–
New vehicles	3.529	-0.1	-0.003	0.13	–	–
New cars and trucks[5, 6]		-0.1		0.13	–	–
New cars[6]		-0.2		0.12	S-Jun.2014	-0.2
New trucks[14, 6]		-0.1		0.13	–	–
Used cars and trucks	1.606	-1.2	-0.019	0.06	–	–
Motor vehicle parts and equipment[4]	0.430	0.4	0.002	0.20	L-Dec.2013	0.4
Tires[4]	0.282	0.5	0.001	0.25	L-Dec.2013	0.6
Vehicle accessories other than tires[4, 5]	0.149	0.3	0.000	0.25	L-Aug.2014	0.7
Vehicle parts and equipment other than tires[4, 6]		0.2		0.22	S-Oct.2014	-0.1
Motor oil, coolant, and fluids[4, 6]		0.8		0.59	L-Aug.2014	1.5
Medical care commodities	1.751	1.0	0.017	0.20	L-May 1989	1.0
Medicinal drugs[4, 12]	1.675	0.6	0.011	0.20	L-Jun.2014	0.6
Prescription drugs	1.328	0.9	0.012	0.21	L-Jun.2014	1.0
Nonprescription drugs[4, 12]	0.348	0.4	0.001	0.47	L-Sep.2014	1.5
Medical equipment and supplies[4, 12]	0.076	-0.1	0.000	0.39	S-Sep.2014	-0.1
Recreation commodities[12]	2.004	-0.3	-0.006	0.17	L-Oct.2014	0.0
Video and audio products[12]	0.291	-1.4	-0.004	0.29	L-Oct.2014	-0.6

See footnotes at end of table.

Table 6. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 1-month analysis table — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	One Month: Seasonally adjusted percent change Nov. 2014-Dec. 2014	One Month: Seasonally adjusted effect on All Items Nov. 2014-Dec. 2014[1]	One Month: Standard error, median price change[2]	Largest (L) or Smallest (S) seasonally adjusted change since:[3] Date	Largest (L) or Smallest (S) seasonally adjusted change since:[3] Percent change
Televisions	0.135	-2.1	-0.003	0.62	L-Oct.2014	-1.2
Other video equipment[4, 5]	0.030	-4.5	-0.001	0.78	S-EVER	–
Audio equipment	0.067	0.1	0.000	0.56	L-Oct.2014	0.3
Audio discs, tapes and other media[4, 5]	0.043	0.7	0.000	0.51	L-Apr.2014	0.7
Pets and pet products[4]	0.655	0.1	0.001	0.32	–	–
Pet food[4, 5, 6]		0.1		0.33	L-Sep.2014	0.4
Purchase of pets, pet supplies, accessories[4, 5, 6]		0.1		0.58	S-Aug.2014	-0.9
Sporting goods[4]	0.401	-0.8	-0.003	0.39	–	–
Sports vehicles including bicycles[4]	0.181	-0.4	-0.001	0.47	L-Oct.2014	-0.2
Sports equipment	0.215	-0.5	-0.001	0.46	–	–
Photographic equipment and supplies	0.059	-1.5	-0.001	0.68	S-Jul.2014	-1.9
Film and photographic supplies[4, 5, 6]		-1.2		0.66	S-Jan.2013	-1.4
Photographic equipment[5, 6]		-1.5		0.69	S-Jul.2014	-1.8
Recreational reading materials[4]	0.218	0.1	0.000	0.40	L-Oct.2014	1.4
Newspapers and magazines[4, 5]	0.122	0.9	0.001	0.45	L-Oct.2014	1.8
Recreational books[4, 5]	0.095	-0.8	-0.001	0.57	S-Jun.2014	-0.9
Other recreational goods[5]	0.379	0.2	0.001	0.53	L-Feb.2014	0.8
Toys	0.275	0.7	0.002	0.56	L-Feb.2014	0.7
Toys, games, hobbies and playground equipment[5, 6]		0.6		0.57	L-Feb.2014	0.7
Sewing machines, fabric and supplies[4, 5]	0.051	-2.0	-0.001	1.16	S-Dec.2013	-2.0
Music instruments and accessories[5]	0.042	-0.1	0.000	0.49	S-Aug.2014	-0.8
Education and communication commodities[12]	0.613	-0.8	-0.005	0.28	L-Oct.2014	-0.1
Educational books and supplies	0.200	1.1	0.002	0.38	L-Aug.2014	1.5
College textbooks[4, 15, 6]		0.7		0.33	L-Oct.2014	0.7
Information technology commodities[12]	0.413	-1.6	-0.007	0.38	S-Aug.2011	-1.7
Personal computers and peripheral equipment[7]	0.276	-2.1	-0.006	0.46	S-Dec.2011	-2.2
Computer software and accessories[4, 5]	0.068	-1.3	-0.001	0.66	S-Dec.2013	-1.7
Telephone hardware, calculators, and other consumer information items[4, 5]	0.068	-0.3	0.000	0.71	L-Aug.2014	0.2
Alcoholic beverages	1.012	-0.3	-0.003	0.16	S-Feb.2014	-0.3
Alcoholic beverages at home	0.596	-0.4	-0.003	0.23	S-Feb.2014	-0.6
Beer, ale, and other malt beverages at home	0.273	-0.3	-0.001	0.27	S-Jul.2014	-0.3
Distilled spirits at home[4]	0.073	0.0	0.000	0.35	S-Aug.2014	0.0
Whiskey at home[6]		0.1		0.38	L-Oct.2014	0.2
Distilled spirits, excluding whiskey, at home[4, 6]		-0.3		0.46	S-Jun.2014	-1.0
Wine at home	0.250	-0.4	-0.001	0.40	S-Oct.2014	-0.6
Alcoholic beverages away from home[4]	0.416	0.0	0.000	0.14	S-Jul.2014	-0.1
Beer, ale, and other malt beverages away from home[4, 5, 6]		-0.1		0.19	S-Jul.2014	-0.1
Wine away from home[4, 5, 6]		0.0		0.32	S-Jul.2014	0.0
Distilled spirits away from home[4, 5, 6]		0.0		0.23	S-Sep.2014	0.0
Other goods[12]	1.621	0.3	0.004	0.18	L-Jun.2014	0.5
Tobacco and smoking products[4]	0.708	0.8	0.006	0.15	L-Jun.2014	1.0
Cigarettes[4, 5]	0.652	0.8	0.005	0.16	L-Jun.2014	1.0
Tobacco products other than cigarettes[4, 5]	0.050	0.5	0.000	0.44	L-Oct.2014	0.7
Personal care products[4]	0.721	-0.2	-0.001	0.42	L-Oct.2014	0.0
Hair, dental, shaving, and miscellaneous personal care products[4, 5]	0.367	-0.2	-0.001	0.52	L-Sep.2014	0.4
Cosmetics, perfume, bath, nail preparations and implements[4]	0.346	-0.2	-0.001	0.54	L-Oct.2014	0.4
Miscellaneous personal goods[5]	0.192	0.0	0.000	0.55	L-Aug.2014	0.1
Stationery, stationery supplies, gift wrap[6]		-0.1		0.53	L-Oct.2014	0.0

See footnotes at end of table.

Table 6. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 1-month analysis table — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	One Month: Seasonally adjusted percent change Nov. 2014-Dec. 2014	Seasonally adjusted effect on All Items Nov. 2014-Dec. 2014[1]	Standard error, median price change[2]	Largest (L) or Smallest (S) seasonally adjusted change since:[3] Date	Percent change
Infants' equipment[4, 8, 6]		0.5		0.58	L-Jun.2014	1.8
Services less energy services	57.953	0.1	0.068	0.04	S-Aug.2014	0.0
Shelter	32.482	0.2	0.055	0.05	S-Oct.2014	0.2
Rent of shelter[16]	32.113	0.2	0.058	0.05	–	–
Rent of primary residence[11]	7.099	0.2	0.012	0.05	S-Oct.2014	0.2
Lodging away from home[5]	0.851	0.2	0.002	1.12	L-Oct.2014	0.7
Housing at school, excluding board[11, 16]	0.171	0.3	0.001	0.07	L-Oct.2014	0.4
Other lodging away from home including hotels and motels	0.680	0.2	0.002	1.39	L-Oct.2014	0.8
Owners' equivalent rent of residences[11, 16]	24.163	0.2	0.038	0.04	–	–
Owners' equivalent rent of primary residence[11, 16]	22.752	0.2	0.036	0.04	–	–
Tenants' and household insurance[4, 5]	0.369	0.9	0.003	0.24	L-May 2014	1.2
Water and sewer and trash collection services[5]	1.210	0.6	0.007	0.11	S-Oct.2014	0.6
Water and sewerage maintenance[11]	0.935	0.7	0.007	0.14	S-Sep.2014	0.4
Garbage and trash collection[4, 14]	0.275	0.1	0.000	0.15	L-Oct.2014	0.2
Household operations[4, 5]	0.845	-0.3	-0.002	0.12	S-Feb.2014	-0.5
Domestic services[4, 5]	0.277	0.1	0.000	0.13	S-Sep.2014	0.0
Gardening and lawncare services[4, 5]	0.278	0.0	0.000	0.07	–	–
Moving, storage, freight expense[5]	0.119	-1.8	-0.002	0.56	S-Nov.2008	-2.0
Repair of household items[4, 5]	0.066	0.8	0.000	0.24	L-Jul.2014	1.6
Medical care services	5.899	0.3	0.019	0.08	S-Oct.2014	0.2
Professional services	3.011	0.2	0.006	0.08	S-Oct.2014	0.2
Physicians' services[11]	1.578	0.3	0.004	0.12	S-Oct.2014	0.1
Dental services[11]	0.799	-0.1	-0.001	0.12	S-Feb.2011	-0.1
Eyeglasses and eye care[4, 9]	0.282	0.1	0.000	0.26	S-Oct.2014	-0.1
Services by other medical professionals[11, 9]	0.352	0.1	0.000	0.10	S-Sep.2014	-0.1
Hospital and related services	2.139	0.6	0.013	0.13	L-Mar.2014	0.7
Hospital services[11, 17]	1.835	0.5	0.009	0.15	L-Apr.2014	0.5
Inpatient hospital services[11, 17, 6]		0.5		0.28	L-Jul.2014	0.5
Outpatient hospital services[11, 9, 6]		0.6		0.29	L-Mar.2014	0.6
Nursing homes and adult day services[11, 17]	0.173	0.1	0.000	0.12	S-Jul.2014	0.1
Care of invalids and elderly at home[4, 8]	0.131	0.4	0.001	0.09	L-Mar.2014	0.4
Health insurance[4, 8]	0.748	0.1	0.001	0.09	–	–
Transportation services	5.624	-0.5	-0.025	0.13	S-Aug.2014	-0.6
Leased cars and trucks[15]	0.394	0.8	0.003	0.43	L-Oct.2014	1.0
Car and truck rental[5]	0.071	-0.9	-0.001	1.51	S-Sep.2014	-3.2
Motor vehicle maintenance and repair[4]	1.161	0.1	0.001	0.09	–	–
Motor vehicle body work[4]	0.056	0.3	0.000	0.13	L-Feb.2014	0.9
Motor vehicle maintenance and servicing[4]	0.490	0.0	0.000	0.15	S-May 2014	-0.3
Motor vehicle repair[4, 5]	0.583	0.1	0.001	0.13	L-Oct.2014	0.5
Motor vehicle insurance	2.279	0.3	0.007	0.21	L-Oct.2014	0.6
Motor vehicle fees[4, 5]	0.561	0.1	0.001	0.07	–	–
State motor vehicle registration and license fees[4, 11, 5]	0.311	0.0	0.000	0.03	L-Oct.2014	0.2
Parking and other fees[5]	0.232	0.3	0.001	0.17	S-Sep.2014	0.0
Parking fees and tolls[4, 5, 6]		0.7		0.20	L-Jul.2013	0.9
Automobile service clubs[4, 5, 6]		-0.1		0.26	–	–
Public transportation	1.159	-3.1	-0.036	0.41	S-Aug.2014	-3.3
Airline fare	0.743	-5.0	-0.037	0.56	S-Jul.2014	-5.9
Other intercity transportation	0.153	-0.2	0.000	0.79	S-Sep.2014	-0.3
Intercity bus fare[4, 7, 6]						
Intercity train fare[7, 6]		1.6		1.80	S-Aug.2014	-1.4

See footnotes at end of table.

Table 6. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 1-month analysis table — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	One Month: Seasonally adjusted percent change Nov. 2014-Dec. 2014	Seasonally adjusted effect on All Items Nov. 2014-Dec. 2014[1]	Standard error, median price change[2]	Largest (L) or Smallest (S) seasonally adjusted change since:[3] Date	Percent change
Ship fare[4, 5, 6]		0.3		0.75	S-Oct.2014	0.3
Intracity transportation[4]	0.258	0.0	0.000	0.03	–	–
Intracity mass transit[4, 12, 6]		0.0		0.05	–	–
Recreation services[12]	3.721	0.2	0.007	0.20	L-Oct.2014	0.4
Video and audio services[12]	1.550	0.3	0.005	0.13	L-Oct.2014	0.9
Cable and satellite television and radio service[14]	1.459	0.4	0.006	0.12	L-Oct.2014	0.8
Video discs and other media, including rental of video and audio[4, 5]	0.090	-1.2	-0.001	0.80	S-Aug.2014	-1.6
Video discs and other media[4, 5, 6]		-2.7		1.02	S-Aug.2014	-2.7
Rental of video or audio discs and other media[4, 5, 6]		1.2		0.38	L-Jan.2012	1.7
Pet services including veterinary[5]	0.396	0.2	0.001	0.14	S-Oct.2014	0.2
Pet services[4, 5, 6]		0.0		0.11	S-Oct.2014	0.0
Veterinarian services[5, 6]		0.3		0.13	S-Oct.2014	0.2
Photographers and film processing[4, 5]	0.061	0.2	0.000	0.49	L-Sep.2014	0.4
Photographer fees[4, 5, 6]		0.1		0.31	L-Oct.2014	0.6
Film processing[4, 5, 6]		0.4		0.39	L-Sep.2014	0.6
Other recreation services[5]	1.714	0.0	0.001	0.41	–	–
Club dues and fees for participant sports and group exercises[5]	0.602	-0.6	-0.004	0.52	S-Aug.2014	-0.7
Admissions[4]	0.632	0.7	0.005	0.53	L-Jul.2014	0.8
Admission to movies, theaters, and concerts[4, 5, 6]		0.6		0.44	L-Jul.2014	0.8
Admission to sporting events[4, 5, 6]		1.2		0.49	L-May 2013	1.4
Fees for lessons or instructions[4, 9]	0.210	0.0	0.000	0.17	–	–
Education and communication services[12]	6.425	0.0	0.001	0.07	–	–
Tuition, other school fees, and childcare	3.106	0.3	0.008	0.07	S-Sep.2014	0.1
College tuition and fees	1.844	0.4	0.007	0.10	–	–
Elementary and high school tuition and fees	0.375	0.3	0.001	0.06	S-Oct.2014	0.3
Child care and nursery school[13]	0.722	0.0	0.000	0.08	S-Jul.2014	0.0
Technical and business school tuition and fees[5]	0.039	0.2	0.000	0.14	S-Sep.2014	0.1
Postage and delivery services[5]	0.144	0.4	0.001	0.02	–	–
Postage[4]	0.129	0.5	0.001	0.00	–	–
Delivery services[4, 5]	0.014	-0.8	0.000	0.26	S-Jul.2013	-1.2
Telephone services[4, 5]	2.454	-0.2	-0.006	0.10	L-Sep.2014	0.0
Wireless telephone services[4, 5]	1.623	-0.5	-0.008	0.04	L-Sep.2014	-0.1
Land-line telephone services[4, 12]	0.830	0.3	0.002	0.21	L-May 2014	0.3
Internet services and electronic information providers[4, 5]	0.709	-0.2	-0.002	0.26	–	–
Other personal services[4, 12]	1.747	0.2	0.003	0.11	L-Oct.2014	0.3
Personal care services[4]	0.631	0.5	0.003	0.15	L-Dec.2012	0.5
Haircuts and other personal care services[4, 5]	0.631	0.5	0.003	0.15	L-Dec.2012	0.5
Miscellaneous personal services	1.116	0.3	0.003	0.09	L-Oct.2014	0.3
Legal services[9]	0.315	-0.2	-0.001	0.19	S-May 2014	-0.3
Funeral expenses[9]	0.172	0.0	0.000	0.15	L-Oct.2014	0.4
Laundry and dry cleaning services[4, 5]	0.275	0.0	0.000	0.09	S-Jul.2014	-0.1
Apparel services other than laundry and dry cleaning[4, 5]	0.033	-0.2	0.000	0.22	S-Sep.2014	-0.4
Financial services[4, 9]	0.226	0.3	0.001	0.22	S-Oct.2014	0.3
Checking account and other bank services[4, 5, 6]		0.2		0.04	L-Jun.2013	4.6
Tax return preparation and other accounting fees[5, 6]		0.2		0.38	S-Sep.2014	0.0

See footnotes at end of table.

Table 6. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 1-month analysis table — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	One Month: Seasonally adjusted percent change Nov. 2014-Dec. 2014	Seasonally adjusted effect on All Items Nov. 2014-Dec. 2014[1]	Standard error, median price change[2]	Largest (L) or Smallest (S) seasonally adjusted change since:[3] Date	Percent change
Special aggregate indexes						
All items less food	85.869	-0.5	-0.409	0.04	S-Dec.2008	-1.0
All items less shelter	67.518	-0.6	-0.428	0.04	S-Dec.2008	-1.2
All items less food and shelter	53.387	-0.9	-0.465	0.05	S-Dec.2008	-1.6
All items less food, shelter, and energy	44.943	-0.1	-0.053	0.05	–	–
All items less food, shelter, energy, and used cars and trucks	43.337	-0.1	-0.034	0.06	S-Aug.2014	-0.1
All items less medical care	92.350	-0.4	-0.409	0.04	S-Dec.2008	-0.9
All items less energy	91.557	0.0	0.039	0.04	S-Aug.2014	0.0
Commodities	38.294	-1.2	-0.475	0.06	S-Dec.2008	-2.1
Commodities less food, energy, and used cars and trucks	17.866	-0.3	-0.046	0.11	–	–
Commodities less food	24.163	-2.1	-0.512	0.09	S-Dec.2008	-3.4
Commodities less food and beverages	23.151	-2.2	-0.510	0.09	S-Dec.2008	-3.5
Services	61.706	0.2	0.105	0.04	–	–
Services less rent of shelter[16]	29.593	0.2	0.058	0.06	L-Oct.2014	0.2
Services less medical care services	55.807	0.2	0.099	0.04	L-Oct.2014	0.2
Durables[4]	8.942	-0.5	-0.042	0.08	L-Oct.2014	-0.2
Nondurables	29.352	-1.3	-0.377	0.08	S-Dec.2008	-2.7
Nondurables less food	15.221	-2.9	-0.441	0.13	S-Dec.2008	-5.2
Nondurables less food and beverages	14.209	-3.1	-0.441	0.14	S-Dec.2008	-5.7
Nondurables less food, beverages, and apparel	10.749	-3.7	-0.404	0.09	S-Dec.2008	-7.5
Nondurables less food and apparel	11.761	-3.4	-0.404	0.09	S-Dec.2008	-6.7
Housing	41.873	0.2	0.074	0.05	–	–
Education and communication[5]	7.037	-0.1	-0.004	0.07	–	–
Education[5]	3.306	0.3	0.010	0.07	–	–
Communication[5]	3.731	-0.4	-0.014	0.09	L-Sep.2014	-0.2
Information and information processing[5]	3.588	-0.4	-0.014	0.10	L-Sep.2014	-0.2
Information technology, hardware and services[18]	1.134	-0.7	-0.008	0.21	S-Jul.2013	-0.9
Recreation[5]	5.725	0.0	0.001	0.14	L-Oct.2014	0.2
Video and audio[5]	1.841	0.1	0.001	0.13	L-Oct.2014	0.6
Pets, pet products and services[5]	1.050	0.2	0.002	0.21	–	–
Photography[5]	0.122	-0.6	-0.001	0.38	S-Oct.2014	-0.6
Food and beverages	15.143	0.2	0.034	0.07	S-Oct.2014	0.1
Domestically produced farm food	7.017	0.5	0.033	0.13	L-May 2014	0.8
Other services	11.893	0.1	0.014	0.08	L-Jul.2014	0.1
Apparel less footwear	2.729	-1.6	-0.043	0.56	S-Sep.1998	-1.7
Fuels and utilities	5.209	0.6	0.032	0.18	L-May 2014	0.9
Household energy	3.999	0.6	0.025	0.23	L-May 2014	1.1
Medical care	7.650	0.5	0.036	0.08	L-Aug.2013	0.5
Transportation	15.743	-3.0	-0.482	0.08	S-Dec.2008	-5.0
Private transportation	14.584	-3.0	-0.446	0.08	S-Dec.2008	-5.3
New and used motor vehicles[5]	5.709	-0.3	-0.020	0.09	L-Oct.2014	0.0
Utilities and public transportation	10.034	0.1	0.009	0.11	L-May 2014	1.0
Household furnishings and operations	4.181	-0.3	-0.014	0.11	S-Aug.2014	-0.3
Other goods and services	3.368	0.3	0.008	0.11	L-Oct.2014	0.3
Personal care	2.660	0.1	0.003	0.13	L-Oct.2014	0.3

[1] The 'effect' of an item category is a measure of that item's contribution to the All items price change. For example, if the Food index had an effect of 0.40, and the All items index rose 1.2 percent, then the increase in food prices contributed 0.40 / 1.2, or 33.3 percent, to that All items increase. Said another way, had food prices been unchanged for that month the change in the All items index would have been 1.2 percent minus 0.40, or 0.8 percent. Effects can be negative as well. For example, if the effect of food was a negative 0.1, and the All items index rose 0.5 percent, the All items index actually would have been 0.1 percent higher (or 0.6 percent) had food prices been unchanged. Since food prices fell while prices overall were rising, the contribution of food to the All items price change was negative (in this case, -0.1 / 0.5, or minus 20 percent).

[2] A statistic's margin of error is often expressed as its point estimate plus or minus two standard errors. For example, if a CPI category rose 0.6

percent, and its standard error was 0.15 percent, the margin of error on this item's 1-month percent change would be 0.6 percent, plus or minus 0.3 percent.

[3] If the current seasonally adjusted 1-month percent change is greater than the previous published 1-month percent change, then this column identifies the closest prior month with a 1-month percent change as (L)arge as or (L)arger than the current 1-month change. If the current 1-month percent change is smaller than the previous published 1-month percent change, the most recent month with a change as (S)mall or (S)maller than the current month change is identified. If the current and previous published 1-month percent changes are equal, a dash will appear. Standard numerical comparisons are used. For example, 0.8% is greater than 0.6%, -0.4% is less than -0.2%, and -0.2% is less than 0.0%. Note that a (L)arger change can be a smaller decline, for example, a -0.2% change is larger than a -0.4% change, but still represents a decline in the price index. Likewise, (S)maller changes can be increases, for example, a 0.6% change is smaller than 0.8%, but still represents an increase in the price index. In this context, a -0.2% change is considered to be smaller than a 0.0% change.

[4] Not seasonally adjusted.

[5] Indexes on a December 1997=100 base.

[6] Special indexes based on a substantially smaller sample. These series do not contribute to the all items index aggregation and therefore do not have a relative importance or effect.

[7] Indexes on a December 2007=100 base.

[8] Indexes on a December 2005=100 base.

[9] Indexes on a December 1986=100 base.

[10] Indexes on a December 1993=100 base.

[11] This index series was calculated using a Laspeyres estimator. All other item stratum index series were calculated using a geometric means estimator.

[12] Indexes on a December 2009=100 base.

[13] Indexes on a December 1990=100 base.

[14] Indexes on a December 1983=100 base.

[15] Indexes on a December 2001=100 base.

[16] Indexes on a December 1982=100 base.

[17] Indexes on a December 1996=100 base.

[18] Indexes on a December 1988=100 base.

NOTE: Index applies to a month as a whole, not to any specific date.

Table 7. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 12-month analysis table
[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Twelve Month: Unadjusted percent change Dec. 2013-Dec. 2014	Unadjusted effect on All Items Dec. 2013-Dec. 2014[1]	Standard error, median price change[2]	Largest (L) or Smallest (S) unadjusted change since:[3] Date	Percent change
All items	100.000	0.8		0.08	S-Oct.2009	-0.2
Food	14.131	3.4	0.473	0.11	L-Feb.2012	3.9
Food at home	8.348	3.7	0.303	0.17	L-Feb.2012	4.5
Cereals and bakery products	1.130	0.5	0.006	0.38	L-Feb.2014	0.5
Cereals and cereal products	0.370	-0.3	-0.001	0.61	S-Jun.2014	-0.4
Flour and prepared flour mixes	0.048	-1.9	-0.001	0.99	S-May 2014	-2.7
Breakfast cereal	0.196	1.3	0.002	0.85	L-Jan.2014	1.9
Rice, pasta, cornmeal	0.127	-2.1	-0.003	0.97	L-Oct.2014	-1.6
Rice[4, 5]		-2.8		1.33	S-Mar.2010	-5.1
Bakery products	0.760	0.9	0.007	0.50	L-Feb.2014	1.1
Bread[4]	0.225	1.2	0.003	1.01	L-Oct.2014	1.3
White bread[5]		0.9		1.53	L-Feb.2014	1.1
Bread other than white[5]		0.8		1.52	L-Oct.2014	2.0
Fresh biscuits, rolls, muffins[4]	0.115	1.9	0.002	1.14	L-Feb.2014	2.4
Cakes, cupcakes, and cookies	0.189	0.6	0.001	1.10	L-Aug.2014	1.3
Cookies[5]		-0.2		1.44	S-Oct.2014	-0.3
Fresh cakes and cupcakes[5]		1.5		1.44	L-Jun.2014	1.8
Other bakery products	0.231	0.4	0.001	1.22	S-Oct.2014	0.4
Fresh sweetrolls, coffeecakes, doughnuts[5]		0.6		2.33	L-Feb.2014	1.2
Crackers, bread, and cracker products[5]		1.0		1.95	S-Aug.2014	0.5
Frozen and refrigerated bakery products, pies, tarts, turnovers[5]		-0.5		1.33	S-Oct.2014	-0.8
Meats, poultry, fish, and eggs	1.998	9.2	0.171	0.36	L-Sep.2014	9.4
Meats, poultry, and fish	1.874	9.1	0.158	0.38	S-Oct.2014	8.5
Meats	1.223	12.7	0.140	0.44	S-Oct.2014	12.5
Beef and veal	0.575	18.7	0.092	0.58	L-Jan.2004	20.4
Uncooked ground beef	0.236	19.2	0.039	0.78	L-Dec.2003	19.5
Uncooked beef roasts[4]	0.083	20.6	0.015	1.32	L-Dec.2003	23.5
Uncooked beef steaks[4]	0.204	16.0	0.029	1.03	L-Sep.2014	16.8
Uncooked other beef and veal[4]	0.052	24.0	0.010	1.34	L-EVER	–
Pork	0.376	8.2	0.028	0.76	S-Mar.2014	5.3
Bacon, breakfast sausage, and related products[4]	0.141	2.4	0.003	0.95	S-May 2013	1.3
Bacon and related products[5]		-1.0		1.63	S-Feb.2013	-1.7
Breakfast sausage and related products[4, 5]		7.3		1.41	S-Nov.2013	1.3
Ham	0.080	13.1	0.009	1.88	S-Oct.2014	12.6
Ham, excluding canned[5]		14.4		1.79	S-Oct.2014	13.9
Pork chops	0.064	10.1	0.006	1.36	S-Mar.2014	4.1
Other pork including roasts and picnics[4]	0.091	12.5	0.010	1.65	S-Mar.2014	7.2
Other meats	0.272	7.4	0.019	0.98	L-Aug.2011	7.7
Frankfurters[5]		12.1		2.37	L-Nov.1990	13.4
Lunchmeats[4, 5]		5.8		0.97	S-Oct.2014	5.7
Lamb and organ meats[5]		8.8		2.07	L-Dec.2011	9.5
Lamb and mutton[4, 5]		3.2		3.91	L-Apr.2012	10.0
Poultry	0.360	1.6	0.006	0.87	S-Oct.2014	-0.1
Chicken[4]	0.293	2.1	0.006	1.02	S-Oct.2014	0.0
Fresh whole chicken[5]		3.0		1.76	S-Oct.2014	2.1
Fresh and frozen chicken parts[5]		1.6		1.29	S-Oct.2014	-1.1
Other poultry including turkey[4]	0.067	-0.5	0.000	1.55	S-Jan.2010	-2.1
Fish and seafood	0.291	4.3	0.012	0.85	S-Oct.2014	3.8
Fresh fish and seafood[4]	0.149	5.6	0.008	1.23	L-Sep.2014	7.4
Processed fish and seafood[4]	0.143	3.0	0.004	1.16	S-Oct.2014	2.7
Shelf stable fish and seafood[5]		1.3		1.47	S-Oct.2014	0.6

See footnotes at end of table.

Table 7. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 12-month analysis table — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Twelve Month: Unadjusted percent change Dec. 2013-Dec. 2014	Unadjusted effect on All Items Dec. 2013-Dec. 2014[1]	Standard error, median price change[2]	Largest (L) or Smallest (S) unadjusted change since:[3] Date	Percent change
Frozen fish and seafood[5]		5.2		2.28	S-Oct.2014	4.5
Eggs	0.124	10.7	0.013	1.14	L-Oct.2011	22.8
Dairy and related products	0.888	5.3	0.045	0.47	L-Oct.2014	5.6
Milk[4]	0.279	4.3	0.012	0.69	S-Feb.2014	2.6
Fresh whole milk[5]		5.2		1.03	S-Feb.2014	2.4
Fresh milk other than whole[4, 5]		4.1		0.71	L-Oct.2014	4.7
Cheese and related products	0.285	8.2	0.022	0.88	S-Sep.2014	6.8
Ice cream and related products	0.122	3.5	0.004	1.19	L-May 2012	6.1
Other dairy and related products[4]	0.202	3.7	0.007	0.80	L-Oct.2014	3.7
Fruits and vegetables	1.355	3.2	0.043	0.54	L-May 2014	3.2
Fresh fruits and vegetables	1.057	4.1	0.042	0.67	L-May 2014	4.2
Fresh fruits	0.573	3.6	0.020	0.94	S-Feb.2014	1.6
Apples	0.084	-2.3	-0.002	1.68	S-Mar.2014	-3.0
Bananas	0.088	-0.7	-0.001	1.11	S-Sep.2014	-0.9
Citrus fruits[4]	0.155	5.4	0.008	2.17	S-Dec.2013	2.8
Oranges, including tangerines[5]		3.7		2.90	S-Sep.2014	3.7
Other fresh fruits[4]	0.247	6.2	0.015	1.62	L-Oct.2014	7.8
Fresh vegetables	0.484	4.6	0.022	0.99	L-Nov.2013	4.6
Potatoes	0.075	-1.8	-0.001	1.79	L-Jul.2014	1.3
Lettuce	0.074	4.4	0.003	2.67	L-Jun.2014	4.6
Tomatoes	0.093	16.5	0.015	2.13	L-Apr.2010	24.4
Other fresh vegetables	0.242	2.3	0.006	1.23	L-Nov.2013	3.5
Processed fruits and vegetables[4]	0.298	0.4	0.001	0.69	L-Oct.2014	1.1
Canned fruits and vegetables[4]	0.154	-0.2	0.000	1.12	L-Oct.2014	1.7
Canned fruits[4, 5]		0.5		1.34	L-Mar.2014	0.5
Canned vegetables[4, 5]		0.0		1.20	L-Oct.2014	2.8
Frozen fruits and vegetables[4]	0.087	1.5	0.001	1.17	L-Sep.2012	3.0
Frozen vegetables[5]		0.9		1.45	L-Sep.2012	2.6
Other processed fruits and vegetables including dried[4]	0.057	0.2	0.000	1.16	L-Oct.2014	0.8
Dried beans, peas, and lentils[4, 5]		4.6		2.11	S-Oct.2014	3.1
Nonalcoholic beverages and beverage materials	0.953	0.7	0.007	0.47	S-Oct.2014	0.6
Juices and nonalcoholic drinks[4]	0.696	0.1	0.001	0.56	S-Sep.2014	-0.4
Carbonated drinks	0.283	1.4	0.004	0.73	L-Sep.2012	1.5
Frozen noncarbonated juices and drinks[4]	0.014	2.3	0.000	1.37	L-May 2014	2.5
Nonfrozen noncarbonated juices and drinks[4]	0.399	-1.0	-0.004	0.86	S-Aug.2014	-1.2
Beverage materials including coffee and tea[4]	0.256	2.6	0.006	0.69	L-Apr.2012	3.5
Coffee	0.158	3.6	0.006	0.97	L-Apr.2012	5.8
Roasted coffee[5]		4.2		1.31	L-Apr.2012	5.9
Instant and freeze dried coffee[5]		0.2		2.43	L-Sep.2014	1.7
Other beverage materials including tea[4]	0.099	1.0	0.001	0.88	S-Oct.2014	-0.6
Other food at home	2.025	1.5	0.031	0.32	L-Sep.2014	1.6
Sugar and sweets	0.295	1.1	0.003	0.75	L-Dec.2012	1.1
Sugar and artificial sweeteners	0.053	0.2	0.000	0.97	L-Aug.2012	0.2
Candy and chewing gum[4]	0.183	1.8	0.003	1.12	L-Sep.2014	1.9
Other sweets[4]	0.060	-0.2	0.000	1.17	S-Oct.2014	-0.6
Fats and oils	0.245	1.0	0.002	0.63	S-Jul.2014	1.0
Butter and margarine[4]	0.077	11.6	0.008	1.05	S-Sep.2014	11.3
Butter[5]		22.5		1.53	S-Aug.2014	18.8
Margarine[5]		2.6		1.48	L-Oct.2014	2.7
Salad dressing[4]	0.061	-4.3	-0.003	1.13	–	–
Other fats and oils including peanut butter[4]	0.107	-2.5	-0.003	0.99	L-Sep.2014	-1.2
Peanut butter[4, 5]		-3.6		1.26	L-Sep.2014	-3.3
Other foods	1.485	1.7	0.025	0.39	–	–

See footnotes at end of table.

Table 7. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 12-month analysis table — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Twelve Month: Unadjusted percent change Dec. 2013-Dec. 2014	Twelve Month: Unadjusted effect on All Items Dec. 2013-Dec. 2014[1]	Twelve Month: Standard error, median price change[2]	Largest (L) or Smallest (S) unadjusted change since:[3] Date	Largest (L) or Smallest (S) unadjusted change since:[3] Percent change
Soups	0.094	-0.6	-0.001	1.30	S-Jun.2014	-1.1
Frozen and freeze dried prepared foods	0.282	1.9	0.005	0.82	S-Oct.2014	1.1
Snacks	0.327	1.8	0.006	1.00	S-Oct.2014	0.5
Spices, seasonings, condiments, sauces	0.288	2.2	0.006	0.92	L-Oct.2014	2.4
Salt and other seasonings and spices[4, 5]		4.8		1.48	L-Aug.2012	6.1
Olives, pickles, relishes[4, 5]		0.2		1.57	L-Oct.2014	0.9
Sauces and gravies[4, 5]		1.7		1.43	L-Oct.2014	2.7
Other condiments[5]		1.8		1.03	L-Aug.2013	6.5
Baby food[4]	0.055	2.1	0.001	0.79	S-Jul.2014	1.7
Other miscellaneous foods[4]	0.439	1.6	0.007	0.82	L-Oct.2014	1.6
Prepared salads[6, 5]		3.9		1.19	L-Sep.2014	4.7
Food away from home	5.783	3.0	0.170	0.17	L-Mar.2012	3.0
Full service meals and snacks[4]	2.800	3.1	0.085	0.27	L-May 2009	3.4
Limited service meals and snacks[4]	2.392	3.2	0.075	0.27	L-Oct.2012	3.2
Food at employee sites and schools[4]	0.211	1.8	0.004	0.67	S-Aug.2014	0.9
Food at elementary and secondary schools[7, 5]		2.3		0.73	S-Aug.2014	0.6
Food from vending machines and mobile vendors[4]	0.063	0.5	0.000	0.80	L-Dec.2013	1.2
Other food away from home[4]	0.317	2.0	0.006	0.43	L-Oct.2014	2.3
Energy	8.443	-10.6	-0.955	0.19	S-Oct.2009	-14.0
Energy commodities	4.691	-20.5	-1.093	0.18	S-Sep.2009	-30.1
Fuel oil and other fuels	0.246	-13.7	-0.038	0.60	S-Oct.2009	-23.5
Fuel oil	0.150	-19.1	-0.033	0.62	S-Oct.2009	-26.3
Propane, kerosene, and firewood[8]	0.096	-4.6	-0.005	1.34	S-May 2013	-5.4
Motor fuel	4.444	-20.8	-1.056	0.19	S-Sep.2009	-30.0
Gasoline (all types)	4.364	-21.0	-1.045	0.19	S-Sep.2009	-29.7
Gasoline, unleaded regular[5]		-21.6		0.55	S-Sep.2009	-30.0
Gasoline, unleaded midgrade[9, 5]		-19.6		0.53	S-Sep.2009	-29.3
Gasoline, unleaded premium[5]		-18.3		0.56	S-Sep.2009	-28.0
Other motor fuels[4]	0.080	-11.9	-0.010	0.23	S-Oct.2009	-28.3
Energy services[10]	3.753	3.7	0.139	0.42	L-Aug.2014	4.6
Electricity[10]	2.903	3.1	0.090	0.49	L-Oct.2014	3.1
Utility (piped) gas service[10]	0.850	5.8	0.048	0.60	L-Sep.2014	5.8
All items less food and energy	77.426	1.6	1.238	0.09	S-Feb.2014	1.6
Commodities less food and energy commodities	19.473	-0.8	-0.155	0.24	S-Sep.2007	-0.8
Household furnishings and supplies[11]	3.336	-1.9	-0.064	0.30	S-Sep.2014	-2.4
Window and floor coverings and other linens[4]	0.271	-3.6	-0.010	0.93	S-Dec.2013	-3.6
Floor coverings[4]	0.047	0.8	0.000	1.29	S-Jun.2014	0.7
Window coverings[4]	0.055	-2.3	-0.001	1.08	S-Oct.2014	-2.9
Other linens[4]	0.170	-5.2	-0.009	1.37	S-Nov.2013	-5.4
Furniture and bedding	0.762	-1.6	-0.013	0.78	L-Jan.2014	-1.6
Bedroom furniture	0.267	-2.4	-0.007	1.08	L-Oct.2014	-2.2
Living room, kitchen, and dining room furniture[4]	0.359	-1.9	-0.007	1.03	L-Jan.2014	-0.7
Other furniture[4]	0.127	0.8	0.001	2.52	S-Oct.2014	-1.0
Infants' furniture[7, 5]						
Appliances[4]	0.271	-5.2	-0.015	0.83	S-Jun.2014	-5.4
Major appliances[4]	0.146	-6.9	-0.011	1.14	L-Oct.2014	-6.6
Laundry equipment[5]		-7.4		1.19	L-Oct.2014	-7.4
Other appliances[4]	0.122	-3.1	-0.004	1.15	S-May 2014	-3.2
Other household equipment and furnishings[4]	0.482	-3.9	-0.020	1.17	S-Jul.2014	-3.9
Clocks, lamps, and decorator items	0.260	-5.8	-0.016	1.84	S-Jul.2014	-6.1
Indoor plants and flowers[12]	0.106	1.9	0.002	1.66	L-May 2011	2.2
Dishes and flatware[4]	0.043	-6.7	-0.003	3.26	S-May 2014	-10.2
Nonelectric cookware and tableware[4]	0.074	-3.7	-0.003	1.34	L-Oct.2014	-2.9

See footnotes at end of table.

Table 7. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 12-month analysis table — Continued
[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Twelve Month: Unadjusted percent change Dec. 2013-Dec. 2014	Unadjusted effect on All Items Dec. 2013-Dec. 2014[1]	Standard error, median price change[2]	Largest (L) or Smallest (S) unadjusted change since:[3] Date	Percent change
Tools, hardware, outdoor equipment and supplies[4]	0.706	0.1	0.001	0.58	L-Mar.2014	0.1
Tools, hardware and supplies[4]	0.188	0.8	0.002	0.71	L-Nov.2013	1.1
Outdoor equipment and supplies[4]	0.366	-0.3	-0.001	0.81	S-Oct.2014	-0.8
Housekeeping supplies	0.844	-0.8	-0.007	0.44	S-Sep.2014	-1.0
Household cleaning products[4]	0.334	-0.9	-0.003	0.67	L-May 2013	-0.3
Household paper products[4]	0.247	-0.7	-0.002	0.72	S-Oct.2014	-0.7
Miscellaneous household products[4]	0.263	-0.7	-0.002	0.79	S-Jan.2014	-0.8
Apparel	3.461	-2.0	-0.068	1.12	S-Dec.2003	-2.1
Men's and boys' apparel	0.864	-3.0	-0.026	1.54	S-Apr.2010	-3.0
Men's apparel	0.680	-3.0	-0.020	1.77	S-Mar.2010	-3.5
Men's suits, sport coats, and outerwear	0.110	-7.1	-0.008	5.75	S-Jul.2009	-9.1
Men's furnishings	0.192	-2.4	-0.005	2.27	S-Feb.2011	-3.8
Men's shirts and sweaters[4]	0.207	-4.5	-0.009	3.39	S-Aug.2014	-5.7
Men's pants and shorts	0.164	1.1	0.002	3.81	S-Oct.2014	-5.0
Boys' apparel	0.184	-2.7	-0.005	3.42	L-Oct.2014	-1.4
Women's and girls' apparel	1.514	-3.6	-0.054	2.28	S-Jan.2009	-3.6
Women's apparel	1.273	-3.5	-0.044	2.46	S-Jan.2009	-3.6
Women's outerwear	0.123	3.6	0.004	8.24	S-Nov.2013	2.3
Women's dresses	0.167	1.6	0.003	12.36	S-Sep.2014	0.1
Women's suits and separates[4]	0.588	-8.2	-0.049	2.48	S-EVER	–
Women's underwear, nightwear, sportswear and accessories[4]	0.385	-0.3	-0.001	1.96	S-Apr.2013	-0.4
Girls' apparel	0.242	-4.0	-0.010	5.18	S-Jan.2014	-8.8
Footwear	0.732	2.8	0.020	1.28	L-Jul.2013	2.9
Men's footwear	0.219	1.8	0.004	1.81	L-Sep.2014	2.0
Boys' and girls' footwear	0.178	6.1	0.010	2.69	S-Jun.2014	3.9
Women's footwear	0.335	1.7	0.005	1.95	L-Aug.2013	3.0
Infants' and toddlers' apparel	0.136	0.4	0.001	1.92	S-Feb.2014	-2.7
Jewelry and watches[8]	0.214	-4.3	-0.009	1.99	S-Jun.2005	-4.5
Watches[8]	0.046	-1.0	0.000	3.43	S-Aug.2013	-2.6
Jewelry[8]	0.168	-5.1	-0.009	2.26	S-Jun.2005	-5.4
Transportation commodities less motor fuel[11]	5.674	-0.9	-0.054	0.21	S-EVER	–
New vehicles	3.529	0.5	0.018	0.30	S-Sep.2014	0.3
New cars and trucks[4, 5]		0.6		0.27	–	–
New cars[5]		-0.1		0.25	S-Sep.2014	-0.4
New trucks[13, 5]		1.3		0.26	–	–
Used cars and trucks	1.606	-4.2	-0.070	0.29	S-Aug.2009	-5.4
Motor vehicle parts and equipment	0.430	-0.7	-0.003	0.37	–	–
Tires	0.282	-1.9	-0.005	0.49	S-Jul.2014	-2.0
Vehicle accessories other than tires[4]	0.149	1.7	0.003	0.64	L-Oct.2013	2.1
Vehicle parts and equipment other than tires[5]		1.5		0.57	L-Apr.2014	1.5
Motor oil, coolant, and fluids[5]		2.4		0.86	L-Oct.2014	2.7
Medical care commodities	1.751	4.8	0.081	0.84	L-Jan.1993	4.8
Medicinal drugs[11]	1.675	5.0	0.081	0.88	L-EVER	–
Prescription drugs	1.328	6.4	0.081	1.06	L-Aug.1992	6.4
Nonprescription drugs[11]	0.348	-0.2	-0.001	0.78	L-Sep.2014	0.6
Medical equipment and supplies[11]	0.076	0.9	0.001	0.84	L-Apr.2013	1.6
Recreation commodities[11]	2.004	-2.6	-0.053	0.41	L-Oct.2014	-2.2
Video and audio products[11]	0.291	-10.5	-0.034	0.58	S-Dec.2010	-10.5
Televisions	0.135	-16.7	-0.027	1.06	S-Apr.2013	-17.4
Other video equipment[4]	0.030	-0.8	0.000	2.08	S-Jun.2014	-1.4
Audio equipment	0.067	-7.3	-0.005	1.23	L-Oct.2014	-6.3
Audio discs, tapes and other media[4]	0.043	-3.6	-0.002	1.19	S-Oct.2014	-3.6
Pets and pet products	0.655	0.3	0.002	0.67	L-Dec.2013	0.3

See footnotes at end of table.

Table 7. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 12-month analysis table — Continued
[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Twelve Month: Unadjusted percent change Dec. 2013-Dec. 2014	Twelve Month: Unadjusted effect on All Items Dec. 2013-Dec. 2014[1]	Twelve Month: Standard error, median price change[2]	Largest (L) or Smallest (S) unadjusted change since:[3] Date	Largest (L) or Smallest (S) unadjusted change since:[3] Percent change
Pet food[4, 5]		0.4		0.76	L-Jan.2014	0.7
Purchase of pets, pet supplies, accessories[4, 5]		0.4		1.15	L-Jun.2012	0.7
Sporting goods	0.401	-2.2	-0.009	0.95	S-Jul.2014	-2.2
Sports vehicles including bicycles	0.181	-1.1	-0.002	1.13	S-Jul.2014	-1.6
Sports equipment	0.215	-3.1	-0.007	1.58	S-Oct.2013	-3.2
Photographic equipment and supplies	0.059	-2.2	-0.001	1.92	S-Jun.2014	-2.4
Film and photographic supplies[4, 5]		23.4		2.36	L-EVER	–
Photographic equipment[4, 5]		-6.1		2.83	S-Jul.2014	-6.4
Recreational reading materials	0.218	2.2	0.005	0.97	L-Oct.2014	2.7
Newspapers and magazines[4]	0.122	4.8	0.006	1.36	L-Oct.2014	5.4
Recreational books[4]	0.095	-0.9	-0.001	1.38	S-Sep.2014	-1.3
Other recreational goods[4]	0.379	-3.8	-0.015	1.25	L-Feb.2014	-3.6
Toys	0.275	-5.4	-0.016	1.48	L-Mar.2014	-5.4
Toys, games, hobbies and playground equipment[4, 5]		-2.9		2.14	L-Mar.2014	-2.6
Sewing machines, fabric and supplies[4]	0.051	0.1	0.000	2.78	L-May 2014	0.3
Music instruments and accessories[4]	0.042	2.4	0.001	2.30	–	–
Education and communication commodities[11]	0.613	-4.9	-0.032	0.69	S-EVER	–
Educational books and supplies	0.200	4.6	0.009	1.03	L-Sep.2014	4.6
College textbooks[14, 5]		5.0		0.95	L-Sep.2014	5.1
Information technology commodities[11]	0.413	-9.0	-0.041	0.93	S-Apr.2012	-9.6
Personal computers and peripheral equipment[6]	0.276	-10.5	-0.032	1.23	S-Jul.2013	-10.6
Computer software and accessories[4]	0.068	-1.2	-0.001	3.85	L-Jul.2009	-1.1
Telephone hardware, calculators, and other consumer information items[4]	0.068	-9.9	-0.008	1.61	L-Oct.2014	-5.8
Alcoholic beverages	1.012	1.3	0.013	0.30	S-Oct.2014	1.1
Alcoholic beverages at home	0.596	0.7	0.004	0.42	S-Oct.2014	0.7
Beer, ale, and other malt beverages at home	0.273	0.7	0.002	0.49	S-Jul.2014	0.4
Distilled spirits at home	0.073	0.9	0.001	0.68	S-Oct.2014	0.8
Whiskey at home[5]		1.5		1.23	L-Oct.2014	1.6
Distilled spirits, excluding whiskey, at home[5]		0.8		0.73	L-Jan.2014	1.1
Wine at home	0.250	0.6	0.001	0.82	S-Oct.2014	0.3
Alcoholic beverages away from home	0.416	2.2	0.009	0.41	L-Dec.2013	2.3
Beer, ale, and other malt beverages away from home[4, 5]		2.1		0.60	S-Oct.2014	1.8
Wine away from home[4, 5]		2.0		0.86	L-Dec.2013	2.4
Distilled spirits away from home[4, 5]		2.2		0.68	L-Jan.2014	2.3
Other goods[11]	1.621	1.3	0.022	0.35	S-Nov.2013	1.2
Tobacco and smoking products	0.708	3.0	0.021	0.43	L-Jun.2014	4.3
Cigarettes[4]	0.652	3.1	0.020	0.47	L-Jun.2014	4.5
Tobacco products other than cigarettes[4]	0.050	1.4	0.001	1.17	S-Oct.2014	0.3
Personal care products	0.721	0.3	0.002	0.67	S-Mar.2014	0.3
Hair, dental, shaving, and miscellaneous personal care products[4]	0.367	-0.3	-0.001	1.06	L-Oct.2014	-0.3
Cosmetics, perfume, bath, nail preparations and implements	0.346	1.0	0.003	0.90	S-Apr.2014	0.9
Miscellaneous personal goods[4]	0.192	-0.6	-0.001	1.02	L-Oct.2014	0.4
Stationery, stationery supplies, gift wrap[5]		0.0		1.31	L-Oct.2014	1.2
Infants' equipment[7, 5]		-0.7		1.70	L-Oct.2013	-0.4
Services less energy services	57.953	2.4	1.393	0.10	S-Sep.2014	2.4
Shelter	32.482	2.9	0.930	0.15	S-Aug.2014	2.9
Rent of shelter[15]	32.113	2.9	0.910	0.15	S-Sep.2014	2.9
Rent of primary residence[10]	7.099	3.4	0.236	0.17	S-Oct.2014	3.3
Lodging away from home[4]	0.851	6.3	0.050	1.35	L-Oct.2014	8.4

See footnotes at end of table.

Table 7. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 12-month analysis table — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Twelve Month				
		Unadjusted percent change Dec. 2013-Dec. 2014	Unadjusted effect on All Items Dec. 2013-Dec. 2014[1]	Standard error, median price change[2]	Largest (L) or Smallest (S) unadjusted change since:[3] Date	Percent change
Housing at school, excluding board[10, 15]	0.171	2.7	0.005	0.27	–	–
Other lodging away from home including hotels and motels	0.680	7.3	0.046	1.66	L-Oct.2014	9.8
Owners' equivalent rent of residences[10, 15]	24.163	2.6	0.624	0.17	S-Jun.2014	2.6
Owners' equivalent rent of primary residence[10, 15]	22.752	2.6	0.587	0.17	S-Jun.2014	2.6
Tenants' and household insurance[4]	0.369	5.6	0.020	0.94	L-Oct.2014	5.6
Water and sewer and trash collection services[4]	1.210	4.6	0.054	0.83	L-May 2013	4.8
Water and sewerage maintenance[10]	0.935	5.6	0.050	1.07	L-Mar.2013	6.1
Garbage and trash collection[13]	0.275	1.4	0.004	0.63	S-May 2012	1.4
Household operations[4]	0.845	2.8	0.023	0.39	S-Sep.2014	2.7
Domestic services[4]	0.277	1.2	0.003	0.43	S-May 2012	1.2
Gardening and lawncare services[4]	0.278	4.4	0.012	0.39	–	–
Moving, storage, freight expense[4]	0.119	2.1	0.002	1.77	S-Jul.2014	1.6
Repair of household items[4]	0.066	4.0	0.003	0.93	L-Oct.2013	4.5
Medical care services	5.899	2.4	0.142	0.24	L-Jul.2014	2.5
Professional services	3.011	1.7	0.052	0.26	S-Oct.2014	1.5
Physicians' services[10]	1.578	1.5	0.023	0.43	–	–
Dental services[10]	0.799	1.8	0.014	0.45	S-Dec.1961	1.1
Eyeglasses and eye care[8]	0.282	2.6	0.007	0.61	–	–
Services by other medical professionals[10, 8]	0.352	2.0	0.007	0.38	L-Dec.2013	2.1
Hospital and related services	2.139	4.5	0.094	0.39	L-Jul.2014	5.5
Hospital services[10, 16]	1.835	4.9	0.087	0.44	L-Jul.2014	6.0
Inpatient hospital services[10, 16, 5]		5.5		0.55	L-Jul.2014	6.8
Outpatient hospital services[10, 8, 5]		4.5		0.88	L-Jul.2014	5.6
Nursing homes and adult day services[10, 16]	0.173	2.9	0.005	0.40	S-Aug.2014	2.9
Care of invalids and elderly at home[7]	0.131	1.8	0.002	0.39	L-Jan.2012	1.9
Health insurance[7]	0.748	-0.5	-0.004	0.28	L-May 2014	-0.1
Transportation services	5.624	1.7	0.097	0.34	S-Sep.2014	1.4
Leased cars and trucks[14]	0.394	-0.1	-0.001	1.24	L-Dec.2009	0.0
Car and truck rental[4]	0.071	0.0	0.000	2.04	S-Oct.2014	-0.1
Motor vehicle maintenance and repair	1.161	2.1	0.024	0.30	–	–
Motor vehicle body work	0.056	2.1	0.001	0.52	L-Aug.2014	2.7
Motor vehicle maintenance and servicing	0.490	2.2	0.011	0.57	S-Oct.2014	1.7
Motor vehicle repair[4]	0.583	2.0	0.012	0.44	L-Oct.2014	2.1
Motor vehicle insurance	2.279	4.7	0.105	0.62	S-Oct.2014	4.7
Motor vehicle fees[4]	0.561	0.3	0.002	0.41	–	–
State motor vehicle registration and license fees[10, 4]	0.311	-1.0	-0.003	0.59	S-Sep.2014	-1.0
Parking and other fees[4]	0.232	2.2	0.005	0.48	L-May 2014	2.6
Parking fees and tolls[4, 5]		2.7		1.10	L-May 2014	3.3
Automobile service clubs[4, 5]		-0.4		0.82	S-Sep.2014	-1.5
Public transportation	1.159	-2.9	-0.033	0.72	S-Oct.2009	-4.5
Airline fare	0.743	-4.7	-0.035	1.05	S-Jan.2014	-4.8
Other intercity transportation	0.153	-0.7	-0.001	1.85	S-Oct.2014	-2.1
Intercity bus fare[6, 5]						
Intercity train fare[6, 5]		3.8		2.00	L-Apr.2013	7.4
Ship fare[4, 5]		-1.9		1.88	S-Oct.2014	-4.1
Intracity transportation	0.258	1.1	0.003	0.45	–	–
Intracity mass transit[11, 5]		1.1		1.80	–	–
Recreation services[11]	3.721	1.5	0.054	0.47	L-Oct.2014	1.5
Video and audio services[11]	1.550	1.8	0.028	0.38	L-Oct.2014	1.9
Cable and satellite television and radio service[13]	1.459	2.2	0.031	0.40	L-Oct.2014	2.4

See footnotes at end of table.

Table 7. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 12-month analysis table — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Twelve Month: Unadjusted percent change Dec. 2013-Dec. 2014	Unadjusted effect on All Items Dec. 2013-Dec. 2014[1]	Standard error, median price change[2]	Largest (L) or Smallest (S) unadjusted change since:[3] Date	Percent change
Video discs and other media, including rental of video and audio[4]	0.090	-3.0	-0.003	1.66	L-Oct.2013	-2.7
Video discs and other media[4, 5]		-6.3		2.39	L-Jun.2014	-6.2
Rental of video or audio discs and other media[4, 5]		1.4		1.00	L-Sep.2012	2.3
Pet services including veterinary[4]	0.396	2.7	0.011	0.47	S-Nov.2013	2.6
Pet services[4, 5]		1.8		0.86	S-Aug.2013	1.1
Veterinarian services[4, 5]		2.9		0.52	S-Nov.2013	2.7
Photographers and film processing[4]	0.061	2.2	0.001	1.07	L-Sep.2014	2.6
Photographer fees[4, 5]		1.1		0.64	–	–
Film processing[4, 5]		3.8		1.03	L-Nov.2011	3.9
Other recreation services[4]	1.714	0.8	0.014	0.91	L-Oct.2014	0.8
Club dues and fees for participant sports and group exercises[4]	0.602	0.4	0.002	1.23	S-Oct.2014	0.2
Admissions	0.632	0.7	0.004	1.50	L-Oct.2014	1.2
Admission to movies, theaters, and concerts[4, 5]		0.4		1.21	L-Oct.2014	1.6
Admission to sporting events[4, 5]		2.7		1.53	L-Jul.2014	3.7
Fees for lessons or instructions[8]	0.210	2.0	0.004	1.41	S-Sep.2014	1.8
Education and communication services[11]	6.425	0.9	0.060	0.23	S-EVER	–
Tuition, other school fees, and childcare	3.106	3.2	0.097	0.34	S-Sep.2014	3.2
College tuition and fees	1.844	3.4	0.062	0.50	S-Sep.2014	3.4
Elementary and high school tuition and fees	0.375	4.0	0.014	0.44	–	–
Child care and nursery school[12]	0.722	2.2	0.016	0.43	S-Jul.2014	2.1
Technical and business school tuition and fees[4]	0.039	1.8	0.001	0.98	S-Sep.2014	1.7
Postage and delivery services[4]	0.144	3.8	0.005	0.48	S-Dec.2012	3.8
Postage	0.129	4.1	0.005	0.51	–	–
Delivery services[4]	0.014	1.1	0.000	0.50	S-Nov.2009	-6.6
Telephone services[4]	2.454	-2.1	-0.054	0.32	S-Feb.2005	-2.1
Wireless telephone services[4]	1.623	-4.0	-0.069	0.39	S-Sep.2011	-4.2
Land-line telephone services[11]	0.830	1.8	0.015	0.59	L-Sep.2014	2.3
Internet services and electronic information providers[4]	0.709	1.6	0.012	1.01	S-Sep.2014	1.3
Other personal services[11]	1.747	1.9	0.033	0.35	–	–
Personal care services	0.631	1.5	0.010	0.58	L-Oct.2014	1.6
Haircuts and other personal care services[4]	0.631	1.5	0.010	0.58	L-Oct.2014	1.6
Miscellaneous personal services	1.116	2.1	0.023	0.40	S-Oct.2014	2.0
Legal services[8]	0.315	1.4	0.005	0.75	S-Oct.2014	1.4
Funeral expenses[8]	0.172	1.2	0.002	0.41	S-EVER	–
Laundry and dry cleaning services[4]	0.275	2.2	0.006	0.44	S-Jul.2014	1.8
Apparel services other than laundry and dry cleaning[4]	0.033	1.8	0.001	0.99	S-Mar.2014	1.5
Financial services[8]	0.226	3.5	0.008	1.00	L-May 2013	4.1
Checking account and other bank services[4, 5]		0.1		3.68	L-May 2014	4.2
Tax return preparation and other accounting fees[4, 5]		6.1		0.85	L-May 2012	6.4
Special aggregate indexes						
All items less food	85.869	0.3	0.283	0.09	S-Oct.2009	-0.1
All items less shelter	67.518	-0.3	-0.173	0.10	S-Oct.2009	-0.6
All items less food and shelter	53.387	-1.2	-0.646	0.11	S-Sep.2009	-2.7
All items less food, shelter, and energy	44.943	0.7	0.309	0.13	S-Feb.2004	0.7
All items less food, shelter, energy, and used cars and trucks	43.337	0.9	0.379	0.14	–	–
All items less medical care	92.350	0.6	0.534	0.08	S-Oct.2009	-0.4

See footnotes at end of table.

Table 7. Consumer Price Index for All Urban Consumers (CPI-U): U.S. city average, by expenditure category, December 2014, 12-month analysis table — Continued

[1982-84=100, unless otherwise noted]

Expenditure category	Relative importance Nov. 2014	Twelve Month: Unadjusted percent change Dec. 2013-Dec. 2014	Unadjusted effect on All Items Dec. 2013-Dec. 2014[1]	Standard error, median price change[2]	Largest (L) or Smallest (S) unadjusted change since:[3] Date	Percent change
All items less energy	91.557	1.9	1.712	0.08	–	–
Commodities	38.294	-2.0	-0.775	0.13	S-Sep.2009	-4.2
Commodities less food, energy, and used cars and trucks	17.866	-0.5	-0.085	0.27	S-Feb.2014	-0.5
Commodities less food	24.163	-5.0	-1.248	0.18	S-Sep.2009	-6.2
Commodities less food and beverages	23.151	-5.2	-1.261	0.19	S-Sep.2009	-6.6
Services	61.706	2.5	1.532	0.11	–	–
Services less rent of shelter[15]	29.593	2.1	0.622	0.14	L-Aug.2014	2.3
Services less medical care services	55.807	2.5	1.390	0.11	–	–
Durables	8.942	-2.0	-0.183	0.17	S-Apr.2009	-2.0
Nondurables	29.352	-2.0	-0.592	0.15	S-Oct.2009	-2.6
Nondurables less food	15.221	-6.7	-1.065	0.25	S-Sep.2009	-9.5
Nondurables less food and beverages	14.209	-7.3	-1.078	0.27	S-Sep.2009	-10.3
Nondurables less food, beverages, and apparel	10.749	-8.9	-1.010	0.17	S-Sep.2009	-13.6
Nondurables less food and apparel	11.761	-8.0	-0.997	0.16	S-Sep.2009	-12.4
Housing	41.873	2.5	1.044	0.14	S-Apr.2014	2.5
Education and communication[4]	7.037	0.4	0.029	0.21	S-Jul.1999	0.4
Education[4]	3.306	3.3	0.106	0.32	–	–
Communication[4]	3.731	-2.0	-0.078	0.27	S-Feb.2007	-2.0
Information and information processing[4]	3.588	-2.2	-0.083	0.28	S-Sep.2011	-2.3
Information technology, hardware and services[17]	1.134	-2.5	-0.029	0.71	S-Mar.2014	-3.0
Recreation[4]	5.725	0.0	0.001	0.31	L-Oct.2014	0.2
Video and audio[4]	1.841	-0.3	-0.006	0.35	L-Oct.2014	0.1
Pets, pet products and services[4]	1.050	1.2	0.012	0.45	L-Dec.2013	1.3
Photography[4]	0.122	0.0	0.000	1.17	S-Apr.2014	0.0
Food and beverages	15.143	3.3	0.487	0.10	L-Feb.2012	3.8
Domestically produced farm food	7.017	4.1	0.285	0.18	L-Feb.2012	4.7
Other services	11.893	1.2	0.147	0.20	–	–
Apparel less footwear	2.729	-3.2	-0.088	1.35	S-May 2003	-3.5
Fuels and utilities	5.209	3.0	0.155	0.36	L-Oct.2014	3.1
Household energy	3.999	2.5	0.101	0.39	L-Oct.2014	2.8
Medical care	7.650	3.0	0.223	0.28	L-Mar.2013	3.1
Transportation	15.743	-6.2	-1.013	0.14	S-Sep.2009	-9.8
Private transportation	14.584	-6.4	-0.980	0.14	S-Sep.2009	-9.9
New and used motor vehicles[4]	5.709	-0.9	-0.052	0.22	S-May 2009	-1.1
Utilities and public transportation	10.034	1.4	0.137	0.24	L-Oct.2014	1.4
Household furnishings and operations	4.181	-0.9	-0.040	0.24	S-Sep.2014	-1.4
Other goods and services	3.368	1.6	0.054	0.26	S-Sep.2014	1.6
Personal care	2.660	1.3	0.034	0.32	S-Jun.2014	1.2

[1] The 'effect' of an item category is a measure of that item's contribution to the All items price change. For example, if the Food index had an effect of 0.40, and the All items index rose 1.2 percent, then the increase in food prices contributed 0.40 / 1.2, or 33.3 percent, to that All items increase. Said another way, had food prices been unchanged for that year the change in the All items index would have been 1.2 percent minus 0.40, or 0.8 percent. Effects can be negative as well. For example, if the effect of food was a negative 0.1, and the All items index rose 0.5 percent, the All items index actually would have been 0.1 percent higher (or 0.6 percent) had food prices been unchanged. Since food prices fell while prices overall were rising, the contribution of food to the All items price change was negative (in this case, -0.1 / 0.5, or minus 20 percent).

[2] A statistic's margin of error is often expressed as its point estimate plus or minus two standard errors. For example, if a CPI category rose 2.6 percent, and its standard error was 0.25 percent, the margin of error on this item's 12-month percent change would be 2.6 percent, plus or minus 0.5 percent.

[3] If the current 12-month percent change is greater than the previous published 12-month percent change, then this column identifies the closest prior month with a 12-month percent change as (L)arge as or (L)arger than the current 12-month change. If the current 12-month percent change is smaller than the previous published 12-month percent change, the most recent month with a change as (S)mall or (S)maller than the current month change is identified. If the current and previous published 12-month percent changes are equal, a dash will appear. Standard numerical comparison is used. For example, 2.0% is greater than 0.6%, -4.4% is less than -2.0%, and -2.0% is less than 0.0%. Note that a (L)arger change can be a smaller decline, for example, a -0.2% change is larger than a -0.4% change, but still represents a decline in the price index. Likewise, (S)maller changes can be increases, for example, a 0.6% change is smaller than 0.8%, but still represents an increase in the price index. In this context, a -0.2% change is considered to be smaller than a 0.0% change.

[4] Indexes on a December 1997=100 base.

[5] Special indexes based on a substantially smaller sample. These series do not contribute to the all items index aggregation and therefore do not have a relative importance or effect.
[6] Indexes on a December 2007=100 base.
[7] Indexes on a December 2005=100 base.
[8] Indexes on a December 1986=100 base.
[9] Indexes on a December 1993=100 base.
[10] This index series was calculated using a Laspeyres estimator. All other item stratum index series were calculated using a geometric means estimator.
[11] Indexes on a December 2009=100 base.
[12] Indexes on a December 1990=100 base.
[13] Indexes on a December 1983=100 base.
[14] Indexes on a December 2001=100 base.
[15] Indexes on a December 1982=100 base.
[16] Indexes on a December 1996=100 base.
[17] Indexes on a December 1988=100 base.
NOTE: Index applies to a month as a whole, not to any specific date.

BUSINESS INSIDER

BofA Now Has One Of The Most Bullish Stock Market Forecasts On Wall Street

Matthew Boesler
Jul. 15, 2013, 11:26 AM

Bloomberg TV

Savita Subramanian

In a note to clients today, BofA Merrill Lynch Head of U.S. Equity Strategy Savita Subramanian ups her year-end target for the S&P 500 to 1750 from 1600 – making hers the second-most bullish forecast on the Street, behind Cannacord's Tony Dwyer, who sees the index finishing 2013 at 1760.

Subramanian's 1750 target implies around 4.2% upside from today's levels at 1680 by the end of 2013.

(Before today, only two Wall Street equity strategists had lower S&P 500 price targets than Subramanian: Gina Martin Adams at Wells Fargo, with a target of 1440 by year-end, and Barry Knapp at Barclays, with a target of 1525.)

"Our new 2013 year-end target of 1750 implies modest upside from current levels, attributable to expected earnings growth, contrasting with returns so far this year driven by multiple expansion," says Subramanian. "While the decline in the equity risk premium (ERP) has been more than twice what we expected, we think it is justified by diminished tail risks, positive surprises in the US economy, and, as expected, a continued decline in earnings volatility."

Table 3: 2013 year-end S&P 500 fair value model

BofAML 2014 Pro Forma EPS Forecast	$115
Normalized 2014 EPS	**$107.50**
Normalized % of Proforma EPS	93%
Nominal Long-Term Risk-Free Rate	3.50%
- Assumed Long-Term Inflation	2.00%
= Normalized Real Risk-Free Rate	1.50%
+ Equity Risk Premium	**475bp**
= Fair Real Cost of Equity Capital (Ke)	6.25%
Fair Forward PE (1 ÷ Fair Ke)	**16.0x**
2013 Year-End Target (Fair PE × Normalized 2014 EPS)	**1,720**

BofA Merrill Lynch US Equity and US Quant Strategy

The biggest input into Subramanian's new S&P 500 price target forecast is the BAML Fair Value model, which assumes a forward price-to-earnings ratio unchanged from current levels at 16 and full-year S&P 500 earnings of $107.50 per share in 2014.

The assumption of a 16x price-to-earnings ratio rests heavily on Subramanian's forecast for the equity risk premium.

Below, Subramanian gives her thoughts on the ERP:

The equity rally over the last eight months has been primarily driven by multiple expansion, with the forward PE multiple on the S&P 500 expanding from 12x to 14x (18%). In our fair value model, we focus on the normalized forward PE multiple, which has also risen from 13.5x to 16.0x (18%). This multiple expansion has predominantly been a function of the significant decline in the equity risk premium (ERP), partially offset by a modest rise in real normalized interest rates.

While current real normalized rates are only modestly higher than our previous year-end assumption of 1.0% (now forecasting 1.5%), the 135bp drop in the ERP is more than double the 50bp that we had originally assumed going into the year. This rapid ERP compression reflects the reality that many of the major uncertainties overhanging the market have been removed or significantly diminished (US election, fiscal cliff, sequestration, Eurozone collapse, China hard landing).

But at 500bp, the ERP is currently still well above the sub-400bp levels preceding the financial crisis, and we think it should continue to decline over the next several years as the memory of the Financial Crisis fades, corporate profits continue to make new highs and some of the macro risks abate. We expect the "wall of worry" to persist as new concerns emerge, but visibility is clearly improving and we still expect global growth to pick up as the year progresses.

As such, we have lowered our normalized risk premium assumption in our fair value model for the end of 2013 from 600bp to 475bp, which assumes roughly another 25bp of ERP contraction by year-end. We have also raised our normalized real risk-free rate assumption for year-end from 1.0% to 1.5%. Not only have current and future inflation expectations declined since last fall, but long-term interest rates have also begun to rise recently. Meanwhile, our Rates Strategist Priya Misra also recently raised her interest rate forecasts.

The chart below shows BAML's ERP forecast.

Chart 2: Normalized equity risk premium

BofAML US Equity & Quant Strategy, Federal Reserve Board, Standard & Poor's, BLS

The Equity Premium

Paul Bostock. **Journal of Portfolio Management**. New York: Winter 2004. Vol. 30, Iss. 2; pg. 104, 8 pgs

Abstract (Summary)
Investors require additional expected returns for bearing costs and risks. The equity premium is the compensation investors require for bearing the additional costs and risks of equity investment compared with government bonds (or cash). In this framework, the equity premium is constructed by assembling the premiums paid for each source of cost and risk. The results appeal to intuition and are closer to theoretical expectations than historical equity and bond return comparisons. [PUBLICATION ABSTRACT]

Full Text (2957 words)

[Headnote]
What level should investors require?

The equity premium relates required returns for equities to returns for cash and bonds. The equity premium is the compensation investors require for bearing the additional costs and risks of equity investment.

Understanding the equity premium is largely a matter of using clear terms. Arnott in "Proceedings" [2002] suggests equity risk premium for the forward-looking expected or required returns and equity excess return for historical performance numbers. It is also useful to refer to the total equity premium, which is the compensation investors require for risk and for non-risk items such as term structure expectations, trading costs, and taxes.

There is a substantial literature on the equity premium. Kocherlakota [1996], Cornell [1999], "Proceedings of Equity Risk Premium Forum" [2002], and Ilmanen [2003] provide excellent reviews with comprehensive references.

Mehra and Prescott [1985] demonstrate theoretically that under standard finance models the equity risk premium should be very low: "The largest premium obtainable with the Model is 0.35%, which is not close to the observed value" (p. 156). Observing that equities had outperformed cash by some 6 percentage points per year over a period of almost 90 years, Mehra and Prescott realized there is a puzzle.

The risk premium is all about expectations and requirements. If assets return their expected rates, there is little dispersion among them. Actual historical returns vary enormously because historical returns also predominantly reflect surprises (departures from, or changes in, expectations.) It is therefore extremely difficult to infer a risk premium from historical returns.

The great 20th century surprise was inflation. In the 19th century, there was no inflation, while the 20th century saw an inflation explosion. Much of the 20th century equity-bond return difference is the effect of unanticipated inflation on cash and bond performance. Wilkie [1995], Arnott and Bernstein [2002], and Hunt and Hoisington [2003] discuss inflation further.

COMPARING REQUIRED RETURNS ACROSS ASSET CLASSES

We develop an intuitive framework for construction of the total equity premium, piece by piece. We do not use historical returns or valuation indicators to assess the equity risk premium, but rather assess how high it j/zowM be, using information from other asset classes whose premiums are arguably more transparent. The approach is neither rigorous nor unique.

As a starting point, equities, bonds, and cash have one important general characteristic in common: Each provides a stream of income over time. For any income-producing asset, we can calculate a fair value by discounting the future expected cash flows at an appropriate rate-one that takes into account all relevant information: credit rating of the issuer, interest rate risk (or duration), discretionary variability of dividend income, trading, and tax costs.

Taking into account the full set of characteristics that investors would use to compare assets leads to a straightforward framework of analysis, illustrated in Exhibit 1. Note that discount rates and required rates of return are the same thing; the price now is the future value discounted back, while the future value is the price now plus its appreciation at the required rate. Required return is a natural characterization of how investors compare assets.

Cash is considered the risk-free asset, and its required return R^sub 0^ is known. The required return on fowg government bonds, over the shorter time horizon, is denoted R^sub L^. This is not the same as the long yield Y^sub L^ because the yield curve reflects expectations about interest rates in later periods as well as an interest rate risk premium.

For the long rate:

R^sub L^ = R^sub 0^, + fn[Duration(Bonds)l (1)

For long corporate bonds, the required return RH differs from the government bond rate solely because of issuer risk (normally expressed as a function of credit rating) . Smithers and Wright [2000] note that issuer differences can be used to refine risk premium measurements (although they do not pursue this). Corporate bonds are included to provide a yardstick for the issuer risk premium:

R^sub B^ = R^sub 0^ + fn[Duration(Bonds)] + fn[Issuer(Bonds)] (2)

The required return for equities, R^sub E^, differs from the long corporate rate because of additional uncertainty in the payout, additional duration, and additional costs. There is no term for price volatility. In the discounted income valuation, a change in the value of equities is either a change in the expected income stream or a change in the discount rate, and the framework includes both these terms:

R^sub E^ = R^sub 0^ + fn[Duration(Equity)] + fn[Issuer(Equity)] + fn(Income Risk) + fn(Tax)+ fn(Trading Costs) (3)

Putting these pieces together, we can construct the equity premium by measuring and extrapolating the duration premium from the yield curve, providing the details for Equation (1); inferring an appropriate issuer premium from corporate bond data [Equation (2)]; calculating tax and trading costs from known rates; and measuring the effect of income volatility in cross-sectional studies of equities, for Equation (3).

ASSIGNING REQUIRED RETURNS TO ASSET CHARACTERISTICS

We use the framework in Exhibit 1 to assign required returns to the various asset characteristics.

Term Structure and Interest Rate Risk

Required returns cannot be taken directly from the yield curve, which shows return expectations over lengthening time horizons. Here we need to compare required returns for different assets over the same time horizon.

Over the longer term, the average yield curve shape should reflect expected interest rate changes split evenly between rises and falls. The yield curve shape is then a measure of the interest rate risk premium. For equities, we must include interest rate risk over and above long bonds.

The going concern equity duration is the reciprocal of the dividend yield, a result implied by the Gordon [1962] model. At a typical U.S. equity market yield of 4%, duration is 25 years. We use this figure to capture the essential property that growth of equity income over time makes equities more interest rate-sensitive than bonds. The duration figure may be model-dependent and may shorten because of buy-backs.

The data in Exhibit 2 show that ten-year bonds have had an average premium of 1.6 percentage points per year over cash. The equity interest rate risk premium is estimated by fitting the yield curve (an exponential shape fits well) and extrapolating it to the equity time horizon (Exhibit 3). The best estimate for the additional annual equity premium is about 3 to 4 percentage points, the error attributable to analysis of the time series volatility of the yield curve slope.

The high differential between long-term and short rates as of December 2002 surely reflects expectations, since the cash rate of 1.2 percentage point is very low relative to its history. To isolate expectations, it is reasonable to assume there is no further interest rate forecasting beyond five years (the yield curve may continue to slope upward as it is the mean value or integral of the forward short rate curve). The choice of five years for the limit of interest rate forecasting is not precise, so we include an error term for this.

According to the best fit, the ten-year yield is explained by term structure alone. This attribution has an indicative error of 0.3%, the interest rate risk premium on the next-higher maturity. Extrapolating to the long duration limit for the currently low equity yield (the analysis is not sensitive to the long duration number) gives an additional interest rate risk premium for equities of 0.8%. The additional equity premium has an error of 1.0%, reflecting the difficulty (and the model-dependence) of separating term structure and interest rate risk in this case.

Issuer Risk

Equities are issued by corporations, and corporations have a risk of default. The total equity premium and the equity risk premium must therefore include some compensation for issuer risk. Issuer risk is readily measurable in the bond markets. We use gross redemption yields on Lehman Corporate Aggregate bond indexes for four credit rating classes of U.S. corporate bonds (AAA, AA, A, BAA) as well as a government bond series (Exhibit 4).

Issuer risk must be aggregated over all companies in the equity market. While not all listed equities have credit-rated debt, it is possible to make reasonable estimates. Equities rank below debt, and companies can cut dividends more readily than they can suspend bond repayments. The larger companies that dominate the equity indexes in capitalization terms are typically rated A or AA. These considerations suggest an average rating of between A and BAA and, for an indicative range for errors, AA to BAA.

Transaction costs are higher for corporate bonds than governments, and an estimated liquidity premium for corporate bonds of 0.5% has been subtracted from yield spreads. Using a series from January 1973, the issuer risk premium is estimated at around 0.9% ± 0.4%. As of the end of 2002, similar analysis produces an estimated issuer premium of 1.4% ± 0.8%.

For an alternative approach that estimates premiums directly using option-based models, see Cooper and Davydenko [2003].

Income Risk

Equities have income risk that government bonds and T-bills do not have, in the sense that dividend payments are not fixed or contractual. This element of unpredictability should require an additional premium in required return. If this income volatility requires additional return, then the more volatile the income, the greater the required return.

The cross-sectional relationship between income volatility and required return may be isolated by grouping equities according to income volatility. From all S&P 500 constituents, over the period January 1960-January 2003, we select companies with a known market value and a dividend record. The five-year dividend volatility is evaluated from quarterly data for each company each year, and companies are assigned to slots of zero to 4% annual dividend volatility, over 4% to under 8%, and so on.

Average dividend yields for these volatility groups are calculated over the entire period. Here, incremental dividend yield is used as a proxy for an incremental discount rate; the steady-state discount rate is dividend yield plus long-term growth, and it is reasonable to assume over so many company-years that average expected growth would not be a function of historical dividend volatility.

Dividend yields are flat to slightly negative across these groups, implying that there is no additional premium for additional volatility (see Exhibits 5 and 6). Running the analysis as of the end of 2002 yields similar results.

This result suggests that investors in equities are not sensitive to dividend variability, and that there should be no additional premium required for the equity market over cash. Variations of the methodology indicate that the result is not explained by the variation of average market yield over the period, or by historical earnings growth, or by recent buybacks. Price volatility gives an even more negative slope. These results are supported by a similar study in the U.K.

Note that we have treated dividend variability and issuer risk separately for convenience. Part of income uncertainty is priced in issuer risk, but since equity income is discretionary and equity ranks below debt, a firm's shares carry more income risk than its corporate bonds.

Transaction Costs

Equities cost significantly more to trade than government bonds. One would expect the rational investor to price securities on the basis of after-cost returns. It is more realistic, however, to look at actual investor holding periods to calculate an appropriate liquidity premium.

Jones [2002] gives a highly informative account of U.S. equity trading volumes and costs over the 20th century. Jones's detailed analysis produces an estimated premium effect of 50 basis points per year, which we use for the long-term adjustment.

For end-2002 costs, we take a simpler approach. Consider a trading time horizon, which is the time it takes for the dollar value of trading in the market to equal the total market capitalization. The liquidity premium is the average round-trip cost taken over the trading time horizon. Using recent trading times (under a year) with current commissions and spreads produces a current U.S. equity liquidity premium of 20 ± 20 basis points.

Tax Costs

Investors should demand a higher return rate from securities that are more highly taxed, because realized net-of-tax returns are what investors actually receive. Government issues are not treated specially in the U.S. In the U.K., for example, government bonds are offered with tax advantages over equities, so in the general case a tax cost term is required.

Assembling the Risk Premium

Estimates of the total equity premium and the equity risk premium are summarized in detail in Exhibit 7. On average, equities should have offered a total premium over government bonds of 1.7% ± 0.6% and a risk premium of 1.2% ± 0.6%.

These results appeal to intuition and are consistent with an increasingly accepted view that the true risk premium is considerably lower than the historical return differential (see, for example, a thorough review in Ilmanen [2003]). We have already shown why historical returns give unreliable results.

The December 2002 total premium is 2.6% ± 1.3% over bonds, reflecting mainly additional issuer risk. The result is very interesting. It means a higher return is required if equities are to be fairly valued against bonds. This premium taken over current long government bond rates of 4.8% gives a total required return over the ten years of 7.4%.

The required long-term growth (with a yield of 1.8% and using the Gordon model again) is 5.6%. In current conditions (a bear market, an economy facing difficulties, and very low inflation), this outcome seems implausible. The analysis quite strongly suggests that the U.S. equity market remained overvalued at the end of 2002.

ESTIMATING THE MEHRA AND PRESCOTT THEORETICAL PREMIUM

Mehra and Prescott's [1985] theory shows how a premium is required for assets that offer uncertain delivery of marginal utility. In terms of securities, this relates both to the volatility of returns and to the timing (in simple terms, the same payment is more valuable in bad times than in good). Measurements or estimates of this premium require us to identify and price only the corresponding characteristics.

An important question arises as to whether issuer risk is part of the theoretical risk premium. Over the very short term (the time horizon for the theoretical risk premium), we would not expect default to be a significant risk other than for already distressed, very low-grade issuers. Equity default is certainly rare (or, at least, it has been). If the Mehra and Prescott theoretical result is strictly a short-term only result, issuer risk should not be included in the premium estimate, which would then be low.

FURTHER WORK

It would be most interesting to explore a framework with a long time horizon and to include the impact of inflation. High and unexpected 20th century inflation explains much of the low real return to cash and bonds. In a real and long-term framework, cash and bonds would be seen as more risky and equities less so, so a smaller risk premium would very probably result.

The analysis here also raises interesting questions of how each premium component should be priced, in theory. In other words, is there a theoretically correct interest rate risk premium, a correct issuer premium, and so on? Mehra [2003] looks at pricing influences including costs and taxes, making modifications to the theory rather than to the measurements.

Refining both the theory and the measurement for each risk premium component will be an interesting task. In other words, our work raises as many new issues as it solves, and it will continue to be interesting to see the subject evolve.

SUMMARY

We have described a procedure for constructing the equity premium by assembling premiums paid for each source of cost and risk. According to historical average data, equities should offer a total premium over government bonds of 1.7% ± 0.6% and a risk premium of 1.2% ± 0.6%.

Investors do not all have the same time horizon and the same inflation risks. For long-term real investors, equities are the natural home, and it does seem that equity buyers accept short-term volatility as part of the package. These results appeal to intuition and are closer to theoretical expectations than historical equity and bond return comparisons.

ENDNOTE

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[Reference]

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[Author Affiliation]

PAUL BOSTOCK is managing director of GMO's London Office in London, UK. paul.bostock@gmo.com

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A re-examination of analysts' superiority over time-series forecasts

Mark T. Bradshaw
Boston College

Michael S. Drake
The Ohio State University

James N. Myers
University of Arkansas

Linda A. Myers
University of Arkansas

CARE Conference
April 10, 2010

Summary of slides from the Inaugural CARE Conference

- #1 "Analysts' forecasts are optimistic"
- #2 "Analysts are better than time-series models"
- #3 We think we know how analysts forecast
- #4 "Analysts' forecasts are inefficient"
- #5 Limited evidence on what analysts do with forecasts
- #6 Most research ignores analysts' multi-tasking
- *#7 Analyst data are helpful for capital markets literature*
- #8 "Analysts are dominated by conflicts of interest"
- #9 We may be focusing on their least important activities
- #10 Researchers eschew alternative methodologies

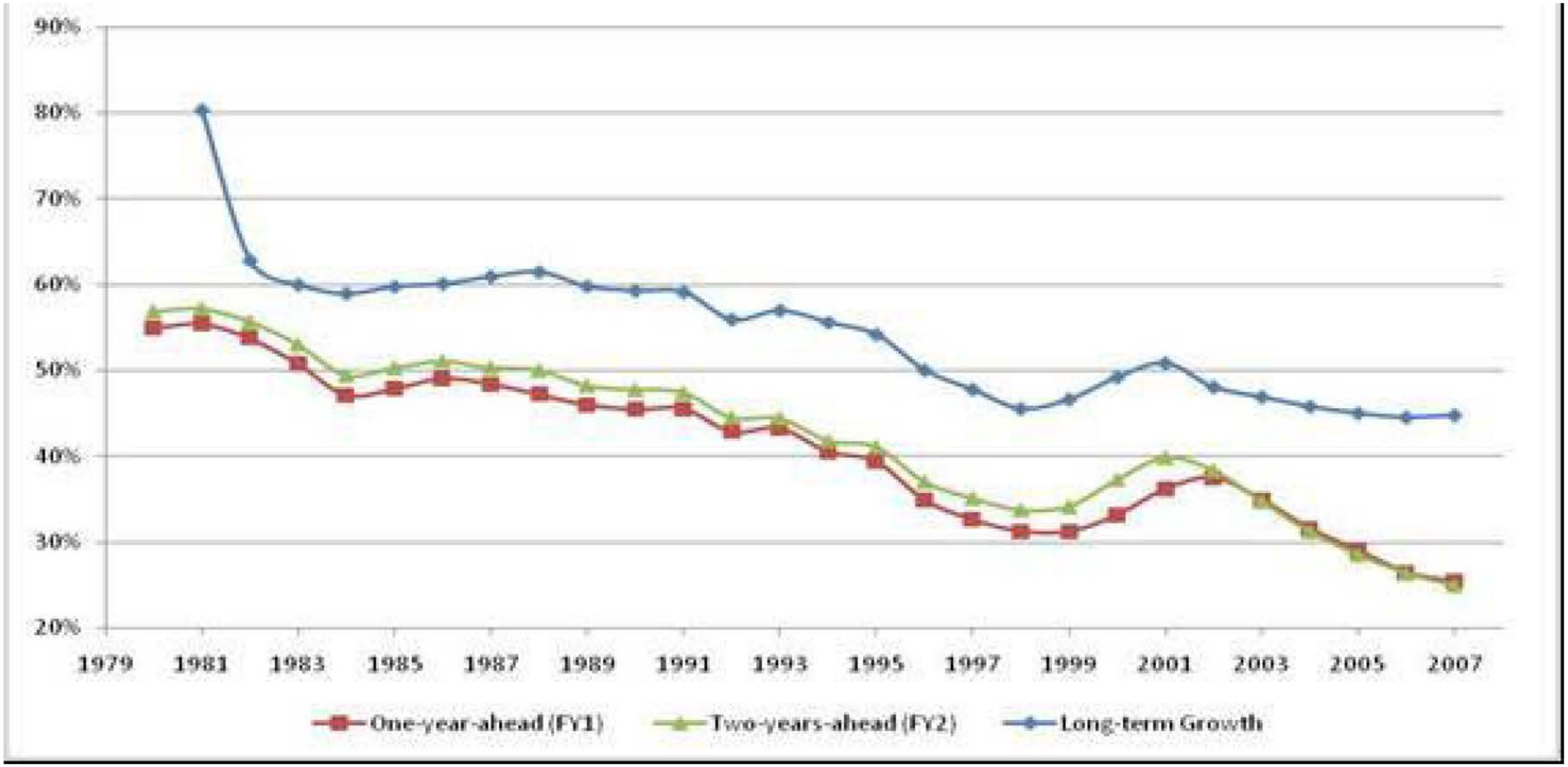
Summary motivation

- Analysts >> Time-series models is widely accepted

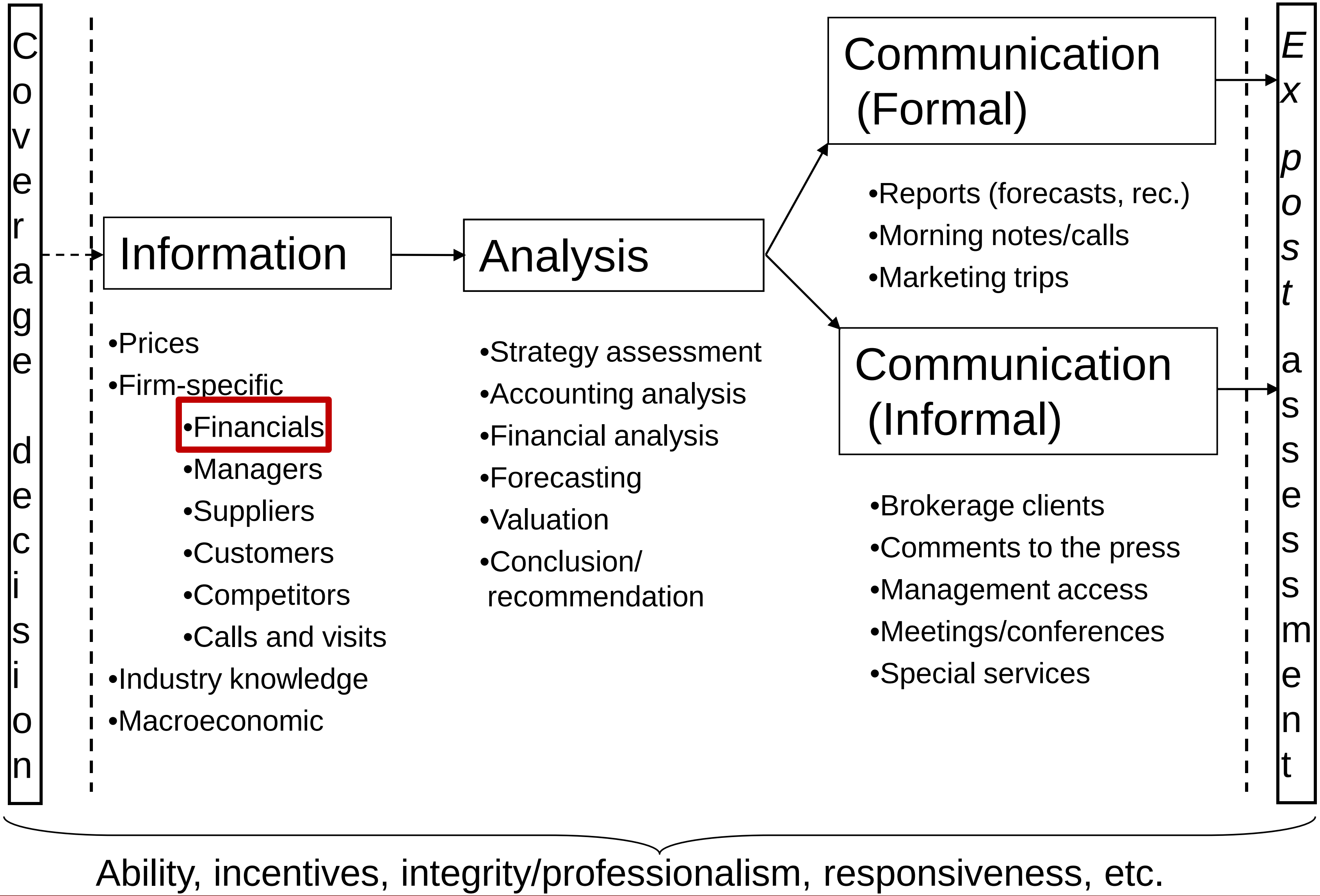
- However, research supporting this view is characterized by:
  - **Tiny samples** relative to current research standards (in capital mkts.)
    - e.g., 50 to a few hundred firms
  - Data demands $\Rightarrow$ **bias towards large, mature firms**
    - e.g., some studies restrict sample to NYSE, or numerous analysts
    - Analyst following correlated with institutional investment
    - e.g., AF and II interact with firms $\Rightarrow$ richer information environment (more severe in earlier years)
  - **Economic significance** of differences seems small
    - Collins & Hopwood (1980): 31.7% vs. 32.9%
    - Fried & Givoly (1982): 16 vs. 19%

- Current-day incorporation of analysts' forecasts into research studies
  - Goes beyond **generalizability** of earlier studies
    - e.g., smaller firms underrepresented in early research,
      longer forecast horizons underrepresented
    - ala Bamber, Christensen & Gaver (AOS2000)

Figure 1: Percentage of firms on Compustat/CRSP *without* analyst coverage



Analysts


Coverage decision
Information
Analysis
Communication (Formal)
Communication (Informal)
Ex post assessment
•Prices
•Firm-specific
•Financials
•Managers
•Suppliers
•Customers
•Competitors
•Calls and visits
•Industry knowledge
•Macroeconomic
•Strategy assessment
•Accounting analysis
•Financial analysis
•Forecasting
•Valuation
•Conclusion/ recommendation
•Reports (forecasts, rec.)
•Morning notes/calls
•Marketing trips
•Brokerage clients
•Comments to the press
•Management access
•Meetings/conferences
•Special services
Ability, incentives, integrity/professionalism, responsiveness, etc.

Research question

- Do analysts’ forecasts *really* dominate time-series forecasts?
  - When and when not?
    - Covariate 1: Forecast horizon (timing advantage)
    - Covariate 2: Firm age (information advantage)
    - Covariate 3: Firm size “ ”
    - Covariate 4: Analyst following “ ”
    - Covariate 5: Magnitude of changes (when analysts stand to add most value)

- Implicit Null: We should see NO significant results

- Conditional on differences in forecast accuracy (in favor of time-series models), do market returns reinforce the primary results?

Observation: Other Evidence re: Experts vs. Time-Series

- Interest rates (Belongia 1987)
- GDP (Loungani 2000)
- Recessions (Fintzen and Stekler 1999)
- Turning points of business cycles (Zarnowitz 1991)
- …

Landscape – 1970s

- Much capital markets research was aimed at understanding the time-series properties of earnings.
  - Ball and Watts 1972, Brooks and Buckmaster 1976, Albrecht et al. 1977, Salamon and Smith 1977, and Watts and Leftwich 1977.

- General Conclusion: <u>Earnings approximate a random walk</u>. Sophisticated time-series models rarely provide an economically significant improvement, and even when they do it comes at high cost.

- *"The ability of random walk models to "outpredict" the identified Box-Jenkins models suggests that the random walk is still a good description of the process generating annual earnings in general, and for individual firms."* Watts and Leftwich (1977, 269)

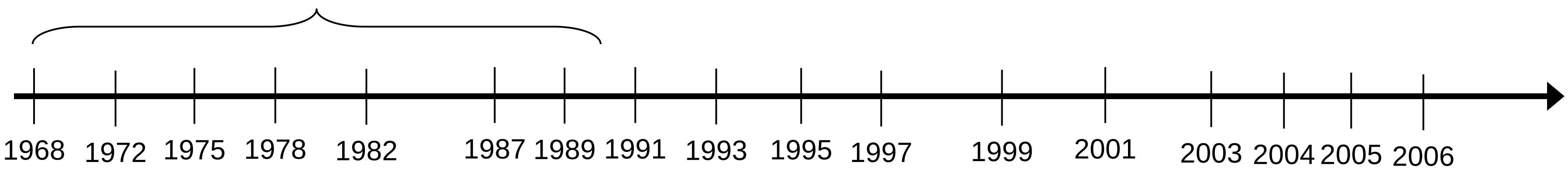
- Brown (1993, 295) declares the issue of whether annual earnings follow a random walk as "*pretty much resolved by the late 1970s.*"

Landscape – 1980s

- Newly available analyst data becomes available (i.e., Value-Line, I/B/E/S).
- "Horse-race studies" comparing time-series and analyst forecasts.
- Brown and Rozeff 1978, Fried and Givoly 1982, and Brown et al. 1987a,b
- General Conclusion: Analyst forecasts generally dominate time-series forecasts of earnings. Analyst superiority is attributed to:
  - **Information Advantage**
    - They know all information in TS and more
  - **Timing Advantage**
    - They issue forecasts after the end of the lagged TS

Timeline of Analysts vs. Time-Series Research

Price association



Cragg & Malkiel JF1968
Elton & Gruber MS1972
Barefield & Comiskey JBR1975
Brown & Rozeff JF1978
Fried & Givoly JAE1982

O'Brien JAE1988
O'Brien JAR1990
Stickel JAR1990
Brown IJF1991

Philbrick & Ricks JAR1991

Brown, Griffin, Hagerman, & Zmijewski JAE1987

Sinha, Brown & Das CAR1997
Mikhail, Walther, & Willis JAR1997
Clement JAE1999

Analysts vs. time-series models

Refinements/extensions

Landscape – Today

- Researchers generally regard this literature as having conclusively shown that analysts' forecasts are a superior proxy for earnings expectations.

- Kothari (JAE2001) concludes that
  - The time-series properties of earnings literature is fast becoming extinct because of "the easy availability of a better substitute" which is "available at a low cost in machine-readable form for a large fraction of publicly traded firms." (p. 145)
  - "[C]onflicting evidence notwithstanding, in recent years it is common practice to (implicitly) assume that analysts' forecasts are a better surrogate for market's expectations than time-series forecasts." (p. 153)

Landscape – Today (cont.)

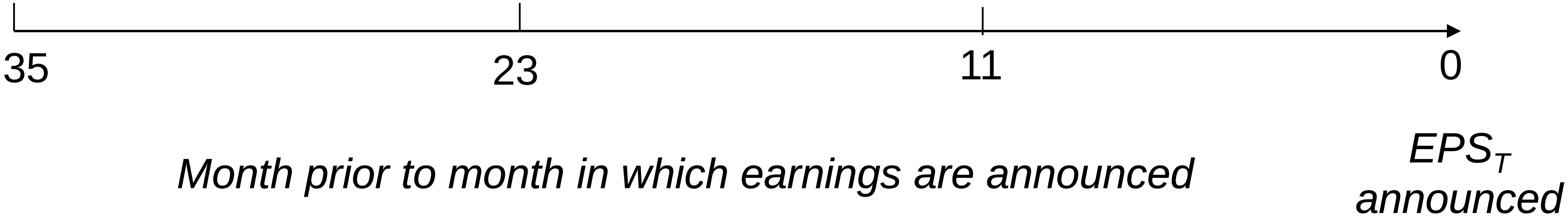
- Random Walk
  - Still descriptive (Lorek, Willinger & Bathke RQFA2008)

- Valuation and cost of capital literature:
  - Researchers use analyst forecasts over some short horizon and then extrapolate to value a perpetuity.
  - Example: Dhaliwal et al. (JAE 2007), Frankel & Lee (JAE1998), etc.
    - One-year-ahead: FY1 (I/B/E/S Consensus forecast)
    - Two-years-ahead: FY2
    - Three-years-ahead: FY3 = FY2 x (1+LTG)
    - Four-years-ahead: FY4 = FY3 x (1+LTG)
    - Five-years-ahead: FY5 = FY4 x (1+LTG)
  - Exceptions: Allee (2009); Hou, Van Dijk and Zhang (2010)

Data

- 1983-2007 (25 years)
- Minimal constraints on data
  - Biggest constraint is presence on *I/B/E/S*
    - EPS forecast, actual EPS, stock price
  - Sales on *Compustat* in year t-1
  - Earnings in year t-1 > 0
    - Hayn (1995): losses less persistent than profits
      $\Rightarrow$ bias results in favor of random walk (but not really)
  - *CRSP* returns for last analysis

- Consensus forecasts in months 0 to -35



Forecast errors

- Random Walk
  - Minimizes data demands
  - Performs as well or better than higher order models (consistent w/ Lorek, WIllinger & Bathke RQFA2008)
  - *We aim to do nothing to "help" RW forecasts*

- Forecast of EPS for year T as of t months prior to the month EPS_T announced
  - Analysts: $|(FEPS_{T,t} – EPS_T)| / Price_t$
  - Time-series: $|(EPS_{T-1} – EPS_T)| / Price_t$

	#Forecasts	#Firm-years	#Firms
FY1:	740,070	69,483	10,140
FY2:	611,132	60,170	9,037
FY3:	468,777	46,226	7,070

- Analyst superiority = RWFE – AFE
  - $>0 \Rightarrow$ analysts more accurate than random walk
  - $<0 \Rightarrow$ random walk more accurate than analysts

Table 2 Descriptive Statistics

	Mean	Q1	Median	Q3
Sales	>374	110	374	1,384
BTM	0.58	0.31	0.50	0.75
Age	8.2	4	7	12
# Analysts	7.6	2	5	10

* A hypothetical data requirement of 10 years (as in Fried and Givoly 1982) would eliminate 70% of the observations in our sample).

Scaling and winsorizing

$$Error = \left| \frac{(\text{Actual} - \text{Predicted})}{|\text{Actual}|} \right|$$

% > 1.00

Months Prior to RDQE	Analysts Forecasts Errors	Random Walk Errors
1 Month (Mature Firms)	2.90%	10.50%
1 Month	5.20%	14.20%
11 Months	16.50%	14.60%
23 Months	22.60%	19.70%
35 Months	29.50%	26.20%

**The 1.00 cut-off was reasonable in earlier studies. Fried and Givoly (1982) report that only 0.5% of their observations have scaled forecast errors that are greater than 1.00.

Table 2 Descriptive Statistics (i.e., Forecast– Actual)

Panel C: Signed Forecast Errors

	Mean	**Median**	**Q1**	**Q3**
Signed Random Walk Errors				
11 Months	0.0086	-0.0055	-0.0153	0.0108
23 Months	0.0033	-0.0091	-0.0260	0.0150
35 Months	-0.0038	-0.0124	-0.0363	0.0166
Signed Analysts' Forecasts Errors				
11 Months	0.0194	0.0028	-0.0041	0.0209
23 Months	0.0272	0.0090	-0.0049	0.0391
35 Months	0.0332	0.0162	-0.0047	0.0541

Table 3 – Main Results
Analysts' forecast superiority, Full sample

FY1			FY2			FY3			
Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority	
0	32,723	0.0245	12	29,072	0.0120	24	21,944	0.0072	
1	66,224	0.0236	13	55,447	0.0106	25	41,766	0.0055	
2	66,104	0.0227	14	56,659	0.0095	26	42,827	0.0044	
3	65,794	0.0212	15	56,575	0.0081	27	42,941	0.0033	
4	65,458	0.0182	16	56,023	0.0063	28	42,588	0.0019	
5	65,158	0.0155	17	55,360	0.0049	29	42,272	0.0007	
6	64,787	0.0131	18	54,458	0.0037	30	41,753	(0.0000)	NS
7	64,361	0.0102	19	53,195	0.0022	31	40,952	(0.0012)	
8	63,869	0.0081	20	51,832	0.0012	32	40,137	(0.0020)	
9	63,200	0.0064	21	49,745	0.0004	33	38,925	(0.0027)	
10	62,103	0.0041	22	46,501	(0.0006)	34	36,836	(0.0035)	
11	60,289	0.0025	23	42,124	(0.0011)	35	33,789	(0.0040)	

Analyst are more accurate than RW by 25 basis-pts

RW is more accurate than Analysts by 40 basis-pts

Table 4 – Analysts' forecast superiority and firm age

Panel A: FY1 – 11 months prior to RDQE

Firm Age	Firm-years	Analysts'Superiority	RW Forecast Error	Analysts' Forecast Error
1	2,534	0.0007	0.0534	0.0527
2	6,321	0.0015	0.0405	0.0391
3	5,867	0.0005	0.0382	0.0378
4	5,109	0.0005	0.0379	0.0374
5+	40,335	0.0033	0.0301	0.0268

Panel B: FY2 – 23 months prior to RDQE

Firm Age	Firm Years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	1,413	(0.0102)	0.0628	0.0730
2	3,969	(0.0072)	0.0528	0.0599
3	3,810	(0.0048)	0.0511	0.0559
4	3,404	(0.0028)	0.0472	0.0500
5+	29,447	0.0008	0.0396	0.0388

Panel C: FY3 – 35 months prior to RDQE

Firm Age	Firm Years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	1,119	(0.0186)	0.0735	0.0871
2	2,954	(0.0147)	0.0647	0.0785
3	3,011	(0.0084)	0.0604	0.0670
4	2,794	(0.0060)	0.0584	0.0618
5+	23,868	(0.0012)	0.0498	0.0488

Table 5: Partitions for size and analyst following

Panel A: Small Firms

FY1			FY2				FY3		
Months Prior	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**		**Months Prior**	**Firm-years**	**Analysts' Superiority**
0	6,897	0.0256	12	5,786	0.0085		24	3,067	0.0007
1	13,845	0.0252	13	10,871	0.0074		25	6,006	(0.0023)
2	13,737	0.0242	14	11,087	0.0060		26	6,192	(0.0040)
3	13,535	0.0225	15	10,885	0.0045		27	6,114	(0.0054)
4	13,396	0.0191	16	10,574	0.0020		28	5,968	(0.0074)
5	13,175	0.0162	17	10,204	0.0004	NS	29	5,836	(0.0086)
6	13,009	0.0132	18	9,799	(0.0012)		30	5,626	(0.0096)
7	12,815	0.0098	19	9,299	(0.0026)		31	5,366	(0.0106)
8	12,607	0.0071	20	8,759	(0.0040)		32	5,055	(0.0119)
9	12,341	0.0052	21	8,023	(0.0055)		33	4,707	(0.0131)
10	11,906	0.0023	22	6,987	(0.0066)		34	4,152	(0.0151)
11	11,314	(0.0003)	23	5,804	(0.0078)		35	3,521	(0.0167)

Table 5: Partitions for size and analyst following

Panel B: Low Analyst Following

FY1				FY2				FY3			
Months Prior	**Firm-years**	**Analysts' Superiority**		**Months Prior**	**Firm-years**	**Analysts' Superiority**		**Months Prior**	**Firm-years**	**Analysts' Superiority**	
0	9,089	0.0314		12	8,001	0.0110		24	8,634	0.0063	
1	18,744	0.0311		13	14,945	0.0102		25	16,197	0.0036	
2	18,704	0.0289		14	15,648	0.0085		26	16,784	0.0022	
3	18,557	0.0267		15	15,890	0.0066		27	16,848	0.0005	NS
4	18,422	0.0224		16	16,055	0.0043		28	16,672	(0.0014)	
5	18,265	0.0185		17	16,138	0.0027		29	16,489	(0.0030)	
6	18,104	0.0151		18	16,319	0.0008	NS	30	16,180	(0.0035)	
7	18,062	0.0109		19	16,646	(0.0009)		31	15,556	(0.0051)	
8	17,880	0.0080		20	16,901	(0.0022)		32	14,941	(0.0063)	
9	17,636	0.0058		21	17,310	(0.0032)		33	13,992	(0.0074)	
10	17,113	0.0026		22	17,924	(0.0041)		34	12,501	(0.0087)	
11	16,264	0.0000	NS	23	18,185	(0.0045)		35	10,544	(0.0099)	

Table 6: Partitions by magnitude of change in EPS

Panel A: The 33% of Forecasts with the $\boxed{\text{Least Extreme Forecasted Change in EPS}}$

FY1			FY2			FY3		
Months Prior	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**
0	10,915	0.0025	12	9,679	0.0174	24	7,305	0.0140
1	22,093	0.0026	13	18,472	0.0156	25	13,910	0.0124
2	22,053	0.0025	14	18,881	0.0143	26	14,268	0.0115
3	21,954	0.0023	15	18,845	0.0125	27	14,300	0.0106
4	21,842	0.0020	16	18,654	0.0106	28	14,185	0.0097
5	21,743	0.0018	17	18,439	0.0087	29	14,075	0.0085
6	21,620	0.0016	18	18,139	0.0074	30	13,907	0.0078
7	21,481	0.0014	19	17,721	0.0058	31	13,645	0.0071
8	21,324	0.0013	20	17,260	0.0051	32	13,382	0.0065
9	21,110	0.0012	21	16,561	0.0041	33	12,968	0.0061
10	20,731	0.0012	22	15,488	0.0034	34	12,277	0.0057
11	20,117	0.0012	23	14,023	0.0029	35	11,263	0.0053

Table 6: Partitions by magnitude of change in EPS

Panel B: The 33% of Forecasts with the Most Extreme Forecasted Change in EPS

FY1			FY2				FY3			
Months Prior	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**		**Months Prior**	**Firm-years**	**Analysts' Superiority**	
0	20,131	0.0025	12	9,695	0.0090		24	7,319	0.0018	
1	10,881	0.0616	13	18,483	0.0077		25	13,924	0.0005	NS
2	22,029	0.0591	14	18,885	0.0067		26	14,272	(0.0007)	NS
3	21,988	0.0566	15	18,865	0.0057		27	14,316	(0.0021)	
4	21,881	0.0530	16	18,684	0.0042		28	14,196	(0.0037)	
5	21,761	0.0453	17	18,463	0.0028		29	14,088	(0.0049)	
6	21,657	0.0381	18	18,157	0.0014		30	13,908	(0.0058)	
7	21,530	0.0320	19	17,728	0.0000	NS	31	13,639	(0.0076)	
8	21,385	0.0244	20	17,276	(0.0012)		32	13,360	(0.0087)	
9	21,217	0.0190	21	16,584	(0.0025)		33	12,964	(0.0095)	
10	20,993	0.0143	22	15,498	(0.0035)		34	12,267	(0.0109)	
11	20,635	0.0083	23	14,042	(0.0040)		35	11,256	(0.0115)	

Market expectation tests

- We estimate:

$$\text{Return} = \alpha + \beta\ \text{RWFE} + \epsilon_{\text{it}}$$
$$\text{Return} = \text{a} + \text{b}\ \text{AFE} + \text{e}_{\text{it}}$$

where the return accumulation period is equaled to forecast horizon.

- Market Expectation Proxy Ratio = β / b

Table 7: Associations with market returns

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = \alpha + b\,\left(Forecasted\ EPS_{T,M} - EPS_T\right) + e_T$$

FY1			FY2				FY3			
Months Prior	Firm-years	β/b	Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b	
0	30,411	0.345	12	28,003	0.602		24	21,097	0.784	
1	62,355	0.395	13	53,654	0.678		25	40,377	0.831	
2	63,455	0.342	14	54,664	0.707		26	41,336	0.843	
3	63,419	0.396	15	54,473	0.742		27	41,369	0.874	
4	63,101	0.540	16	53,882	0.798		28	40,992	0.908	
5	62,790	0.632	17	53,196	0.833		29	40,674	0.928	
6	62,441	0.685	18	52,319	0.888		30	40,151	0.962	
7	62,016	0.735	19	51,113	0.912		31	39,409	1.001	
8	61,540	0.795	20	49,789	0.953		32	38,624	1.017	NS
9	60,915	0.838	21	47,783	1.007	NS	33	37,455	1.057	NS
10	59,936	0.905	22	44,672	1.008	NS	34	35,435	1.081	
11	58,261	0.939	23	40,500	1.032		35	32,530	1.099	

The association between returns and RW is 94% of the association between returns and analyst forecast errors.

Table 8: Market returns, by size & analyst following

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = \alpha + b\left(Forecasted\ EPS_{T,M} - EPS_T\right) + e_T$$

Panel A: Small Firms

FY1				FY2				FY3			
Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b	
0	6,558	0.1813		12	7,275	0.6957		24	3,396	0.9083	
1	13,382	0.3422		13	13,711	0.7238		25	6,575	0.8822	
2	13,474	0.4286		14	14,068	0.7550		26	6,814	0.9084	
3	13,364	0.4433		15	13,887	0.7793		27	6,757	0.9330	
4	13,227	0.5309		16	13,468	0.8111		28	6,552	0.9392	NS
5	13,001	0.6186		17	12,974	0.8496		29	6,422	0.9495	NS
6	12,838	0.6610		18	12,424	0.9076		30	6,173	0.9550	NS
7	12,643	0.7170		19	11,713	0.8973		31	5,844	0.9762	NS
8	12,431	0.8323		20	10,906	0.9676	NS	32	5,491	1.0016	NS
9	12,176	0.8551		21	9,808	1.0151	NS	33	5,028	1.0965	
10	11,750	0.9273	NS	22	8,168	1.0043	NS	34	4,258	1.1229	
11	11,167	0.9431	NS	23	6,392	1.0277	NS	35	3,431	1.1230	

Table 8: Market returns, by size & analyst following

Panel B: Low analyst following

FY1				FY2				FY3			
Months Prior	Firm-years	*β/b*		Months Prior	Firm-years	*β/b*		Months Prior	Firm-years	*β/b*	
0	8,522	0.4728		12	5,691	0.6681		24	3,010	0.9507	NS
1	17,567	0.5084		13	10,710	0.6871		25	5,901	0.9674	NS
2	17,746	0.4986		14	10,912	0.7337		26	6,077	0.9682	NS
3	17,688	0.5739		15	10,706	0.7421		27	5,993	0.9786	NS
4	17,582	0.6328		16	10,395	0.8069		28	5,842	1.0100	NS
5	17,437	0.7040		17	10,026	0.8506		29	5,706	1.0230	NS
6	17,289	0.7165		18	9,631	0.9414	NS	30	5,502	1.0464	NS
7	17,220	0.7617		19	9,140	0.9273	NS	31	5,247	1.0736	NS
8	17,039	0.8377		20	8,606	0.9721	NS	32	4,941	1.0892	NS
9	16,825	0.9025		21	7,878	1.0209	NS	33	4,596	1.1288	
10	16,383	0.9530	NS	22	6,849	1.0100	NS	34	4,045	1.2025	
11	15,615	0.9823	NS	23	5,687	1.0570	NS	35	3,426	1.1849	

Table 9: Market returns, by magnitude of change in EPS

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = \alpha + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

Panel A: The 33% of Forecasts with the Least Extreme Forecasted Change in EPS

FY1				FY2				FY3			
Months Prior	Firm-Years	β/b		Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b	
0	9,023	0.9388	NS	12	7,763	0.6330		24	5,840	0.7597	
1	18,254	0.9280	NS	13	14,935	0.7053		25	11,227	0.7974	
2	18,188	0.9300	NS	14	15,145	0.7316		26	11,462	0.8336	
3	18,083	0.9620	NS	15	15,057	0.7808		27	11,466	0.8514	
4	18,018	0.9882	NS	16	14,865	0.8222		28	11,356	0.8433	
5	17,921	0.9764	NS	17	14,697	0.8603		29	11,264	0.8631	
6	17,807	0.9807	NS	18	14,479	0.8661		30	11,101	0.9067	
7	17,710	0.9866	NS	19	14,147	0.9241		31	10,891	0.9716	NS
8	17,566	0.9767	NS	20	13,783	0.9412		32	10,696	0.9870	NS
9	17,398	0.9794	NS	21	13,218	0.9643	NS	33	10,337	1.0165	NS
10	17,143	0.9772	NS	22	12,365	0.9747	NS	34	9,777	1.0334	NS
11	16,646	0.9791	NS	23	11,269	0.9930	NS	35	9,034	1.0473	NS

Panel B: The 33% of Forecasts with the Most Extreme Forecasted Change in EPS

FY1			FY2			FY3			
Months Prior	Firm-Years	β/b	Months Prior	Firm-years	β/b	Months Prior	Firm-years	β/b	
0	8,795	0.2981	12	7,575	0.5937	24	5,566	0.8875	
1	17,647	0.3710	13	14,701	0.6814	25	10,831	0.8781	
2	17,619	0.3270	14	14,892	0.7739	26	10,975	0.8875	
3	17,498	0.3560	15	14,823	0.7831	27	10,950	0.9032	
4	17,319	0.5213	16	14,617	0.7384	28	10,811	0.9513	NS
5	17,210	0.6093	17	14,426	0.8124	29	10,741	0.9741	NS
6	17,103	0.6808	18	14,171	0.9003	30	10,587	0.9953	NS
7	16,903	0.7110	19	13,800	0.9175	31	10,376	1.0477	
8	16,709	0.7550	20	13,433	1.0186	32	10,130	1.0967	
9	16,438	0.7822	21	12,856	1.0476	33	9,823	1.0626	
10	16,084	0.8471	22	11,983	1.0304	34	9,269	1.1096	
11	15,650	0.8717	23	10,852	1.0735	35	8,493	1.1257	

Table 10: Panel multivariate regression

$$Analysts'Superiority_{T,M} = \gamma_0 + \gamma_1\,\#Analysts_T + \gamma_2\,STD_{T,M} + \gamma_3\,BTM_{T-1} + \gamma_4\,Sales_{\,T-1} + \gamma_5\,Forecast\Delta_{T,M} + \varepsilon_T$$

Months Prior RDQE	Intercept	#Analysts	STD	BTM	Sales	Forecasted Δ
0	-0.0083	-0.0021	0.0055	0.0035	0.0015 ^{NS}	0.0279
1	-0.0072	-0.0022	0.0052	0.0028	0.0017	0.0262
2	-0.0079	-0.0013	0.0043	0.0030	0.0017	0.0253
3	-0.0079	-0.0013	0.0047	0.0029	0.0012	0.0238
4	-0.0071	-0.0005	0.0039	0.0024	0.0005 ^{NS}	0.0206
5	-0.0055	0.0003 ^{NS}	0.0027	0.0025	-0.0002 ^{NS}	0.0175
6	-0.0054	0.0006	0.0025	0.0022	0.0001 ^{NS}	0.0148
7	-0.0050	0.0011	0.0015	0.0019	0.0004 ^{NS}	0.0115
8	-0.0047	0.0015	0.0009	0.0017	0.0007 ^{NS}	0.0092
9	-0.0041	0.0016	0.0004	0.0015	0.0010	0.0069
10	-0.0026	0.0015	-0.0003	0.0010	0.0012	0.0043
11	-0.0017	0.0018	-0.0011	0.0008	0.0012	0.0025
12	0.0076	-0.0002 ^{NS}	0.0050	0.0045	0.0058	-0.0064
13	0.0070	0.0003 ^{NS}	0.0031	0.0041	0.0055	-0.0057
14	0.0056	0.0008	0.0031	0.0042	0.0053	-0.0057
15	0.0046	0.0011	0.0020	0.0042	0.0049	-0.0050
16	0.0028	0.0017	0.0010	0.0037	0.0052	-0.0048
17	0.0012	0.0022	0.0000 ^{NS}	0.0036	0.0054	-0.0043
18	0.0005 ^{NS}	0.0028	-0.0007	0.0036	0.0048	-0.0043
19	-0.0015	0.0031	-0.0014	0.0033	0.0049	-0.0037
20	-0.0023	0.0037	-0.0019	0.0030	0.0048	-0.0035
21	-0.0029	0.0038	-0.0023	0.0026	0.0054	-0.0036
22	-0.0036	0.0038	-0.0028	0.0024	0.0057	-0.0035
23	-0.0079	0.0057	-0.0027	0.0019	0.0062	-0.0035
24	0.0048	0.0009	-0.0005 ^{NS}	0.0051	0.0094	-0.0074
25	0.0026	0.0023	-0.0016	0.0059	0.0090	-0.0074
26	0.0026	0.0025	-0.0023	0.0056	0.0093	-0.0078
27	0.0019	0.0029	-0.0026	0.0053	0.0094	-0.0083
28	0.0007 ^{NS}	0.0035	-0.0028	0.0052	0.0096	-0.0089
29	-0.0007 ^{NS}	0.0039	-0.0028	0.0047	0.0096	-0.0090
30	-0.0020	0.0042	-0.0033	0.0046	0.0106	-0.0093
31	-0.0027	0.0046	-0.0035	0.0042	0.0104	-0.0097
32	-0.0036	0.0049	-0.0038	0.0038	0.0108	-0.0099
33	-0.0040	0.0051	-0.0040	0.0035	0.0111	-0.0103
34	-0.0060	0.0054	-0.0044	0.0030	0.0133	-0.0108
35	-0.0062	0.0058	-0.0048	0.0019	0.0127	-0.0108

Conclusion

- DISCLAIMER: Prior research was appropriately deliberate in its sample selection and other research design choices, and the conclusions drawn are warranted.
    - However, as is common in our field, it is the subsequent researcher who over-generalizes findings from prior studies.

- **Analysts** only appear persistently superior to a simple earnings extrapolation for **short horizons for large firms**.
- Equivalently, **time-series** forecasts perform as well or better than analysts over **moderate-to-long forecast horizons, and especially for smaller, younger firms**.

TYPICAL STUDY:
1. Data from 1960 and 1970.
2. Sample size ranges from fifty to a few hundred.
3. Models require a minimum of 10 years of data, and some require as many as 20 years of data.
4. Forecast horizons range from 1 quarter-ahead to 18 months-ahead.
5. Reported differences are typically statistically significant in favor of analysts, only modest magnitudes .

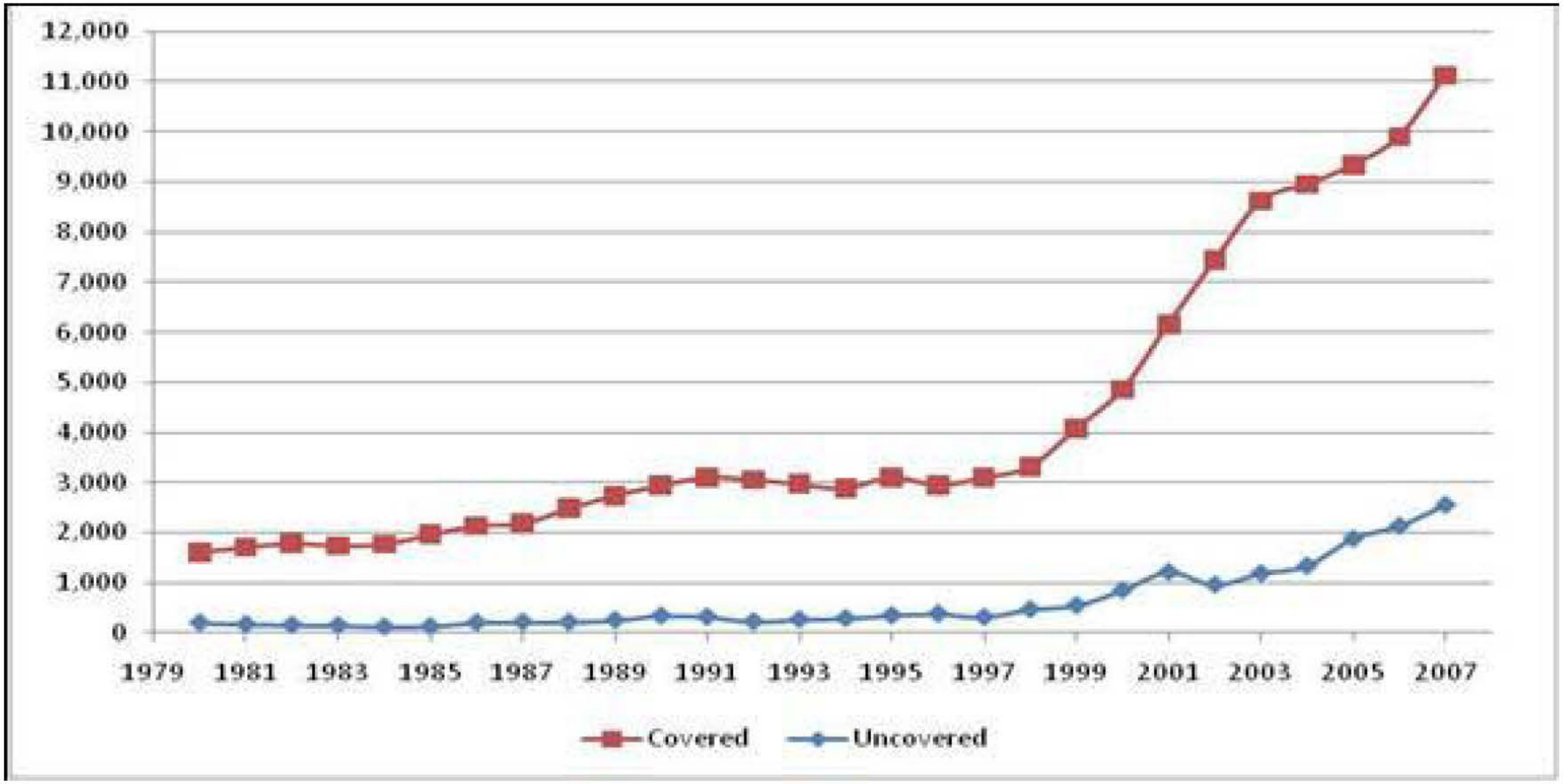
Table 1

Paper	Sample and Time Period	Time-Series (TS) Models and Data Requirements	Outliers	Forecast Horizon	Difference in Forecast Accuracy	Analysts' Superiority Determinants
Brown and Rozeff (1978)	50 firms from 1972 through 1975.	Three TS models using quarterly data, requiring complete data for 20 years.	Winsorized forecast errors at 1.0	One to five quarters ahead.	Median difference in forecast errors between all univariate forecasts and the analysts' forecast is significantly greater than zero.	
Collins and Hopwood (1980)	50 firms from 1951 through 1974.	Four TS models, requiring a minimum of 76 quarters of data.	Winsorized forecast errors at 3.0	One to four quarters ahead.	Four quarters out, analysts' forecast errors are 31.7% compared to the best TS error of 32.9%. One quarter out, mean analysts' forecast error are 9.7% compared to the best TS error of 10.9%.	
Fried and Givoly (1982)	424 firms from 1969 through 1979.	Modified submartingale models, requiring a minimum of 10 years of past data.	Winsorized forecast errors at 1.0	8 months prior to the fiscal end.	Analysts' forecast errors are 16.4% of realized EPS compared to 19.3% for the best TS model.	
Hopwood and McKeown (1982)	258 firms from 1974 through 1978.	Random walk and 7 other TS models, requiring at least 12 years (48 quarters) of data.		One to four quarters ahead.	Four quarters out (annual), absolute analysts' forecasts errors are 22.5% compared to absolute forecast errors of 26.1% for random walk.	Number of days separating TS and analysts' forecast – positive
Brown, Hagerman, Griffin, and Zmijewski (1987)	233 firms from the 1975 through 1980.	3 TS models, requiring a minimum of 60 quarters of data.	Winsorized forecast errors at 1.0	One, two, and three quarters ahead.	Three-quarters-ahead, analysts' forecast errors are 28.7% and TS forecast errors are 33%.	Forecast horizon – negative
Brown, Richardson, and Schwager (1987)	Sample 1: 168 firms from Q1-1977 through Q4-1979.	Quarterly random-walk model.		One, two, and three quarters ahead.	For the one month horizon, the log of the squared ratio of TS to analysts' forecast errors is 0.56.	Firm size – positive; Prior analysts' forecast dispersion – negative

Table 1 (cont.)

Brown, Richardson, and Schwager (1987)	Sample 2: 168 firms from 1977 through 1979.	Annual random-walk model.		Horizons of 1, 6, and 18 months prior to the fiscal year-end date.	For the one month horizon, the log of the squared ratio of TS to analysts' forecast errors is 1.08.	Firm size – positive; Prior analysts' forecast dispersion – negative
Brown, Richardson, and Schwager (1987)	Sample 3: 702 firms from 1977 through 1982.	Annual random-walk model.		Horizons of 1, 6, and 18 months prior to the fiscal year-end date.	Log of the squared ratio of TS to analysts' forecast errors is 1.01 for the one month horizon.	Firm size – positive; Prior analysts' forecast dispersion – negative
O'Brien (1988)	184 firms from 1975 through 1982.	Two TS models, requiring 30 consecutive quarters of data.	Deleted absolute forecast errors larger than $10	Horizons of 5, 60, 120, 180, and 240 trading days prior to the earnings announcement date.	At 240 trading days (one year), analysts' forecast errors are $0.74 compared to TS forecast errors of $0.96.	Forecast horizon – positive
Kross, Ro, and Schroeder (1990)	279 firms from 1980 through 1981.	Box-Jenkins model, requiring 28 quarters of data.		Last available one-quarter-ahead forecast.	Natural log of 1 + absolute TS error - absolute analysts' error is positive across all industries (ranging from (0.043 to 0.385)).	Earnings variability – positive; *Wall Street Journal* coverage – positive; # of days separating TS and analysts' forecasts – positive
Lys and Soo (1995)	62 firms from 1980 through 1986.	Box-Jenkins model, requiring 20 years of data.	Removed one firm	Up to 8 quarters ahead.	Across all horizons, the mean (median) absolute analysts' forecast error is 4.4% (2.8%) and the mean (median) absolute TS error is 26.8% (1.4%).	Forecast horizon – negative
Branson, Lorek, and Pagach (1995)	223 firms from 1988 through 1989.	ARIMA model, requiring 11 years of complete data.		One quarter ahead.	The median absolute percentage forecast error (Actual - predicted)/actual)) from TS minus analysts' forecasts is 7.22%.	Conditional on the firm being small: earnings variability – positive; firm size – negative

Figure 3: Mean assets for firms with (in maroon) and without (in blue) earnings forecasts on I/B/E/S



I have no idea what you're talking about...

...so here's a bunny with a pancake on its head.

A re-examination of analysts' superiority over time-series forecasts of annual earnings

Mark T. Bradshaw
Boston College

Michael S. Drake
The Ohio State University

James N. Myers
University of Arkansas

Linda A. Myers
University of Arkansas

Draft: August 2010

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A re-examination of analysts' superiority over time-series forecasts of annual earnings

Abstract: In this paper, we re-examine the widely-held belief that analysts' earnings per share (EPS) forecasts are superior to forecasts from a time-series model. Using a naive random walk time-series model for annual earnings, we investigate whether and when analysts' annual EPS forecasts are superior. We also examine whether analysts' forecasts approximate market expectations better than expectations from a simple random walk model. Our results indicate that simple random walk EPS forecasts are more accurate than analysts' forecasts over longer forecast horizons and for firms that are smaller, younger, or have limited analyst following. Moreover, analysts' superiority is less prevalent when analysts forecast large changes in EPS. These findings recharacterize generalizations about the superiority of analysts' forecasts over even simple time-series-based earnings forecasts and suggest that they are incomplete and/or misleading. Our findings suggest that in certain settings, researchers can reliably use time-series-based forecasts in studies requiring earnings expectations.

A re-examination of analysts' superiority over time-series forecasts of annual earnings

1 Introduction

Research on analysts' forecasts originated from a need within capital markets research to find a reliable proxy for investor expectations of earnings per share (EPS). The need for a proxy was necessitated by a growing interest in the relation between accounting earnings and stock returns that began with Ball and Brown (1968). Prior to the widespread availability of analysts' forecasts, much capital markets research was aimed at better understanding the time-series properties of earnings in an effort to gauge the association between earnings expectations and stock prices (e.g., Ball and Watts 1972; Brooks and Buckmaster 1976; Albrecht et al. 1977; Salomon and Smith 1977; Watts and Leftwich 1977). Numerous time-series specifications are examined in these studies, but the overall evidence points towards *sophisticated* time-series models of annual earnings rarely providing an economically significant improvement over a *simple* random walk model in terms of reduced forecast errors.[1] This led Brown (1993, 295) to observe that the general consensus among researchers is that earnings follow a random walk, which he states was "pretty much resolved by the late 1970s."

In a parallel stream of studies between 1968 and 1987, many researchers examined whether *analysts*' forecasts are superior to *time-series* forecasts. The culmination of that research is Brown et al. (1987a), who conclude that analysts' forecasts are superior to time-series forecasts because of both an information advantage and a timing advantage. This conclusion was followed by a sharp decline in research on the properties of time-series forecasts. Indeed, in a review of the capital markets literature, Kothari (2001, 145) observes that the time-series

[1] We note that prior research finds consistent evidence that sophisticated time-series models of *quarterly* earnings outperform a simple random walk model (see, for example, Lorek (1979) and Hopwood et al. (1982)). However, we focus our examination on forecasts of annual earnings as we explain later in the introduction.

properties of earnings literature is fast becoming extinct because of "the easy availability of a better substitute" which is "available at a low cost in machine-readable form for a large fraction of publicly traded firms."[2] Thus, it appears that academics have generally concluded that analysts' forecasts of annual earnings are superior to those from time-series models.

In this paper, we re-examine the widely-held belief that analysts' annual EPS forecasts are superior to those from time-series models. We do this by comparing the performance of simple random walk annual earnings forecasts to that of analysts' annual earnings forecasts, and by correlating the associated forecast errors with long-window market returns. Given information and timing advantages (Brown et al. 1987a), it seems improbable that analysts would *not* provide more accurate forecasts than a simple random walk model. However, the prior research upon which the conclusion that analysts are superior is based is subject to numerous caveats (e.g., small samples, bias towards large firms, questionable economic significance, etc.), as we further discuss below. Moreover, analysts are subject to a number of conflicting incentives that can result in biased or inaccurate forecasts (Francis and Philbrick 1993; Dugar and Nathan 1995; McNichols and O'Brien 1997; Lin and McNichols 1998).

As noted in Bradshaw (2009), the accounting literature is unique in its conclusion that expert forecasts are superior to forecasts from time-series models. For example, findings from research in economics, genetics, and physics are largely consistent with time-series models outperforming experts.[3] Obviously, forecasts of macroeconomic variables like interest rates, unemployment, and GDP are different from forecasts of accounting earnings because firm

[2] Kothari (2001, 153) further states that "conflicting evidence notwithstanding, in recent years it is common practice to (implicitly) assume that analysts' forecasts are a better surrogate for market's expectations than time-series forecasts."

[3] For example, in the economics literature, Belongia (1987) examines expert and time-series forecasts of interest rates and finds that time-series forecasts are more accurate. Similarly, Fintzen and Stekler (1999) and Loungani (2000) find that time-series forecasts of recessions and of gross domestic product (GDP) are more accurate than expert forecasts. In addition, in the genetics literature, Orr (1998) finds that random walk describes the time-series properties of genetic drift, and in physics, Mazo (2002) finds that random walk describes Brownian motions.

managers can affect both analysts' forecasts (through guidance) and accounting earnings (through financial reporting discretion) (Watts and Zimmerman 1990; Matsumoto 2002). This interaction clearly gives financial analysts' forecasts of EPS an advantage vis-à-vis expert forecasts of 'less controllable' economic outcomes like interest rates or GDP.

Furthermore, relative to the extensive amount of analyst forecast data currently available, the empirical results of the early studies examining analysts versus time-series models are based on very small samples. For example, Brown and Rozeff (1978) use forecasts for only 50 firms from 1972 through 1975, and Fried and Givoly (1982) – arguably the most extensive sample in this early literature – use forecasts for only 424 firms from 1969 through 1979. In addition to the limited availability of machine readable data when these studies were performed, another explanation for the small sample sizes is the data demands of ARIMA models, which require a long time series of earnings (e.g., 10 to 20 years) to estimate time-series parameters. Other common research design choices, such as the selection of only December fiscal year-end firms or only firms trading on the New York Stock Exchange (which bias samples towards large, mature, and stable firms), may also affect early results. Finally, as is well-known, the firms followed by analysts are biased towards larger firms with institutional following (Bhushan 1989) and with more extensive disclosures (Lang and Lundholm 1996), which censors the availability of analysts' forecasts for other firms. The generalizability of the early evidence on analysts' forecast superiority is accordingly limited, as is made clear by descriptions in these studies about their sample characteristics and by other important caveats.

Researchers now utilize analysts' earnings forecasts as a proxy for expected earnings for samples of firms that are not well-represented in these early studies. For example, Lee (1992), Clement et al. (2003), and Jegadeesh and Livnat (2006) use analysts' forecasts to proxy for earnings expectations for small firms (which are underrepresented in the early studies on the accuracy of analysts' versus time-series forecasts). Similarly, researchers sometimes use analysts' forecasts of earnings over horizons that are not represented in these early studies (which rarely examine forecast horizons beyond one year). For example, in the valuation and cost of capital literature (e.g., Frankel and Lee 1998; Claus and Thomas 2001; Gebhardt et al. 2001; Easton et al. 2002; and Hribar and Jenkins 2004), analysts' earnings forecasts are often used as a proxy for longer-horizon earnings expectations, such as two- to five-year-ahead earnings. One notable exception is Allee (2010) who utilizes exponential smoothing time-series forecasts for two-year horizons to estimate the firm-specific cost of equity capital. He finds that cost of equity capital estimates using time-series forecasts are reliably associated with risk proxies (e.g., market volatility, beta, leverage, size, book-to-price, etc.) and concludes that researchers and investors may use time-series forecasts of earnings to estimate the implied cost of equity capital for firms not covered by analysts.

Our empirical tests are based on annual earnings with forecast horizons ranging from 1 month through 36 months. We focus solely on annual earnings because we are interested in evaluating analysts' superiority over both short and long forecast horizons and the availability of quarterly analysts' earnings forecasts is generally limited to several quarters ahead. Furthermore, it is unlikely that random walk forecasts are superior to analysts' forecasts in the quarterly setting, where both the information and timing advantage of analysts are greatest.[4] Our focus on annual earnings forecasts is also consistent with the extensive use of these forecasts in research on the cost of equity capital and valuation, where longer horizon forecasts are the most cogent in terms of their influence on valuation-related estimates.

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[4] We do not directly examine this conjecture, but our near-term forecasts of annual earnings are analogous to quarterly forecasts for the fourth quarter and for these very short forecast horizons, the results are consistent with analysts dominating time-series models.

We document several surprising findings. First, for longer forecast horizons, analysts' forecasts do *not* consistently provide more accurate estimates of future earnings than time-series models, even when analysts have timing and information advantages. Second, for forecast horizons where analysts *are* more accurate than random walk forecasts (i.e., shorter forecast horizons of several months), the differences in forecast accuracy are economically small. Third, random walk forecasts are more accurate than analysts' forecasts for estimating two-year-ahead earnings in approximately half of the forecast horizons analyzed, and random walk forecasts strongly dominate analysts' forecasts of three-year-ahead earnings. Fourth, over longer forecast horizons, analysts' forecast superiority is prevalent only in limited settings, such as when analysts forecast negative changes or small absolute changes in EPS. Finally, the associations between random walk versus analysts' forecast errors and stock returns track the results of our forecast accuracy tests. Over the shortest forecast horizon, when analysts' forecasts and earnings announcements occur almost simultaneously, the association between analysts' forecast errors and returns is three times larger than that between random walk forecast errors and returns. However, over longer forecast horizons, returns are more strongly associated with random walk forecast errors than with analysts' forecast errors, suggesting that random walk forecasts are a better proxy for market expectations of earnings than consensus analysts' forecasts over all but very limited forecast horizons.

These results conflict with common (often implicit) assertions that analysts' forecasts are uniformly a better proxy for investor expectations than are forecasts from time-series models. For example, Frankel and Lee (1998, 289) state that *I/B/E/S* earnings forecasts "should result in a more precise proxy for market expectations of earnings." They use these forecasts as a proxy for expected earnings for horizons of up to three years. Similarly, Easton et al. (2002) proxy for expected earnings using analysts' forecasts for horizons of up to four years, and Claus and Thomas (2001) use analysts' forecasts for horizons of up to five years. The evidence that time-series forecasts perform as well or better than analysts' forecasts suggests that the generalizability of research typically confined to firms for which analysts forecast long-term earnings (i.e., large, mature firms) might be reliably enhanced by substituting time-series forecasts for those of analysts and by expanding the samples of firms examined.

Although the tenor of our conclusions appears to contradict conclusions in early analysts' forecast research and questions the use of analysts' forecasts in more recent studies, we emphasize that early research was deliberate in its sample selection and other research design choices, and the conclusions were drawn appropriately. As in many literatures, it is the subsequent researcher who over-generalizes findings in the prior literature (Bamber et al. 2000). The early research examines the relative accuracy of time-series versus analysts' forecasts using samples of firms that are large, mature, and stable, and studies fairly limited forecast horizons. For these types of firms, over relatively short horizons, we also find that analysts' forecasts consistently outperform forecasts from a random walk model (and from all of the other time-series models that we evaluate).[5] However, we do emphasize that for all but the very shortest of forecast horizons, analysts' forecast superiority is economically small for the average firm. Moreover, for smaller firms and for firms with low analyst following, we find that analysts' superiority is quite small, and over longer horizons, analysts' forecasts are not superior to random walk forecasts.

[5] In untabulated analyses, we also find that random walk forecasts are superior to forecasts from more complicated time-series models such as random walk with a drift. This superiority exists for two reasons. First, analysts are better at estimating earnings for firms with sufficient data to calculate the time-series parameters in some complicated time-series models because longer time-series availability is associated with more mature firms. Second, adding time-series parameters to a random walk forecast does not help much because the negative serial correlation in EPS changes is very small.

Our study is also subject to an unavoidable sample bias because to assess analysts' forecasts relative to time-series forecasts, we are necessarily constrained to use data for firms with available analyst forecasts. Thus, we cannot avoid biasing our sample towards covered firms. However, as we document, the percentage of firms without analyst coverage has fallen from more than 50% in the 1990s to approximately 25% and firms without analyst coverage have median total assets of less than $100 million. A second design choice is that, because analysts forecast earnings purged of transitory or special items, we use actual earnings per *I/B/E/S* (rather than earnings from Compustat) to calculate forecast errors based on analysts' forecasts and random walk. This is necessary in order to make the analyst and random walk forecast errors comparable.

The remainder of this paper proceeds as follows. In section 2, we review the prior literature. We describe our data and develop hypotheses in section 3. We present the results of our tests in section 4, and section 5 concludes.

2 Prior research and motivation

2.1 Prior Research

Numerous studies examine the time-series properties of annual earnings, motivated by a need for a well-specified expectations model to be used in asset pricing tests. The early studies (e.g., Little 1962; Ball and Watts 1972) provide evidence that annual earnings approximate a simple random walk process. Subsequent studies (e.g., Albrecht et al. 1977; Watts and Leftwich 1977) find that this simple time-series characterization performs at least as well as more complex models of annual earnings, such as random walk with drift or Box Jenkins.[6] Based on this

[6] Albrecht et al. (1977) also show that the choice of scalar is important to the relative accuracy of predictions from random walk versus random walk with drift models. Specifically, a random walk model outperforms a random walk

evidence, Brown (1993, 295) concludes that earnings follow a random walk and that this was "pretty much resolved by the late 1970s." In addition to the empirical evidence, the random walk model is advantageous because it does not require a long time series of data, which restricts the sample size and induces survivor bias.

A stream of literature based on these prior studies compares the accuracy of earnings forecasts from time-series models to that of analysts' forecasts. These studies can be broadly classified into one of two lines of research. The first line asks whether analysts' forecasts *are superior to* forecasts derived from time-series models. These studies are motivated by the intuition that analysts' forecasts should be more accurate than time-series forecasts for a number of reasons (e.g., analysts have access to more information and have a timing advantage), and these studies provide evidence that analysts' forecasts are more accurate than time-series forecasts. For example, Fried and Givoly (1982) argue that analysts' superiority is related to an *information advantage* because analysts have access to a broader information set, which includes non-accounting information as well as information released after the prior fiscal year. They compare prediction errors (defined as (forecasted EPS – realized EPS) / |realized EPS|) based on analysts' forecasts made approximately eight months prior to the fiscal-end date to those based on forecasts from two time-series models. The eight-month forecast horizon roughly corresponds to the annual forecast horizon of time-series models based on earnings releases, which typically occur by four months after fiscal year-end. Fried and Givoly (1982) report prediction errors of 16.4 percent using analysts' forecasts versus 19.3 percent using a modified sub-martingale random walk model and 20.3 percent using a random walk model.[7] The

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with drift model when earnings are deflated by stockholders' equity but underperforms when earnings are not deflated.

[7] Fried and Givoly (1982) analyze a modified submartingale model that uses the firm's past earnings growth as the drift term as well as an index model that uses past earnings growth of the Standard & Poor's 500 as the drift term.

differences among these prediction errors seem small but are statistically significant. Fried and Givoly (1982) also find that analysts' forecast errors are more closely associated with security price movements than are forecast errors from time-series models. Collins and Hopwood (1980) document similar evidence using a slightly longer forecast horizon. Using forecasts made four quarters prior to year-end, they find mean analysts' forecast errors of 31.7 percent compared to 32.9 percent for their most accurate time-series forecast, again, an economically small but statistically significant difference.

A related line of research investigates the source of this apparent superiority. For example, Brown et al. (1987b) find that analysts' forecast superiority is positively (negatively) related to firm size (forecast dispersion). Similarly, Brown et al. (1987a) provide evidence consistent with analysts possessing an information advantage in that they better utilize information available on the date on which the time-series forecast is made, which Brown et al. (1987a) label a "contemporaneous advantage," and with analysts better utilizing information acquired between the date on which the time-series forecast is made and the date on which the analysts' forecast is made, which they label a "timing advantage." Subsequent research supports their conclusion that analysts' superiority is negatively associated with the forecast horizon (Kross et al. 1990; Lys and Soo 1995). Finally, O'Brien (1988) argues that analysts' superiority stems from their use of time-series models along with a broader information set that includes information about industry and firm sales and production, general macroeconomic information, and other analysts' forecasts. Consistent with this, Kross et al. (1990) find that the analysts' advantage is positively associated with firm coverage in the *Wall Street Journal*.

Our focus is limited to the random walk model out of simplicity; refinement to incorporate past earnings growth would likely improve the performance of time-series forecasts relative to analysts' forecasts, but would require longer time series, thus biasing the sample.

Collectively, these studies use samples comprised mainly of large firms. One exception is Branson et al. (1995) who re-examine the question of whether analysts' forecasts are superior to forecasts from time-series models using a sample of small market capitalization firms (where the median market value of equity is $215 million). Using one-quarter-ahead forecasts, they find that analysts' forecasts are also more accurate than time-series forecasts for their sample, but conclude that time-series models might be useful for small firms without analyst following. More recently, Allee (2010) examines cost of equity capital estimates based on time-series forecasts, so is able to extend his analyses to firms without analyst following. He uses two-year-ahead annual forecasts combined with the Easton (2004) implementation of the Ohlson and Jeuttner-Nauroth (2005) earnings growth valuation model to back-out the implied cost of equity capital. His results are also encouraging with respect to the usefulness of time-series forecasts in a valuation setting.

To succinctly summarize and place some structure on the prior research on analysts' versus time-series forecasts, table 1 summarizes twelve important studies on the relative performance of time-series and analysts' forecasts. We compile summary data on the sample size and time-period, the time-series models investigated, data requirements, treatment of outliers, forecast horizon, and summary results. Several observations are noteworthy. First, these studies typically use time-series data from the 1960s and 1970s. Second, the sample sizes are small by current capital markets research standards, ranging anywhere from only 50 to only a few hundred firms. Third, the time-series models used require a minimum of 10 years of data, and some require as many as 20 years of data. Fourth, the forecast horizons studied range from one quarter ahead in the quarterly setting to 18 months ahead in the annual setting, with the majority focused on the quarterly forecast horizon. Fifth, forecast accuracy is generally evaluated using the absolute value of forecast errors scaled by either actual EPS or stock prices. Sixth, the reported differences in forecast accuracy between analysts and time-series models are typically statistically significant and analysts typically 'win,' but the economic magnitudes of the differences appear modest at best. Finally, the analysts' forecast advantage is positively associated with firm size and is negatively associated with prior dispersion in analysts' forecasts and forecast horizon.

2.2 Why re-examine the relative forecast accuracy of analysts versus time-series models?

Two factors, combined with the availability of analysts' forecasts for a large number of public firms, motivate our re-examination of the superiority of analysts' forecasts over time-series forecasts. First, our review of the accounting and finance literature above suggests that it took approximately two decades (i.e., the 1970s and 1980s) for the literature to conclude that analysts are better at predicting future earnings than are time-series models. As Kothari (2001) notes, due to this conclusion and the increased availability of analysts' forecast data in machine-readable form, the literature on time-series models quickly died.[8] However, as noted above and as evident in table 1, this generalized conclusion is primarily based on studies investigating small samples of firms that are large, mature, and stable, and the margin of analysts' superiority over time-series forecasts is not overwhelming. However, analysts' forecasts are used pervasively in the literature as proxies for market expectations for all firms, both large and small. This general reliance on analysts' forecasts contrasts with Walther (1997), who concludes that the market does not consistently use analysts' forecasts or forecasts from time-series models to form expectations of future earnings; her evidence indicates that market participants place more

[8] Since the 1980s, the forecasting literature has focused on refinements to better understand various features of analysts' forecasts, such as the determinants of analysts' forecast accuracy (Clement 1999), bias in analysts' forecasts (Lim 2001), and the efficiency of analysts' forecasts with respect to public information (Abarbanell 1991).

weight on time-series forecasts relative to analysts' forecasts as analyst following decreases. Additionally, it is not obvious that analysts are equally skilled at predicting earnings for large and small firms (or for firms that differ on other dimensions).

The second motivation for our re-examination is that a significant number of firms were not covered by analysts during the sample periods studied in early research and, therefore, are excluded from research that requires longer-term earnings forecasts. If analysts' forecasts over long horizons are not superior to time-series forecasts, then requiring firms to have available analysts' forecasts unnecessarily limits the data upon which this research is based and hence, is a costly restriction. To get a sense of the cost (in terms of sample exclusion) of requiring analysts' forecasts, we identify the number of firms with available financial and market data not included in *I/B/E/S*. Figure 1 plots of the percentage of public firms with available data in *Compustat* and in the Center for Research in Securities Prices (*CRSP*) that *do not* have analysts' one- and two-year-ahead earnings forecasts and long-term growth forecasts available in *I/B/E/S*.[9] As illustrated in figure 1, the percentage of firms with available *Compustat* and *CRSP* data that do not have one-year-ahead analyst forecast data in *I/B/E/S* was approximately 50% through the early 1990s but in recent years, the percentage of firms without one-year-ahead analyst forecasts has declined to approximately 25%. Figure 2 plots the median assets of firms with available *Compustat* and *CRSP* data, sorted by whether they are covered by analysts on *I/B/E/S*. As noted in prior research, the uncovered firms are considerably smaller (Bhushan 1989). Whereas the difference in median total assets between covered and not covered firms was relatively small through the early 1990s, it is now quite large; the median total assets of firms without analysts' forecasts is generally below $100 million. Thus, broadly speaking, the evidence in figures 1 and

[9] We identify this sample by starting with all firms in *Compustat* with positive total assets. We retain all firms with monthly stock price data as of the fiscal-end month available from *CRSP*. Finally, we use *I/B/E/S* data to identify whether consensus forecast data as of the fiscal-end month are available for the remaining firms.

2 highlights the sample effects of requiring analysts' forecasts in terms of excluding otherwise useable data. As noted in the introduction, we cannot avoid this sample selection issue, but because analyst coverage is much greater in recent years, we are able to include the majority of public firms in our analyses.

2.3 Empirical Methodology

In the first set of tests, we compare the accuracy of analysts' forecasts of annual earnings to that of time-series forecasts over various horizons ranging from 1 through 36 months prior to the earnings announcement date. The time-series forecasts that we examine are based on both annual realizations and annual realizations updated with subsequent quarterly realizations. We employ a random walk time-series forecast for three reasons. First, as noted above, there is very little evidence suggesting that more sophisticated time-series models are more accurate than simple time-series models of annual earnings (Albrecht et al. 1977; Watts and Leftwich 1977; Brown et al. 1987a). Second, random walk requires no parameter estimates and so, does not have the data demands of more complicated ARIMA models. That is, using the random walk forecast rather than more complex time-series models frees us from further data requirements that would skew our analyses to large, mature firms, as in prior research.[10] Third, Klein and Marquardt (2006) find that losses occur with increasing frequency over time, suggesting that the earnings process is becoming more volatile. Thus, random walk may be more descriptive than more complicated ARIMA models.

Consistent with prior studies, we expect analysts' superiority to decrease as the forecast horizon increases (Brown et al. 1987a). Next, we investigate settings where we would expect analysts to have less of an information advantage. That is, we compare the forecast accuracy of

[10] In addition, the use of random walk is consistent with Occam's razor, which advocates simplicity.

analysts' forecasts to that of a time-series model for young firms, small firms, and firms with low analyst following. We also examine how much information analysts add when they forecast positive versus negative changes in EPS and when they forecast large versus small changes in EPS.[11]

In the second set of tests, we examine the association between random walk forecast errors and stock returns, and the association between analysts' forecast errors and stock returns.[12] Here, we also expect the relative strength of the correlation between analysts' forecast errors and returns over the correlation between random walk forecast errors and returns to decrease as the forecast horizon increases and expect the relative strength of the correlation between analysts' forecast errors and returns to be lower in settings where analysts should have less of an advantage or when analysts forecast greater changes in future earnings.

As a final test, we investigate analysts' superiority in a multivariate setting. For each forecast horizon, we estimate regressions with our measure of analysts' superiority as the dependent variable and proxies for the quality of the information environment, firm risk, and the analysts' forecasted changes in earnings as covariates. The objective of this test is to investigate the incremental impact of these factors on analysts' superiority and to assess whether the impact changes across the various forecast horizons.

3 Data

We first collect data from the *I/B/E/S* consensus file and from the *Compustat* annual file. Our sample spans a 25 year period, from 1983 through 2008. We attempt to impose minimal

[11] When analysts forecast no change in EPS, the random walk forecast and the analysts' forecasts are equal; thus, analysts' forecasts differ most from random walk forecasts when analysts forecast large changes in EPS.
[12] Thus, we our tests following Foster (1977) who first put forth the dual evaluative criteria of predictive ability and capital market association.

constraints on data availability. For a firm-year observation to be included in our sample, the prior year's EPS, at least one earnings forecast, the associated stock price, and the EPS realization for the target year must be available from *I/B/E/S*. For supplementary tests using quarterly data to form annual earnings forecasts, we further require that quarterly EPS realizations be available from *I/B/E/S*. We require that sales (our proxy for size) be available from *Compustat* for the year immediately preceding the forecast.[13] Because losses are less persistent than positive earnings (Hayn 1995), we further limit our analyses to firm-years with positive earnings in the base year.[14] In sensitivity analyses, we find that including loss firms does not change our overall conclusions.[15] Finally, for the market-based tests, we require sufficient monthly data from *CRSP* to calculate returns over the specified holding periods, which slightly reduces the sample for these tests.

For each target firm-years' earnings (EPS_T), we collect the *I/B/E/S* consensus analysts' forecast made in each of the previous 36 months. For the first 12 previous months (i.e., 0 through 11 months prior), we use FY1 (the one-year-ahead earnings forecast) as the measure of the analysts' forecast of earnings, and the EPS one year prior (EPS_{T-1}) as the random walk forecast of earnings. Thus, for the first year prior to the target year's earnings announcement, we

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[13] For the analyses that can be done without *Compustat* data (i.e., the main results, analyses related to firm age, and analyses related to the number of analysts following), the *Compustat* restriction makes no substantive difference in the results. However, we impose this restriction across all analyses to facilitate sample consistency between the tables.

[14] The base year is defined as the year immediately preceding the forecast. For example, letting the target year be year T, when forecasting one-year-ahead earnings, the base year is year T-1; when forecasting two-year-ahead earnings, the base year is T-2; etcetera.

[15] In unreported analyses, we find that random walk forecasts perform poorly for fiscal periods following a loss; however, analysts' forecasts also perform poorly for these firms. While including loss firms does not change the results over horizons of one year or less, the random walk results improve somewhat relative to analysts' forecasts for forecast horizons of two and three years when loss firms are included. Although the lack of persistence of losses makes random walk a poor predictor of future earnings when the base year's earnings are negative, analysts are aware of the base year's earnings before they make their forecasts, so this data restriction does not provide time-series models with a natural advantage.

have 12 pairs of forecast errors.[16] For each pair, the analysts' forecast error is the difference between the analysts' forecast and realized earnings (EPS_T) and the random walk forecast error is the difference between EPS_{T-1} and EPS_T. We then take the absolute value of the forecast errors and scale by price as of the analysts' forecast date. We obtain 844,643 consensus forecasts, representing 77,013 firm-years and 10, 919 firms, with sufficient data to be included in the one-year-ahead (FY1) analyses.

For the 12 through 23 months prior to the target year's earnings announcement date, we use the *I/B/E/S* forecasts of FY2 (the two-year-ahead earnings forecast). As with the forecasts of FY1, there are 12 monthly forecasts of FY2. For these months, the random walk forecast of earnings is equal to EPS_{T-2}. We obtain 715,730 consensus forecasts, representing 68,870 firm-years and 9, 870 firms, with sufficient data to be included in the two-year-ahead (FY2) analyses.

Finally, for the 24 through 35 months prior to the target year's earnings announcement date, we construct estimates of FY3 (the three-year-ahead earnings forecast) because few analysts forecast three-year-ahead earnings directly. We construct these estimates using the method outlined in studies like Frankel and Lee (1998), Lee et al. (1999), Gebhardt et al. (2001), and Ali et al. (2003). This method generates the FY3 forecast from the FY2 forecast adjusted by the mean analysts' long-term growth forecast as follows:

$$\mathrm{FY3} = \mathrm{FY2} \times (1 + \mathrm{LTG\%}) \tag{1}$$

where FY2 is defined above and LTG is the long-term growth forecast from *I/B/E/S*. Thus, to be included in the FY3 sample, a firm must report positive base year earnings (EPS_{T-3}) and have a

[16] Note that when the earnings announcement is made early in the calendar month, there will not be an earnings forecast in that calendar month. For these observations, there are only 11 forecasts of FY1. Thus, there are approximately half as many month 0 observations as there are month 1 observations.

FY2 forecast and a long-term growth forecast available in *I/B/E/S*.[17] We next calculate the pairs of forecast errors, analogous to the FY1 and FY2 analyses. We obtain 545,354 *I/B/E/S* consensus forecasts, representing 53,561 firm-years and 7, 636 firms, with sufficient data to be included in the three-year-ahead (FY3) analyses.

Our primary random walk-based forecasts of future earnings are simply the lagged annual realized earnings:

$$\mathrm{E}_{\mathrm{T}-\tau}(\mathrm{EPS}_{\mathrm{T}}) = \mathrm{EPS}_{\mathrm{T}-\,\tau} \quad \in \tau = \{1, 2, 3\} \tag{2}$$

For FY1 forecasts, the random walk forecast is the realized EPS from the previous fiscal year, and for FY2 (FY3), the random walk forecast is the realized EPS two (three) years prior to the forecast year. We also examine the sensitivity of the results to the alternative random walk forecast formed using the sum of the prior four quarters of EPS ($QEPS_{T-1}$). Note that 11 months prior to the earnings announcement, the random walk forecast based on annual realizations (EPS_{T-1}) and the random walk forecast based on quarterly realizations ($QEPS_{T-1}$) will be equal because they are based on the same four quarters. However, 9 months prior to the earnings announcement, EPS_{T-1} will not change but $QEPS_{T-1}$ will be equal to the sum of quarterly EPS from the prior four quarters (in this case, Q2 through Q4 of the prior year (T-1) and Q1 of the current year (T)).

4 Results

4.1 Descriptive Statistics

Panel A of table 2 presents descriptive statistics for the 68,870 firm-years with sufficient data to estimate random walk forecast errors and analysts' forecast errors 11 months prior to the

[17] We also test the robustness of our results to using explicit FY3 forecasts when available in *I/B/E/S*. We find that our general conclusions are unchanged.

target earnings announcement. Untabulated statistics reveal that a hypothetical data requirement of 10 years of prior earnings data (e.g., Fried and Givoly 1982) would eliminate more than 60 percent of the observations, so estimating more complex time-series forecasts would result in a considerable loss of sample observations. We also find that the mean (median) observation has only 7.6 (5) analysts following, consistent with a large number of the firms in our sample having relatively sparse analyst coverage (i.e., only 1 or 2 analysts following).

As noted in table 1, prior literature frequently scales forecast errors by reported earnings and many important studies in this literature (e.g., Brown and Rozeff 1978; Fried and Givoly 1982; Brown et al. 1987a) winsorize forecast errors at 100 percent. For a sample comprised of large, mature firms and for forecasts with short horizons, this winsorization rule is reasonable because it results in very few of the analysts' forecast errors being winsorized. For example, Fried and Givoly (1982) find that approximately 0.5 percent of their sample observations have scaled forecast errors that are greater than 100 percent. Moreover, for the subsample of firms in our study that are at least 10 years old, we find that one month prior to the earnings announcement date, only 4.3 percent of scaled absolute analysts' forecast errors are greater than 100 percent. However, we find that for younger firms and over longer forecast horizons, many more extreme forecast errors exist. When we include younger firms in the analyses, the proportion of analysts' forecast errors (at the same one month forecast horizon) that are greater than 100 percent of reported earnings increases to 6.0 percent. Moreover, this proportion rises dramatically as the forecast horizon lengthens.

In panel B of table 2, we present the proportion of the absolute forecast errors (scaled by reported earnings) that are greater than 100 percent to illustrate the consequences of scaling forecast errors by reported earnings. Thirty-five months prior to the earnings announcement, almost 32 percent of analysts' forecast errors and 26 percent of random walk forecast errors are greater than 100 percent. Because winsorizing 32 percent of the sample could severely affect the reported results, in the analyses that follow, we scale forecast errors by price, as reported in *I/B/E/S*.[18] Scaling by price limits the number of extreme observations so that less than one percent of observations for both random walk forecast errors and analysts' forecast errors are greater than 100 percent at every forecast horizon. Thus, scaling by price provides a more accurate picture of the relative forecast accuracy of analysts versus random walk.

In panel C of table 2, we examine the bias in both types of forecasts. We report descriptive statistics for signed analysts' forecast errors and signed random walk forecast errors scaled by price at 11, 23, and 35 months prior to the earnings announcement date. We find that both forecast errors are biased, and that the absolute magnitudes of the bias for the median forecast errors are similar, but the biases are in the opposite direction. Specifically, the median random walk forecasts are negatively biased, while the median analysts' forecast errors are positively biased. The negative bias in random walk forecast errors occurs because EPS tends to grow by approximately 50 basis points per year and the random walk model does not allow for this growth. Analysts' forecast errors are biased such that the median analysts' forecast error is consistently positive and is much larger at longer horizons. This pattern of bias in analysts' forecast errors is consistent with findings in Richardson et al. (2004).

4.2 Tests of Analysts' Superiority Using Absolute Forecast Errors

We present the main results of our tests in table 3. In panel A of table 3, we compare the forecast accuracy of random walk forecasts based on annual EPS to that of the analysts'

[18] The price reported in *I/B/E/S* is usually the price at the end of the day prior to the day on which the forecast is released. However, our results are insensitive to the measurement date for price. Specifically, our results are essentially unchanged when we scale by the first price for the fiscal year.

consensus forecasts for the full sample. We calculate the analysts' superiority over the random walk model as follows (firm subscripts omitted):

$$Analysts' \, Superiority = \frac{|EPS_{T-1} - EPS_T| - |Forecasted \; EPS_{T,M} - EPS_T|}{Price_{T,M}} \quad (3)$$

where *Forecasted EPS* is the consensus analysts' forecast (i.e., FY1, FY2, or FY3) issued M months prior to the earnings announcement for year T earnings. At each forecast horizon, we calculate mean *Analysts' Superiority*. A positive mean indicates that analysts are superior to a random walk model at that particular forecast horizon, on average, and a negative mean indicates that a random walk model is superior to analysts at that particular forecast horizon, on average.[19]

The first set of columns in panel A, labeled FY1, presents the mean analysts' superiority during months 0 through 11 prior to the earnings announcement. For the full sample, our results confirm those in the prior literature – analysts' forecasts *are* more accurate than forecasts from time-series models (specifically, forecasts from a random walk model) and their superiority is more evident as the earnings announcement approaches. For forecasts made in the same month as the earnings announcement (i.e., 0 months prior), analysts' forecasts are more accurate than random walk forecasts by 282 basis points. This result is not surprising given that this is the forecast horizon where analysts have the greatest timing and information advantages. In other words, for most firms, the random walk forecast is approximately one year old at this time and analysts have the advantage of having access to all of the news that has occurred over the year and to the earnings announcements made in the first three quarters of the year (i.e., to three of the four quarterly earnings numbers used to calculate EPS_T). In contrast, 11 months prior to the

[19] Note that the measurement of analysts' forecast superiority requires matched pairs of random walk forecasts and analysts' forecasts. That is, for a given firm-year observation, we require both a random walk forecast (so a prior earnings realization) and a consensus analysts' forecast, as well as the reported earnings.

earnings announcement date, analysts' superiority is only 35 basis points, which is approximately 88 percent smaller than analysts' superiority in month 0.

The second set of columns, labeled FY2, presents the mean analysts' superiority from 12 through 23 months prior to the earnings announcement. Here, we use the consensus analysts' forecasts of two-year-ahead earnings and the random walk forecast is earnings reported two years prior to the target date. Again, analysts' forecasts are significantly more accurate than random walk forecasts from 12 through 21 months prior to the earnings announcement, but as with FY1, their relative superiority falls monotonically as the forecast horizon lengthens. Moreover, at month 21, analysts' superiority is only 3 basis points, and by months 22 and 23, the random walk forecast is significantly more accurate than analysts' forecasts on average, so time-series forecasts are superior. However, the difference in accuracy is economically trivial, at 7 and 14 basis points respectively.

The third set of columns, labeled FY3, presents the mean analysts' superiority from 24 through 35 months prior to the earnings announcement. Again, analysts' superiority falls monotonically, from 66 basis points at 24 months prior to -41 basis points at 35 months prior, as their timing and information advantages increase.

In panel B of table 3, we compare the forecast accuracy of random walk forecasts based on quarterly EPS (i.e., the sum of EPS for the prior four quarters) to that of the analysts' consensus forecasts for the full sample. We find that the magnitude of analysts' superiority is smaller with quarterly updating than with the annual random walk forecast (reported in panel A) at every horizon. To illustrate, in panel B, analysts' superiority ranges from 62 basis points to -26 basis points, compared to a range of 282 basis points to -41 basis points in panel A. This decrease in magnitude is to be expected since quarterly updating reduces analysts' information and timing advantages. We also find that the sign and significance of analysts' superiority for the FY1 and FY2 horizons are very similar to those in panel A. Specifically, in FY1, we find that analysts are more accurate at every horizon. In FY2, we find that analysts and random walk forecasts are no different at 21 and 22 months prior, and that random walk forecasts are more accurate at 23 months prior. However, in FY3, we find a marked difference from the pattern in panel A. Here, random walk forecasts are more accurate than analysts' forecasts (or, at least, as accurate as analysts' forecasts) for almost all horizons.

Finally, in panel C of table 3, we compare the forecast accuracy of random walk forecasts using explicit FY3 forecasts to that of the analysts' consensus forecasts for the full sample. By construction, the results for FY1 and FY2 are identical to those in panel A. For FY3, we find that analysts' superiority falls monotonically from 54 basis points at 24 months prior to 20 basis points at 35 months prior. This pattern is similar to that in panel A, but the magnitudes are smaller at every horizon in FY3.

Overall, the results presented in table 3 reveal that, consistent with prior literature, analysts are better than time-series models at predicting earnings over relatively short windows. However, as the forecast horizon grows, analysts' superiority decreases and becomes negative, so that random walk forecasts are superior to analysts' forecasts when the forecast horizon is sufficiently long. Moreover, the results across the various panels reveal that quarterly updating to the random walk forecasts reduces the magnitude of analyst superiority and that random walk forecasts for FY3 based on long-term growth forecasts and explicit FY3 forecasts are very similar. For the remainder of our analyses, we focus on random walk forecasts based on annual EPS because these forecasts give the analysts the greatest information and timing advantages, thus biasing our results against random walk.

4.2.1 Partitioning on firm age

Table 4 partitions observations based on firm age, measured as the number of years that the firm's earnings have been reported in *I/B/E/S*. Because samples in prior literature are comprised of mature firms, we separate observations into young firms versus mature firms to compare the relative forecast accuracy between the two groups. Panel A reveals that even one-year-ahead earnings are much more difficult to forecast for young firms than for mature firms. Specifically, for firms in their first year on *I/B/E/S*, the mean analysts' forecast error 11 months prior is 409 basis points while the matching random walk forecast error is 426 basis points. For firms that have been on *I/B/E/S* for at least five years, the mean analysts' forecast error is approximately 25 percent smaller, at 305 basis points, while the random walk forecast error is 347 basis points. Thus, it appears that mature firms are inherently more predictable, and although the random walk forecast error is smaller for mature firms than for young firms, the superiority of analysts' forecasts is greater for mature firms. For firms in their first year on *I/B/E/S*, analysts' superiority is only 18 basis points, but for the firms that are at least five years old, analysts' superiority is 41 basis points.

The difference in second year forecast accuracy is even more striking. At month 23, analyst superiority is negative for firms that are four years old or less, indicating random walk forecast superiority. Moreover, for firms in their first year on *I/B/E/S*, the differences are quite large, with random walk forecast superiority of 56 basis points. Thus, for firms in their first year on *I/B/E/S*, analysts' forecasts are less accurate than random walk forecasts by more than one-half percent of price at the 23 month forecast horizon. In contrast, for firms that have been on *I/B/E/S* for at least five years, analysts' forecasts are only slightly more accurate than random walk forecasts (by 3 basis points).

The results for FY3 presented in panel C are even more striking. At month 35, time-series forecast superiority is evident regardless of firm age. For firms in their first year on *I/B/E/S*, random walk forecasts are superior to analysts' forecasts by 116 basis points. However, for firms that have been on *I/B/E/S* for at least five years, the superiority of random walk forecasts is only 12 basis points at month -35.

4.2.2 Partitioning on firm size

Table 5 partitions observations based on firm size or on analyst following. To partition on firm size, each year, we partition all firms on *Compustat* with positive sales into two groups, large firms and small firms, using the median sales in the year as the threshold. Because *I/B/E/S* firms are generally larger than *Compustat* firms, fewer than half of the firms are classified as small using this threshold. As reported in panel A, analysts' superiority for small firms is much smaller than for large firms. In fact, for small firms, random walk is superior in 5 and 10 of the 12 monthly forecast horizons during FY2 and FY3, respectively. Moreover, some of these differences are economically significant. For example, at the 23 month forecast horizon, the difference is almost one and a half percent of price, and at the 35 month forecast horizon, the difference is more than one percent of price.

4.2.3 Partitioning on analyst following

In panel B, we report similar results for lightly followed firms (i.e., those followed by one or two analysts). While analysts' forecasts are superior in most months, for early fiscal-year forecasts, the difference in the accuracy of random walk forecasts and analysts' forecasts is economically trivial (e.g., it is only 12 basis points 11 months prior). Consistent with the results in table 4, results for FY2 and FY3 are similar, with random walk forecasts dominating analysts' forecasts at numerous forecast horizons.

4.3 The Relation between Analysts' Superiority and the Sign of the Forecasted Change in EPS

Table 6 partitions observations based on the sign of the analysts' forecasted change in EPS. Comparing the results in panels A (positive forecasted changes) with those in panel B (negative forecasted changes) across all horizons, we find that analysts forecast negative earnings changes less often than positive earnings changes, but when they do forecast negative changes, analysts' superiority is much stronger. Most strikingly, at 11 months prior to the earnings announcements, analysts' superiority is less than 1 basis point for the 59,086 positive forecasted changes in EPS, and is 209 basis points for the 11,789 negative forecasted changes in EPS.

We find similar evidence over FY2 forecast horizons. At 23 months prior to the earnings announcement, random walk forecasts are superior to analysts' forecasts by 29 basis points (see panel A) when analysts forecast positive changes in EPS. However, over this same horizon, analysts' superiority is 168 basis points when analysts forecast negative changes in EPS (see panel B). Here, we also find that analysts rarely forecast negative changes in two-year-ahead EPS. For example, at month -23, there are 47,260 positive forecasted changes and only 3,903 negative forecasted changes.

Finally, for FY3, when analysts forecast positive changes in EPS, random walk forecasts are superior to analysts' forecasts starting 30 months prior to the earnings announcement. The difference between analysts' forecast error and random walk forecast error is almost one half percent of price in month -35. However, when analysts forecast negative changes in earnings, analysts' superiority is very large, ranging from 8.52 percent of price at month -24 to 10.6 percent of price at month -35. That said, the small number of negative forecasted changes in

FY3 across these horizons indicates that analysts very rarely forecast negative changes in three-year-ahead earnings (i.e., approximately 1 in 1,000 forecasted changes are negative over this horizon).

4.4 The Relation between Analysts' Superiority and Absolute Forecasted Change in EPS

Table 7 partitions observations based on the absolute magnitude of the analysts' forecasted change in EPS. As discussed above, when analysts forecast no change in EPS, the random walk forecasts and the analysts' forecasts are equal. Thus, to further examine whether analysts' superiority varies with the forecasted change in EPS, we partition the observations into small, moderate, and large forecasted changes in EPS. For this analysis, we calculate the absolute value of the analysts' forecasted change in EPS and let the lowest and highest 33 percent represent small and large forecasted changes respectively. The difference in analysts' superiority between the extreme forecasts and the moderate forecasts is always large, but the direction of the effect differs for short and long forecast horizons.

Comparing the results in panel A (for the partition with the least extreme forecasted changes) with those in panel B (for the partition with the most extreme forecasted changes), we find that for short horizons (i.e., FY1 forecasts), analysts' superiority is strongest when the absolute forecasted change in EPS is extreme. At the one month forecast horizon, for the group of firms with the smallest forecasted change, analysts' superiority is only 44 basis points, but for the group of firms with the largest forecasted change, analysts' superiority is 570 basis points. However, this relative superiority deteriorates as the horizon lengthens. For example, for the group of firms with small forecasted changes, analysts' superiority is only 17 basis points 10 months prior to the earnings announcement, while at the same horizon, analysts' superiority is

117 basis points for the group of firms with large forecasted changes. Although analysts' superiority diminishes as the horizon lengthens, in the first year, analysts' superiority is always significantly greater for the group of firms with large forecasted changes in EPS than for the group of firms with small forecasted changes in EPS.

The results differ, however, over longer horizons. For the group of firms with small forecasted changes, analysts' forecasts are more accurate than random walk forecasts over each of the 36 monthly horizons in FY2. However, for the group of firms with large forecasted changes, random walk dominates in a large number of forecast horizons. At 23 months prior to the earnings announcement, when analysts have no timing advantage and a slight information advantage, random walk forecasts are 61 basis points more accurate than analysts' forecasts for the group of firms with large forecasted changes and are 27 basis points more accurate for the group of firms with small forecasted changes. In addition, analysts are not superior to random walk for the group of firms with large forecasted changes in FY2 until month 18, when analysts have a 4 month timing advantage. This compares to month 21 for the full sample.

The difference in accuracy between the groups with large versus small forecasted changes is even greater for forecasts made for FY3. As with two-year-ahead forecasts, analysts' forecasts of three-year-ahead earnings are always superior to random walk forecasts for the group of firms with the least extreme forecasted changes in EPS. However, for the groups of firms with the most extreme forecasted changes, analysts' superiority is significantly positive in only 3 of the 12 forecast horizons; this occurs 26 months prior to the earnings announcement, when analysts have an 9 month timing advantage. From 28 through 35 months prior to the earnings announcement, random walk forecasts are superior to analysts' forecasts, and the difference is 69 basis points at the 35 month horizon. In other words, when analysts forecast large changes in three-year-ahead earnings, a simple random walk estimate of those earnings is more accurate by approximately 70 percent of price on average. Over the same horizon, when analysts forecast a small change in earnings, their forecasts are more accurate than a simple random walk estimate by approximately 20 percent of price.

4.5 Tests of Analysts' Superiority Using Market Expectations

Next, we examine the associations between time-series forecast errors and stock returns and between analysts' forecast errors and stock returns over various forecast horizons. To the extent that stock prices react to earnings surprises, higher associations between forecast errors and stock returns indicate a greater correspondence between the forecasts and ex ante market expectations. We regress stock returns measured from the month of the forecast through the month of the earnings announcement on forecast errors from random walk and analysts' forecasts using a seemingly unrelated regression system:

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T \tag{4}$$

$$Return_{T,M} = a + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T \tag{5}$$

The coefficient β measures the relation between returns and random walk forecast errors, and the coefficient b measures the relation between returns and analysts' forecast errors. We report tests on the ratio of the regression coefficients β to b. We estimate this system for each of the 36 forecast horizons from 0 months prior (i.e., when analysts' forecasts and earnings are announced in the same month) to 35 months prior to the earnings announcement. Thus, we measure stock returns and forecast errors contemporaneously such that the returns accumulation period and the forecast horizon are equal. For example, when the forecast horizon is 12 months in length, the returns accumulation period is also 12 months in length and the forecast horizon and returns accumulation period represent the same 12 months.

In panel A of table 8, we present the estimation results for models (4) and (5) across all forecast horizons using annual EPS. As the forecast horizon lengthens, the association between stock returns and forecast errors increases for both random walk and analysts' forecasts. The random walk coefficient ranges from 0.069 in the 1 month forecast horizon regression to 3.454 in the 24 month forecast horizon regression. Similarly, the analysts' forecast coefficient ranges from 0.148 in the 1 month forecast horizon regression to 3.354 in the 24 month forecast horizon regression. While the coefficients on both errors increase with the length of the forecast horizon, they grow at different rates.

We find that the relative weights that the market seems to assign to random walk forecast errors and analysts' forecast errors tend to track fairly closely to the accuracy tests in table 3. Over the shortest forecast horizon, when analysts' forecasts and earnings announcements coincide in the same calendar month, the association between stock returns and random walk forecast errors is 47 percent of the association between stock returns and analysts' forecast errors. However, the relative magnitudes of the stock return associations grow nearly monotonically, so that at the 11 month forecast horizon, the random walk coefficient is 72 percent of the analysts' forecast error coefficient. To summarize, at the one year horizon, analysts' forecasts dominate random walk-based forecasts as a proxy for market expectations, which mirrors the accuracy results from table 3. However, the relative ability of analysts' forecasts to proxy for market expectations is much stronger at the one month forecast horizon than over longer forecast horizons.

The pattern for FY2 forecasts is similar, but analysts' forecasts are a significantly better proxy for market expectations than random walk forecasts only for horizons shorter than 21 months. For the 23 month forecast horizon, the random walk forecast is a significantly better proxy for market expectations, on average. Finally, for forecasts of FY3, analysts' forecasts are a better proxy in only 6 of the 12 months. For forecast horizons of 32 through 35 months, random walk is again a significantly better proxy for market expectations. Overall, it appears that market expectations track fairly closely to the forecast accuracy results. Over horizons where analysts' forecasts are more accurate than random walk forecasts, analysts' forecasts seem to provide a better proxy for market expectations. However, over horizons where random walk forecasts are more accurate than analysts' forecasts, random walk forecasts seem to provide a better proxy for market expectations.

In panel B of table 8 we present the results using random walk forecasts based on quarterly EPS (i.e., the sum of EPS for the prior four quarters). For FY1, we find that random walk forecasts are as good a proxy for market expectations as analysts' forecasts in the month of the earnings announcement. Thereafter (i.e., in months 1 through 11), we find that analysts' forecasts are a better proxy for market expectations. In addition, in FY2, we find that analysts' forecasts are the better proxy for market expectations in only 5 of the 12 months, and in FY3, random walk forecasts are a better proxy in all of the months.

4.5.1 Partitioning on firm size and on analyst following

Panels A and B of table 9 present the estimation results for models (4) and (5) for small firms and for lightly followed firms, respectively. In panel A, for FY1, we find that β/b ranges from 44 percent for the shortest forecast horizon to 84 percent for the 11 month forecast horizon. Moreover, analysts' forecasts are no better than random walk forecasts as a proxy for market expectations 10 and 11 months prior to the earnings announcement. For FY2 and FY3, we find that analysts' forecasts are no better than random walk forecasts over horizons of 19 through 23 months and 26 through 31 months prior to the earnings announcement, respectively, and that random walk forecasts dominate analysts' forecasts over horizons of 32 through 35 months prior.

The results for lightly followed firms are reported in panel B, and are very similar to those reported in panel A (for small firms) for FY1 and FY2. That is, analysts' forecasts dominate random walk forecasts as a proxy for market expectations only over shorter forecast horizons. For three-year-ahead forecasts, analysts' forecasts are not a better proxy than random walk forecasts starting in month 30. Overall, the results reported in table 9 for small and lightly followed firms are consistent with the analysts' forecast accuracy results reported in table 5.

4.5.2 Partitioning on the sign of the forecasted change in EPS

Panels A and B of Table 10 present the estimation results for models (4) and (5) for firms with positive and negative forecasted changes in EPS, respectively. In panel A, when analysts forecast increasing EPS, we find that analysts' forecasts are no better than random walk forecasts as a proxy for market expectations across all horizons. Moreover, beginning 7 months prior to the earnings announcement, random walk forecasts dominate analyst forecasts. In stark contrast, in panel B, when analysts forecast decreasing EPS, we find that analysts' forecasts dominate random walk forecasts as a proxy for market expectations across all horizons. This evidence is consistent with that presented in table 6 and suggests that analysts do much better than random walk forecasts when they forecast negative changes in earnings.

4.5.3 Partitioning on the absolute forecasted change in EPS

Panels A and B of table 11 present the estimation results for models (4) and (5) for firms with small and large analysts' forecasts of the change in EPS, respectively. In panel A, for FY1, FY2, and FY3, we find no statistical differences between the coefficients on the random walk forecast errors and on the analysts' forecast errors when analysts forecast the least extreme changes in EPS. Thus, analysts' forecasts are no better than random walk forecasts as a proxy for market expectations when analysts forecast small changes in EPS.

In panel B, we present the results when analysts forecast the most extreme changes in EPS. For FY1, we find that analysts' forecasts dominate random walk forecasts as a proxy for market expectations in all months. However, in FY2, we find that random walk forecasts are as good a proxy for market expectations as analysts' forecasts over horizons greater than 22 months, and in FY3, we find that random walk forecasts dominate for horizons of 34 and 35 months. Overall, the market expectation results in Table 11 track fairly closely to the forecast accuracy results presented previously.

4.6 Multivariate Tests

As a final test, we investigate analysts' superiority in a multivariate setting which controls for the information environment of the firm as well as for risk factors. Specifically, we estimate the following regression separately for each of the 36 forecast horizons:

$$\begin{aligned} Analysts'\,Superiority_{T,M} = \gamma_0 + \gamma_1\,\#Analysts_T + \gamma_2\,STD_{T,M} + \gamma_3\,BTM_{T-1} \\ + \gamma_4\,Sales_{\,T-1} + \gamma_5\,Forecast\ Increase_{T,M} + \gamma_6\,|Forecast\ \Delta|_{T,M} + \\ + \gamma_7 Post\ FD_{T,M} + \varepsilon_T \end{aligned} \qquad (6)$$

where: *#Analysts* is the number of analysts in the consensus forecast of EPS in year T made in month M; *STD* is the standard deviation of analysts' forecasts for year T earnings as measured in month M; *BTM* is the book-to-market ratio (from *Compustat*) measured at the end of year T-1; *Sales* (from *Compustat*) is measured at the end of year T-1; *Forecast Increase* is an indicator variable set equal to one if analysts forecast a positive change in EPS and to zero otherwise; $|Forecast\Delta|$ is the absolute value of the forecasted change in EPS (i.e., $|Forecasted\ EPS_T - EPS_{T-1}|$) implied by the analysts' forecast of year T earnings as measured in month M; and *Post FD* is an indicator variable set equal to one if the forecast is issued after passage of Regulation Fair Disclosure in October 2000, and zero otherwise. We include this control for the pre- versus post-Regulation Fair Disclosure (Reg FD) environment based on evidence in prior research that after passage of Reg FD, analysts invest more time gathering information about the firms they cover and that their forecasts are less biased (see, e.g., Mohanram and Sunder (2006) and Drake and Myers (2009)).

In table 12, we present the estimation results for equation (6) for each of the 36 forecast horizons. We find that the book-to-market ratio, sales revenue (size), the forecasted increase in EPS indicator variable, the absolute value of the analysts' forecasted change in EPS, and the *Post FD* indicator variable are all significantly related to the level of analysts' superiority over almost every forecast horizon. In addition, the number of analysts' estimates and the standard deviation of the estimates are significantly related to the level of analysts' superiority in the majority of the forecast horizons. Although several factors (such as the number of analysts and sales) are correlated with one another, each is significantly related to analysts' superiority over the vast majority of horizons. In addition, the most consistent and strongest relation is that the forecasted increase in EPS indicator variable is highly significant at every horizon. For forecasts that are in the same fiscal year as the earnings being forecasted (i.e., FY1 forecasts), the coefficient on the forecasted increase indicator variable is consistently negative, revealing that analysts' forecasts of decreasing EPS are more accurate than random walk forecasts across all forecast horizons. This is true even after controlling for the number of forecasts, variance in those forecasts, size, book-to-market, the absolute forecasted change in EPS, and whether the forecast is made post Reg FD. We also find that the coefficient on the post Reg FD indicator variable is positive and significant in all but 4 of the 36 horizons, suggesting that the regulation has lead to an increase in the accuracy of analysts' forecasts.

5 Conclusion

In this paper, we show that the widely held belief that analysts' forecasts of annual earnings are superior to time-series forecasts is not fully descriptive. Although analysts' earnings forecasts consistently beat random walk earnings forecasts over short windows, for longer forecast horizons, analysts' superiority declines, and at certain horizons, analysts' forecasts are dominated by random walk forecasts. This is especially true for small firms, young firms, thinly followed firms, and when analysts forecast positive or more extreme changes in earnings. We link this finding to stock returns, and show that the market seems to rely on random walk forecasts (or similar simple models of earnings) at longer horizons, but tends towards analysts' forecasts as the forecast horizon becomes shorter.

While our results are not inconsistent with prior literature that concludes that analysts' forecasts are superior to forecasts from time-series models in a general sense, we find that over longer horizons, analysts' forecasts lose their relative superiority to time-series forecasts. In fact, we show that even a simple random walk forecast performs as well, in both an economic and statistical sense, relative to analysts' forecasts. This is important because analysts' forecasts are not available for a large number of firms. Our findings suggest that investors can reasonably rely on random walk forecasts when implementing long-term buy-and-hold valuation strategies, and similarly, researchers interested in phenomena that require longer-term earnings expectations can work with larger samples than those comprised of firms with long-term analysts' forecasts. In addition, because our results suggest that the use of a simple random walk model to form forecasts in securities analysis is feasible, we suggest that declining analyst coverage alleged to have resulted from increased regulation in the securities industry (Mohanram and Sunder 2006) may be less detrimental than some assume.

It is important to note that our results do not refute the results of studies that use analysts' forecasts to proxy for market expectations. Moreover, our finding that random walk forecasts are more accurate than analysts' forecasts over long horizons does not imply that random walk forecasts would improve prediction models of firm value, the cost of capital, or stock returns. We leave these issues for future research.

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Table 1 Prior Literature

Paper	Sample and Time Period	Time-Series (TS) Models and Data Requirements	Outliers	Forecast Horizon	Difference in Forecast Accuracy	Analysts' Superiority Determinants
Brown and Rozeff (1978)	50 firms from 1972 through 1975.	Three TS models using quarterly data, requiring complete data for 20 years.	Winsorized forecast errors at 1.0	One to five quarters ahead.	Median difference in forecast errors between all univariate forecasts and the analysts' forecast is significantly greater than zero.	
Collins and Hopwood (1980)	50 firms from 1951 through 1974.	Four TS models, requiring a minimum of 76 quarters of data.	Winsorized forecast errors at 3.0	One to four quarters ahead.	Four quarters out, analysts' forecast errors are 31.7% compared to the best TS error of 32.9%. One quarter out, mean analysts' forecast error are 9.7% compared to the best TS error of 10.9%.	
Fried and Givoly (1982)	424 firms from 1969 through 1979.	Modified submartingale models, requiring a minimum of 10 years of past data.	Winsorized forecast errors at 1.0	8 months prior to the fiscal end.	Analysts' forecast errors are 16.4% of realized EPS compared to 19.3% for the best TS model.	
Hopwood and McKeown (1982)	258 firms from 1974 through 1978.	Random walk and 7 other TS models, requiring at least 12 years (48 quarters) of data.		One to four quarters ahead.	Four quarters out (annual), absolute analysts' forecasts errors are 22.5% compared to absolute forecast errors of 26.1% for random walk.	Number of days separating TS and analysts' forecast – positive
Brown, Hagerman, Griffin, and Zmijewski (1987)	233 firms from the 1975 through 1980.	3 TS models, requiring a minimum of 60 quarters of data.	Winsorized forecast errors at 1.0	One, two, and three quarters ahead.	Three-quarters-ahead, analysts' forecast errors are 28.7% and TS forecast errors are 33%.	Forecast horizon – negative
Brown, Richardson, and Schwager (1987)	Sample 1: 168 firms from Q1-1977 through Q4-1979.	Quarterly random-walk model.		One, two, and three quarters ahead.	For the one month horizon, the log of the squared ratio of TS to analysts' forecast errors is 0.56.	Firm size – positive; Prior analysts' forecast dispersion – negative

Brown, Richardson, and Schwager (1987)	Sample 2: 168 firms from 1977 through 1979.	Annual random-walk model.		Horizons of 1, 6, and 18 months prior to the fiscal year-end date.	For the one month horizon, the log of the squared ratio of TS to analysts' forecast errors is 1.08.	Firm size – positive; Prior analysts' forecast dispersion – negative
Brown, Richardson, and Schwager (1987)	Sample 3: 702 firms from 1977 through 1982.	Annual random-walk model.		Horizons of 1, 6, and 18 months prior to the fiscal year-end date.	Log of the squared ratio of TS to analysts' forecast errors is 1.01 for the one month horizon.	Firm size – positive; Prior analysts' forecast dispersion – negative
O'Brien (1988)	184 firms from 1975 through 1982.	Two TS models, requiring 30 consecutive quarters of data.	Deleted absolute forecast errors larger than $10	Horizons of 5, 60, 120, 180, and 240 trading days prior to the earnings announcement date.	At 240 trading days (one year), analysts' forecast errors are $0.74 compared to TS forecast errors of $0.96.	Forecast horizon – positive
Kross, Ro, and Schroeder (1990)	279 firms from 1980 through 1981.	Box-Jenkins model, requiring 28 quarters of data.		Last available one-quarter-ahead forecast.	Natural log of 1 + absolute TS error - absolute analysts' error is positive across all industries (ranging from (0.043 to 0.385)).	Earnings variability – positive; *Wall Street Journal* coverage – positive; # of days separating TS and analysts' forecasts – positive
Lys and Soo (1995)	62 firms from 1980 through 1986.	Box-Jenkins model, requiring 20 years of data.	Removed one firm	Up to 8 quarters ahead.	Across all horizons, the mean (median) absolute analysts' forecast error is 4.4% (2.8%) and the mean (median) absolute TS error is 26.8% (1.4%).	Forecast horizon – negative
Branson, Lorek, and Pagach (1995)	223 firms from 1988 through 1989.	ARIMA model, requiring 11 years of complete data.		One quarter ahead.	The median absolute percentage forecast error (Actual - predicted)/actual)) from TS minus analysts' forecasts is 7.22%.	Conditional on the firm being small: earnings variability – positive; firm size – negative

Table 2 Descriptive Statistics

Panel A: Firm Characteristics

	Mean	Median	Q1	Q3
Sales	2,921	410	125	1,504
BTM	0.5823	0.4985	0.3124	0.7391
Age	8.9340	7	3	13
# Analysts	7.5832	5	2	10

The sample consists of all firms with data available 11 months prior to the earnings announcement date. Sales are in $ millions. Book-to-Market (BTM) and Sales are measured as of the end of the base year. Age is measured as the number of prior years for which *I/B/E/S* has recorded annual EPS for the firm. # Analysts is the number of analysts following measured as NUMEST for the statistical period 11 months prior to the report date of annual earnings.

Panel B: Percent of Forecast Errors Greater than the Absolute Value of Reported Earnings

Months Prior to the Earnings Announcement Date	Analysts' Forecasts Errors	Random Walk Errors
Mature firms:		
1 Month	4.9%	16.4%
All firms:		
1 Month	6.4%	16.4%
11 Months	16.5%	19.5%
23 Months	28.8%	23.9%
35 Months	31.9%	25.6%

Panel percentages represent the proportion of forecast errors that exceed 100 percent of realized earnings. In the first row, the sample is restricted to mature firms with at least 10 prior years of annual EPS reported on *I/B/E/S*.

Panel C: Signed Forecast Errors

	Mean	Median	Q1	Q3
Signed Random Walk Errors				
11 Months	0.0020	-0.0052	-0.0156	0.0131
23 Months	-0.0050	-0.0082	-0.0260	0.0180
35 Months	-0.0013	-0.0108	-0.0357	0.0204
Signed Analysts' Forecasts Errors				
11 Months	0.0214	0.0030	-0.0043	0.0224
23 Months	0.0308	0.0104	-0.0044	0.0422
35 Months	0.0359	0.0173	-0.0041	0.0553

Forecast errors are measured as the difference between forecasted and actual earnings scaled by price 11, 23 or 35 months prior to the earnings announcement.

Table 3 Main Results Analysts' Forecast Superiority, Full Sample

Panel A: Based on Annual Updates of Random Walk

FY1			FY2			FY3			
Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority	
0	36,688	0.0282	12	33,822	0.0134	24	25,418	0.0066	
1	73,618	0.0267	13	63,869	0.0118	25	48,196	0.0050	
2	73,791	0.0255	14	65,413	0.0105	26	49,347	0.0040	
3	73,853	0.0237	15	65,660	0.0089	27	49,452	0.0031	
4	73,953	0.0201	16	65,415	0.0066	28	49,293	0.0018	
5	74,006	0.0172	17	65,059	0.0050	29	49,167	0.0007	
6	74,030	0.0147	18	64,362	0.0038	30	48,769	(0.0000)	NS
7	73,935	0.0117	19	63,185	0.0023	31	48,083	(0.0012)	
8	73,759	0.0095	20	61,837	0.0013	32	47,301	(0.0019)	
9	73,505	0.0076	21	59,738	0.0003	33	46,096	(0.0026)	
10	72,630	0.0051	22	56,207	(0.0007)	34	43,869	(0.0035)	
11	70,875	0.0035	23	51,163	(0.0014)	35	40,363	(0.0041)	

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Panel B: Based on Quarterly Updates of Random Walk

FY1			FY2			FY3		
Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority
0	28,332	0.0062	12	25,715	0.0060	24	19,763	0.0012
1	58,314	0.0061	13	51,185	0.0048	25	39,156	(0.0001)
2	58,425	0.0054	14	52,235	0.0035	26	40,141	(0.0013)
3	55,886	0.0058	15	49,960	0.0028	27	38,484	(0.0021)
4	56,006	0.0073	16	49,820	0.0022	28	38,666	(0.0018) [NS]
5	57,093	0.0066	17	50,588	0.0014	29	39,459	(0.0019) [NS]
6	54,560	0.0062	18	47,991	0.0009	30	37,520	(0.0022) [NS]
7	54,628	0.0068	19	47,387	0.0008	31	37,237	(0.0018)
8	55,815	0.0059	20	47,732	0.0003	32	37,852	(0.0016)
9	53,366	0.0053	21	44,733	(0.0001) [NS]	33	35,630	(0.0004)
10	52,741	0.0054	22	42,586	0.0001 [NS]	34	34,384	(0.0008)
11	52,754	0.0046	23	40,529	(0.0003)	35	33,059	(0.0026)

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Panel C: Based on Explicit FY3 Forecasts

FY1			FY2			FY3			
Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority	Months Prior	Firm-years	Analyst Superiority	
0	36,688	0.0282	12	33,822	0.0134	24	17,038	0.0054	
1	73,618	0.0267	13	63,869	0.0118	25	28,659	0.0038	
2	73,791	0.0255	14	65,413	0.0105	26	25,958	0.0026	
3	73,853	0.0237	15	65,660	0.0089	27	22,901	0.0016	
4	73,953	0.0201	16	65,415	0.0066	28	19,800	0.0005	NS
5	74,006	0.0172	17	65,059	0.0050	29	17,938	(0.0000)	NS
6	74,030	0.0147	18	64,362	0.0038	30	16,441	(0.0003)	NS
7	73,935	0.0117	19	63,185	0.0023	31	14,842	(0.0008)	
8	73,759	0.0095	20	61,837	0.0013	32	13,831	(0.0008)	
9	73,505	0.0076	21	59,738	0.0003	33	12,917	(0.0011)	
10	72,630	0.0051	22	56,207	(0.0007)	34	11,496	(0.0016)	
11	70,875	0.0035	23	51,163	(0.0014)	35	10,295	(0.0020)	

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 4 Analysts' Forecast Superiority and Firm Age

Panel A: FY1 – 11 Months Prior to RDQE

Firm Age	Firm-years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	6,175	0.0018	0.0426	0.0409
2	5,862	0.0015	0.0453	0.0438
3	4,983	0.0014	0.0491	0.0477
4	4,263	0.0031	0.0488	0.0458
5+	49,592	0.0041	0.0347	0.0305

Panel B: FY2 – 23 Months Prior to RDQE

Firm Age	Firm Years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	3,914	(0.0056)	0.0539	0.0596
2	3,756	(0.0065)	0.0590	0.0656
3	3,214	(0.0068)	0.0577	0.0645
4	2,802	(0.0049)	0.0541	0.0590
5+	37,477	0.0003	0.0427	0.0424

Panel C: FY3 – 35 Months Prior to RDQE

Firm Age	Firm Years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	2,338	(0.0116)	0.0671	0.0756
2	2,387	(0.0126)	0.0652	0.0746
3	2,081	(0.0094)	0.0619	0.0694
4	1,891	(0.0084)	0.0642	0.0697
5+	28,330	(0.0012)	0.0498	0.0491

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 5 Analysts' Forecast Superiority for Small Firms

Panel A: Small Firms

FY1			FY2			FY3		
Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority
0	7,352	0.0301	12	6,283	0.0104	24	3,527	0.0026
1	14,882	0.0290	13	12,176	0.0091	25	7,158	(0.0002) NS
2	14,909	0.0276	14	12,490	0.0079	26	7,378	(0.0015)
3	14,914	0.0251	15	12,444	0.0061	27	7,383	(0.0024) NS
4	14,974	0.0213	16	12,305	0.0037	28	7,321	(0.0038)
5	14,997	0.0182	17	12,127	0.0019	29	7,273	(0.0048)
6	15,003	0.0153	18	11,852	0.0005 NS	30	7,121	(0.0059)
7	15,010	0.0120	19	11,473	(0.0009)	31	6,928	(0.0071)
8	14,991	0.0094	20	11,022	(0.0019)	32	6,683	(0.0077)
9	14,971	0.0070	21	10,462	(0.0030)	33	6,383	(0.0085)
10	14,758	0.0043	22	9,398	(0.0039)	34	5,818	(0.0096)
11	14,376	0.0022	23	8,161	(0.0047)	35	5,150	(0.0105)

Panel B: Low Analyst Following

FY1			FY2			FY3		
Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority
0	9,949	0.0377	12	8,908	0.0130	24	9,743	0.0059
1	19,810	0.0365	13	16,062	0.0118	25	18,072	0.0037
2	19,863	0.0343	14	16,883	0.0099	26	18,780	0.0025
3	19,896	0.0309	15	17,358	0.0083	27	18,915	0.0012
4	19,966	0.0257	16	17,749	0.0056	28	18,849	(0.0004) NS
5	20,016	0.0212	17	18,153	0.0038	29	18,795	(0.0019)
6	20,099	0.0172	18	18,546	0.0020	30	18,549	(0.0025)
7	20,215	0.0130	19	19,060	0.0000 NS	31	17,996	(0.0041)
8	20,168	0.0097	20	19,515	(0.0012)	32	17,413	(0.0051)
9	20,144	0.0071	21	20,173	(0.0025)	33	16,399	(0.0060)
10	19,755	0.0037	22	21,079	(0.0036)	34	14,886	(0.0073)
11	19,030	0.0012	23	21,483	(0.0042)	35	12,764	(0.0082)

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 6 Analysts' Forecast Superiority Observations Partitioned by Positive and Negative Forecasted Change in EPS

Panel A: Positive Forecasted Changes in EPS

FY1			FY2			FY3		
Months Prior	Firm-years	Analysta' Superiority	Months Prior	Firm-Years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority
0	22,706	0.0115	12	26,015	0.0059	24	25,314	0.0062
1	46,516	0.0113	13	50,326	0.0049	25	48,012	0.0046
2	47,310	0.0107	14	52,229	0.0039	26	49,171	0.0036
3	48,343	0.0098	15	53,645	0.0029	27	49,310	0.0028
4	49,986	0.0083	16	54,891	0.0016	28	49,181	0.0016
5	51,569	0.0070	17	55,685	0.0008	29	49,066	0.0005 NS
6	53,028	0.0058	18	55,951	0.0002 NS	30	48,689	(0.0002)
7	54,927	0.0044	19	56,044	(0.0007)	31	48,007	(0.0013)
8	56,506	0.0035	20	55,513	(0.0012)	32	47,234	(0.0020)
9	57,816	0.0024	21	54,164	(0.0017)	33	46,042	(0.0026)
10	59,104	0.0010	22	51,572	(0.0025)	34	43,813	(0.0036)
11	59,086	(0.0000) NS	23	47,260	(0.0029)	35	40,322	(0.0042)

Panel B: Negative Forecasted Changes in EPS

FY1			FY2			FY3		
Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority
0	13,982	0.0553	12	7,807	0.0382	24	104	0.0852
1	27,102	0.0531	13	13,543	0.0373	25	184	0.1048
2	26,481	0.0521	14	13,184	0.0364	26	176	0.1083
3	25,510	0.0500	15	12,015	0.0361	27	142	0.1002
4	23,967	0.0449	16	10,524	0.0328	28	112	0.0915
5	22,437	0.0405	17	9,374	0.0298	29	101	0.0849
6	21,002	0.0370	18	8,411	0.0278	30	80	0.0603
7	19,008	0.0330	19	7,141	0.0251	31	76	0.0600
8	17,253	0.0293	20	6,324	0.0227	32	67	0.0514
9	15,689	0.0267	21	5,574	0.0203	33	54	0.0492
10	13,526	0.0234	22	4,635	0.0196	34	56	0.0688
11	11,789	0.0209	23	3,903	0.0168	35	41	0.1060

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. NS Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 7 Analysts' Forecast Superiority Observations Partitioned by the Magnitude of the Forecasted Change in EPS

Panel A: The 33% of Forecasts with the Least Extreme Forecasted Change in EPS

FY1			FY2			FY3		
Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority
0	11,355	0.0044	12	12,195	0.0039	24	9,674	0.0025
1	23,178	0.0044	13	22,983	0.0038	25	17,997	0.0023
2	23,433	0.0043	14	23,360	0.0036	26	18,096	0.0017
3	23,851	0.0040	15	23,220	0.0032	27	17,798	0.0013
4	24,359	0.0035	16	22,701	0.0030	28	17,103	0.0009
5	24,512	0.0031	17	22,080	0.0028	29	16,628	0.0011
6	24,915	0.0028	18	21,526	0.0028	30	16,114	0.0015
7	25,348	0.0024	19	20,586	0.0027	31	15,386	0.0018
8	25,358	0.0021	20	19,591	0.0027	32	14,704	0.0016
9	25,588	0.0019	21	18,521	0.0027	33	13,975	0.0023
10	25,396	0.0017	22	16,872	0.0027	34	12,854	0.0024
11	24,480	0.0015	23	14,874	0.0027	35	11,443	0.0021

Panel B: The 33% of Forecasts with the Most Extreme Forecasted Change in EPS

FY1			FY2			FY3		
Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority	Months Prior	Firm-years	Analysts' Superiority
0	14,178	0.0593	12	11,127	0.0275	24	7,794	0.0066
1	27,629	0.0570	13	20,632	0.0237	25	14,711	0.0041
2	27,293	0.0549	14	21,304	0.0207	26	15,300	0.0022
3	26,628	0.0519	15	21,289	0.0172	27	15,513	0.0006 NS
4	25,784	0.0450	16	21,303	0.0119	28	15,792	(0.0016)
5	25,356	0.0385	17	21,499	0.0082	29	16,128	(0.0022)
6	24,567	0.0334	18	21,328	0.0055	30	16,243	(0.0033)
7	23,438	0.0273	19	21,122	0.0020	31	16,430	(0.0043)
8	22,900	0.0221	20	20,974	(0.0002) NS	32	16,507	(0.0042)
9	22,104	0.0177	21	20,413	(0.0024)	33	16,390	(0.0048)
10	21,216	0.0117	22	19,453	(0.0046)	34	15,886	(0.0066)
11	20,745	0.0074	23	18,141	(0.0061)	35	15,094	(0.0069)

Observations are partitioned into thirds based on the analysts' forecasted change in EPS as a percentage of price. The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 8 Market Expectations Random Walk Forecast Error versus Analysts' Forecast Error and Market Returns

Panel A: Based on Annual Updates of Random Walk

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = a + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

FY1			FY2				FY3			
Months Prior	Firm-years	β/b	Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b	
0	34,601	0.471	12	32,710	0.437		24	24,848	0.841	
1	69,470	0.426	13	62,350	0.587		25	47,490	0.867	
2	70,881	0.414	14	63,729	0.651		26	48,554	0.885	
3	71,313	0.454	15	63,867	0.734		27	48,585	0.916	
4	71,428	0.580	16	63,566	0.829		28	48,413	0.932	
5	71,515	0.640	17	63,203	0.874		29	48,302	0.956	
6	71,596	0.644	18	62,531	0.909		30	47,915	0.987	NS
7	71,574	0.651	19	61,460	0.935		31	47,262	1.031	NS
8	71,485	0.702	20	60,223	0.959		32	46,534	1.049	
9	71,347	0.738	21	58,282	0.995	NS	33	45,401	1.068	
10	70,721	0.730	22	54,919	1.014	NS	34	43,240	1.085	
11	69,243	0.717	23	50,114	1.030		35	39,842	1.102	

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from *CRSP*, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. ^{NS} indicates that the difference between the estimates of the β and b coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Panel B: Based on Quarterly Updates of Random Walk

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = a + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

FY1				FY2				FY3			
Months Prior	Firm-years	*β/b*		Months Prior	Firm-years	*β/b*		Months Prior	Firm-years	*β/b*	
0	27,344	0.948	NS	12	25,052	0.995	NS	24	19,667	0.961	NS
1	56,436	0.815		13	50,170	0.987	NS	25	39,011	0.984	NS
2	57,647	0.796		14	51,194	0.956	NS	26	39,983	0.987	NS
3	55,432	0.792		15	48,927	0.949		27	38,307	0.997	NS
4	55,544	0.735		16	48,817	0.911		28	38,446	0.998	NS
5	56,645	0.732		17	49,591	0.919		29	39,277	0.995	NS
6	54,086	0.680		18	47,022	0.932		30	37,318	1.004	NS
7	54,153	0.656		19	46,432	0.953		31	36,996	1.034	
8	55,321	0.710		20	46,839	0.976	NS	32	37,605	1.040	
9	52,924	0.727		21	43,910	0.993	NS	33	35,437	1.050	
10	52,370	0.626		22	41,911	1.002	NS	34	34,230	1.058	
11	52,361	0.589		23	39,915	1.007	NS	35	32,889	1.067	

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from *CRSP*, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. NS indicates that the difference between the estimates of the *β* and *b* coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Table 9 Market Expectations Subsamples Random Walk Forecast Error versus Analysts' Forecast Error and Market Returns

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = a + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

Panel A: Small Firms

FY1			FY2			FY3		
Months Prior	Firm-years	*β/b*	Months Prior	Firm-years	*β/b*	Months Prior	Firm-years	*β/b*
0	7,099	0.440	12	6,263	0.629	24	3,522	0.894
1	14,435	0.360	13	12,141	0.698	25	7,152	0.919
2	14,695	0.508	14	12,452	0.745	26	7,372	0.953 NS
3	14,847	0.591	15	12,405	0.793	27	7,376	0.967 NS
4	14,906	0.587	16	12,266	0.841	28	7,314	0.979 NS
5	14,927	0.631	17	12,090	0.889	29	7,266	0.988 NS
6	14,934	0.628	18	11,815	0.941	30	7,114	1.009 NS
7	14,944	0.659	19	11,439	0.963 NS	31	6,921	1.071 NS
8	14,923	0.743	20	10,993	0.974 NS	32	6,675	1.086
9	14,904	0.785	21	10,435	1.023 NS	33	6,376	1.096
10	14,695	0.815 NS	22	9,373	1.015 NS	34	5,812	1.126
11	14,323	0.826 NS	23	8,139	1.049 NS	35	5,144	1.137

Panel B: Low Analyst Following

FY1			FY2			FY3		
Months Prior	Firm-years	*β/b*	Months Prior	Firm-years	*β/b*	Months Prior	Firm-years	*β/b*
0	8,969	0.562	12	8,190	0.696	24	9,239	0.871
1	17,936	0.557	13	15,134	0.721	25	17,456	0.888
2	18,217	0.545	14	15,859	0.760	26	18,086	0.919
3	18,369	0.631	15	16,277	0.796	27	18,156	0.946
4	18,462	0.729	16	16,621	0.879	28	18,067	0.959
5	18,532	0.767	17	16,991	0.897	29	18,034	0.978
6	18,650	0.720	18	17,396	0.931 NS	30	17,791	1.001 NS
7	18,788	0.757	19	17,966	0.935 NS	31	17,268	1.042 NS
8	18,809	0.822	20	18,478	0.961 NS	32	16,738	1.062 NS
9	18,873	0.851	21	19,209	0.999 NS	33	15,794	1.076
10	18,653	0.901 NS	22	20,214	1.013 NS	34	14,349	1.091
11	18,123	0.908 NS	23	20,774	1.033 NS	35	12,323	1.113

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from *CRSP*, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. ^{NS} indicates that the difference between the estimates of the β and b coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Table 10 Market Expectations Subsamples Observations Partitioned by Positive and Negative Forecasted Change in EPS

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = a + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

Panel A: Analysts' Forecasts of Increasing EPS

FY1				FY2			FY3		
Months Prior	Firm-Years	β/b		Months Prior	Firm-Years	β/b	Months Prior	Firm-years	β/b
0	21,676	0.959	NS	12	25,186	1.232	24	21,607	1.129
1	44,354	0.906	NS	13	49,177	1.178	25	41,861	1.117
2	45,611	1.034	NS	14	50,958	1.151	26	43,129	1.114
3	46,747	0.964	NS	15	52,275	1.158	27	43,671	1.114
4	48,353	0.961	NS	16	53,470	1.146	28	44,215	1.107
5	49,930	1.024	NS	17	54,238	1.133	29	44,576	1.106
6	51,402	1.064	NS	18	54,516	1.133	30	44,663	1.112
7	53,308	1.075		19	54,667	1.117	31	44,566	1.127
8	54,921	1.088		20	54,212	1.112	32	44,141	1.128
9	56,301	1.113		21	52,964	1.121	33	43,277	1.135
10	57,728	1.154		22	50,510	1.136	34	41,448	1.152
11	57,891	1.170		23	46,378	1.143	35	38,310	1.160

Panel B: Analysts' Forecasts of Decreasing EPS

FY1			FY2			FY3		
Months Prior	Firm-Years	β/b	Months Prior	Firm-Years	β/b	Months Prior	Firm-years	β/b
0	12,923	0.477	12	7,522	0.177	24	3,239	0.636
1	25,114	0.395	13	13,171	0.368	25	5,627	0.686
2	25,268	0.373	14	12,769	0.448	26	5,423	0.713
3	24,564	0.417	15	11,590	0.540	27	4,912	0.756
4	23,073	0.529	16	10,094	0.677	28	4,196	0.748
5	21,583	0.584	17	8,963	0.726	29	3,724	0.753
6	20,192	0.552	18	8,013	0.755	30	3,250	0.810
7	18,264	0.523	19	6,791	0.785	31	2,694	0.853
8	16,562	0.541	20	6,009	0.813	32	2,391	0.866
9	15,044	0.546	21	5,316	0.840	33	2,122	0.885
10	12,991	0.450	22	4,407	0.831	34	1,790	0.857
11	11,350	0.337	23	3,734	0.840	35	1,530	0.872

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from *CRSP*, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. ^{NS} indicates that the difference between the estimates of the β and b coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Table 11 Market Expectations Subsamples Observations Partitioned by the Magnitude of the Forecasted Change in EPS

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = a + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

Panel A: The 33% of Forecasts with the Least Extreme Forecasted Change in EPS

FY1				FY2				FY3			
Months Prior	Firm-Years	β/b		Months Prior	Firm-Years	β/b		Months Prior	Firm-years	β/b	
0	11,398	0.945	NS	12	12,553	0.967	NS	24	10,350	0.961	NS
1	22,489	0.952	NS	13	23,006	0.971	NS	25	18,658	0.969	NS
2	22,944	0.960	NS	14	22,810	0.971	NS	26	18,285	0.967	NS
3	23,211	0.967	NS	15	22,218	0.975	NS	27	17,500	0.970	NS
4	23,571	0.995	NS	16	21,522	0.977	NS	28	16,659	0.973	NS
5	23,804	0.989	NS	17	21,082	0.981	NS	29	16,189	0.975	NS
6	24,157	0.987	NS	18	20,548	0.986	NS	30	15,533	0.978	NS
7	24,524	0.989	NS	19	19,623	0.984	NS	31	14,672	0.978	NS
8	24,334	0.986	NS	20	18,719	0.984	NS	32	13,858	0.982	NS
9	24,264	0.985	NS	21	17,712	0.984	NS	33	13,023	0.984	NS
10	23,747	0.979	NS	22	16,178	0.985	NS	34	11,982	0.991	NS
11	22,880	0.981	NS	23	14,539	0.986	NS	35	10,689	0.990	NS

Panel B: The 33% of Forecasts with the Most Extreme Forecasted Change in EPS

FY1				FY2				FY3			
Months Prior	Firm-Years	β/b		Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b	
0	12,988	0.475		12	10,651	0.296		24	6,983	0.729	
1	26,091	0.428		13	20,446	0.470		25	13,955	0.764	
2	26,280	0.414		14	21,302	0.546		26	14,806	0.791	
3	26,011	0.454		15	21,406	0.642		27	15,283	0.837	
4	25,071	0.573		16	21,287	0.758		28	15,696	0.854	
5	24,272	0.628		17	21,009	0.804		29	15,950	0.884	
6	23,395	0.615		18	20,751	0.842		30	16,160	0.929	
7	22,294	0.595		19	20,323	0.871		31	16,364	0.989	NS
8	21,723	0.640		20	20,011	0.898		32	16,389	1.010	NS
9	21,079	0.668		21	19,399	0.943		33	16,316	1.029	NS
10	20,607	0.626		22	18,472	0.962	NS	34	16,066	1.044	
11	20,210	0.580		23	16,945	0.980	NS	35	15,035	1.063	

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from *CRSP*, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. [NS] indicates that the difference between the estimates of the β and b coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Table 12 Multivariate Regression of Analysts' Superiority by Months Prior to Earnings Announcement Date

$$Analysts'Superiority_{T,M} = \gamma_0 + \gamma_1\,\#Analysts_T + \gamma_2\,STD_{T,M} + \gamma_3\,BTM_{T-1} + \gamma_4\,Sales_{\,T-1} + \gamma_5\,Forecast\ Increase_{T,M} + \gamma_6\,|Forecast\ \Delta|_{T,M} + \gamma_7 Post\ FD_{T,M} + \varepsilon_T$$

	γ_0	*#Analysts*	*STD*	*BTM*	*Sales*	*Forecast Increase*	*|Forecast Δ|*	*Post FD*
0	0.025	-0.004	0.004	0.009	-0.007	-0.031	0.023	0.003
1	0.024	-0.004	0.002	0.008	-0.006	-0.029	0.022	0.003
2	0.024	-0.003	0.001	0.008	-0.005	-0.029	0.021	0.003
3	0.023	-0.003	0.000 NS	0.007	-0.005	-0.029	0.021	0.004
4	0.023	-0.002	-0.001	0.006	-0.004	-0.028	0.019	0.003
5	0.022	-0.002	-0.001	0.005	-0.004	-0.026	0.017	0.002
6	0.021	-0.001	-0.002	0.005	-0.004	-0.025	0.015	0.002
7	0.019	0.000 NS	-0.003	0.004	-0.003	-0.024	0.013	0.003
8	0.018	0.000 NS	-0.003	0.004	-0.003	-0.022	0.011	0.003
9	0.017	0.001	-0.003	0.003	-0.002	-0.021	0.009	0.003
10	0.016	0.001	-0.003	0.002	-0.001	-0.02	0.007	0.003
11	0.015	0.001	-0.003	0.001	0.000 NS	-0.018	0.005	0.003
12	0.027	0.000 NS	-0.004	0.003	0.000 NS	-0.032	0.013	0.001 NS
13	0.026	0.000 NS	-0.004	0.003	0.001 NS	-0.032	0.012	0.001
14	0.026	0.000 NS	-0.005	0.004	0.001	-0.032	0.011	0.001
15	0.028	0.000 NS	-0.005	0.003	0.002	-0.033	0.01	0.002
16	0.026	0.001	-0.005	0.002	0.002	-0.031	0.007	0.001
17	0.022	0.001	-0.005	0.002	0.003	-0.028	0.005	0.001
18	0.02	0.002	-0.005	0.002	0.003	-0.025	0.004	0.002
19	0.017	0.002	-0.004	0.002	0.004	-0.023	0.002	0.002
20	0.016	0.002	-0.004	0.001	0.003	-0.021	0.001	0.002

21	0.014	0.002	-0.004	0.001	0.004	-0.018	0.000 NS	0.002
22	0.014	0.002	-0.004	0.000 NS	0.005	-0.018	-0.001	0.002
23	0.012	0.002	-0.004	-0.001 NS	0.005	-0.015	-0.001	0.001
24	0.029	0.000 NS	0.000 NS	0.001	0.002	-0.03	0.006	-0.001
25	0.028	0.000 NS	0.000 NS	0.002	0.002	-0.029	0.005	-0.001
26	0.029	0.000 NS	0.000 NS	0.002	0.002	-0.03	0.005	0.000 NS
27	0.028	0.001	0.000 NS	0.002	0.002	-0.03	0.004	0.001
28	0.029	0.002	0.000 NS	0.001	0.002	-0.031	0.002	0.001
29	0.026	0.002	0.000 NS	0.001	0.002	-0.029	0.001	0.002
30	0.024	0.002	0.000 NS	0.001 NS	0.003	-0.027	0.000 NS	0.002
31	0.022	0.002	-0.001	0.000 NS	0.002	-0.024	-0.001	0.002
32	0.019	0.003	-0.001	0.000 NS	0.002	-0.021	-0.002	0.002
33	0.018	0.003	-0.001	-0.001 NS	0.002	-0.019	-0.003	0.003
34	0.017	0.003	-0.001	-0.001	0.003	-0.019	-0.004	0.003
35	0.013	0.003	-0.001	-0.002	0.003	-0.014	-0.004	0.003

In this table, we regress analysts' superiority on a number of factors separately for each of the 36 forecast horizons. # Analysts is the number of analysts following measured as NUMEST for the statistical period 11 months prior to the report date of annual earnings. *STD* is the standard deviation of analysts' forecasts for year T earnings as measured in month M. Book-to-Market (BTM) and Sales are measured as of the end of the base year. |*Forecast*Δ| is the absolute value of forecasted change in EPS (i.e., $|Forecasted\ EPS_T - EPS_{T-1}|$) implied by the analysts' forecast of year T earnings as measured in month M. *Post FD* is an indicator variable set equal to one if the forecast is issued after passage of Regulation Fair Disclosure in October 2000, and zero otherwise. [NS] indicates that the coefficient is not significantly different from zero at the 5 percent level, two-sided.

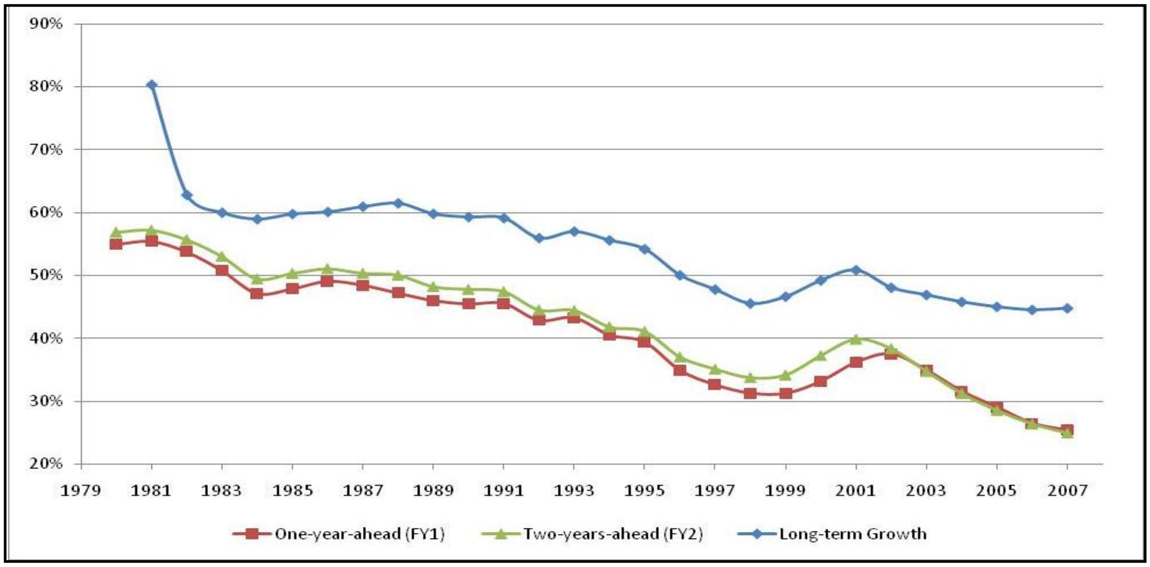

Fig. 1 Percentage of Firms with Available Data in *Compustat* and *CRSP* that are Uncovered in *I/B/E/S*

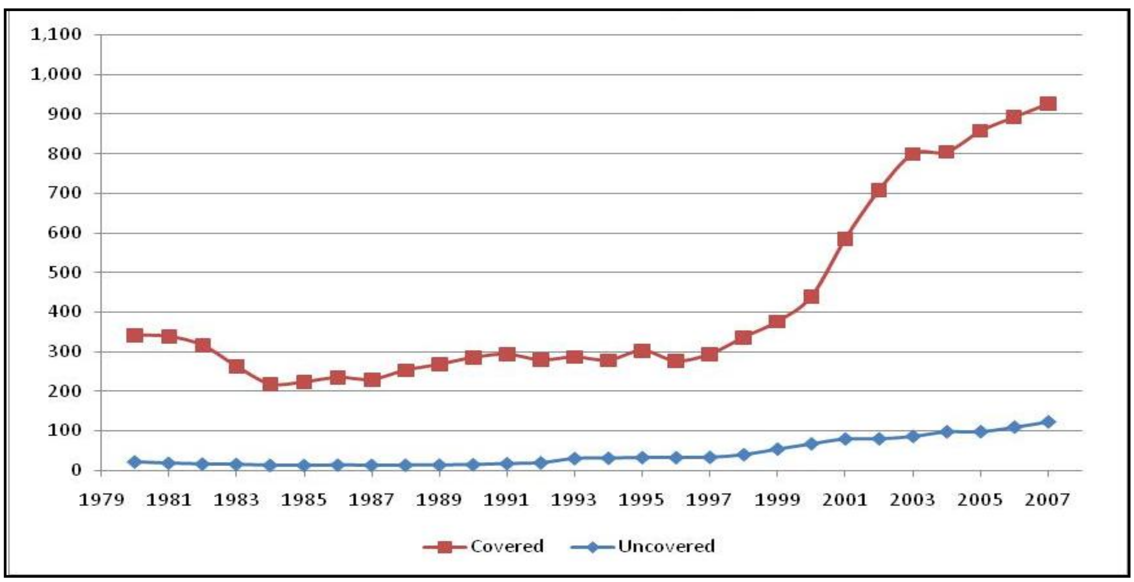

Fig. 2 Median Assets for Firms with and without One-year-ahead Earnings Forecasts in *I/B/E/S*

Analysts' Forecasts:
What Do We Know After Decades of Work?

Mark T. Bradshaw*
Boston College

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SYNOPSIS: Sell-side analysts have been the subject of hundreds of academic studies. In this paper, I offer perspectives on the state of our understanding of analysts based on prior academic research. Additionally, several observations are offered, which question how descriptive certain widely held beliefs are in light of the evidence. These observations on the literature serve as both criticisms and suggestions for future research.

Data Availability: Data used in this paper came from publicly available sources.

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INTRODUCTION

Accountants are interested in the production and use of financial information. Consequently, a large number of academic accounting studies are concerned with whether sophisticated users of financial data understand such information and how they process it. Sophisticated users include sell-side analysts, short sellers, institutional investors, regulators, the financial press, and other market participants. However, a seemingly disproportionate amount of research has focused on sell-side analysts. For example, Brown (2000) highlights over 575 studies on expectations research, most of which are devoted to sell-side analysts' earnings forecasts and stock recommendations. Additionally, as of early 2006 there are over 500 papers listed on ssrn.com that have some emphasis placed on analysts, with most of these being posted after 1995.

Clearly, interest in sell-side analysts is great. As a result of this interest, our understanding of their role in the capital markets has grown over the past several decades during which academics have extensively studied sell-side analysts. Our understanding of sell-side analysts' behavior is not only beneficial to academics interested in a working framework that describes capital markets, but is also of interest to practitioners who operate in these markets. Managers of public companies must be able to communicate with analysts, and in particular, need to understand what information they want and how they process and communicate it. Investors with limited abilities or time to analyze individual securities often rely on the work of sell-side analysts, typically through the analysts' reports. Finally, regulators are keenly interested in the flow of information that facilitates functional and liquid markets, and analysts are one contributor to the critical flow of information.

The purpose of this commentary is to survey what we have learned about analysts' role in the capital markets and to comment on the state of our understanding of their analysts' activities. A primary conclusion is that our focus almost exclusively on earnings forecasts now obstructs the growth in our understanding of analysts' role in the capital markets. Whereas the initial reason researchers began examining analysts' earnings forecasts was to gauge their usefulness as a surrogate for time-series forecasts in studies of the efficiency of the capital markets, interest in analysts has grown such that analysts are perceived as an interesting economic agent in their own right, much like the literature that studies CEO's or CFO's. Thus, it is necessary for the literature to expand its focus on other activities performed by analysts and attempt to better model their incentives than has typically been done.

The literature on analysts is vast, and I make no representation to provide a comprehensive review of the literature. To the extent that I do mention specific studies, the citations are necessarily incomplete, so apologies are requested in advance. Second, to the extent that I mention work that I have done, it is done because it is convenient. Finally, many of the critical comments I have to make about the analyst literature are probably applicable to other streams of literature that purport to describe decision processes of capital market participants.

For those seeking comprehensive reviews of the literature, Givoly and Lakonishok (1984) provide a review of the very early literature, and Brown (1993) reviews literature up through the early 1990s. Discussions by P. Brown (1993), O'Hanlon (1993), Thomas (1993), and Zmijewski (1993) of L. Brown's (1993) literature review are each excellent and almost orthogonal to one another in the points they raise. Zmijewski's (1993) discussion is particularly recommended as relevant to the current state of the literature, which will be revisited later in the paper. Kothari (2001) provides a comprehensive review of the broader capital markets literature, which encompasses studies on analysts. Finally, Ramnath, Rock, and Shane (2008) review the literature since 1993 and provide taxonomy of that research.

Finally, Schipper's (1991) commentary that appeared in this journal did not have as its purpose a comprehensive review of the literature, but it is part of the 'required background reading' on sell-side analysts. The tenor of many of my views on the literature are present in her commentary, and many of the observations made by Schipper (1991) are perhaps even more applicable in assessing the current state of our knowledge of analysts' activities than they were in 1991. Indeed, the title of my paper is derived from an observation that surprisingly little research has been produced since her review that capitalizes on several observations made in that commentary.

The rest of the paper proceeds as follows. The next section discusses how research on analysts fits in with other capital markets research. I then briefly summarize the evolution of the current state of knowledge on analysts. Following this summary, ten observations on regularities and widely held beliefs from this literature are discussed. Many of these beliefs are critiqued and challenged, the result being suggestions for further work. The final section concludes.

WHAT IS IT WE SEEK TO UNDERSTAND?

As mentioned above, there are hundreds of studies performed by academics, aimed at understanding various aspects of analysts' activities. After decades of research, and the associated attention on this research by both academics and practitioners, it seems reasonable to articulate what it is we have been attempting to gain from this collective effort. To provide a context for the discussion that follows, it is worthwhile describing the analyst's role within the capital markets. Figure 1a provides a schematic that describes analysts' activities.

The first aspect of figure 1a that is important is that analysts reach some coverage decision. Analysts generally specialize by industry (Dunn and Nathan 2005), but within an industry analysts (or their employers) must decide what particular stocks to cover. For practical purposes, analysts tend to cover firms within an industry that is biased towards larger firms. Next, for any given stock that is covered, the analyst has access to a wide array of information, including security prices, firm-specific financial and operating information, industry data, and macroeconomic factors. Presumably, the value-added activity of the analyst is, not surprisingly, 'analysis.' Analysis encompasses the process through which the analyst considers a company's strategy, accounting policies, historical financial performance, future prospects for sales and earnings growth, and ultimately a valuation and purchase or sell recommendation. Based on the analysis, the analyst presumably draws a conclusion, most succinctly conveyed by a purchase or sell recommendation, but conclusions are likely more complex than a discrete stock recommendation and are conveyed through various communication channels.

The analysts' conclusions are conveyed to clients, investors, company management, and other market participants via *formal* or *informal* channels. Formal channels are the source of most of the data examined by academics, primarily drawn from analysts' formal reports and morning broker notes – archived by data providers such as Value Line and I/B/E/S. Analysts also give formal presentations to major clients and other investor groups. Similarly, they communicate results of their analyses informally through brokerage client communication, press interviews, industry meetings and conferences, and also by coordinating meetings between institutional investors and the firm managers. The end result is that part of the information communicated to the markets can be assessed *ex post* in terms of earnings forecast accuracy, recommendation profitability, and so on. Underlying this entire process are qualitative factors that affect the information gathering, analysis, and communication processes such as the analyst's ability, incentives, integrity, responsiveness to clients, and other such behavioral effects.

A potential problem for academics attempting to use the body of knowledge generated from research on analysts is demonstrated in figure 1b. For the most part, research methods do not really measure the most interesting part of the schematic, which is the analysts' analysis. This is literally a 'black box' in the figure. However, this is only a potential problem. What academics generally do instead of directly observing the analysts' decision process of analysis is to examine correlations between inputs, outputs, and conditioning variables to understand the analysis process.

A general characterization of the literature is as follows. Outputs extensively studied primarily include earnings forecasts and recommendations. A long line of research simply examines distributional properties of these outputs. As for inputs, researchers have primarily focused on prices and financial statement information. Additionally, recent research has begun to examine whether analyst ability and incentives affect the processing of inputs into forecasts and recommendations. The direction of a typical research study is typically two-way, meaning that the researcher measures a correlation between outputs (i.e., earnings forecasts, recommendations) and some other variable such as stock prices. For example, a typical approach is to examine whether forecasts or recommendations affect stock prices, as well as whether information in prices affects forecasts and recommendations. Other relations typically examined by researchers are unidirectional, examining whether inputs such as the information in financial statements is captured in earnings forecasts or recommendations. Similarly, researchers examine whether proxies for analysts' abilities and incentives affect the accuracy of forecasts and profitability of recommendations.

It should not matter that researchers do not directly observe the activities represented by the black box in figure 1b. In this literature, like many others that are archival in method, outputs from some economic setting are observed to infer how agents have behaved. For example, if forecasts made by analysts are observed and errors are measured, this can be informative about how well the analyst forecasted, which may give insight into the process by which the analyst derived the forecast. Indeed, most current studies designed to examine correlations between analysts' inputs and outputs draw conclusions in terms of what information analysts used, how they used this information, and whether the analysts 'fully used' such information. Unfortunately, the literature has evolved to the point where some penetration of the black box is now necessary to push the literature foreword. The latter part of the paper discusses areas where this might be possible. In summary, however, an important observation on the current state of the analyst literature is that it is almost exclusively based on indirect evidence.

The earliest research on financial analysts developed as a by-product of capital markets research focused on correlations between accounting earnings and stock prices. In that line of research, it was necessary to quantify the amount of 'news' in earnings announcements. Thus, a measure of 'expected' earnings was required, which was compared to earnings actually reported, allowing a quantification of the 'unexpected' component of earnings. In an informationally efficient market, this unexpected news should lead to immediate short-window stock price reactions.

The interest in tests of market efficiency and value relevance of accounting earnings prompted a significant amount of research on time-series modeling of earnings. This literature is extensive and generated much discussion about then new topics in the accounting literature such as earnings response coefficients (ERCs), ARIMA parameters, impulse response functions, and so on. This literature seems to have reached its peak during the late 1970s and early 1980s, at which time researchers gravitated towards using analysts' forecasts of earnings as a substitute for the complex time-series models. This launched a number of studies that ran horse races between analysts' forecasts and time-series models to see which was a better measure of the 'expected' component of earnings. Fried and Givoly (1982) are often given credit as the paper that supported the definitive conclusion that analysts are a better proxy for expected earnings than estimates from time-series models.

Although there remains scattered interest in the time-series properties of earnings, Kothari (2001) recently commented that the literature on time-series modeling of earnings is "fast becoming extinct … [due to] the easy availability of a better substitute: analysts' forecasts are available at a low cost in machine-readable form for a large fraction of publicly traded firms." As it became generally accepted that analysts' forecasts were superior to time-series forecasts, academics became interested in a deeper understanding of analysts' forecasts and analysts' themselves. Among academic accountants, analysts were elevated to the status of an economic agent in the capital markets worthy of extensive study. As a result, more recent work attempts to understand analysts' incentives, conflicts of interest, loss functions, and so on. Prior to briefly reviewing what we know about analysts, it is important to articulate why we *still* study analysts.

The cynical response to why academics still study analysts is that the data are easy and cheap to access. Several companies like First Call, I/B/E/S, Value Line, and Zacks maintain databases on the forecasts and recommendations of thousands of analysts covering thousands of companies, allowing easy use of these data by academic researchers. Perhaps an even more cynical response is that academics very much enjoy analyzing distributions (i.e., means, medians, standard deviations, etc.) and correlations. Analyst data are easily converted into variables that provide interesting distributions and correlations (e.g., signed forecast error, forecast accuracy, ERCs, etc.).

However, the real reason I believe research on analysts continues is that we are interested in how the capital markets function, and examining analysts furthers such knowledge. On one hand, analysts are one of the preeminent market information intermediaries, distributing forecasts and results of their analysis to institutional and individual investors. Thus, examining properties of the analysts' forecasts and analysis helps us understand the nature of the information that seems to be impounded in stock prices. Another perspective is that analysts are a good proxy for beliefs held by investors in general, so examining properties of analyst data provides insight into how investors in general utilize and process accounting information like financial statements, footnotes, and other financial disclosures. Finally, having elevated analysts to the status of an interesting set of economics agents for detailed study, it is intrinsically interesting to study what analysts do and how they utilize financial accounting information. This final reason explains most of the current work on analysts.

OVERVIEW OF WHAT WE KNOW (OR THINK WE KNOW)

Early survey research and anecdotal evidence suggest that analysts are voracious for all kinds of information (e.g., Tevelow 1971, Chandra 1974, Frishkoff, Frishkoff, and Bouwman 1984, Epstein and Palepu 1999). It is not surprising, however, that in responding to surveys, analysts would tend indicate they always prefer more information to less. It is one thing to simply express a desire for information and another to incur costs to acquire or process it, particularly given a drastic increase in the length of annual reports in recent years (Li 2006). Research on analysts' information needs and preferences is generally regarded as 'descriptive' and is frequently overlooked in empirical research. This is unfortunate, because investigations on what information analysts might use and how they use it should incorporate these findings, if for no other reason than to see if what analysts say is consistent with what it appears they actually do.

Prior to discussing specific observations on generally accepted findings in the literature, a very brief discussion of the evolution of the literature is in order. Figure 2 provides a timeline that highlights general trends in the literature between the 1960s and early 2000s. Let me again emphasize that this is not meant to be a literature review or a comprehensive summary of all primary questions examined. Additionally, figure 2 is employed as a heuristic to place the subsequent discussion of specific observations in context. The reader is directed to the literature reviews identified in the introduction for a full list of questions and a more comprehensive coverage of relevant studies. Also, I will provide very brief highlights of each paper, and the brevity of these oversimplified highlights will necessarily oversimplify and undersell the full contribution of the paper.

As previously discussed, the initial impetus for examining analysts forecasts was the need for a better proxy for earnings expectations to be used in capital markets research. This literature spanned approximately two decades (1968-1987) and appears in the lower left quadrant of figure 2. Brief highlights of notable conclusion from these studies are as follows:

- Cragg and Malkiel (1968): Five-year growth rates forecasted by analysts were no different than simple algebraic extrapolations.
- Elton and Gruber (1972): Annual forecasts by various groups (pension fund, investment advisors, investment bank analysts) were no different between naïve time-series model and each group of analysts.
- Barefield and Comiskey (1975): Analysts' forecasts outperformed a simple no-change earnings forecast model.
- Brown and Rozeff (1978): Analysts' forecasts outperformed 'less naïve' time-series models, especially at longer forecast horizons.
- Fried and Givoly (1982): Using a (then) large sample of panel data (100 forecasts per year for 1969-1979), analysts' forecasts were more accurate than those from various time-series models.
- Brown, Griffin, Hagerman, and Zmijewski (1987): Analysts' forecast superiority over time-series models is due to (i) a timing advantage and (ii) an information advantage.

These studies primarily appeared in finance journals, employed small samples relative to those typical in current analyst research (e.g., hundreds of observations vs. hundreds of thousands), and used research designs that ran horse races between different forecasts. Fried and Givoly (1982) is generally recognized as having provided the most compelling evidence that analysts are superior to time-series models and several years later, Brown et al. (1987) clarified the source of analysts' superiority. Thus, it took almost two decades for researchers to settle comfortably on the conclusion that analysts were better than time-series models at forecasting earnings. However, as discussed below, the economic magnitude of analysts' superiority appears to be small, suggesting that analysts' value to the capital markets likely rests on other roles than simply forecasting earnings.

Building on the research that compared analysts relative to time-series models, research considered refinements and extensions to research designs, with the goal of identifying factors that are correlated with incremental earnings forecast accuracy. These studies also appear in the lower left quadrant of figure 2, and are briefly highlighted below:

- O'Brien (1988): The most recent forecast more accurate than consensus.
- O'Brien (1990): There is no evidence of an analyst-level effect on forecast accuracy, thus no analysts are persistently better than others.
- Stickel (1990): Analysts ranked as an Institutional Investor All-Star are superior forecasters than a matched sample based on forecast recency.
- Brown (1991): The accuracy of the consensus forecast gets more accurate if older forecasts are dropped.
- Sinha, Brown, and Das (1997): Careful controls for forecast recency yield evidence that some analysts are more accurate than others
- Mikhail, Walther, and Willis (1997): Individual analyst experience increases forecast accuracy
- Clement (1999): Analysts' forecast accuracy is increasing in resources and decreasing in complexity.

Thus, the literature moved beyond concern over analysts being superior to time-series models, and began investigating whether some analysts were better than others. As with the previous efforts on analysts versus time-series models, this series of research initially showed no differences, but subsequently found the existence of differences.

Simultaneous to these two sets of studies, research was also considering the association of analysts' forecasting activities with stock prices. Some of the papers highlighted above also examined market reactions to forecasts and earnings surprises. For example,

- Fried and Givoly (1982) and others: Earnings forecast accuracy generally corresponds to a greater association between unexpected earnings based on such forecasts and announcement period stock returns.
- O'Brien (1988): Even though Standard & Poors and I/B/E/S analysts exhibit higher forecast accuracy, they have no stronger association with stock returns than time series models.
- Philbrick and Ricks (1991): The actual definition of what income statement level earnings being forecasted varies across forecast data providers. Value Line forecast errors are the smallest, but various combinations of forecasts and actual earnings across the databases yields the strongest association with announcement period stock returns (e.g., unexpected earnings based on Value Line earnings forecasts and I/B/E/S actual earnings)

This focus on the correlation between analysts-based earnings surprises and stock prices prompted researchers to examine whether analysts' themselves appeared to be efficient with respect to information cues. Such studies tend to examine whether analyst forecast errors are correlated with publicly available information. If a correlation exists, research concludes that analysts are inefficient with respect to such information. This area of research arose around 1990 and continues to the present. Studies shown in the top right quadrant of figure 2 are highlighted below:

- De Bondt and Thaler (1990): Analysts overreact to past earnings changes, resulting in forecasts that are overoptimistic.
- Lys and Sohn (1990) and Abarbanell (1991): Analysts' forecasts underreact to information in prior stock price changes.
- Mendenhall (1991) and Abarbanell and Bernard (1992): Analysts underestimate the serial correlation in quarterly earnings (i.e., post-earnings announcement drift), but to a lesser extent than investors do through stock prices.
- Elliott, Philbrick, and Wiedman (1995): Analysts systematically underreact to their own sequential prior forecast revisions.
- Easterwood and Nutt (1999): Analysts underreact to negative information and overreact to positive information, both reactions leading to analysts being persistently overoptimistic.
- Bradshaw, Richardson, and Sloan (2001): Analysts underreact to predictable earnings patterns following extreme accruals.

As can be seen from the highlights, there does not appear to be a general consensus on whether analysts over- or underreact to information. Either way, the conclusions that are inevitably that analysts are 'inefficient' with respect to numerous pieces of information. This literature is vast, with almost any information cue one can consider having been subjected to an analyst forecast analysis. In the next section, I argue that drawing conclusions about the efficiency of analysts' forecasts based on correlations may not be a strong test of analysts' processing of information.

A second wave of research on the efficiency of analysts attempts to understand whether analysts are internally efficient with respect to their own information outputs. For example, given the correspondence between earnings expectations and value, do analysts efficiently use their own earnings forecasts in valuing companies and generating stock recommendations? Select papers include:

- Bradshaw (2004): Analysts' recommendations are consistent with the use of heuristic valuations incorporating their own earnings forecasts.

- Asquith, Mikhail, and Au (2005): Qualitative information in analysts' reports explains a significant amount of their recommendations, target prices, and the price reaction to these forecasts.
- Loh and Mian (2006): More accurate forecasts lead to more profitable stock recommendations.

This research is noteworthy in that it necessarily considers simultaneously more outputs from the analyst than just the earnings forecasts. As argued in the next section, the literature on analysts suffers from an overemphasis on earnings forecasts relative to other important tasks performed by analysts. In this spirit, many of what some consider to be the most interesting papers on analysts focus on their activities within the context of what their individual and employer-level incentives are. A sampling of these types of papers is as follows:

- Francis and Philbrick (1993): Analysts trade off earnings forecast accuracy for intentional optimism to curry favor with managers.
- McNichols and O'Brien (1997): Analysts' exhibit a self-selection bias such that negative views are censored, and hence unobservable to investors or researchers.
- Lin and McNichols (1998): Analysts exhibit overoptimism when their employers perform investment banking services for covered firms.
- Michaely and Womack (1999): After the quiet period following an initial public offering, affiliated analysts are more likely to issue buy recommendations than are unaffiliated analysts.
- Mikhail, Walther, and Willis (1999): Forecast accuracy is negatively related to analyst job turnover.
- Hong and Kubik (2003): Promotions and demotions at investment banks depend more on optimism than accuracy.
- Gu and Wu (2003) and Basu and Markov (2004): These papers question analysts' loss functions implied by prior work that uses ordinary least squares models to link forecast errors and various measures (implying a quadratic loss function) by proposing that analysts' might prefer to minimize the absolute error instead.
- Raedy, Shane, and Yang (2006): Evidence of analyst underreaction might not be due to them ignoring publicly available information, but due to their asymmetric loss function whereby they incur greater reputation cost

of forecast errors when the error has the opposite sign as the analysts' prior earnings forecast revision. (i.e., bad to 'overshoot').

Left out of the terse listing of papers in figure 2 are many important studies on (i) the analyst coverage decision, (ii) dispersion and its association with prices and accuracy, (iii) recent changes in the regulatory environment (FD), and (iv) experimental research that has a bearing on decision processes (but I'll defer discussion of these until later). I have also focused the studies listed here on those involving earnings forecasts, which is consistent with the representativeness of earnings forecasts as the focus of most studies in this literature. It is only recently that researchers have begun investigating recommendations (Womack 1996), growth projections (LaPorta 1996), and target prices (Brav and Lehavy 2003).

The overall takeaways from the above discussion is that approximately four decades of research on analysts focuses heavily on the earnings forecasting task, with only recently increasing interest in other activities performed by analysts. Second, the literature moves relatively carefully, with the conclusion that analysts dominate time-series models taking two decades. Third, beginning in the 1990s, much work has been positioned as attempts to understand what information analysts use and how they use it (i.e., the black box). Finally, as research studies have begun to consider activities beyond basic earnings forecasting, it has become necessary (and interesting) to examine analysts' incentives and investigate what role they might play in the empirical regularities developed over the past several decades of research (e.g., optimism). The next section provides ten specific observations that may guide future thought on how to interpret and advance the evidence on analysts' and their roles in the capital markets.

SPECIFIC OBSERVATIONS ON WHAT WE KNOW (OR THINK WE KNOW)

1. Analysts' Forecasts are Optimistic

Of all the regularities regarding sell-side analysts, the understanding that analysts' forecasts are routinely optimistic is the most pervasive. Numerous studies document that analysts' forecasts of earnings end up, on average, being too high. The problem is that this is a sweeping generalization that is not *on average* descriptive. There are at least three qualifications to the generalization that analysts are routinely optimistic. First, what specific forecasts are believed to be optimistic – quarterly earnings per share forecasts, annual earnings per share forecasts, growth forecasts, target prices, sales forecasts, cash forecasts, etc.? The typical explanation for why analysts would be persistently optimistic is that they wish to maintain cordial relationships with management, and optimistic forecasts further this goal. However, with regards to the most prevalent forecast made by analysts, earnings per share, it is difficult to understand why the managers analysts are presumably trying to please would prefer optimistic earnings forecasts. Research makes it clear that forecast errors (measured as actual earnings minus the forecast) are positively correlated with stock price reactions. Thus, forecasts that are too high (i.e., optimistic) create negative forecast errors and negative stock price reactions. On average, managers would seem to desire avoiding such reactions. Indeed, recent evidence in the accounting literature examines the 'meet or beat' phenomenon, which describes the preference by managers and tendency for quarterly earnings announcements to equal or slightly exceed analysts' forecasts. Overall, it appears that at least for short-term forecasts, it is not descriptive to generalize that analysts' forecasts are optimistic.

Second, we seem to be well aware of selection biases in analyst forecast data which form the basis of most of our research. Several studies indicate that analysts seem to follow the old adage, 'if you don't have anything good to say, don't say anything at all.' For example, analysts are reluctant to issue negative recommendations (i.e., 'sell'), and more important, having issued favorable recommendations, they exhibit a reluctance or sluggishness in downgrading recommendations. Even though this is a well-known phenomenon, we apparently disregard knowledge of this selection bias in drawing generalities about the overall level of analyst optimism. In other words, what is interpreted as persistent optimistic bias by analysts could simply reflect the fact that we do not get to observe analysts' pessimistic views. With the recent implementation of NASD 2711 and NYSE 472 rules that, among other things, require analyst research reports to provide benchmark distributions of the brokerage's recommendations and target prices, we may witness an increasing tendency for analysts to convey previously non-communicated pessimistic views.

Finally, a recent body of research on 'street' or 'pro forma' earnings has revealed issues with analyst forecast data that systematically result in optimistically biased forecasts. Firm managers have always highlighted earnings in earnings releases that exclude the effect of various one-time charges. However, this practice escalated beginning in the 1990s, and firms began reporting earnings excluding an even greater number of income statement line items, including, for example, research and development expense, advertising expense, customer acquisition costs, and so on. As these examples suggest, the types of income statement amounts excluded were disproportionately expenses (rather than gains or revenues). Both Bradshaw and Sloan (2002) and Abarbanell and Lehavy (2007) note that forecast data providers such as First Call and I/B/E/S claim to archive actual earnings figures that match the earnings definition being forecasted by the majority of analysts. This is important because the standard practice to calculate analyst forecast error (and hence bias) is to subtract the actual earnings figure from the forecast database from the forecast. Thus, if analysts forecast earnings before the effects of one-time items and research and development expense, then the forecast data providers include the actual earnings before one-time items and research and development expense in the historical database used by academics. Evidence presented in both papers referenced above indicate that the forecast data providers seem to have only gradually adjusted the actual earnings figures on the database to correspond to figures being forecasted by analysts. Both papers identify 1992 as representing a marked shift in the correspondence of actual and forecasted earnings. As much of the research supporting the inference that analysts are persistently optimistic was published using pre-1992 data, the non-correspondence between the actual earnings used in those studies (i.e., bottom-line 'net income' from Compustat or one of the forecast data providers) would have systematically resulted in mechanically upwardly biased forecast errors.

2. Analysts' Forecasts Are Superior to Time-Series Model Forecasts

The second presumably well-known feature of analysts' forecasts is that they are superior to forecasts from time-series models. Accounting research aimed at modeling earnings using ARIMA models was at its peak during the 1970's and seems to have effectively ended in the mid-1980's. Brown (1993) provides a comprehensive review of much of this literature, which is also briefly summarized by Kothari (2001), who states at the outset (p. 145), "I deliberately keep my remarks on the earnings' time-series properties short because I believe this literature is fast becoming extinct. … [due to] easy availability of a better substitute: analysts' forecasts…."

On one hand, if analysts are efficient in any sense, as has been noted before by Brown et al. (1987), it has to be the case that analysts' forecasts outperform time-series model forecasts, because analysts have both a timing and information advantage. Analysts can easily calculate any anointed time-series model and incorporate that information into their overall information set. Moreover, because time-series models are parsimonious, the information available to analysts is greater than that which can be quantified by any time-series model. Thus, for most forecast dates, an analyst will have an information advantage over a time-series model, which necessarily relies on historical inputs. Nevertheless, it took scores of papers spanning two decades (i.e., approximately 1968-1987) for academic research to conclude that analysts' are superior to time-series models.

Many of the papers that concluded examined the relative forecasting ability of analysts versus time-series models were based on limited samples. For example, Barefield and Comiskey (1975) examine forecasts for 100 firms (and conclude that analysts outperformed a simple random walk forecast) and Brown and Rozeff (1978) examine forecasts for 50 firms (and conclude that most time-series models are outperformed by analysts, particularly at longer horizons). Fried and Givoly (1982) is generally credited as one of the decisive studies in this area, primarily due to the significantly expanded sample size. They examine 100 forecasts per year for the period 1969-1979 and conclude that analysts were superior to time-series models. However, what seems to have been overshadowed in subsequent research that wholly abandoned time-series models is the slim margin by which analysts won this contest. For example, Fried and Givoly calculate absolute forecast errors scaled by actual earnings per share. Their primary results indicate an average absolute forecast error for analysts of 16% relative to a comparable forecast error for two time-series models of 19% and 20%, respectively. Furthermore, results for individual years are often closer than this 3-4% spread. This seems to be a slim margin of victory for analysts given the information and timing advantages they have over the time-series models. The increasing tendency for managers to provide earnings guidance (Matsumoto 2002) and earnings preannouncements (Soffer, Thiagarajan, and Walther 2000) should have increased analysts' superiority over time-series models, but no research of which I am aware has examined this.

If one restricts their consumption of research to accounting journals, then it would appear that research using time-series models is indeed extinct.[1] However, outside of the accounting literature, continued use of time-series forecasts as an alternative and as a benchmark for expert forecasts is prevalent. Indeed, the economics literature largely concludes that time-series forecasts are superior to those of various experts. For example, this is argued to be the case for forecasts of interest rates (Belongia 1987), gross domestic product (Loungani 2000), recessions (Fintzen and Stekler 1999), and business

[1] This is not meant to dispute the conclusion in Kothari (2001) referenced above, which is indeed accurate.

cycles (Zarnowitz 1991). This discrepancy in conclusions across research paradigms is surely related to the unit of analysis. Forecasts of earnings is done frequently with the input of the preparers of the earnings being forecasted, accounting procedures for those earnings are well-understood, and such accounting standards often have the objective of smoothing reported earnings (e.g., pension assumptions). In contrast, items like interest rates, GDP, recessions, and business cycles are not generally subject to the control of an individual manager or follow a prescribed set of rule governing their reporting.

3. Analysts' Forecasts are Inefficient

A large number of research papers spanning the late 1980s through the present examine whether analysts' forecasts are 'efficient.' Similar to how efficient market prices are defined, forecasts are said to be efficient if they incorporate all information available to the analyst. Thus, studies have examined whether analysts incorporate information in past earnings, past market prices, and past forecast revisions; similarly, more recent studies examine whether analysts' forecasts are efficient with respect to information in financial statement information like accruals, management forecasts, and various other financial disclosures.

These studies inevitably draw conclusions about the efficiency of analysts' forecasts. If forecast errors are correlated with some information available *ex ante* to the analyst, the forecast is said to be inefficient with respect to that information. In these cases, the analyst is said to have either 'underreacted' or 'overreacted' to the information. As it turns out, it is rare to witness empirical results which support an efficient use of information. The likely reason is that the data we rely upon is noisy, which inevitably leads to coefficients in empirical tests that are consistent with inefficient use of information.

To clarify this, consider a simple correlation between some analyst variable AV (e.g., annual forecast revision) and some variable of interest X (e.g., information in a quarterly earnings announcement). What the researcher wants to measure is corr(AV, X). However, X is likely measured with error, so the researcher ends up measuring X+error, rather than X. In the typical regression framework, the researcher would estimate the following regression:

$$AV = \alpha + \beta(X+error)+e,$$

leading to the well-known downward bias in the estimate of β (absent other covariates). This downward bias inevitably leads researchers to conclude that, with respect to the information in the phenomenon measured by X, analysts appear to be inefficient. The often overlooked or unstated alternative is that the tyranny of measurement error contaminates our ability to draw strong conclusions regarding analysts' efficiency in processing particular pieces of information.[2]

4. Most Academic Research Ignores Analysts' Multi-Tasking

Of the hundreds of papers published on sell-side analysts, casual empiricism supports the conclusion that most focus exclusively on the earnings forecasting process. Thus, if someone unfamiliar with sell-side analysts went to the accounting and finance

[2] Of course, if the left hand side were some analyst variable, like forecast error, measurement error would tend to bias this simple univariate specification towards a conclusion of efficiency rather than inefficiency. The variety of empirical specifications in the literature and the multivariate (rather than simple univariate) nature of such specifications leads to ambiguous directional predictions regarding measurement error induced bias, but it is reasonable to presume that conclusions that generally fall between full efficient use of information by analysts and complete inefficiency are most likely.

literature to understand what it is they do, they would likely come away with the impression that analysts' primary goal is to issue accurate earnings per share forecasts.

In contrast, consideration of all the roles performed by an analyst suggests that earnings per share forecasts are either tangential or at best just one of many inputs into the analysts' other (primary) activities. Thus, a focus on earnings forecasts by academics is useful to understanding what analysts do, but it is a means not an end. Schipper (1991) noted early on in this literature that, "The general focus of accounting research on accuracy and bias of analysts' earnings forecasts has yet to capitalize on whatever opportunities for insights might arise from considering these forecasts in the context of *what the analyst does* … [emphasis added] (p. 112). Similarly, Zmijewski (1993) argued shortly thereafter that one of the primary areas of research that could further our knowledge are studies that lead to "expansion of our analysis of financial analysts' earnings forecasts to encompass more of what they actually do [emphasis added] (p. 338).

The easiest means of understanding what analysts do is to examine other outputs provided by them. In recent years, research into these other outputs has been growing, with studies on stock recommendations (e.g., Womack 1996), growth projections (e.g., Dechow and Sloan 1997), target prices (e.g., Brav and Lehavy 2003), and risk ratings (Lui, Markov, and Tamayo 2007). A second step is to simultaneously examine these outputs. In other words, if one of analysts' primary objectives is to issue an investment recommendation for a security, then one might examine how earnings forecasts and growth projections are associated with the actual recommendation (e.g., Bradshaw 2004). To gather a quick feel for how active research is along these suggestions, I performed a global search of scholarly articles on ABI/INFORM using various keywords, and found the following:

analyst+earnings	867 articles
analyst+recommendation	149 articles
analyst+long+term+growth	54 articles
analyst+target+price	14 articles
analyst+earnings+recommendation	27 articles
analyst+earnings+long+term+growth	22 articles
analyst+earnings+target+price	3 articles
analyst+earnings+recommendation+long+term+growth	1 article

This is not to suggest that research studies that incorporate more than one analyst variable are superior, but rather, that furthering our understanding of what analysts do and why they do it requires consideration of their portfolio of activities. For example, Loh and Mian (2006) examine whether analysts who provide superior earnings forecasts also provide more profitable stock recommendations, which is a useful question to answer as it pertains directly to the use of earnings forecasts as an input into the arguably more important role of providing investment advice.

Clearly, as discussed above, the overwhelming bulk of research effort appears to focus on earnings forecasts, with some distant level of interest on analysts' stock recommendations. However, beyond that the interest level suggested by the above ABI/INFORM search seems to drop substantially. The simple explanation may simply be that data on these other metrics have not been widely available until recently. For example, whereas large samples of machine-readable earnings forecast data have been available since the early 1970s, data for long-term growth forecasts became available in 1981, for recommendations in 1992, and for target prices in 1996. I return to this theme later when I comment on research that is aimed at understanding what analysts' do with their own earnings forecasts.

5. Analysts are Dominated by Conflicts of Interest

Besides the first point raised regarding the belief that analysts' forecasts are persistently overoptimistic, perhaps the second most prevalent belief is that analysts' behavior is dominated by conflicts of interest. There are at least six sources of conflicts that have been discussed either in the literature or the financial press and that are purported to lead to analysts being overoptimistic. The following briefly lists, in my assessment, the sources of conflict in descending order of the relative emphasis given to them in the literature.

1. Investment banking fees. Managers periodically require access to the capital markets and require the assistance of investment banking professionals, who are frequently employed by firms that also run sell-side research shops. It has long been argued, and recent anecdotal evidence is consistent with the charge, that sell-side research departments are rewarded by the investment banking side of operations for providing favorable coverage of deals that the firm underwrites. Such fees are the fuel of such firms, and typical large placements bring in millions of dollars in fees. Accordingly, sell-side research, which is generally a cost rather than a profit center, is argued to be predisposed towards overoptimism due to the lure of lucrative investment banking fees. This explanation is the most prevalent.

2. Currying favor with management. Distinct from the incentive to appease managers to obtain investment banking business, sell-side analysts have also been accused of being optimistic so that they maintain access to firm managers who are a primary source of information flow (Francis and Philbrick 1993). The recently implemented Regulation FD is meant to curb this practice, and requires that managers refrain from selectively releasing private information. Several studies have attempted to examine whether the implementation of this regulation led to less optimistic forecasts and recommendations by analysts. However, around the same time that Regulation FD was implemented, there were other regulations and market sentiment changes that make it difficult to attribute any observed change in overall analyst optimism to this single piece of regulation (e.g., NYSE 472, Nasdaq 2711, Sarbanes-Oxley, large interest rate changes, severe currency

exchange changes, etc.). Even in the presence of regulation disallowing selective disclosure, there remain reasons for analysts to maintain cordial relations with managers (e.g., simply getting managers to return phone calls, receiving favorable queuing during conference calls, etc.).

3. Trade generation incentives. Another reason analysts are allegedly predisposed towards optimism is that their firms also receive compensation through handling investor trades. As the argument goes, it is easier to convince an investor to buy a stock that they do not own rather than convincing them to sell a stock they must already own. Consequently, to generate investor purchases, analysts will optimistically bias their reports. Recent evidence by Cowen et al. (2006) and Jacob et al. (2008) suggests that incentives for optimistic bias are stronger for trading than for investment banking. They partition investment banks into those that provide investment banking and those that do not, where trading fees are the primary source of revenues, and find that *ex post* optimistic bias is stronger for analysts working at the non-investment bank firms. Also, Jacob et al. (2008) provide some evidence that affiliated analysts are actually more accurate than unaffiliated analysts, and moreover, the differential forecast accuracy appears due to the employment of better analysts and the presence of greater resources.

4. Institutional investor relationships. The close ties between institutional investors and investment banks also provide sources of conflicts for sell-side analysts. As recipients of sell-side research, institutions may take positions in securities based on the information and recommendations conveyed in analysts' formal reports. If an analyst then downgraded a security that an institution had taken a position in, this would clearly be viewed unfavorably by the institution.

5. Research for hire. Given that approximately one-third of public companies have no analyst coverage and over half have at most two analysts, a recent phenomenon in equity research is for companies to pay for research to be conducted on their company. Several consortiums have been established, such as the National Research Exchange and the Independent Research Network. The conflicts of interest in these arrangements are obvious, and it remains to be seen how these will be managed.

6. Themselves. Finally, an often overlooked source of conflicts for analysts is the behavioral bias inherent in the analysis of securities. Similar to the well-documented home bias in the finance literature, the familiarity analysts develop with firms and their managers can lead analysts to develop close affinity to a firm.

> This affinity may then result in analysts seeing the firm 'through rose-colored glasses,' and being incapable of downgrading or forecasting negative outcomes.

Of these six sources of analyst conflicts, the allegation that lucrative investment banking fees is the most cogent. Clearly, regardless of the reputation of a particular investment bank, any right-minded manager would steer clear of their services if sell-side analysts employed by that investment bank held negative views on the firm. Researchers have investigated such effects extensively, and it would appear that most researchers subscribe to the belief that these conflicts have strong effects on observed optimism in analysts' reports. Numerous studies document significantly more optimistic forecasts and recommendations for affiliated analysts (e.g., Lin and McNichols 1998, Michaely and Womack 1999, Dechow, Hutton, and Sloan 2000, Lin, McNichols, and O'Brien (2005).

One explanation other than analysts' deliberate optimism inspired by investment banking business is that among the distribution of investment banks, some will be the employers of analysts that are more optimistic about a particular firm, and it is the selection of those investment banks by the managers that explains the documented optimism by affiliated analysts. Research is unable to distinguish between these two explanations, but Ljungqvist, Marston and Wilhelm (2006) offer some evidence consistent with management choice. They examine investment banking deal flows and find no evidence that overoptimistic recommendations by analysts explain investment banking selection, the main determinant being the strength of prior investment banking relationships. Another explanation is that there is a collective level of heightened positive sentiment about firms that are in the growth stage and hence need external financing. Consistent with this, Bradshaw, Richardson, and Sloan (2006) document that both affiliated and unaffiliated analysts display increasing optimism around periods of external financing and both groups show declines in the levels of optimism subsequent to external financing. This is not inconsistent with investment banking conflicts leading to optimism in research, but it does attenuate the degree of sinister interpretation given to the reports of analysts that are viewed as 'affiliated.' If analysts (as well as other market participants) tend to be optimistic about subsets of firms, it is not surprising that it would be the subset that is growing and seeking external financing.

However, it is instructive to review the economic significance of investment banking conflicts as documented in the literature. Lin and McNichols (1998) provide one of the most compelling studies to review because of the relatively large sample and well-executed matched sample design. They examine approximately 2,400 seasoned equity offerings (SEO) spanning 1989-1994. Primary results examine for significant differences in one-year ahead and two-year ahead earnings per share forecasts, growth projections, and stock recommendations. A summary of their results is as follows:

	One-year ahead EPS	Two-year ahead EPS	Earnings growth	Stock Recommendation
Unaffiliated	0.071	0.098	0.207	3.901
Affiliated	0.070	0.099	0.213	4.259
Difference	-0.001	0.001	0.006	0.358
Significant difference?	No	No	Yes	Yes

Note: EPS forecasts are scaled by price. Earnings growth projections reflect forecasts of annual percentage growth. Stock recommendations are coded on a 1 to 5 scale, with 1 being 'strong sell' and 5 being 'strong buy'.

They find no differences in optimism in earnings forecasts, but they find analysts affiliated with SEOs provide higher growth projections and more positive recommendations. However, the economic significance of the differences do not seem large. For annual earnings growth projections, the difference is less than one percent, and the difference in stock recommendations is approximately one-third of a change in ranking. Adherents to the paradigm arguing that investment banking biases analysts to be optimistic would highlight that the analysts that are unaffiliated are almost as optimistic as the affiliated analysts because they too were using research to court the managers for the investment banking business, which is in conflict to the evidence discussed earlier in papers like Jacob et al. (2006).

6. Limited Evidence Exists Regarding What Analysts Do with Their Own Forecasts

It is presumed that analysts are sophisticated and their analyses are internally consistent. However, very little research has examined their outputs in a multivariate setting. For example, research has examined analysts' forecasting abilities extensively, and there have been moderate efforts to understand their recommendation abilities. Clearly, recommendations should be linked in some manner to analysts' valuations, and we believe from many capital markets studies (i.e., Ball and Brown 1968, etc.) that earnings expectations are positively correlated with prices. Thus, rational behavior by analysts would mean that their own earnings forecasts are correlated with their valuations that provide the basis for their stock recommendations.

Francis and Philbrick (1993) provided the earliest systematic study of the interplay between analysts' various forecasts. Although their sample prevents an examination of how individual analysts use their own forecasts. Nevertheless, their study is one of the first to attempt to understand how analysts incorporate specific information into their forecasts. They examined Value Line analysts, who issue earnings forecasts but include in their reports a ‘timeliness ranking’ of a stock, akin to an individual analyst’s stock recommendation but prepared by other analysts at Value Line. They hypothesized that analysts would attempt to curry favor with managers by diffusing unfavorable timeliness rankings by optimistic forecasts, and they conclude that Value Line analysts appear to behave in this manner.

Another early study that attempted to directly examine the within-analyst correlation of various outputs is Bandyopadhyay, Brown, and Richardson (1995), who examine analysts’ target prices and earnings forecasts. Based on the presumption that analysts use their own forecasts in deriving stock valuations, they hypothesize that both one-year ahead and two-year ahead earnings forecasts will be correlated with analysts target prices (i.e., valuations), and that the correlations will be stronger for longer horizon forecasts. Indeed, they document R^2s of approximately 30% (60%) when correlating changes in target prices with changes in one-year ahead (two-year ahead) earnings forecasts. Similarly, Loh and Mian (2006) find that analysts with more accurate earnings forecasts provide more profitable stock recommendations, consistent with analysts using their own forecasts as inputs into their valuations and recommendations.

Recently, there seems to be a growing understanding of the benefits of understanding analysts’ use of information, and attempts to measure within-analyst correlations of data are becoming more common. For example, Bradshaw (2002) performed a content analysis and found that analysts’ valuations are almost always based on various earnings-multiple heuristics, and Bradshaw (2004) documented that researcher-generated recommendations based on simple residual income valuations using analysts' earnings forecasts as inputs outperform the analysts' recommendations that are based on heuristics. Similarly, Barker (1999) and Asquith, Mikhail, and Au (2005) document a high degree of reliance by analysts on qualitative factors in communicating their analyses, supplementing their heuristic use of earnings forecasts to assess valuations of firms. Given increasing availability of line item forecasts other than earnings, there is also an increasing interest in the internal consistency of those measures as well. For example, Ertimur, Mayew, and Stubben (2008) examine the multiple-level forecast accuracy of analysts that provide disaggregated forecasts (i.e., sales and earnings).

The trend towards research that simultaneously considers multiple analyst outputs is a step in the right direction if our goal is to increase our knowledge of analysts using large sample databases. One of the common objectives of research on analysts is to provide evidence that allows us to peer inside the decision-making processes they follow. However, though there are benefits from the typical archival empirical approach, the methodology is necessarily limited in its ability to garner insights into how analysts make decisions. Alternatively, research methodologies that work with data other than the databases provided by I/B/E/S and other providers are likely to provide complementary approaches. The next two sections expand on these

7. We Think We Know *How* Analysts Forecast

As the literature on analysts has grown, researchers have moved beyond straightforward investigations of distributional properties of forecast errors and profitability of analysts' recommendations. The tenor of most studies is that the researchers are interested in *how* analysts perform their tasks. However, with few exceptions, none provide direct evidence on *how* analysts go about generating forecasts or making stock recommendations. The problem appears to be a preference for archival research, which is subject to data and methodological constraints. Thus, researchers tend towards similar approaches and typically regress forecast errors on different independent variables to explain forecast errors. Some papers attempt to provide indirect evidence, but the nature of these analyses limits the strength of conclusions we can draw about analysts' actual decision processes.

The typical research design adopted when a researcher holds some hypothesis about how analysts use some information signal is to estimate a regression of analyst forecast error on the information variable,

$$\text{Forecast Error} = \alpha+\beta X + e,$$

where X is the variable of interest. As summarized in figure XX, right-hand side variables have included past earnings changes, past price changes, analysts' forecast errors, income statement line items, balance sheet line items, financial statement footnote information, management forecasts, macroeconomic variables, and so on. From these econometric analyses, conclusions are drawn as to whether the analyst incorporated the information captured by the variable X in their earnings forecast process.

Such a research design is a study of associations, not behavior. However, it has become prevalent to draw conclusions regarding analysts' behavior from these tests. Notwithstanding the fact that the combination of the research designs and the conclusions do not actually speak to analysts' behavior, these results do not map into the way that forecasting is covered in most financial statement analysis courses and textbooks. This suggests that either the research designs that are utilized in an attempt to see into the forecasting process or the pedagogical approach to prospective analysis needs revision. At a minimum, it is important for researchers to be careful about drawing strong conclusions about analysts' behavior based only on data that can be quantified and used as inputs in a specification like that above.

One alternative is to continue the trend in simultaneously examining multiple analyst forecasts and other information, as discussed earlier. Though limited by the research design that relies on archival data, this approach allows extended insights into statistical associations. Combined with prior findings of associations between forecast errors and various information signals, multivariate analyses of analysts' outputs can address numerous interesting questions (e.g., does forecasting cash flows lead to more accurate forecasts, more profitable recommendations, and so on). The second alternative is to embrace alternative research methodologies, discussed next.

8. Empiricists Have Traditionally Not Embraced Alternative Methodologies (but This is Changing)

As noted above, the primary methodology employed in the analyst literature is the empirical analysis of archival data. With a few exceptions, only recently have other methodologies received more attention in the literature. A likely explanation for the disproportionate focus on analysis of archival data is that it is much less costly to download a panel of I/B/E/S data than it is to conduct an experiment or perform a content analysis of a distribution of analyst reports. This explanation mirrors the likely explanation for the disproportionate analysis of earnings forecast data relative to other analyst outputs for which data availability is lower, such as risk ratings and target prices.

An early paper by Larcker and Lessig (1983) is a good example of the limitation of statistical analysis of archival data. In this study, Larcker and Lessig perform an experiment with 31 subjects who were asked to make buy or no-buy decisions for 45 stocks. They were interested in the competing ability of linear modeling (i.e., regression analysis) and retroactive process tracing (i.e., ex post interviews of subjects) to accomplish two objectives: (i) predicting subjects buy and no-buy decision and (ii) identifying the relative importance of various information cues used by the subjects. These objectives continue to map very well into those of many analyst studies that employ archival data.

They found that both linear models and process tracing performed reasonably well at predicting the buy and no-buy decisions of the subjects. However, there were frequent differences between the two approaches in identifying relative cue importance to the subject's buy and no-buy decisions. These findings lead the authors to conclude that if the goal of a research study is the *prediction of a judgment decision*, then both approaches appear valid, and lower cost and complexity would favor linear modeling. However, if the goal of a research study is *to understand what information is used and how it is used*, a technique like retroactive process tracing seems necessary. This point cannot be emphasized enough, as it bears directly on the 'black box' in figure 1b.

The current shortcoming of the literature on sell-side analysts is our lack of understanding of what goes on inside the black box of what an analyst actually does. Fortunately, there is a growing use of alternative methodologies that complement research that uses linear models. Alternative approaches to understanding analysts' activities include surveys and interviews, experiments, rigorous content analysis approaches, and focused analysis of representative firms). Clearly, alternatives to linear modeling also have weaknesses (i.e., surveys risk biased responses, experiments have difficulty replicating complex unstructured tasks, content analysis only has access to the final communication medium rather than the process itself, analyzing a single brokerage firm may have no external validity, etc.). For such reasons, these approaches are to be viewed as complementary. Together, consistent evidence across alternative methodologies increases validity of research conclusions and is necessary for this literature to progress.

The popularity of the recent survey of managers by Graham, Harvey, and Rajgopal (2005) is testament to the level of potential interest in the results of a survey of financial executives. Although there are a number of various surveys of financial analysts, most are relatively limited in scope or geography.[3] A notable exception is a survey by Block (1999), who surveyed members of the Association for Investment Management and Research (AIMR). His survey was broadly focused and queried analysts on their uses of valuation models, importance of financial inputs, bases for recommendations, various opinions regarding market efficiency and dynamics. The most remarkable finding in his survey is that analysts overwhelmingly do not emphasize present value models to value firms. Additionally, he found that analysts do not pay much attention to dividend policy, they focus more on the long-term prospects than near-term quarterly results, and analysts believe that skilled portfolio managers can beat the market.

[3] For example, surveys have focused on analysts' opinions of cash flow accounting (McEnroe 1996) and forecast revisions (Moyes, Saadouni, Simon, and Williams 2001), and have been conducted in various international markets including Saudi Arabia (Alrazeen 1999), Japan (Mande and Ortman 2002), Belgium (Orens and Lybaert 2007), and China (Hu, Lin, and Li 2008).

As noted above, surveys provide useful insights, but a weakness is the possibility that respondents do not truthfully report. However, as also noted above, if this survey evidence is combined with alternative research methodologies and the results consistently point towards the same conclusion, concerns over threats to validity can be minimized. As an example of how a conclusion can be compelling based on the collective results from studies using alternative methodologies, consider the conclusion in Block (1999) that analysts do not rely very much on present value models. This could be due to some form of non-response bias, a miscommunication of what was meant by present value techniques, or analysts' concerns that their approaches are proprietary and they bias their responses. However, subsequent studies that adopted content analysis (Bradshaw 2002) and linear modeling (Bradshaw 2004) provide uniformly consistent results that analysts indeed do not appear to make stock recommendations consistent with present value-based models.

Published surveys on analysts are relatively rare, as are content analyses and focused studies of individual brokerage firms. Moreover, those that are published appear to be concentrated outside of what are typically considered 'top-tier' journals. This is unfortunate, because other than my own personal interactions with analysts and users of analysts' information, where most of my knowledge of analysts has been obtained, I have learned a great deal from reading these studies. On an optimistic note, research utilizing experimental research methods is much more common and seems to be increasingly acceptable to top-tier journals. Many of these types of studies employ undergraduate or graduate students as subjects, but it is becoming increasingly common to see actual analysts serving as subjects. For example, Libby et al. (2008) employ a sample of 81 experience analysts and examine the tension between maintenance of relationships with firm managers and optimism and pessimism in earnings forecasts. Perhaps more interesting than the actual experimental results, the post-experiment subject interviews provide insights into how analysts are aware of the optimism-to-pessimism pattern in earnings across fiscal periods, but believe this pattern helps them receive preferential treatment in conference calls. Again, echoing the theme that multiple research designs can be combined to increase the validity of a research conclusion, the evidence in Libby et al. (2008) regarding analysts' desire to receive preferential or favorable treatment in conference calls (even in a post-Regulation FD environment) is also shown by Mayew (2008), who extracted data from conference call transcripts. His archival empirical study also confirms that analysts' with optimistic research on a company get more attention during conference calls. Together the Mayew and Libby et al. studies give increased comfort that analysts are indeed still concerned about currying favor with managers.

A final trend that is serving to make research on analysts more cohesive across methodologies is a growing prevalence of accounting academics properly trained in experimental research techniques. Moreover, this is accompanied by the gaining acceptance of 'behavioral finance' research, which is incorporating psychology research on decision making. The majority of experimental accounting research relies on similar theories (Koonce and Mercer 2005). Further, researchers appear to be realizing that certain methodologies are suited for specific research questions. For questions which arise around situations of decision-making and information processing, experiments seem useful because of their ability to minimize confounding 'real-world' variables and manipulate the variables of interest (Bloomfield, Libby, and Nelson 2002).

9. Academics May Be Focusing Too Much on the Least Important Activities

As has been noted, the vast majority of research on analysts is focused on their ability to forecast earnings. The early literature pitted analysts against time-series forecasts, then gravitated towards identifying superior analysts with more accurate earnings forecasts. Recently, researchers have been simultaneously considering the interplay among various analyst outputs (e.g., earnings and recommendations), but the anchor of the analysis remains earnings forecast accuracy. If an individual with no understanding of sell-side analysts were to attempt to understand what they do based on a reading of our academic literature, that person would surely conclude that one of the things most important to analysts is their earnings forecasts. I contend that this would be a gross mischaracterization of the analyst's job function, and hence his/her incentives. I believe such a view characterizes that of many academics, and as a result impedes our ability to further our understanding of sell-side analysts.

To provide some perspective on the importance of earnings forecasts, table 1 provides a panel of data reflecting traits of analysts ranked in order of importance by respondents to the annual Institutional Investor Ranking of analysts. This ranking is the first-order determinant of an analyst's compensation (Groysberg, Healy, and Maber 2008). Thus, if we assume that analysts wish to maximize their compensation, then providing institutional investors with what they need, as reflected in the rankings, will be descriptive of aspects of their job towards which they devote significant effort.

The data in table 1 span 1998-2005, and show that the number of criteria reported in the rankings each year range from a low of eight items in 1998 to fifteen during 2002-

2004. The rankings indicate that the most important trait valued by institutional investors is industry knowledge, which has been the number one trait for all years of the survey. Clearly, analysts' are valued for their ability to see individual companies within the context of the industry as a whole. Other traits appear relatively stable in their importance across recent years, with two exceptions – earnings forecast and stock selection. Whereas earnings forecasts were ranked fifth in importance in 1998, they are ranked last in the most recent year in table 1. Similarly, stock selection was ranked as high as second in 1998, but has fallen to second-to-last in the last year of table 1. As a statistical measure of whether these changes are meaningful, table 2 provides a simple test of whether the changes in the ranking are significant. The mean change in rank is calculated for the annual changes in ranking, where rankings are converted to a [0,1] interval.[4] For both earnings forecast and stock selection traits, the average change in ranking across 1998-2005 is significantly negative, indicating that both measures have become less important to institutional investors, and presumably less important to analysts, relative to other characteristics. Of course, one explanation is that earnings forecasts and stock selection are viewed as necessary by institutional investors, and presumably by analysts as well, but that other aspects of their jobs are relatively more important. This is consistent with earnings forecasts and stock selection being important; however, as suggested above, it also is consistent with these aspects of an analyst's job being relatively unimportant when their roles are viewed in context.

[4] Each ranking is converted to RANK' to span the interval [0,1] as

$$RANK' = ((NRANK+1)-RANK)/NRANK,$$

where NRANK is the number of characteristics listed in the annual ranking and RANK is the numerical rank of the characteristic. Characteristics ranked in other years but not on the ranking in any individual year are assigned RANK'=0.

I believe that part of our focus on earnings forecast accuracy is driven simply by the wide availability of data on analysts' earnings forecasts and actual earnings and a predilection of accounting academics towards the investigation of phenomena that can be quantified. Measuring the accuracy of an earnings per share forecast suits our comfort zone. Similarly, measuring recommendation profitability is also appealing, despite numerous alternative measurement criteria decisions (i.e., return accumulation period, raw or adjusted returns, etc.). What is a lot more difficult to measure is the measurement of important aspects of the analysts' job function such as industry knowledge, assessment of firm strategy or quality of management, accessibility, the tone of their contextual reports, and so on. Nevertheless, researchers in this area must be open to alternative methodologies and data if the literature on analysts is to proceed in a meaningful way.

10. Analyst Data are Indirectly Helpful to Other Work Examining the Functioning of Capital Markets

In contrast to other critical points raised above, the following point is a commendation of research on analysts. As noted above, research on analysts has become pervasive with the elevation of analysts to a status of interesting economic agent worthy of individual examination. Comments numbered one through nine focus on this aspect of analysts. There is another very useful role of research using analyst data, which is that these data can provide insights into questions that arise in other capital market studies. Specifically, the identification and examination of asset pricing anomalies is an active area of research in the finance and accounting literatures. In the typical study, researchers demonstrate that future stock returns are systematically associated with information available *ex ante* (e.g., past earnings changes, past price changes, accounting accruals, insider trading, etc.). Such studies are always subject to the 'bad model' criticism, which argues that the correlation reflects an incomplete control for priced risk rather than a true asset pricing anomaly that can be costlessly arbitraged away.

Because of the difficulty of convincingly capturing priced risk (or priced risk factors), an alternative to addressing the bad model criticism is to use a research design that skirts the risk issue. Whereas capital market anomalies all pertain to how investors incorporate information into prices, and analysts' roles include the incorporation of information into their research, it is frequently useful to examine documented anomalies in the context of analysts' research. For example, as an extension of the seminal studies by Bernard and Thomas (1989, 1990) on the post-earnings announcement drift anomaly, Abarbanell and Bernard (1992) examine whether analysts incorporate the autocorrelation structure documented in the Bernard and Thomas papers into their forecasts. They find that similar to market prices, analysts underreact to prior earnings changes. Accordingly, critics that dismissed the post-earnings announcement drift anomaly as a mis-measurement of risk must also explain why the phenomenon shows up in a non-asset pricing setting. Similar analyses have been conducted with respect to the glamour anomaly (Frankel and Lee 1998), the January effect (Ackert and Athanassakos 2000), and the accruals anomaly (Bradshaw, Richardson, and Sloan 2001; Barth and Hutton 2004),

CONCLUSION

In summary, we have learned a lot about analysts and their role in capital markets. However, research has focused on a narrow set of analyst outputs to draw conclusions regarding what analysts do and how they do it. Further, this research is largely limited to variables that can be quantified, there is limited but growing investigation of the co-determination of analysts' outputs, and there is a disproportionately large emphasis on what is likely a relatively unimportant activity – forecasting earnings. For this literature to progress, research that provides any kind of penetration of the 'black box' of how analysts actually process information should be encouraged, even if methods or approaches are imperfect.

This literature finds itself at an interesting juncture of time, with numerous recent shocks to the capital markets (e.g., Regulation FD, $1.4 billion SEC/state regulator settlement against ten large investment banks, a new independent brokerage research requirement, disclosure requirements of NASD Rule 2711 and NYSE Rule 472, and a trend towards paying for analyst coverage). Thus, there are numerous opportunities for the literature to progress if researchers move beyond the current prevailing paradigm of performing univariate analyses of earnings forecasts. Zmijewski (1993) discussed a literature review by Brown (1993), and echoed similar sentiments to those offered here. In commenting on the state of the literature at that time, he stated, "That is not to say, however, that researching the 'same old' issues using the 'same old' methodologies will be informative.… It will, naturally, become more and more challenging to identify interesting questions and to design interesting and meaningful empirical tests."

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Figure 1a – Analyst Decision Process Schematic

Panel A: Decision process schematic

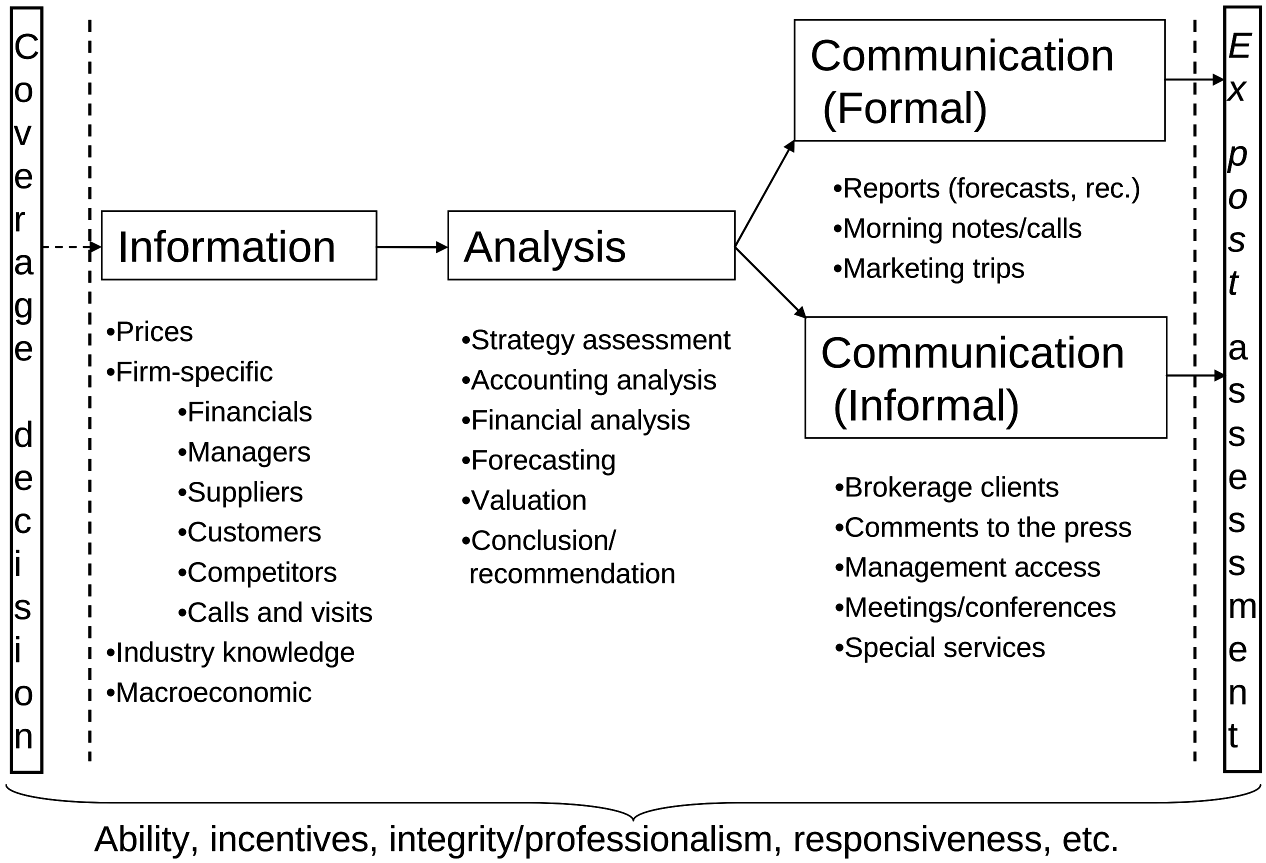


Figure 1b – Analyst Decision Process Schematic (cont.)

Panel A: Decision process schematic with most common research designs indicated

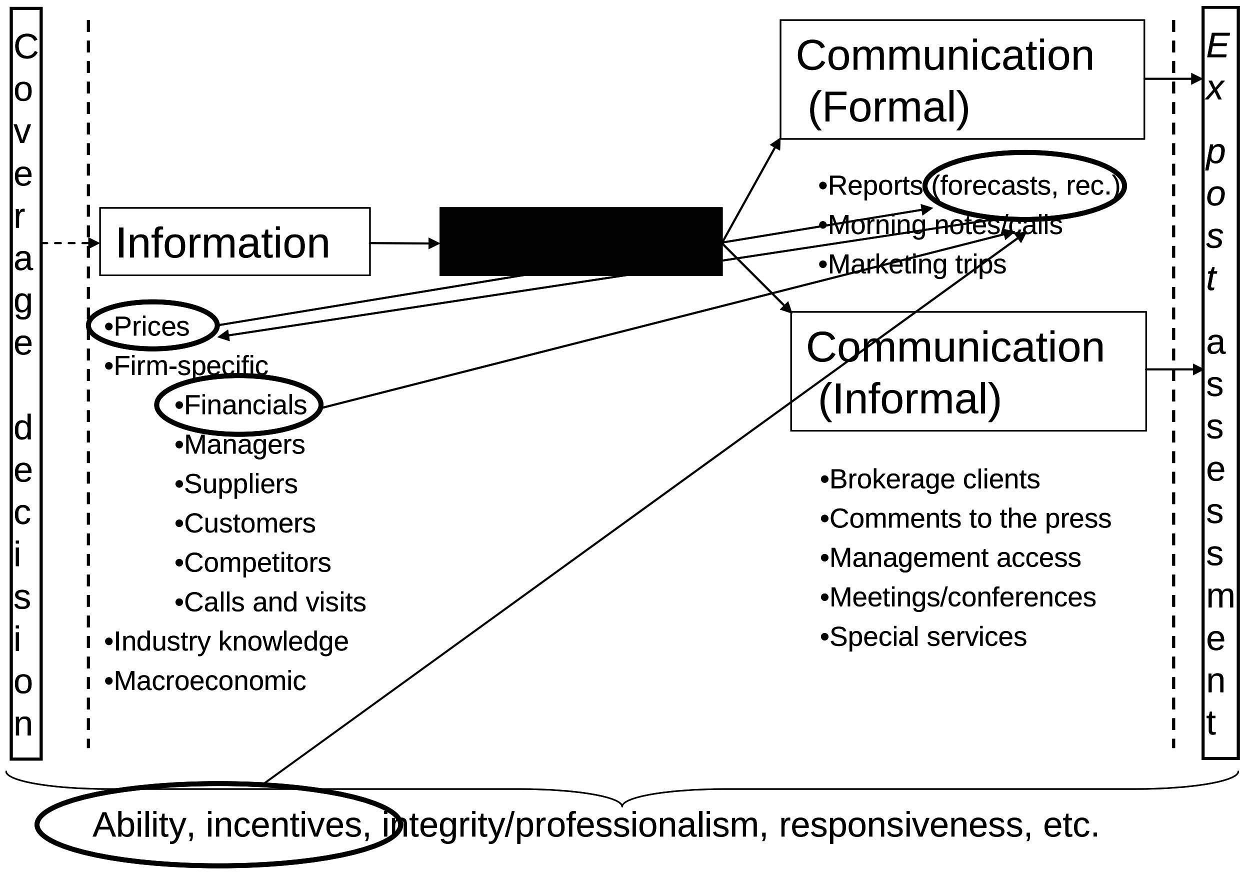


Figure 2 – Timeline of Major Areas of Research 1968-2006

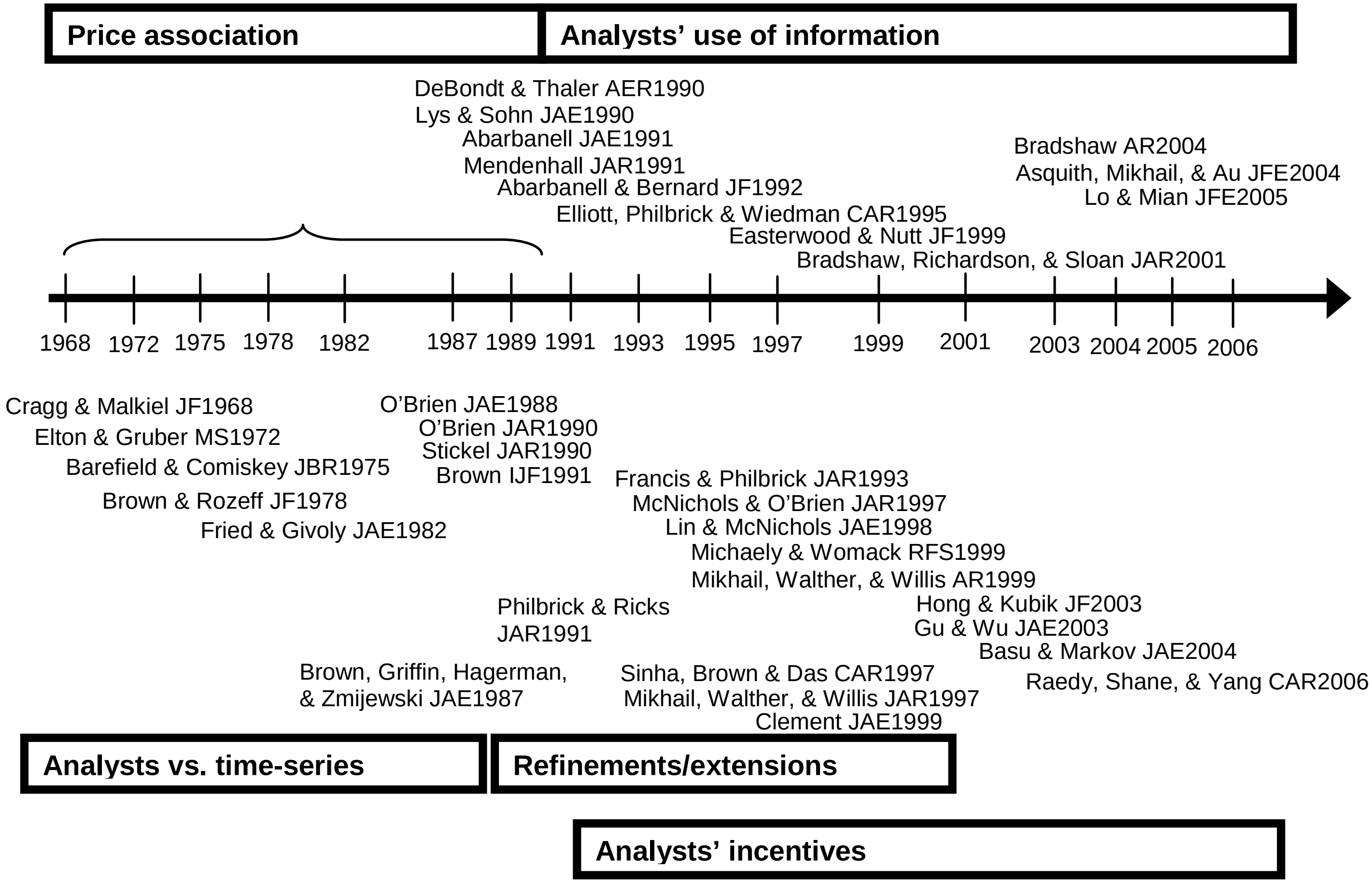


Table 1 – Summary of Institutional Investor Ranking Surveys 1998-2005

	1998	1999	2000	2001	2002	2003	2004	2005
Industry knowledge	1	1	1	1	1	1	1	1
Integrity/professionalism					2	2	2	2
Accessibility/responsiveness				2	3	3	3	3
Management access				7	5	5	4	4
Special services	4	3	2	5	7	6	5	5
Written reports	3	2	4	6	8	7	7	6
Timely calls and visits				4	4	4	6	7
Communication skills					10	9	8	8
Financial models			3	8	9	10	10	9
Management of conflicts of interest				3	6	8	9	10
Stock selection	2	5	7	10	11	11	11	11
Earnings estimates	5	6	5	9	12	12	12	12
Quality of sales force	7	7	8	11	13	13	13	
Market making	8	8	9	12	14	14	14	
Primary market services			10		15	15	15	
Servicing	6	4	6					

Table 2 – Change in Ranked Characteristics, Institutional Investor Ranking Surveys 1998-2005

	Avg. rank change, 98-05
(#2) Integrity/professionalism	0.13
(#3) Accessibility/responsiveness	0.12
Management access	0.11
Timely calls and visits	0.07
Communication skills	0.06
Financial models	0.05
Management of conflicts of interest	0.04
Special services	0.01
(#1) Industry knowledge	0.00
Primary market services	0.00
Market making	-0.02
Written reports	-0.02
Quality of sales force	-0.04*
Servicing	-0.05
Earnings estimates	-0.06*
Stock selection	-0.10***

Analyst Forecasting Errors: Additional Evidence

Lawrence D. Brown

Analyst forecasting errors are approximately as large as Dreman and Berry (1995) documented, and an optimistic bias is evident for all years from 1985 through 1996. In contrast to their findings, I show that analyst forecasting errors and bias have decreased over time. Moreover, the optimistic bias in quarterly forecasts was absent for S&P 500 firms from 1993 through 1996. Analyst forecasting errors are smaller for (1) S&P 500 firms than for other firms; (2) firms with comparatively large amounts of market capitalization, absolute value of earnings forecast, and analyst following; and (3) firms in certain industries.

In recent issues of this journal, David Dreman, Michael Berry, and I have presented alternative views of analysts' earnings forecast errors and their implications for security analysis (Dreman and Berry 1995, Brown 1996, Dreman 1996). The first two papers provided alternative views concerning several issues, including whether (1) analysts' earnings forecast errors are "too large," (2) analysts' earnings forecast errors have increased over time, and (3) analysts' earnings forecasts are optimistically biased.

In the opinion of Dreman and Berry, analysts' earnings forecast errors are too large, and using the deflators the authors suggested (e.g., actual or predicted earnings), analyst forecasting errors do appear large. If analysts' earnings forecast errors are deflated by stock price, however, or compared with forecasts based on extrapolative techniques, they do not appear too large. Dreman–Berry also maintained that analysts' earnings forecasting errors have increased over time. My analysis of their findings, however, suggested that the accuracy of analysts' earnings forecasts has actually improved over time. In addition, Dreman–Berry provided evidence that analysts' earnings forecasts are biased toward optimism. Relying on information provided by I/B/E/S International, I showed that an optimistic bias was absent for S&P 500 firms for the 11 quarters from first-quarter 1993 through third-quarter 1995.

In his letter to the editor, Dreman (1996) responded to the views I expressed in my article, disagreeing with most of them. He correctly observed that much of my analysis was based on the Abel–Noser database, which Dreman–Berry had used but which was inaccessible to me; my analysis relied on summary information provided in the Dreman–Berry article. Moreover, although not stated by Dreman, neither did I examine the I/B/E/S data that I had relied on in my 1996 article. Instead, I relied on summary information provided to me by I/B/E/S.

This article is based on I/B/E/S data for fourth-quarter 1983 through second-quarter 1996. It presents evidence regarding the following issues:

- Is the Dreman–Berry result that analyst forecasting errors are "too large" robust to using a different data source than the Abel–Noser database?
- Is the Dreman–Berry conclusion that analysts' forecasting errors have increased over time robust to using I/B/E/S data? Does it pertain equally to S&P 500 firms and other firms?
- Is the optimistic bias documented by Dreman–Berry robust to using I/B/E/S data? Does this optimism pertain equally to S&P 500 and other firms? Has it been mitigated over time? Is the extent of mitigation similar for both S&P 500 firms and other firms?
- Do analyst forecasting errors and bias differ depending on such firm-specific factors as market capitalization, absolute value of predicted EPS, analyst following, and industry classification?

PRELIMINARY RESULTS

Dreman and Berry relied on the Abel–Noser database, which uses information from Value Line, Zacks Investment Research, I/B/E/S, and First Call. Because different vendors of analyst forecasts define both forecasted and actual earnings numbers differently, mixing data from different vendors introduces error (Philbrick and Ricks 1991), potentially making analysts' earnings forecast errors appear larger than they actually are. For this study, I used the data of a single vendor, I/B/E/S, for the

Lawrence D. Brown is Controllers RoundTable Research Professor at Georgia State University.

time period from fourth-quarter 1983 through second-quarter 1996. The sample consists of all U.S. firms for which analyst earnings forecast errors could be calculated.

Figure 1 provides frequency distributions using the SURPE and SURPF definitions of analyst forecasting errors (earnings surprise), defined as

SURPE = (Actual quarterly earnings – Predicted quarterly earnings)/|Actual quarterly earnings|

SURPF = (Actual quarterly earnings – Predicted quarterly earnings)/|Predicted quarterly earnings|.

Predicted quarterly earnings were obtained from the I/B/E/S summary tape using the last consensus (mean) estimate prior to the firm's quarterly earnings announcement.[1]

SURPE and SURPF are two of the four definitions of earnings surprise Dreman–Berry and I used in our research.[2] My Figure 1 corresponds to their Figure 1 pertaining to SURPE and SURPF, and my results are very similar to theirs. More specifically, the modal and median values of earnings surprise are zero; *small* positive errors are more frequent than negative errors; and *large* negative errors outnumber positive errors. These findings suggest that whereas analysts are more likely to be on target than anywhere else, managers manipulate earnings in a way to generate a considerable number of small positive (relative to small negative) surprises and large negative (relative to large positive) surprises ("big baths").[3]

I/B/E/S VERSUS ABEL–NOSER DATA

Table 1 provides summary statistics on the I/B/E/S and Abel–Noser data. The I/B/E/S results are based on my analysis of these data; the Abel–Noser results are reproduced from Dreman–Berry's Table 1. The average error (mean absolute surprise) using the I/B/E/S data is substantially larger than that using the Abel–Noser data. The I/B/E/S SURPE of 0.590 is approximately one-third greater than the Abel–Noser SURPE of 0.438, and the I/B/E/S SURPF of 0.916 is more than twice as large as the Abel–Noser SURPF of 0.415. Moreover, the mean surprise (bias) using the I/B/E/S data is also substantially larger in absolute value than that documented by Dreman–Berry using the Abel–Noser data. More particularly, the I/B/E/S SURPE and SURPF are –0.316 and –0.414, respectively, compared with the Abel–Noser SURPE and SURPF of –0.250 and –0.111.

My results could differ from Dreman–Berry's because of different sample-selection procedures. Dreman–Berry's sample is confined to firms with fiscal years ending in March, June, September, or December that are followed (after 1981) by at least four analysts. When the I/B/E/S sample is similarly restricted, the results are nearly identical to Dreman–Berry's.[4] More particularly, for the 46,859 I/B/E/S observations that satisfy these criteria, the average absolute surprise of 0.416 (SURPE definition) is similar to Dreman–Berry's 0.438, and the mean SURPE of –0.218 using the I/B/E/S sample closely approximates Dreman–Berry's –0.250.

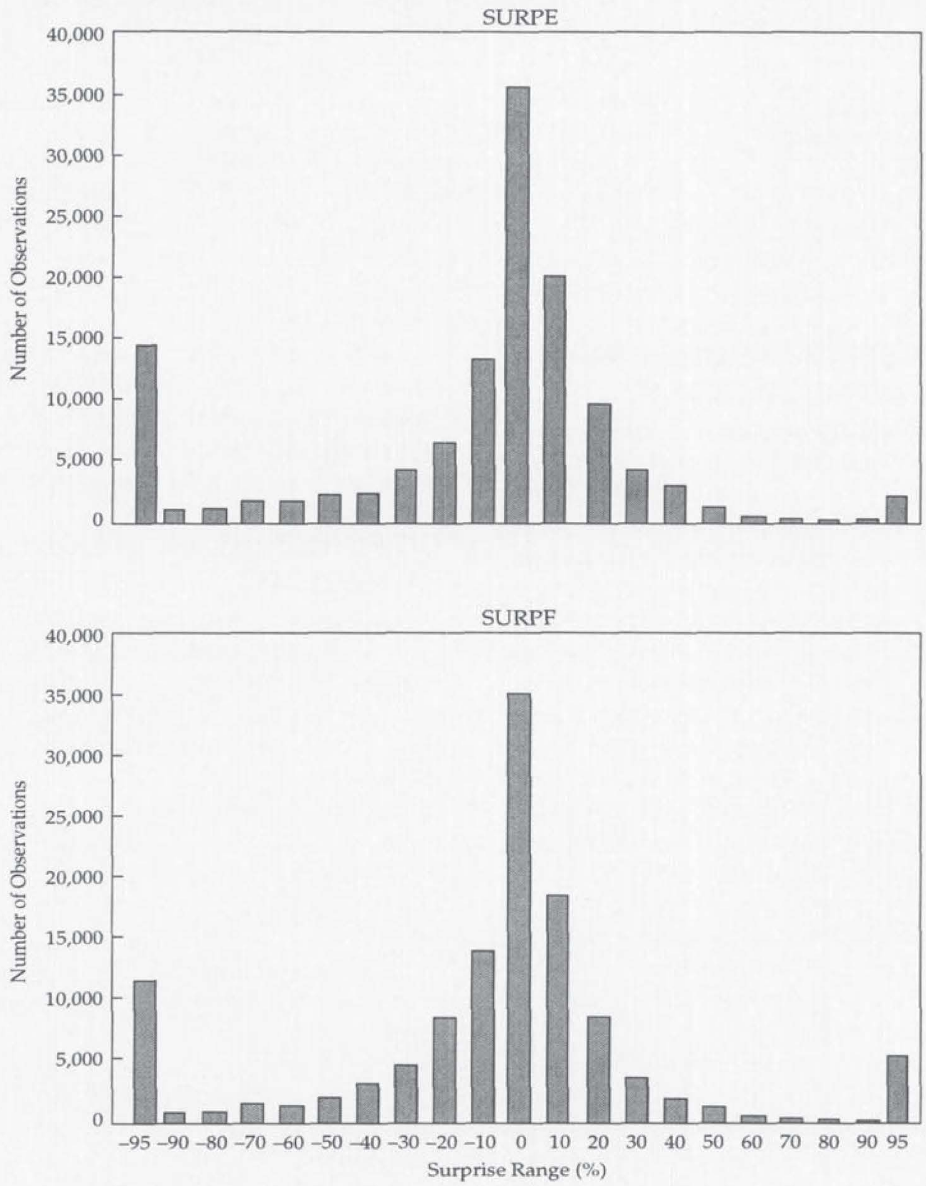
From these results, I conclude that the Dreman–Berry finding of large analyst forecasting errors is robust to using a different data source. Dreman–Berry used Abel–Noser data and examined the first-quarter 1974 through fourth-quarter 1991 time period; I obtained similar results using the I/B/E/S data for fourth-quarter 1983 through second-quarter 1996.

HAVE FORECASTING ERRORS CHANGED?

Evidence regarding five definitions of error—mean absolute surprise, mean surprise (bias), and the proportion of errors outside the +/–10 percent, +10 percent, and –10 percent bandwidths—is presented in Table 2 for all firms, S&P 500 firms, and non-S&P 500 firms.[5] All five error metrics use the SURPF definition of earnings surprise, which has predicted quarterly earnings as its deflator. Dreman–Berry provided evidence pertaining to three +/– bandwidths: 5 percent, 10 percent, and 15 percent. I focused on the second of these bandwidths, +/–10 percent, and considered its plus and minus sides separately.[6]

Dreman–Berry concluded that analyst forecasting errors increase over time. In contrast, Table 2 reveals that both mean absolute surprise and mean surprise (bias) have *decreased* significantly over time. This result is borne out by the rank correlations of analyst forecasting error with year, which are –0.973 and 0.489 for mean absolute surprise and mean surprise, respectively.[7] Nevertheless, the mean surprise is negative and significant in every year from 1985 through 1996, suggesting that, although the optimistic bias has been mitigated, it remains significant. The rank correlations of time with the proportion of errors outside the +/–10 percent, +10 percent, and –10 percent bandwidths are –0.995, –0.038, and –0.945, respectively. The –10 percent bandwidth result is significant, but the +10 percent bandwidth result is not. Thus, the temporal reduction of error results from mitigation of the optimistic bias. Indeed, no temporal reduction in the percentage of large positive errors (i.e., earnings *underestimates*) has occurred.

Figure 1. Histograms of SURPE and SURPF



Comparison of S&P 500 firms with other firms is important because many investors invest exclusively in S&P 500 firms and/or use the S&P 500 Index as a benchmark. Analyst forecasting errors are much smaller for S&P 500 firms than for other firms. More specifically, in *every* year, the mean absolute surprise and the proportion of forecasts outside the +/–10 percent, +10 percent, and –10 percent bandwidths is smaller for the S&P 500 firms than it is for the other firms. Clearly, the earnings of S&P 500 firms are easier to forecast than are those of non-S&P 500 firms.

Although forecasts for S&P 500 firms exhibit a significant optimistic bias for the 1984–96 period as a whole, the optimistic bias in forecasting quarterly earnings of S&P 500 firms disappeared as of 1993. More specifically, for S&P 500 firms, a significant optimistic bias is evident in every year in the 1985–92 period but not in the four most recent years, 1993 through 1996. In contrast, the bottom panel of Table 2 reveals that the optimistic bias in forecasting quarterly earnings of other (non-S&P 500) firms exists in all 12 years, 1985 through 1996. Perhaps the disappearance of the optimistic bias for S&P 500 firms is attributable to mitigation of the big-bath phenomenon or a lessening of the tendency of these firms' managers to manipulate earnings in a way to generate a large number of small positive (relative to small negative) surprises.[8]

Table 1. Descriptive Statistics for Earnings Forecast Errors

	I/B/E/S (4Q 1983–2Q 1996)		Abel–Noser (1Q 1974–4Q 1991)	
Statistic	SURPE	SURPF	SURPE	SURPF
Number of forecasts	129,436		66,100	
Mean absolute surprise	0.590	0.916	0.438	0.415
Mean surprise (bias)	–0.316*	–0.414*	–0.250*	–0.111*
Median	0.000	0.000	0.000	0.000
Maximum	314.000	863.000	49.000	48.000
Minimum	–186.259	–819.000	–216.000	–282.600

Note: SURPE (SURPF) is consensus EPS surprise as a percent of absolute value of actual (forecast) EPS.
*Significant at the 5 percent level, two-tailed test.

DO FORECASTING ERRORS DIFFER BY FIRM-SPECIFIC FACTORS?

Table 3 shows whether errors differ by market capitalization, absolute value of earnings forecast, or analyst following. Such comparisons are relevant because many investors invest primarily in large firms, firms with comparatively large earnings forecasts, or firms with relatively heavy analyst following. For these investors, the average analyst earnings forecast error per se is less relevant than the average forecasting error for these firm-specific subsamples.

The market capitalization results are monotonic for four of the five error measures: mean absolute surprise, mean surprise, and proportion of errors outside the +/–10 percent and –10 percent bandwidths. The highest capitalization group (i.e., firms with market caps in excess of $3 billion) has a smaller proportion of errors outside the +10 percent bandwidth than do any of the other market cap groups. Regarding bias, a significant optimistic bias (negative mean surprise) is evident for all market caps except the largest one.

The absolute value of earnings forecast results is not monotonic for any of the five definitions of error. Nevertheless, the mean absolute surprise and the mean surprise (bias) results are nearly monotonic; the exception occurs when forecasted earnings are at least $1. For this group, the mean absolute surprise and the mean surprise (bias) are approximately halfway between what they are for the [$0.10, $0.25) and [$0.25, $0.50) groups. The bandwidth results are similar to the mean absolute surprise and bias results in that the largest absolute value of earnings forecast group (i.e., ≥ $1) does not have the smallest proportion of errors outside the +/–10 percent, +10 percent, or –10 percent bandwidths.[9]

Similar to the absolute value of earnings forecast results, the analyst-following results are not monotonic for any of the five definitions of error. Nevertheless, the results are monotonic for all five error measures as the number of analysts increases from 1 to 5, and the smallest errors are obtained for the largest analyst following (10 or more) for four of the error measures.[10] Moreover, the rank correlations for the five error measures range from an absolute value of 0.782 to 0.988, and they all are statistically significant. Thus, error generally decreases when analyst following increases.

DO FORECASTING ERRORS DIFFER BY SECTOR?

The five error metrics are provided in Table 4 for each of the 14 industries in the I/B/E/S sample with data pertaining to at least 50 firms. The mean absolute surprise ranges from a low of 0.255 to a high of 1.663. Two industries have a mean absolute surprise below 0.400: food and kindred products (0.255) and holding companies and other investment offices (0.392). At the other extreme, two industries have mean absolute surprises in excess of 1.0: oil and gas extraction (1.663) and primary metal industries (1.267).

Eleven of the 14 industries evidence a significant optimistic bias. Optimistic bias for the other three—transportation equipment, communications, and insurance carriers—is not significant. The mean surprises range from a low of –0.068 to a high of –0.721. Three industries have an optimistic bias below 0.080 in absolute value: food and kindred products (–0.068), transportation equipment (–0.070), and communications (–0.076). At the other extreme, two industries have an optimistic bias above 0.500 in absolute value: oil and gas extraction (–0.721) and primary metal industries (–0.532).

The proportion of analyst forecasting errors outside the +/–10 percent bandwidth ranges from a low of 0.361 to a high of 0.780. Two industries have less than 40 percent of their observations outside the +/–10 percent bandwidth: food and kindred products (0.361) and depository institutions (0.369). At the other extreme, two industries have more than two-thirds of their observations outside the +/–10 percent bandwidth: oil and gas extraction (0.780) and primary metal industries (0.683). Twelve of the 14 industries have more errors outside the –10 percent than outside the +10 percent

Table 2. Forecast Errors by Year: All Firms, S&P 500 Firms, and Other Firms

Year/Statistic	Number of Firms	Number of Forecasts	Mean Absolute Surprise	Mean Surprise	+/–10 Percent[a]	+10 Percent[a]	–10 Percent[a]
All firms							
1984	2,109	2,246	2.525	0.795	0.697	0.311	0.386
1985	2,525	8,608	1.593	–0.667*	0.651	0.226	0.426
1986	2,580	8,506	1.773	–1.007*	0.656	0.245	0.412
1987	2,829	8,856	1.362	–0.700*	0.650	0.264	0.386
1988	2,804	9,041	1.067	–0.468*	0.620	0.269	0.351
1989	2,874	9,461	0.959	–0.537*	0.615	0.240	0.374
1990	2,890	9,627	1.034	–0.685*	0.600	0.215	0.384
1991	2,875	9,583	0.802	–0.444*	0.598	0.242	0.356
1992	3,195	10,702	0.688	–0.330*	0.557	0.261	0.296
1993	3,630	12,563	0.583	–0.230*	0.544	0.258	0.286
1994	4,193	14,213	0.494	–0.189*	0.514	0.258	0.256
1995	4,476	15,013	0.541	–0.244*	0.510	0.256	0.255
1996	4,593	11,008	0.527	–0.173*	0.501	0.260	0.241
Mean			0.916	–0.414*	0.577	0.252	0.326
Rank Correlation			–0.973*	0.489*	–0.995*	–0.038	–0.945*
S&P 500 firms							
1984	431	452	0.701	0.237	0.593	0.305	0.288
1985	443	1,743	0.748	–0.474*	0.503	0.186	0.317
1986	453	1,714	0.620	–0.250*	0.496	0.225	0.271
1987	463	1,791	0.487	–0.137*	0.487	0.245	0.243
1988	466	1,852	0.382	–0.143*	0.470	0.259	0.211
1989	473	1,842	0.427	–0.166*	0.447	0.203	0.245
1990	476	1,896	0.331	–0.113*	0.441	0.191	0.249
1991	481	1,892	0.442	–0.267*	0.467	0.189	0.277
1992	485	1,887	0.467	–0.148*	0.420	0.205	0.215
1993	486	1,983	0.345	0.027	0.409	0.220	0.189
1994	492	1,993	0.233	0.027	0.335	0.208	0.126
1995	492	1,936	0.190	–0.008	0.335	0.196	0.139
1996	494	1,314	0.310	0.002	0.318	0.177	0.141
Mean			0.418	–0.129*	0.431	0.211	0.220
Rank Correlation			–0.868*	0.357	–0.978*	–0.462	–0.819*
Other firms							
1984	1,678	1,794	2.985	0.935	0.724	0.312	0.411
1985	2,082	6,865	1.807	–0.716*	0.689	0.236	0.453
1986	2,127	6,792	2.064	–1.198*	0.697	0.250	0.447
1987	2,366	7,074	1.583	–0.843*	0.692	0.269	0.422
1988	2,338	7,189	1.244	–0.552*	0.659	0.272	0.387
1989	2,401	7,619	1.087	–0.626*	0.655	0.250	0.406
1990	2,414	7,731	1.206	–0.825*	0.639	0.221	0.417
1991	2,394	7,691	0.890	–0.488*	0.630	0.255	0.376
1992	2,710	8,815	0.735	–0.369*	0.586	0.274	0.313
1993	3,144	10,580	0.628	–0.278*	0.569	0.265	0.305
1994	3,701	12,220	0.537	–0.225*	0.543	0.266	0.277
1995	3,984	13,077	0.593	–0.279*	0.536	0.264	0.272
1996	4,099	9,694	0.557	–0.197*	0.526	0.272	0.254
Mean			1.019	–0.473*	0.608	0.260	0.348
Rank Correlation			–0.973*	0.489*	–0.984*	0.088	–0.912*

Note: Mean absolute surprise, mean surprise, and the percentage of surprises outside the three bandwidths use absolute value of earnings forecast as the deflator.

[a]Proportion of surprises outside bandwidth.

*Significant at the 5 percent level, two-tailed test.

Table 3. Forecast Errors Classified by Market Capitalization, Absolute Value of Earnings Forecast, and Analyst Following

	Number of Firms	Number of Forecasts	Mean Absolute Surprise	Mean Surprise	+/−10 Percent[d]	+10 Percent[d]	−10 Percent[d]
Market capitalization ($ millions)[a]							
<50	3,137	18,247	2.198	−1.445*	0.774	0.242	0.532
[50–100)	3,316	17,572	1.228	−0.616*	0.679	0.266	0.412
[100–500)	4,529	46,349	0.749	−0.271*	0.585	0.267	0.318
[500–3,000)	2,350	33,777	0.511	−0.096*	0.481	0.246	0.234
≥3,000	652	12,445	0.278	−0.019	0.370	0.203	0.167
Rank correlation			−1.000*	1.000*	−1.000*	−0.300	−1.000*
Absolute value of earnings forecast (cents)[b]							
<5	2,731	8,588	5.407	−2.564*	0.819	0.348	0.471
[5–10)	3,750	13,796	1.528	−0.681*	0.827	0.363	0.464
[10–25)	5,863	40,552	0.644	−0.300*	0.598	0.258	0.340
[25–50)	5,210	37,857	0.380	−0.159*	0.499	0.218	0.282
[50–100)	2,957	22,100	0.297	−0.105*	0.444	0.199	0.245
≥100	1,094	6,544	0.607	−0.250*	0.507	0.277	0.281
Rank correlation			−0.829*	0.829*	−0.771	−0.771	−0.943*
Analyst following (number of analysts)[c]							
1	6,189	35,979	1.421	−0.593*	0.707	0.293	0.414
2	5,011	22,983	1.035	−0.578*	0.629	0.272	0.358
3	3,913	15,728	0.790	−0.364*	0.581	0.251	0.330
4	3,077	11,411	0.674	−0.294*	0.544	0.246	0.298
5	2,384	8,532	0.581	−0.225*	0.519	0.241	0.278
6	1,898	6,775	0.762	−0.460*	0.482	0.217	0.266
7	1,555	5,354	0.553	−0.285*	0.465	0.207	0.258
8	1,296	4,356	0.795	−0.135	0.449	0.191	0.258
9	1,090	3,664	0.486	−0.233*	0.452	0.208	0.244
≥10	1,023	14,654	0.354	−0.126*	0.387	0.192	0.195
Rank correlation			−0.782*	0.842*	−0.988*	−0.939*	−0.988*

Note: Mean absolute surprise, mean surprise, and the percentage of surprises outside the three bandwidths use absolute value of earnings forecast as the deflator.

[a]Stock price multiplied by number of common stocks outstanding.

[b]Earnings forecast is the I/B/E/S mean forecast.

[c]Number of analysts whose forecast is included in the calculation of the I/B/E/S mean forecast.

[d]Proportion of surprises outside bandwidth.

*Significant at the 5 percent level, two-tailed test.

bandwidth, indicating that when large errors occur, analysts are more likely to overestimate earnings (optimistic bias) than to underestimate them (pessimistic bias). The two exceptions are depository institutions and insurance carriers. Perhaps these two industries are less likely than the other 12 to take big baths, which induce large negative errors and give the appearance of analyst optimism.

CONCLUSION

Using the Abel–Noser database for 1974 through 1991, Dreman and Berry argued that analyst forecasting errors are too large. Based on the I/B/E/S database for 1983 through 1996, I show that analysts' earnings forecast errors are approximately as large as Dreman–Berry documented. Thus, their results appear to have external validity.

Dreman–Berry maintained that analyst forecasting errors have increased over time. In a 1996 article, I argued that the Abel–Noser data, as summarized by Dreman–Berry, suggest precisely the opposite. In his critique of my analysis, David Dreman correctly pointed out that I did not access the data Dreman–Berry used to reach their conclusions. In this study, I used I/B/E/S data to examine five error metrics to determine whether analyst forecasting accuracy has deteriorated over time. I found that analyst forecasting errors have *decreased* significantly over time, especially for mean absolute surprise and the proportion of errors outside the +/−10 percent and −10 percent bandwidths.[11] My finding that analysts' earnings forecast errors have decreased over time is robust to firms included in as opposed to those excluded from the S&P 500.

I examined whether analyst forecasting errors differ according to certain firm-specific factors:

Table 4. Forecast Errors by Industry

SIC Code	Industry Name	Number of Firms	Number of Forecasts	Mean Absolute Surprise	Mean Surprise	+/−10 Percent[a]	+10 Percent[a]	−10 Percent[a]
13	Oil and gas extraction	73	1,681	1.663	−0.721*	0.780	0.338	0.442
20	Food and kindred products	55	1,644	0.255	−0.068*	0.361	0.166	0.195
28	Chemicals and allied products	128	3,910	0.454	−0.159*	0.422	0.189	0.233
33	Primary metal industries	63	1,619	1.267	−0.532*	0.683	0.298	0.385
35	Industrial, commercial machinery and computer equipment	128	3,958	0.794	−0.243*	0.596	0.274	0.322
36	Electronics and other equipment companies	104	2,824	0.856	−0.370*	0.556	0.237	0.319
37	Transportation equipment	66	2,096	0.820	−0.070	0.553	0.249	0.305
38	Measurement instruments; photo goods; watches	76	1,991	0.445	−0.186*	0.425	0.186	0.239
48	Communications	56	1,292	0.455	−0.076	0.429	0.202	0.227
49	Electric, gas, and sanitary services	190	6,766	0.436	−0.130*	0.560	0.261	0.299
60	Depository institutions	421	7,298	0.543	−0.336*	0.369	0.197	0.171
63	Insurance carriers	189	4,453	0.512	−0.142	0.517	0.285	0.232
67	Holding; other investment offices	82	777	0.392	−0.151*	0.539	0.175	0.364
73	Business services	78	2,111	0.540	−0.263*	0.448	0.182	0.266

Notes: Mean absolute surprise, mean surprise, and the percentage of surprises outside the three bandwidths use absolute value of earnings forecast as the deflator. To be included in Table 4, an industry must have more than 50 firms in the sample.

[a]Proportion of forecast errors (using absolute value of earnings forecast as a deflator) outside bandwidth.

*Significant at the 5 percent level, two-tailed test.

inclusion in the S&P 500, market capitalization, absolute value of earnings forecast, analyst following, and industry membership. I showed that: (1) analyst forecasting errors for S&P 500 firms are smaller than for other firms; (2) analyst forecasting errors are relatively small for firms with comparatively large market cap, absolute value of earnings forecast, and analyst following; and (3) analyst forecasting errors for firms in certain industries are substantially larger than those in other industries. Thus, depending on the nature of the firms followed by investors, analysts' earnings forecast errors may be considerably larger or smaller than average.

Dreman and Berry showed that analysts' earnings forecasts exhibit an optimistic bias. I had argued in my 1996 paper that the optimistic bias was not evident for S&P 500 firms for the period from first-quarter 1993 through third-quarter 1995. Moreover, according to I/B/E/S, the optimistic bias has not been evident for S&P 500 firms for the subsequent period, fourth-quarter 1995 through second-quarter 1997.[12]

Based on the I/B/E/S data, which include both S&P 500 and other firms, I documented an optimistic bias in analysts' quarterly earnings forecasts for all years, 1985 through 1996, and in 11 of 14 industries. I also showed that the optimistic bias in quarterly forecasts has diminished significantly over time for both S&P 500 and other firms and that it was absent for S&P 500 firms for each year from 1993 through 1996. The optimistic bias in quarterly forecasts for non-S&P 500 firms remains.[13]

NOTES

1. Because earnings forecast errors cannot be calculated when the actual or quarterly earnings forecast equals zero, these observations were omitted from the analysis. To be consistent with Dreman–Berry, I did not adjust outliers in any manner.
2. The other two definitions of earnings surprise are SURP8 and SURPC7, which respectively use the standard deviation of trailing eight-quarter actual earnings per share and the standard deviation of trailing seven-quarter changes in earnings per share.
3. Other studies have documented that managers manipulate earnings in order to report positive earnings, positive earnings growth, and/or earnings that exceed analyst expectations. When managers cannot succeed in these goals, they are likely to take a "big bath." See Lowenstein (1997).
4. For simplicity, I do not provide these results in a table.
5. These results and those that follow are based on the full I/B/E/S sample of 129,436 observations described in Table 1.
6. This suggestion was made when I presented an earlier version of this article at the 1997 Prudential Securities Quantitative Research Seminar for Institutional Investors.
7. The positive rank correlation for mean surprise indicates that the bias has become less negative (i.e., there has been a temporal reduction in the optimistic bias).
8. Such an analysis is beyond the scope of this study but is on the author's research agenda.
9. When I presented results at the 1997 Prudential Securities

Quantitative Research Seminar for Institutional Investors, I used the actual EPS as a deflator. It was suggested to me that the aberrant results for the largest EPS group may be attributable to large random shocks in the actuals. When I substituted forecasted EPS for actual EPS (as in this article), the tenor of my results was unchanged.

10. The exception is the proportion of errors outside the +10 percent bandwidth, for which the proportion of 19.2 percent for the analyst following of ≥10 slightly exceeds the proportion of 19.1 percent for the analyst following of 8.
11. The exception is that the percentage of errors outside the +10 percent bandwidth has not decreased significantly for either the entire I/B/E/S sample or the non-S&P 500 subsample.
12. According to information provided to me by I/B/E/S, the mean surprises for S&P 500 firms for these seven quarters (sample sizes are in parentheses) are 1.7 percent (488), 2.4 percent (492), 2.6 percent (490), 2.4 percent (490), 1.9 percent (481), 3.3 percent (492), and 2.2 percent (491). The optimistic bias is still present for S&P 500 firms for annual forecasts.
13. I am grateful to Deres Tegenaw for providing me with excellent research assistance.

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THE WALL STREET JOURNAL.

Analysts: Still Coming Up Rosy --- Over-Optimism on Growth Rates Is Rampant, and the Estimates Help to Buoy Market's Valuation

By Ken Brown. **Wall Street Journal**. (Eastern edition).New York, N.Y.: Jan 27, 2003. pg. C.1

WALL STREET IS pretty downcast these days, what with a $1.5 billion settlement pending with regulators over stock-research conflicts, continuing layoffs at big securities firms and a stock market that is teetering yet again -- not to mention a cold snap that could freeze the thumbs of Blackberry users.

Yet stock analysts are unshaken in their optimistic, if delusional, belief that most of the companies they cover will have above-average, double-digit growth rates during the next several years. That is, of course, highly unlikely. Historically, corporate earnings have grown at about the same rate as the economy over time, and few expect the economy to grow at a double-digit rate any time soon.

But analysts refuse to bend to reality. Of the companies in the Standard & Poor's 500-stock index, analysts expect 345 of them to boost their earnings more than 10% a year during the next three to five years, and 123 companies to grow more than 15%, according to Multex, a stock-market-data firm.

"Hope springs eternal," says Mark Donovan, who manages Boston Partners Large Cap Value Fund. "You would have thought that, given what happened in the last three years, people would have given up the ghost. But in large measure they have not."

These overly optimistic growth estimates also show that, even with all the regulatory focus on too-bullish analysts allegedly influenced by their firms' investment-banking relationships, a lot of things haven't changed: Research remains rosy and many believe it always will.

In some ways, these high estimated growth rates underpin the market's current valuation, which remains pricey by historical standards. Investors expect to pay a higher price for stocks that are growing strongly. So if people realize these long-term growth-rate numbers are largely fictional, then a pillar of support for the market's valuation -- the S&P 500 currently trades at a price-to-earnings ratio of 18.5 based on 2002 earnings -- could go out of the stock market, sending prices lower.

The long-term growth figures come from the earnings estimates Wall Street analysts post for the companies they cover. Besides issuing buy and sell recommendations and predicting earnings during the next few quarters, analysts typically estimate how quickly the companies' earnings will grow during the next few years. Such long-term growth-rate numbers, which are imprecise by nature, give a hint of how analysts feel about companies' future prospects.

A long-term growth-rate number is often used by investors to determine whether a stock is cheap or expensive. Online auctioneer eBay Inc., for example, trades at a price-to-earnings ratio of 88 based on the past year's earnings. Some investors take solace in the fact that the company is expected to expand earnings 40% a year, but even with that growth, it would take until 2006 for the company's price-to-earnings ratio to fall to 22, assuming the stock price remained stalled at today's level.

These rosy figures come on top of three years of little or no growth for many companies. For example, Charles Schwab Corp. hasn't grown at all since 2000 as it has struggled with the stock-market collapse. But analysts, on average, still expect the company will expand its earnings 18% a year during the next several years. While that doesn't justify the company's price-to-earnings ratio of 33, it does give some hope to shareholders that the company one day indeed could resume its old growth rate.

Not surprisingly, the glow is rosiest in the technology sector. Of the 91 tech companies in the S&P 500, analysts expect 82 to grow faster than 10% a year, and 18 to grow better than 20% a year, meaning tech companies account for more than half of the index's 35 top growers.

To be sure, many of these companies could actually meet those growth expectations, if only because earnings have been in such a slump they are bound to rebound at some point. Analysts expect Schwab, for example, to earn 40 cents a share in 2003, up from the 29 cents it earned last year. If the analysts are right, that would be a healthy 38% jump in earnings.

But some also concede that their growth rates are optimistic. Guy Moszkowski, who covers Schwab for Salomon Smith Barney, and whose long-term growth estimate of 18% matches the consensus, concedes that this figure might be optimistic in the years after the expected short-term earnings pop. "If we can get enough of a recovery in the market that they can achieve that 40 cents in earnings, then they'll be on the way to establishing a kind of mid-teens growth track," he says. "But I think it's really hard to make the case they can do much better than that."

Mark Constant, who covers the company for Lehman Brothers and has a 15%-a-year growth estimate, also says the company probably won't reach his target. "I've always characterized it in print as an optimistic growth rate," he says.

If it were true that analysts were expecting a rebound following the current slump and ratcheting up their expectations accordingly, they might now be able to argue that they aren't being overly optimistic. The truth is, however, they have been growing increasingly pessimistic since the tech-stock bubble burst. Back in mid 2000, when earnings had been soaring for years, analysts were predicting that earnings for the S&P 500 would continue growing 15% a year, according to Morgan Stanley. Now, they are predicting 12% annual earnings growth for these same companies.

You can't blame analysts for everything,though. Companies themselves are guilty of being overly optimistic as well. "I think there's an immense amount of inertia in the system. That's the problem," says Steve Galbraith, Morgan Stanley's chief investment strategist. "One of the things people are struggling with are creative ways of reducing your guidance without reducing your guidance."

The problem, he adds, is that many companies set their growth expectations a decade ago, when interest rates and inflation were higher than today. Growth rates are measured in nominal terms, meaning inflation gives them a boost. With virtually no inflation and interest rates near zero, it is harder for companies to post double-digit growth. "I do think this is something that corporate America broadly is wrestling with: How do we ratchet down expectations that we set 10 years ago when things were different?" he says.

The danger comes from companies that can't face the reality that their growth has slowed. "Where I think clients should get concerned is where a company is claiming they're a 15% grower and they're setting their capital expenditures accordingly," Mr. Galbraith says. If the market is pricing in that level of growth, then the company will likely keep investing in itself in an attempt to keep returns high. The danger of that: Companies could be throwing away capital that could be given back to investors in the form of dividends or share buybacks.

Every chief financial officer who took Corporate Finance 101 knows that the bigger the portion of earnings a company reinvests in its business, the faster it conceivably can grow. Sending cash out to investors reduces the amount the company can invest in itself, ultimately lowering its potential growth rate.

But there are signs -- including Microsoft Corp.'s plan to pay a dividend -- that executives are starting to realize that reinvesting all their excess cash in their own business might not produce the highest returns. "It hasn't gotten quite that far, but I think it's going to get there," says Jeff van Harte, who manages Transamerica Premier Equity fund. "It just takes a long time to change attitudes. Some companies are forever lost."

The Superiority of Analyst Forecasts as Measures of Expectations: Evidence from Earnings
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THE SUPERIORITY OF ANALYST FORECASTS AS MEASURES OF EXPECTATIONS: EVIDENCE FROM EARNINGS

LAWRENCE D. BROWN AND MICHAEL S. ROZEFF*

ACCURATE MEASUREMENT OF EARNINGS expectations is essential for studies of firm valuation, cost of capital and the relationship between unanticipated earnings and stock price changes. Under the rational expectations hypothesis [23], market earnings expectations should be measured by the best available earnings forecasts. Univariate time series forecasts are often used for this purpose ([1], [3], [4], [5], [12], [13], [14], [16], [18], [20]) instead of direct measures of earnings expectations such as security analysts' forecasts. Univariate time series forecasts neglect potentially useful information in other time series and therefore do not generally provide the most accurate possible forecasts [24]. Since security analysts process substantially more data than the time series of past earnings, their earnings forecasts *should* be superior to time series forecasts and provide better measures of market earnings expectations.

However, the mere existence of analysts as an employed factor in long run equilibrium means that analysts *must* make forecasts superior to those of time series models. To reach this conclusion, one need only assume that participants in the market for forecasts act in their own best interests and that both forecast producers and consumers demand forecasts solely on the basis of their predictive ability.[1] Since analysts' forecasts cost more than time series forecasts, the continued employment of analysts by profit-maximizing firms implies that analysts' forecasts must be superior to those of the lower cost factor, time series models.

Past comparisons of analysts' forecasts to sophisticated time series models conclude that analysts' forecasts are not more accurate than time series forecasts (Cragg and Malkiel (CM) [9]; Elton and Gruber (EG) [11]). This evidence plainly conflicts with basic economic theory. Hence, the predictive accuracy of analysts' forecasts is re-examined in this paper. In contrast with other studies, the results overwhelmingly favor the superiority of analysts over time series models.

Part I considers statistical tests and experimental design. Part II contains the empirical results. Summary and implications appear in Part III.

* College of Business Administration, The University of Iowa, Iowa City.

1. We assume that forecast purchasers do not derive nonmonetary benefits from forecasts.

I. Experimental Design

A. *Statistical Evaluation of Forecast Methods*

Without direct information on the costs of imperfect forecasts to forecast users, comparative forecast accuracy is usually evaluated by comparing the error distributions of different forecast methods statistically. However, statistical comparisons in past studies ([9], [11]) utilize test statistics improperly, particularly Theil's U [25] and Student's t. In this section, after discussing the defects of these statistics for evaluating two or more forecast methods, the alternative statistical methods used in this study are introduced.[2]

Theil's U-statistic (applied to earnings) is the square root of

$$U_{ij}^2 = \frac{\sum_{t=1}^{T} (\dot{P}_{ijt} - \dot{A}_{it})^2}{\sum_{t=1}^{T} \dot{A}_{it}^2},$$

where $\dot{A}_{it}$ = change in actual earnings per share of firm i from $t-1$ to t,
$\dot{P}_{ijt}$ = predicted change in earnings per share of firm i from $t-1$ to t by forecast method j, and
T = total number of time series observations.

For its computation, it requires *time series* data on a firm's earnings *changes*.[3] Given forecast method j and earnings time series data on firm i, Theil's U compares the forecast accuracy of method j to that of a naive, no change, earnings forecast model.[4,5] Since analysts' earnings forecasts are currently available only in short time series, use of Theil's U for comparative forecast evaluation necessarily relies on small samples.[6] Larger sample sizes are possible by testing forecast methods on a cross-section of firms. Finally, no procedure is available with tests of significance which uses Theil's U to compare two forecast methods when neither is a no-change method. Direct hypothesis tests are preferable to inferences drawn from ranking the U statistics of different forecast methods.

For hypothesis tests of two forecast methods, an appropriate design is a one-sample or matched pairs case with self-pairing by firm. The members of each pair

2. Past studies also contain experimental biases: CM compare analysts' five-year forecasts with realizations over three and four-year horizons; EG compare analysts' forecasts with the "best" of nine time series models selected from the same time period in which comparisons with analysts' forecasts are made. This procedure introduces *ex post* selection bias.

3. EG computed "Theil's U" using earnings *levels* rather than *changes*. This statistic has unknown sampling properties.

4. $\dot{P}_{ijt} = \dot{A}_{it}$ and $U_{ij} = 0$ if prediction is perfect in every period. If no change is predicted in each period (i.e., $\dot{P}_{ijt} = 0$), $U_{ij} = 1$; $0 < U_{ij} < 1$ if prediction is less than perfect but better than the no-change prediction and $U_{ij} > 1$ if forecast method j is less accurate than the no-change prediction.

5. CM used *cross-sectional* rather than temporal data. This "Theil's U" statistic has unknown sampling properties because each error is drawn from a different error distribution, one for each firm.

6. EG's sample size in computing Theil's U varied between two and six.

are the errors from the two methods; the matched pair is reduced to a single observation by taking the difference in the errors. The usual parametric test of the mean difference is the paired t-test [17]. An alternative non-parametric test of the median difference is the Wilcoxon Signed Ranks test [8].

The parametric paired t-test is inappropriate for testing mean error differences of forecast methods applied to cross-section earnings data. If applied to error measures stated in level form (e.g., $|P_{ijt} - A_{it}|$, where P_{ijt} = firm i's forecasted earnings per share for period t by method j and A_{it} = firm i's actual earnings per share in period t), the test's assumption that paired differences are drawn from the same population is violated since each error difference depends upon each firm's earnings per share level. If applied to error measures stated in ratio form (e.g., $|P_{ijt} - A_{it}|/|A_{it}|$), the distributional assumptions of the paired t-test are also unlikely to be fulfilled since ratio measures applied to earnings per share data are dominated by outliers because actual earnings per share are often close to zero.[7]

Meaningful pairwise comparisons require test statistics which are insensitive to error definition and outliers. We adopt the Wilcoxon Signed Ranks test which meets these requirements and has power comparable to the parametric paired t-test [8, p. 213].

For tests of several forecast methods, the generalization of the paired t-test, two-way analysis of variance, is inapplicable.[8] The Friedman test [8], which is based on two-way analysis of variance by ranks and is independent of error definition, is used instead.

For an error measure, we choose relative error ignoring sign, $|P_{ijt} - A_{it}|/|A_{it}|$, a metric which is likely to be of interest to forecast purchasers.[9] In any event, the Wilcoxon test statistic is insensitive to error definition (see fn. 16).

B. *Forecast Horizon*

Because economic theory provides no guidance concerning the association of analyst superiority with a particular forecast horizon, several horizons should be investigated.[10] Our choice of horizons reflects the following considerations: (i) micro-level information obtained by analysts often concerns earnings of the following several quarters or fiscal year; (ii) current fiscal and monetary policies affect earnings of the subsequent one to five quarters; (iii) published forecasts are available mainly for short horizons. We thus investigate point estimates of quarterly earnings per share for forecast horizons of one to five quarters. We also examine annual earnings forecasts. The basic time series data are quarterly primary

7. EG's cross-section parametric t-test is inappropriate. Their use of an error measure stated in terms of levels squared (mean square error) appears to compound the inherent difficulty in applying the paired t-test to cross-section earnings data (see fn. 16).

8. Preliminary tests indicated serious violation of the homogeneity of variances and additivity assumptions, basically because of error outliers. Violation of the ANOVA assumptions also prevents application below of a factorial design with sample year and forecast horizon as factors, forecast method as treatment and firm as replication.

9. For a discussion of the deficiencies of using $|P_{ijt}|$ or $|P_{ijt} + A_{it}|/2$ in the denominator see [25].

10. The forecast horizons studied in the past have been five years (CM) and one year (EG).

earnings per share before extraordinary items, adjusted for stock splits, stock dividends and other capitalization changes for the years 1951–1975.

Ex ante conditional predictions of all forecast methods are determined as follows for a sample of 50 firms for each of the four years 1972–1975. Starting with third quarter 1971 earnings (III/1971), conditional earnings per share predictions for the ith firm by the jth method are obtained for the individual quarters of 1972. The forecasts of 1972 quarterly earnings, conditional on III/1971, are denoted $P_{ij}(\mathrm{I}/1972\,|\,\mathrm{III}/1971)$, $P_{ij}(\mathrm{II}/1972\,|\,\mathrm{III}/1971)$, $P_{ij}(\mathrm{III}/1972\,|\,\mathrm{III}/1971)$ and $P_{ij}(\mathrm{IV}/1972\,|\,\mathrm{III}/1971)$. Moving ahead one quarter, predictions are again obtained for each of the four quarters of 1972 made conditional upon IV/1971 earnings data. Again moving ahead one quarter, predictions are obtained for the last three quarters of 1972 conditional upon knowledge of I/1972 earnings, etc. Table 1 shows the set of 1972 predictions so obtained. With these conditional predictions, relative forecast errors ignoring sign are computed for each forecast method j over five distinct quarterly forecast horizons for use in the quarterly error comparisons. Annual earnings forecasts for 1972 are the sum of the forecasts $P_{ij}(\mathrm{I}/1972\,|\,\mathrm{IV}/1971)$, $P_{ij}(\mathrm{II}/1972\,|\,\mathrm{IV}/1971)$, $P_{ij}(\mathrm{III}/1972\,|\,\mathrm{IV}/1971)$, and $P_{ij}(\mathrm{IV}/1972\,|\,\mathrm{IV}/1971)$, that is, the one to four period ahead point forecasts made conditional upon knowledge of the prior year's fiscal earnings.[11] After obtaining analogous forecasts for the years 1973, 1974 and 1975, quarterly and annual comparisons are repeated for these years.

TABLE 1

SUMMARY OF PREDICTIONS BY FORECAST HORIZON FOR 1972[a,b]

1 Quarter Ahead	2 Quarters Ahead	3 Quarters Ahead	4 Quarters Ahead	5 Quarters Ahead[c]
$P_{ij}(\mathrm{I}/1972\,|\,\mathrm{IV}/1971)$	$P_{ij}(\mathrm{I}/1972\,|\,\mathrm{III}/1971)$			
$P_{ij}(\mathrm{II}/1972\,|\,\mathrm{I}/1972)$	$P_{ij}(\mathrm{II}/1972\,|\,\mathrm{IV}/1971)$	$P_{ij}(\mathrm{II}/1972\,|\,\mathrm{III}/1971)$		
$P_{ij}(\mathrm{III}/1972\,|\,\mathrm{II}/1972)$	$P_{ij}(\mathrm{III}/1972\,|\,\mathrm{I}/1972)$	$P_{ij}(\mathrm{III}/1972\,|\,\mathrm{IV}/1971)$	$P_{ij}(\mathrm{III}/1972\,|\,\mathrm{III}/1971)$	
$P_{ij}(\mathrm{IV}/1972\,|\,\mathrm{III}/1972)$	$P_{ij}(\mathrm{IV}/1972\,|\,\mathrm{II}/1972)$	$P_{ij}(\mathrm{IV}/1972\,|\,\mathrm{I}/1972)$	$P_{ij}(\mathrm{IV}/1972\,|\,\mathrm{IV}/1971)$	$P_{ij}(\mathrm{IV}/1972\,|\,\mathrm{III}/1971)$

[a] Predictions missing from the table (e.g., $P_{ij}(\mathrm{I}/1972\,|\,\mathrm{II}/1971)$, $P_{ij}(\mathrm{II}/1972\,|\,\mathrm{II}/1971)$) are absent because our source of analyst data does not contain these forecasts.

[b] i and j refer to firm i and method j, respectively.

[c] Five quarter ahead are available for BJ and V only.

C. *Time Series Models and Analysts' Forecasts*

Within the class of univariate time series models, Box and Jenkins (BJ) [6] models are highly regarded for their ability to make the most efficient use of the time series data. The BJ modelling technique enables one to select the most appropriate time series model consistent with the process generating each firm's time series of quarterly earnings per share data. BJ models, by not making *a priori* assumptions about the processes generating the data, subsume autoregressive,

11. Beaver [1] concludes that a quarterly approach to predicting annual earnings is at least as good as an annual approach to predicting annual earnings. Also see [7], [19] and [22] for other aspects of the usefulness of quarterly earnings per share data.

moving average and mixed models as special cases.[12] Forecasts of individually fitted BJ models should, therefore, perform better than forecasts of a particular class of time series models applied to all firms' time series data. We adopt the BJ modelling technique in this paper. Two other time series models are also included, a "seasonal martingale" (denoted M) and a "seasonal submartingale" (S). These models have been used as standards of comparison in the earnings forecast literature and are available for forecast producers and users at minimal cost.

As a source of analysts' forecasts we choose the Value Line Investment Survey since it contains one to five quarter ahead earnings forecasts which can be accurately dated and measured. Value Line makes earnings forecasts for 1,600 firms in contrast with institutional research firms which provide fewer, more expensive forecasts. Our hypothesis test thus compares a relatively sophisticated time series model with an "average" source of analysts' forecasts.

BJ conditional forecasts are obtained by standard methods after identifying and estimating each firm's appropriate model [6].[13] Value Line's conditional forecasts are taken directly from individual issues of the Value Line Investment Survey. The Survey, published weekly, makes quarterly earnings predictions four times a year for each firm included.

To define conditional forecasts of the naive models for each firm i, let A_{it} denote the tth actual quarterly earnings per share for firm i, where $t=1,\ldots,96$ (I/1951–IV/1974).

Seasonal submartingale (S) conditional one to four quarter ahead forecasts at time t are

one quarter ahead	$A_{it-3}+(A_{it}-A_{it-4})$
two quarters ahead	$A_{it-2}+(A_{it}-A_{it-4})$
three quarters ahead	$A_{it-1}+(A_{it}-A_{it-4})$
four quarters ahead	$A_{it}\quad+(A_{it}-A_{it-4})$.

Seasonal martingale (M) conditional one to four quarter ahead forecasts made in period t are A_{it-3}, A_{it-2}, A_{it-1}, and A_{it}. M's forecasts for a given quarter do not change as actual earnings per share data become available. S modifies M's forecasts with the change of the latest period's quarter over that of the previous year.

Actual quarterly earnings data are announced for most firms approximately five to six weeks into the subsequent quarter. Time series forecasts then become

12. The *ad hoc* time series models used in previous studies at a time when BJ techniques were unavailable are special cases of BJ models.

13. Recent research by Froeschle [15] and diagnostic tests of Dent and Swanson [10] were helpful in identifying the BJ models in addition to the standard diagnostic tests. As an aid to identifying the BJ models, most of which had multiplicative seasonal components, theoretical autocorrelation and partial autocorrelation functions for many quarterly multiplicative seasonal models were obtained. The coefficients of the BJ models, estimated with data through IV/1974, were not re-estimated with less data for earlier periods or more data for later periods. Foster [13] has shown that coefficient re-estimation of BJ quarterly earnings models is unnecessary due to its negligible effect on forecast errors. In any event, our procedure (no re-estimation) favors BJ in nearly all comparisons with Value Line.

possible and Value Line forecasts are published, on average, forty to fifty days later.[14]

The pattern of forecasts for all models is summarized in Table 1. Note that models M and S are not used to generate five quarter ahead forecasts.

II. Empirical Results

A. *Sample Selection*

Fifty firms were randomly selected from Moody's Handbook of Common Stocks. Each firm has complete quarterly earnings data available from 1951, is included in the Value Line Investment Survey since 1971 and has a December fiscal year. The resulting sample (Appendix A) is representative of the New York Stock Exchange firms included in Moody's and Value Line. Utilities were excluded due to insufficient quarterly earnings data. Sample sizes are reduced in those rare instances when the Value Line conditional forecasts are unavailable.

B. *Annual Comparisons*

The error distributions of relative annual forecast errors are shown in Table 2 for each of the years 1972–75 using the four forecast methods, seasonal martingale (M), seasonal submartingale (S), Box-Jenkins (BJ) and Value Line (V). Table 2 also contains Friedman test statistics (Chi-square with 3 degrees of freedom) and Wilcoxon test statistics (Student's t with $N-1$ degrees of freedom where N is sample size). The Friedman test statistic examines the null hypothesis that *all four* error distributions are identically distributed; the Wilcoxon statistic tests the null hypothesis that the median error difference of *two* methods being compared exceeds zero.

Using the Friedman test, the null hypothesis is rejected at the 1% level in 1972, 1973 and 1975. In the 12 pairwise hypothesis tests of V's errors against those of M, S, and BJ, the sign of the Wilcoxon test statistic favors Value Line in every instance. Statistical significance occurs 8 times; 6 times at the 1% level and twice at the 5% level. Thus, V generally produces smaller annual errors than the three time series models suggesting that Value Line annual earnings forecasts are superior to those of time series models.

As argued earlier, BJ forecasts should be superior to forecasts of *ad hoc* time series models. The annual comparisons show that the BJ models generally yield smaller forecast errors than the other time series models studied. In 8 comparisons with M and S, the Wilcoxon test favors BJ 7 times with statistical significance 3 times. These findings suggest that BJ's forecasts are superior to those of *ad hoc* naive time series models.

While the annual results provide strong support for the hypothesis of analyst superiority, they use only a fraction of the data. More powerful tests are achieved using the larger sample sizes of the quarterly data and many more comparative tests can be performed with these data. We turn next to quarterly comparisons.

14. The time interval from announcement to forecast varies from approximately 7 to 70 days for our sample firms. The fact that the Investment Survey, published in 13 installments, makes forecasts for different firms each week accounts for the variation.

TABLE 2

WILCOXON AND FRIEDMAN TEST STATISTICS AND ERROR DISTRIBUTIONS, ANNUAL COMPARISONS OF VALUE LINE AND TIME SERIES MODEL PREDICTION ERRORS, 1972–1975[c]

1972

Error Distribution[d]

	<.05	.05–.10	.10–.25	.25–.50	.50–.75	.75–1.00	>1.00
M	3	7	14	17	4	3	2
S	11	6	12	10	3	1	7
BJ	10	6	12	12	4	1	5
V	13	7	17	12	0	0	1

SAMPLE SIZE = 50
Friedman Statistic = 27.10[a]
Wilcoxon Statistics[e]

	S	BJ	*V*
M	−.55	.24	4.46[a]
S		.46	3.50[a]
BJ			3.45[a]

1973

Error Distribution[d]

	<.05	.05–.10	.10–.25	.25–.50	.50–.75	.75–1.00	>1.00
M	2	6	16	18	6	0	2
S	11	8	14	9	4	1	3
BJ	8	6	15	16	3	0	2
V	10	9	13	16	0	0	2

SAMPLE SIZE = 50
Friedman Statistic = 33.19[a]
Wilcoxon Statistics[e]

	S	BJ	*V*
M	3.15[a]	2.51[a]	4.61[a]
S		−1.89[b]	0.34
BJ			2.17[b]

1974

Error Distribution[d]

	<.05	.05–.10	.10–.25	.25–.50	.50–.75	.75–1.00	>1.00
M	8	6	12	15	4	1	4
S	12	3	11	12	6	2	4
BJ	5	8	16	13	4	0	4
V	6	7	15	13	5	0	4

SAMPLE SIZE = 50
Friedman Statistic = 4.68
Wilcoxon Statistics[e]

	S	BJ	*V*
M	−.21	2.37[a]	2.23[b]
S		1.24	1.44
BJ			0.61

TABLE 2 (*continued*)

1975

Error Distribution[d]

	<.05	.05–.10	.10–.25	.25–.50	.50–.75	.75–1.00	>1.00
M	4	7	13	10	2	3	11
S	3	5	12	7	9	4	10
BJ	7	3	13	12	2	3	10
V	7	5	18	5	3	3	9

SAMPLE SIZE = 50

Friedman Statistics = 12.84[a]

Wilcoxon Statistics[e]

	S	BJ	*V*
M	−1.77[b]	0.86	3.29[a]
S		2.99[a]	3.11[a]
BJ			1.28

[a] Significant at the 1% level, one-tailed test.

[b] Significant at the 5% level, one-tailed test.

[c] *V* = Value Line, *M* = Seasonal Martingale, *S* = Seasonal Submartingale, BJ = Box-Jenkins.

[d] Each entry below designates the number of observations for a given model whose relative error ignoring sign is within the stated fractiles.

[e] Each Wilcoxon test statistic below results from comparing the method at the top with the method on the side. Thus, positive Wilcoxon statistics indicate superiority of model on top.

C. *Quarterly Comparisons*

In each year, 1972 to 1975, quarterly forecasts are obtained for the forecast methods in the manner shown in Table 1. Relative forecast errors of all four methods are compared over 1–4 quarter forecast horizons; BJ and V are also compared over 5 quarter horizons. In each of the four years, sample sizes are approximately 200 for the 1 and 2 quarter ahead comparisons, 150 for the 3 quarter ahead comparisons, and 100 for the 4 quarter ahead comparisons. Test results over all horizons appear in Table 3 and are summarized in Table 4.

With minor exceptions (3 and 4 quarter horizons in 1974), the Friedman statistics are highly significant when the four methods are tested as a group; the null hypothesis of identically distributed distributions is rejected in 14 of the 16 Friedman tests. Using Wilcoxon test statistics, V's errors are tested pairwise against M's and S's errors 16 times each and against BJ's errors 20 times. The resulting 52 hypothesis tests of V against M, S and BJ are summarized in Table 4A. In the 34 instances of significant Wilcoxon test statistics, V is statistically superior 33 times. In the remaining 18 tests, the sign of the t-statistic favors V 12 times. In total, V is favored 45 times out of 52, revealing an overwhelming dominance of V over the time series models.

The data are also summarized in Table 4 by the mean Wilcoxon t-value ($\bar{t}$), the estimated standard deviation of the mean t-value ($s(\bar{t})$) and the ratio $\bar{t}/s(\bar{t})$. The latter ratio is itself a t-statistic only if each t-value being averaged is drawn from the same distribution. Since the distribution of t-values is likely to depend upon the horizon, model and/or year that the experiment is conducted, we refrain from

TABLE 3

WILCOXON AND FRIEDMAN TEST STATISTICS, QUARTERLY COMPARISONS OF VALUE LINE AND TIME SERIES MODEL PREDICTION ERRORS, 1972–1975[c,d]

		Forecast Horizon												
		One Quarter			Two Quarter			Three Quarter			Four Quarter			Five Quarter
		S	BJ	*V*	*S*	BJ	*V*	*S*	BJ	*V*	*S*	BJ	*V*	*V*
1972	*M*	2.14[b]	6.87[a]	8.15[a]	0.79	5.41[a]	6.87[a]	−1.09	2.50[a]	5.77[a]	−3.09[a]	1.41	5.22[a]	—
	S	—	4.62[a]	5.25[a]	—	4.62[a]	5.57[a]	—	3.03[a]	5.42[a]	—	3.38[a]	5.30[a]	—
	BJ	—	—	1.75[b]	—	—	2.51[a]	—	—	4.09[a]	—	—	3.93[a]	3.11[a]
		Sample Size = 200			Sample Size = 200			Sample Size = 150			Sample Size = 100			Sample Size = 50
		Friedman Stat. = 73.45[a]			Friedman Stat. = 60.54[a]			Friedman Stat. = 41.14[a]			Friedman Stat. = 43.43[a]			
		S	BJ	*V*	*S*	BJ	*V*	*S*	BJ	*V*	*S*	BJ	*V*	*V*
1973	*M*	8.02[a]	8.98[a]	10.66[a]	5.81[a]	6.41[a]	8.70[a]	4.81[a]	3.52[a]	6.31[a]	2.55[a]	1.69[b]	4.63[a]	—
	S	—	−0.60	1.62	—	−1.83[b]	1.04	—	−3.57[a]	−0.02	—	−1.59	1.04	—
	BJ	—	—	2.48[a]	—	—	3.47[a]	—	—	3.34[a]	—	—	2.79[a]	1.66
		Sample Size = 199			Sample Size = 200			Sample Size = 150			Sample Size = 100			Sample Size = 50
		Friedman Stat. = 173.51[a]			Friedman Stat. = 119.91[a]			Friedman Stat. = 75.22[a]			Friedman Stat. = 29.12[a]			
		S	BJ	*V*	*S*	BJ	*V*	*S*	BJ	*V*	*S*	BJ	*V*	*V*
1974	*M*	3.35[a]	6.29[a]	6.19[a]	0.84	4.88[a]	3.78[a]	−0.25	2.59[a]	1.29	−2.69[a]	1.41	0.29	—
	S	—	2.34[a]	2.95[a]	—	2.31[b]	1.50	—	1.53	0.97	—	2.67[a]	2.80[a]	—
	BJ	—	—	1.16	—	—	−1.45	—	—	−1.04	—	—	−0.92	−2.20[b]
		Sample Size = 199			Sample Size = 199			Sample Size = 149			Sample Size = 100			Sample Size = 50
		Friedman Stat. = 47.57[a]			Friedman Stat. = 22.63[a]			Friedman Stat. = 5.40			Friedman Stat. = 2.92			
		S	BJ	*V*	*S*	BJ	*V*	*S*	BJ	*V*	*S*	BJ	*V*	*V*
1975	*M*	2.07[b]	5.76[a]	8.22[a]	−2.64[a]	3.63[a]	5.29[a]	−4.49[a]	2.93[a]	2.95[a]	4.89[a]	−0.78	−0.05	—
	S	—	4.70[a]	6.36[a]	—	6.02[a]	6.14[a]	—	6.13[a]	5.14[a]	—	3.62[a]	3.28[a]	—
	BJ	—	—	3.51[a]	—	—	1.62	—	—	−0.22	—	—	0.08	0.45
		Sample Size = 199			Sample Size = 199			Sample Size = 149			Sample Size = 100			Sample Size = 50
		Friedman Stat. = 80.32[a]			Friedman Stat. = 44.49[a]			Friedman Stat. = 33.25[a]			Friedman Stat. = 15.66[b]			

[a] Significant at the 1% level, one-tailed test.

[b] Significant at the 5% level, one-tailed test.

[c] V = Value Line, M = Seasonal Martingale, S = Seasonal Submartingale, BJ = Box-Jenkins.

[d] Each Wilcoxon test statistic entered in the table results from comparing method at the top with method on the side. Thus, positive Wilcoxon statistics indicate superiority of model on top.

TABLE 4

SUMMARY OF WILCOXON TEST COMPARISONS

A: Value Line vs. Time Series Models[a]

		Forecast Horizon					Forecast Model			Year			
	Total	1Q	2Q	3Q	4Q	5Q	M	S	BJ	1972	1973	1974	1975
Number of Comparisons	52	12	12	12	12	4	16	16	20	13	13	13	13
Comparisons Favorable to V[b]	45	12	11	9	10	3	15	15	15	13	12	9	11
Comparisons Statistically Favorable to V[c]	33	10	8	7	7	1	13	10	10	13	8	4	8
Comparisons Statistically Unfavorable to V	1	0	0	0	0	1	0	0	1	0	0	1	0
Mean Wilcoxon Test Statistic ($\bar{t}$)	3.25	4.86	3.75	2.83	2.37	.76	5.27	3.40	1.51	4.84	3.67	1.18	3.29
$\bar{t}/s(\bar{t})^d$	8.27	5.45	4.51	3.81	3.72	.67	5.65	6.24	3.48	9.98	4.18	1.81	4.24

B: BJ vs. Naive Time Series Models

		Forecast Horizon				Forecast Model		Year			
	Total	1Q	2Q	3Q	4Q	M	S	1972	1973	1974	1975
Number of Comparisons	32	8	8	8	8	16	16	8	8	8	8
Comparisons Favorable to BJ[b]	27	7	7	7	6	15	12	8	4	8	7
Comparisons Statistically Favorable to BJ[c]	24	7	7	6	4	13	11	7	4	6	7
Comparisons Statistically Unfavorable to BJ	2	0	1	1	0	0	2	0	2	0	0
Mean Wilcoxon Test Statistic ($\bar{t}$)	3.15	4.87	3.93	2.33	1.48	3.97	2.34	3.98	1.63	3.00	4.00
$\bar{t}/s(\bar{t})^d$	6.37	4.70	4.16	2.41	2.25	6.23	3.25	6.46	1.05	4.99	4.96

[a] V = Value Line, M = Seasonal Martingale, S = Seasonal Submartingale, BJ = Box-Jenkins.

[b] Comparisons are favorable if Wilcoxon statistic in Table 3 is positive.

[c] Comparisons are statistically favorable if Wilcoxon statistic in Table 3 is positive and significant at the 5% level or better.

[d] Both $\bar{t}$ and $s(\bar{t})$ are computed using the number of comparisons in each column of the Table.

hypothesis tests on $\bar{t}$ and present $\bar{t}$ and $\bar{t}/s(\bar{t})$ without formal tests of significance. For the 52 comparisons involving V, the mean Wilcoxon test statistic is 3.25 and $\bar{t}/s(\bar{t})$ is 8.27.

Table 4A also decomposes the 52 comparisons of V with the time series models by forecast horizon, model and year.[15] The data show that Value Line's forecast superiority holds over all horizons studied with a tendency for its superiority to decline as horizon lengthens. V's predominance model-by-model is, as hypothesized, quite evident with somewhat less superiority over BJ than over M and S. Turning our attention to the 20 comparisons between V and BJ, V is superior in 10 of 11 cases in which the test statistic is significant. In 5 of the remaining 9 comparisons, the sign of the Wilcoxon test statistic favors V. For completeness, Table 4A summarizes Wilcoxon tests by year. Again we expect V to be superior, on average, but have no hypothesis concerning particular years. Comparisons unfavorable to V tend to be confined to 1974, but even in this year, 4 of the 5 statistically significant comparisons favor Value Line.

In summary, the evidence strongly supports the hypothesis that Value Line consistently makes significantly better predictions than time series models. The statistically significant experiments overwhelmingly favor Value Line. In the remaining experiments the majority of the Wilcoxon tests also favor Value Line, providing additional support for the hypothesis of analyst superiority.

Table 4B summarizes the 32 comparisons of BJ with the naive time series models. The mean Wilcoxon test statistic is 3.15 and $\bar{t}/s(\bar{t})$ equals 6.37. In 26 cases, there are significant differences with BJ statistically superior 24 times. BJ is superior to M and S in 3 of the remaining 6 comparisons. Hence, BJ is favored in 27 of 32 comparisons, providing strong support for the hypothesis that BJ predicts earnings better than *ad hoc* time series models.

Table 4B also summarizes comparisons involving BJ by horizon, model and year. BJ's superiority over the naive models is clearly evident over each forecast horizon with a tendency for its superiority to decline as horizon lengthens. In comparison to individual models, BJ outperforms both M and S with somewhat less dominance over S. Turning to comparisons by year, the superiority of BJ is consistent over time, with most of the comparisons unfavorable to BJ occurring in 1973. Even in this year, the mean Wilcoxon test statistic is 1.63 and 4 of the 6 significant comparisons favor BJ.[16]

In conclusion, the quarterly and the annual comparisons provide convincing evidence both of Value Line's superiority over each of the three time series models and BJ's superiority over the naive models. The quarterly results also show that V's superiority over the time series models and BJ's superiority over the naive models

15. The decomposition is an alternative to analysis of variance which is inapplicable to the error distribution (see fn. 8).

16. As noted earlier, the Wilcoxon tests should be insensitive to error definition. Wilcoxon test statistics were recomputed on annual and selected quarterly comparisons using three additional error measures, mean square error, root mean square error and relative error squared. The small changes in the test statistics left the results virtually unchanged. Parametric t-tests were also applied to the four error measures. Both the sign and magnitude of these test statistics were highly sensitive to error definition. The hypothesis tests using the parametric t-test most often gave results in disagreement with the Wilcoxon test when mean square error was chosen as the error definition. This may account for EG's results differing from ours.

are not confined to particular models, horizons, or years. The very general character of Value Line's superiority in predicting earnings, evidenced over all models, horizons, and years in 64 separate hypothesis tests involving sample sizes averaging 125, lends extraordinary support to the hypothesis of analyst superiority.

D. *Further Analysis*

The superiority of Value Line over time series models follows from the rational behavior of forecast producers and consumers and should be generalizable to other sources of analyst forecasts and other time periods. As a preliminary test of the sensitivity of our results to choice of analyst, we obtained predictions of 1975 annual earnings per share made by the Standard and Poor's Earnings Forecaster (SP) for each firm included in the 1975 annual earnings sample.[17] Wilcoxon tests of SP against M, S, and BJ favored SP, yielding t-statistics of 3.18, 2.85 and 1.45 respectively. These results are remarkably similar to those using Value Line.[18] This evidence suggests that Value Line's forecast superiority over time series models is not unique.

To ascertain whether the sample period posed unusual difficulties for time series earnings forecasting, a BJ model was fitted to the Quarterly Earnings Index of the Dow Jones Industrial Average over the 1951–1975 time period.[19] Average quarterly percentage errors ignoring sign produced by the BJ model for 1972–1975 were 7.31%, 6.61%, 9.99%, and 15.47% respectively. Since the mean and standard deviation of average percentage forecast errors over the 1951–1975 period were 10.14% and 4.38%, it appears that the 1972–1975 period was not a particularly difficult one in which to predict earnings. Indeed, from this standpoint, the 1972–1975 period is comparable to the "stable" years of the sixties, 1962–1967, studied by CM and EG.[20]

These results indicate that if appropriate hypothesis tests are applied to other analysts and time periods, the results are likely to parallel those using Value Line and the 1972–1975 time period.

E. *A Brief Investigation of Value Line Superiority*

To produce forecasts superior to time series models, Value Line must utilize information not contained in the time series of quarterly earnings. During the period between the most recent quarterly earnings announcement and the subsequent Value Line prediction, Value Line acquires incremental information which, if an important part of its total information set, may explain Value Line's

17. SP, published weekly, contains annual predictions made by Standard and Poor's and other investment firms. The SP prediction for each firm is that made by Standard and Poor's on the date closest to the Value Line prediction date.

18. V's t-statistics versus M, S, and BJ were 3.29, 3.11, and 1.28 respectively (See Table 2). A direct Wilcoxon test between V and SP favored $V(t=.77)$.

19. The sample period, 1972–1975, may appear "unusual" since it includes peacetime wage and price controls, high inflation and inventory profits, large changes in employment and new accounting requirements. If events arising during the sample period caused the earnings generating process to change, the forecast ability of the BJ modelling technique may be hampered, unintentionally favoring the analyst.

20. The average percentage errors were 12.67%, 10.71%, 7.03%, 4.93%, 6.08% and 5.26%, respectively for 1962–1967.

superiority. Information arising during this interval is likely to be most important for predicting next quarter's earnings. Assuming that the generation of this incremental information is positively related to the passage of time, earnings should be relatively easier to predict the further Value Line's prediction date is from the most recent earnings announcement date, and one quarter horizon forecast errors should be negatively related to the corresponding intervals.

To test this hypothesis, we obtained for the firms in the 1975 one quarter horizon sample their Value Line errors and the time intervals (7–70 days) since their most recent earnings announcements. A rank correlation was applied to these variables. The insignificantly negative Spearman rho which was obtained suggests that information obtained by Value Line during this interval has a negligible effect on its ability to predict next quarter's earnings.[21] This evidence is consistent with the hypothesis that Value Line's superiority can be attributed to its use of the information set available to it on the quarterly earnings announcement date, and not to the acquisition of information arising after the quarterly earnings announcement date.

III. Summary and Implications

Basic economic theory and the equilibrium employment of analysts, a higher cost factor than time series models, imply that analysts must produce better forecasts than time series models. Past studies ([9], [11]) of comparative earnings forecast accuracy have concluded otherwise but use inappropriate parametric tests and contain experimental biases. Using nonparametric statistics which provide proper yet powerful tests, we find that (1) BJ models consistently produce significantly better earnings forecasts than martingale and submartingale models; (2) Value Line Investment Survey consistently makes significantly better earnings forecasts than the BJ and naive time series models. The findings are in accord with rationality in the market for forecasts and the long-run equilibrium employment of analysts.

If market earnings expectations are rational [23], it follows that the best available earnings forecasts should be used to measure market earnings expectations. Given rational market expectations, our evidence of analyst superiority over time series models means that analysts' forecasts should be used in studies of firm valuation, cost of capital and the relationship between unanticipated earnings and stock price changes until forecasts superior to those of analysts are found.[22] Past findings ([2], [21]) that share price levels are significantly better explained by analysts' earnings

21. The lack of a significant negative correlation between prediction error and time since last announcement date may occur if the interval is intentionally lengthened by Value Line in order to acquire more information about the firms whose earnings are more difficult to predict. To test this possibility, we measured each firm's prediction "difficulty" by its average one quarter horizon percentage error ignoring sign yielded by its BJ model. No significant correlation was found between this variable and the time interval between the most recent quarterly earnings announcement and the Value Line prediction date.

22. In examining the relationship between unanticipated earnings and stock price changes, for example, the sign of the forecast error from a time series is often used ([7], [12], [13]) as a device for classifying unanticipated earnings into "favorable" or "unfavorable" categories. With this methodology, BJ and V classify earnings differently 213 times out of the 797 one quarter ahead forecasts in our sample.

forecasts than by those of time series models are consistent with our evidence and with market rationality.

The hypothesis of analyst superiority versus univariate time series models is derived from basic economic theory and is not limited to the case of earnings. It is therefore applicable to all types of forecasts subject to the market test. There is no presumption that other, non-market forecasts such as those made by corporate executives or government agencies should be better (or worse) than those generated by univariate time series models.

Appendix A

Sample Firms

Abbott Laboratories
Allegheny Ludlum Industries, Inc.
American Airlines, Inc.
Anaconda Company
Boeing Company
Borg-Warner Corporation
Braniff International Corporation
Caterpillar Tractor Company
Champion International Corporation
Chrysler Corporation
Clark Equipment Company
Colgate-Palmolive Company
Continental Can Company, Inc.
Curtiss-Wright Corporation
Cutler-Hammer, Inc.
Eastern Airlines, Incorporated
Eastman Kodak Company
Flintkote Company
Freeport Minerals Company
Fruehauf Corporation
GATX Corporation
General Electric Company
Goodrich (B. F.) Company
Gulf Oil Corporation
Homestake Mining Company
International Business Machines Corporation
International Paper Co.
Kennecott Copper Corporation
Leheigh Portland Cement Co.
Ligget Group Inc.
Lowenstein (M.) & Sons, Inc.
Nabisco, Inc.
National Distillers & Chemical Corporation
National Steel Corporation

Pan American World Airways, Inc.
Pepsico, Inc.
Phelps Dodge Corporation
Phillips Petroleum Co.
Pullman, Incorporated
Raybestos-Manhattan, Inc.
Republic Steel Corporation
Standard Brands, Inc.
Standard Oil Company of Indiana
Sterling Drug, Incorporated
St. Regis Paper Company
Timken Company
United States Gypsum Company
United States Steel Corporation
United Technologies Corp.
Wrigley (W. M.) Jr. Company

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