When Sell-Side Analysts Meet High-Volatility Stocks: An Alternative Explanation for the Low-Volatility Puzzle[1]

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Abstract

Empirically, high-volatility stocks tend to deliver low average returns; this result is robust globally and has been documented in various studies. We confirm this finding using a global equity dataset that includes emerging markets data. We also show that high-volatility stocks exhibit high analyst bias in earnings growth forecasts. Although sell-side analysts are predictably optimistic, the relationship between the degree of optimism and a stock's volatility has not been documented before. We hypothesize that analysts inflate earnings forecasts more aggressively for volatile stocks, in part because the inflation would be more difficult for investors to detect. Because investors are known to overreact to analyst forecasts (under-adjust to analyst bias), this can lead to systematic overvaluation and low returns for high-volatility stocks. Additionally, we find sell-side analysts' research informative despite the analysts' biases; stocks that have high forward E/P ratios based on analyst earnings forecasts tend to outperform and produce significantly positive Fama–French alphas. This evidence rejects the cynical view of some in our industry that sell-side analysts are unskilled. More interestingly, we find high forward E/P stocks also exhibit high analyst bias, which supports an interpretation that analysts are more willing to inflate earnings forecasts for stocks that they believe are likely to deliver high returns—or for which their inflated forecasts are likely to do no harm.

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1. Introduction

Somewhat counter to the general intuition, empirical research shows that high-volatility stocks tend to deliver lower average returns than low-volatility stocks. Various explanations of this "puzzle" have been hypothesized, but the topic remains an active area for theoretical research. This paper is empirical in nature and primarily aims to document a new pattern in analyst earnings growth forecast bias in the cross-section for stocks. We also seek to contribute to the low-volatility puzzle literature by arguing that analyst behavior may partially explain the low-volatility anomaly.

We extend the research in two ways. First, we replicate the low-volatility effect using a global dataset that includes emerging markets data. Our results show that the low-volatility effect is robust even after controlling for regions, industrial sectors, and various firm characteristics. Second, we explore a possible link between analyst forecasts and the performance of low- (or high-) volatility stocks and find that high-volatility stocks tend to experience high upward bias in analyst earnings growth forecasts; this cross-sectional relationship has not been identified before. Additionally, high bias (optimistic forecast) generally leads to low stock returns—an observation which suggests that investors underestimate the magnitude of the bias and therefore overreact to analyst growth forecasts.[5] These empirical facts and their interpretations fit neatly together to suggest a new linkage between analyst behaviors and the low-volatility puzzle. As we will discuss later, sell-side analysts have strategic reasons to prefer to inflate growth forecasts for volatile stocks. Because investors overreact to analyst growth forecasts, which creates excess demand for high-volatility stocks, this mechanism produces low returns for volatile stocks and can partially account for the low-volatility effect.

We also find that, despite the upward bias, analyst earnings forecasts are informative for trading. Our evidence suggests that sell-side analysts are likely more skilled than widespread industry cynicism would suggest, and their behaviors are not merely dictated by the incentive to

[5] See La Porta [1996], Dechow and Sloan [1997], Rajan and Servaes [1997], Dechow, Hutton, and Sloan [1999] and Hayes and Levine [2000] for evidence on and interpretation of investor overreaction to analyst growth forecasts.

maintain positive relationships with banking clients and prospects. Specifically, stocks with a high analyst-forecasted earnings-to-price (forward E/P) ratio tend to deliver significantly higher returns and positive Fama–French alphas—that is, *stocks that analysts find "cheap" based on their forecasts tend to subsequently outperform*.[6]

The outline of the paper is as follows. We first review the relevant literature on the low-volatility puzzle and sell-side analyst forecast bias. Next, we propose a simple model of analyst behavior, which can explain the low-volatility puzzle and predict a number of interesting equity return patterns. We then describe our global dataset that includes emerging countries. A key contribution of our research is in demonstrating that the low-volatility effect is robust globally and is not driven by country or sector effects or by firm characteristics. Using global equity data and the I/B/E/S database, we next document that high return volatilities are associated with high upward biases in analyst earnings growth forecasts. Finally, we document that analyst forecasts, although systematically biased upward, do indeed contain useful cross-sectional information regarding future stock returns. This last finding argues in favor of the skill and value of sell-side analyst research.

2. Literature Review

Low-Volatility Puzzle

The literature on the low volatility puzzle has typically examined the two components of volatility—systematic and idiosyncratic—separately. The earlier literature on the rejection of the CAPM found that low-beta stocks produce higher risk-adjusted returns than high-beta stocks.[7] These findings are related to the low-volatility effect because low- (high-) beta stocks are more likely to exhibit low (high) volatility. The low-beta effect does not, however, subsume

6 Although secondary to the primary focus of our paper, our new findings suggest that not only do sell-side analysts express valuable information in their earnings forecasts, but that investors underreact to the information long (i.e., months) after the forecasts become available, allowing profitable trading strategies to be constructed based on clever manipulation of I/B/E/S data. This evidence is consistent with the findings of Womack [1996], Barber, Lehavy, McNichols, and Trueman [2001], Mikhail, Walther, and Willis [2004] and Li [2005] on investor underreaction to analyst recommendations.

7 See Black, Jensen, and Scholes [1972], Miller and Scholes [1972], and Haugen and Heins [1975].

the low-volatility effect. More recent literature has focused on idiosyncratic volatility and has generally found that stocks with low idiosyncratic volatility tend to produce higher risk-adjusted returns than stocks with high idiosyncratic volatility.[8] This finding is also related to the low-volatility puzzle since stocks with low idiosyncratic volatility usually exhibit low total volatility. Using developed-country equity data from 1985 to 2006, Blitz and van Vliet [2007] reported that low-volatility stocks outperformed high-volatility stocks. Frazzini and Pedersen [2011] also documented similar results using an expanded time horizon (1984–2009).

Various conjectures have been presented for explaining the low-beta and/or the low-idiosyncratic-volatility effect. Excellent syntheses of the related theories and empirical evidence has been provided by Baker, Bradley, and Wurgler [2011] and Pedersen and Frazzini [2011]. Baker, Bradley, and Wurgler summarized and argued the behavioral explanation for the low-volatility effect: investors are assumed to have a “preference for lotteries” and views high volatility stocks as speculation/gambling tools, which inflates the price for high-volatility stocks and depresses their future returns.[9] Rational asset managers are unable to arbitrage away this behavioral anomaly because over-weighting low-volatility stocks creates too much tracking error against their benchmarks.[10] Pedersen and Frazzini [2011] advocated a rational model in which investors are leverage constrained. In this model, investors use high-beta stocks to improve portfolio expected returns even though leveraging low-volatility stocks would produce better results. This excess demand for high-volatility stocks results in high prices in the present day followed by low future returns for these securities.[11] Because all investors are leverage and shorting constrained to varying degrees, the low-volatility premium is not arbitraged away. In the rational model, high beta stocks would have lower returns than “fair” but would not be expected to actually have lower returns than low beta stocks, which is what has been documented in a number of empirical studies.

In this paper, we provide another explanation for the low-volatility effect based on sell-side analyst behavior and investor reactions to analyst forecasts. We find that volatility can be a proxy for analyst bias—high-volatility stocks tend to experience more analyst optimism.

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8 See Malkiel and Xu [2002], Spiegel and Wang [2006], Ang et al. [2006, 2009], and Bali and Cakici [2008].

9 See Mitton and Vorkink [2007], Barberis and Huang [2008] and Kumar [2009] for more detailed discussions regarding the investor preference for lottery-like payoffs and for high-volatility stocks.

10 See Brennan [1993] and Brennan, Cheng, and Li [2012] for more detailed discussions of the theoretical motivation for and the empirical evidence that supports why benchmark-sensitive institutional equity managers are unwilling to take advantage of the low-volatility premium.

11 The original insight into the effect of leverage constraints was provided by Black [1972].

Since the market is fooled, partly by the rosy forecasts, this leads to high prices and low returns for high-volatility stocks.

Sell-Side Analyst Behavior

It is well known that sell-side analysts tend to issue upward-biased earnings forecasts; anecdotal evidence and theoretical research suggest that the optimism may be strategic rather than indicative of a lack of skill.[12,13] Interestingly, despite the strong evidence on sell-side analyst optimism, investors do not seem to properly adjust for this bias. For stocks that are associated with high analyst optimism, the literature documents initial price overreaction to the rosy forecasts, followed by mean-reversion when high growth fails to materialize.[14]

Because investors do not fully adjust for sell-side analyst optimism, the ability to forecast analyst bias for stocks can be a valuable tool for investors. Frankel and Lee [1998] hypothesized that analysts, like naïve investors, can exhibit the behavioral tendency to over-extrapolate recent firm growth in making their own forecasts. They also found that growth-oriented stocks—those with high P/B ratios, high past sales growth, and high long-term earnings forecasts and ROE forecasts—tend to experience high analyst optimism. In this paper, we identify two additional stock characteristics—high volatility and high forward E/P—that predict analyst optimism. Our variables, however, are motivated by rational and strategic analyst behaviors and not by analysts' mistakes.

Although analysts are encouraged to produce rosy forecasts, they are also incentivized to provide high-quality research and profitable stock recommendations. Research finds that analyst reputation drives brokerage order flows.[15] Research also supports that analyst promotions are related to their relative forecast accuracy and the profitability of their stock picks.[16] This finding, according to Francis and Philbrick [1993], suggests a complex optimization problem for sell-side analysts. Jackson [2005] claimed that an equilibrium can exist in which sell-side analysts inflate earnings growth forecasts, but these forecasts are still informative. Empirical evidence seems to

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12 See Ramnath, Rock, and Shane [2008] for a comprehensive review of the analyst forecast literature as well as a suggested list of the unexplored questions in the literature.

13 See Francis and Philbrick [1993], Kang, O'Brien and Sivaramakrishnan [1994], Dugar and Nathan [1995], Lin and McNichols [1998], Michaely and Womack [1999], and Dechow, Hutton and Sloan [2000].

14 See Dechow and Sloan [1997], Rajan and Servaes [1997], Dechow, Hutton and Sloan [1999], and Purnanandam and Swaminathan [2004].

15 See Irvine [2004], Jackson [2005], and Cheng, Liu, and Qian [2006].

16 See Dechow, Hutton, and Sloan [2000] and Hong, Kubik, and Solomon [2000].

support the informativeness of analyst research in spite of the observed bias: Kim, Lin, and Slovin [1997] and Green [2006] found that early access to sell-side analyst stock picks leads to abnormal profits.

It is an interesting question to explore whether sell-side analyst stock recommendations are valuable when investors do not have privileged early access. In our paper, we are able to extract information from analyst forecasts by examining the forward E/P for stocks based on the sell-side analyst earnings forecast. We found that stocks with high forward E/P ratios based on publicly available I/B/E/S analyst 12-month earnings forecasts produced higher subsequent 12-month returns. This is a new finding in the sell-side analyst literature and is consistent with earlier results supporting market under-reaction to analyst recommendations.[17]

3. A Model of Analyst Behavior and an Explanation for the Low-Volatility Puzzle

We propose a simple model to reconcile the empirical observation that sell-side analyst earnings forecasts are upward biased and unreliable on the one hand, yet are informative in producing abnormal profits for investors on the other. Although sell-side analysts have been shown to display over-optimism regarding firm earnings growth, it is hard to believe that analyst forecasts are arbitrarily positive. Analysts are presumably skilled and rational economic agents who optimize their behaviors to satisfy competing objectives.[18] Sell-side research, considered by some to be valuable, can drive significant brokerage trade flows.[19] Thus, because sell-side research can influence client investment activities, analysts are rated and the rankings are publicized. Presumably, research quality rankings matter to the employer investment banks.

[17] Frankel and Lee [1998], using an accounting valuation method (the residual income model) based on analyst forecasts, found that analyst forecasts are informative for predicting long-term returns. Barber, Lehavy, McNichols and Trueman [2001] and Loh and Mian [2006] formed trading portfolios based on published analyst recommendations and produced abnormal profits.

[18] See Francis and Philbrick [1993].

[19] See Brennan and Chordia [1993], Hayes [1998], Conrad, Johnston, and Wahal [2001] and Irvine [2000].

Theoretical and empirical research support the thesis that forecast accuracy and stock recommendations are linked with analysts' promotions and turnover.[20]

On the flip side, theories and empirical evidence also suggest that relationships with investment banking clients and prospects could influence analysts to bias their earnings growth forecasts upward and to set target stock prices higher than they otherwise would.[21] So, how might a skilled sell-side analyst achieve the complex objective of producing rosy earnings growth forecasts without appearing obviously biased and, at the same time, providing profitable trading recommendations to clients?

We propose a simple model of analyst behavior that produces both (1) the observed cross-sectional pattern in which high-volatility stocks experience high analyst forecast bias and (2) forecasts that are informative for trading. Imagine that analysts are skilled at ascertaining the mean and standard deviation of earnings growth for the stocks they cover. These analysts need to produce quality research and profitable recommendations to further their careers and reputations, while at the same time remaining sensitive to senior management's desire to maintain investment banking relationships. We posit that there is an equilibrium behavior such that all analysts inflate their reported growth estimates upward by, say, half a standard deviation in order to (1) be investment banking business friendly[22] and (2) avoid detection for inflating growth forecasts in certain situations.

This equilibrium behavior would predict higher growth forecast bias for firms with higher earnings growth variability and would, in turn, predict higher return volatility for these firms. This prediction is consistent with our empirical finding that high-volatility stocks are associated with high analyst forecast bias. Further, because evidence suggests that investors do not fully appreciate the upward bias, and thus overreact to analyst optimism in the short run, volatile stocks tend to be overvalued and experience low subsequent returns. This could then explain, in part, the documented underperformance of high-volatility stocks.

Our simple model also posits that analysts express valuable information in their forecasts in order to signal their skill to clients and management, but they strategically obfuscate the

[20] See Mikhail, Walther, and Willis [1999], Hong, Kubik, and Solomon [2000], and Clarke and Subramanian [2006].

[21] See Dugar and Nathan [1995], Lin and McNichols [1998] and Clarke, Khorana, and Rau [2004].

[22] The literature primarily focuses on the relationship between analyst earnings forecast inflation and the investment banking client relationship. Evidence also exists, however, that investment banks use inflated earnings growth to justify high price targets and strong buy recommendations in order to encourage more trading for their brokerage businesses (see Irvine [2000]).

information in an attempt to provide client-friendly inflated forecasts. If true, this suggests that profitable trading information can be potentially backed out of biased analyst forecasts; investors simply need to decode the analyst signal more effectively. We know that analysts overwhelmingly prefer to communicate equity attractiveness using E/P ratios,[23] so we can interpret the forward E/P ratio as a proxy for the analyst's private information on the attractiveness of a stock.

In our research, we find that stocks with high forward E/P forecasts outperform stocks with low forward E/P forecasts. Thus, while the complex strategic behavior of analysts leads to persistent upward bias and poor reliability in analysts' published growth forecasts, we find evidence that analysts are still able to communicate valuable recommendations through forward E/P forecasts. Our new evidence that analysts are more skilled than would be suggested by their lack of forecasting accuracy is, if anything, a vindicating discovery for sell-side analysts, given the prevailing industry wisdom regarding the value of their research.

4. Data

Our global equity dataset represents a broader dataset than has been used in previous research on the low-volatility premium puzzle; specifically, we expand the global dataset to include emerging markets. We use the I/B/E/S database to gather consensus analyst earnings forecasts. For each stock in the I/B/E/S database, the consensus earnings forecast is generally provided for at least the next two fiscal years. At the start of each fiscal year, the database records the reported previous fiscal year earnings per share (EPS) and also reports the consensus fiscal year-end EPS forecast for the current fiscal year and the following fiscal year. Table 1 shows the I/B/E/S monthly data structure for Company A, which has a fiscal year ending in September. At month-end October 2000, the database records realized EPS for the prior fiscal year (1999) as well as the consensus forecast for the current fiscal year (2000), which ends September 2001, and the next fiscal year (2001), which ends September 2002. We denote the prior fiscal year as FY0, the current fiscal year as FY1, and the next fiscal year as FY2.

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[23] See Block [1999], Bradshaw [2004] and Demirakos, Strong, and Walker [2004].

Table 1. I/B/E/S Consensus Forecast for Company A

Date	Previous Fiscal Year End (FY0)	Current Fiscal Year End (FY1)	Next Fiscal Year End (FY2)	FY0 Realized EPS	FY1 Consensus EPS Forecast	FY2 Consensus EPS Forecast
⋮	⋮	⋮	⋮	⋮	⋮	⋮
Jun-2000	Sep-1999	Sep-2000	Sep-2001	1.35	1.93	2.18
Jul-2000	Sep-1999	Sep-2000	Sep-2001	1.35	1.95	2.25
Aug-2000	Sep-1999	Sep-2000	Sep-2001	1.35	1.95	2.25
Sep-2000	Sep-1999	Sep-2000	Sep-2001	1.35	1.95	2.25
Oct-2000	Sep-2000	Sep-2001	Sep-2002	1.76	1.21	1.39
Nov-2000	Sep-2000	Sep-2001	Sep-2002	1.76	1.19	1.39

A key variable of interest is the analyst forecast bias for current fiscal-year EPS. Analyst forecast bias is simply the time-series average of the forecast errors or the differences between the consensus EPS estimates and the subsequent realized EPS numbers. Operationally, we define the forecast error for Company A associated with the month of October 2000 as the 12-Month-Forward Realized EPS minus the 12-Month-Forward Consensus EPS Forecast. The forward consensus EPS is the time-weighted average of the current and next year's consensus EPS, and the forward realized EPS is also the time-weighted average. Because EPS_t is neither standardized (EPS_t gives no information for making cross-sectional comparisons) nor stationary (EPS_t generally grows over time and is unbounded), we elect to work with a transformed variable, EPS_t/BPS_{t-1}. Dividing earnings per share by book value per share creates a variable that is standardized across stocks and is stationary. EPS_t/BPS_{t-1} is also referred to as the return on shareholder equity, or ROE_t.[24]

We do not have an explicit interest in ROE. We are merely interested in standardizing the EPS variable so that it can be more meaningfully compared on a cross-sectional and inter-temporal basis. Other transformations, such as EPS/Asset or EPS/Sales, would accomplish the same goal and produce similar analyses. We then define earnings growth as $(EPS_{12\ months\ forward} - EPS_{past\ 12\ months})/BPS$. We do not use the traditional definition of earnings growth, $EPS_{12\ months\ forward}/EPS_{past\ 12\ months}$, because EPS can often be negative and can switch signs from year to

24 Here and hereafter, all subindex t are not necessary because the context makes the interpretation obvious. Incidentally, $t-1$ means the prior fiscal year, not the previous month.

year, so that the resulting growth rate measurement can become difficult to interpret.[25] For example, two extremely opposite earnings growth profiles—$2 per share last year declining to –$2 per share versus –$2 per share growing to $2 per share—would result in the same growth rate, which is clearly undesirable for our econometric examination.

Corporate accounting data are sourced from Worldscope and total return data are from IDC Exshares. The sample period for our study ranges from January 1987 through December 2011 for developed countries and from December 1994 through December 2011 for emerging countries.[26,27] All return-related statistics are computed using excess returns, which are calculated as the net return in excess of local three-month interest rates. Our universe of stocks draws from the union of the MSCI and FTSE index memberships across all developed and emerging market countries.[28]

Because we use I/B/E/S consensus and reported EPS in our study, our universe is restricted to stocks for which both variables are available. The average number of stocks in the unrestricted universe is 3,308 and 910 for the developed and emerging markets, respectively. After eliminating stocks without consensus EPS, the universe reduces to 2,846 for the developed markets[29] and 537 for the emerging markets. We examine the effect of the sample selection rules and conclude that they do not adversely influence our results. We do not report these tests for the brevity of exposition. For robustness, we have repeated the tests with "winsorized" outlier observations. We do not separately report these results as our research appears to be unaffected by outliers.

5. Portfolios Sorted on Volatility

Low-Volatility Premium in Developed and Emerging Markets

We begin our analysis by examining the pattern of returns in the cross-section of global stocks,

[25] In very rare situations, book value per share can also be negative. We discard data points with negative book value per share.
[26] Before January 1987 and December 1994, the numbers of stocks are too small.
[27] For the study of analyst forecast biases, however, we need the next fiscal year realized earnings. This would reduce the sample range up to December 2009.
[28] We follow the definition of countries used by the MSCI World (Developed Countries) Index and Emerging Markets Index.
[29] The mean numbers of stocks are 1,138 for North America; 898 for Europe; 596 for Japan; and 214 for Asia Pacific ex-Japan.

sorted by volatility. At the end of each month, we rank stocks based on their volatility using the past five years of monthly data. We then report the annualized buy-and-hold return for each decile portfolio. We note, however, that in a simple global sort, the constituents for each volatility decile could be dominated by a particular country or global sector because stocks from a particular country or industry sector may share a similar level of volatility. As a result, country and/or sector effects can become indistinguishable from the volatility effect. Additionally, we observe that small-capitalization stocks tend to be more volatile than average. To adjust for the impact of country, sector, and firm characteristics, we perform a global volatility portfolio sort neutralizing these effects. Specifically, we sort on adjusted volatility using the following equation:

$$\log(Vol_i) = \beta_1 \cdot Size_i + \beta_2 \cdot BP_i + \sum_j \gamma_j \cdot SD_{i,j} + \sum_k \delta_k \cdot Ctry_{i,k} + \varepsilon_i, \qquad (1)$$

where Vol_i is the total volatility of stock i measured from the previous 60 months, $Size_i$ is the market capitalization at the end of the preceding month, $SD_{i,j}$ is a dummy variable for industrial sector j (as classified by GICS 10 sectors), $Ctry_{i,k}$ is a dummy for country k, and ε_i is the adjusted volatility residual net of the influences of country, sector, and firm characteristics. Using Equation (1), we compute the adjusted volatility for each stock in our global universe and then sort stocks into decile portfolios based on this adjusted measure.

We report the returns and characteristics of the adjusted volatility portfolios in Table 2. The decile portfolios D1 and D10, in the top panel, contain firms with the lowest and highest adjusted volatilities, respectively, for the developed markets. The quintile portfolios follow the same format and report results for the emerging markets. For the developed markets, the returns of the low-volatility portfolios are higher than those of the high-volatility portfolios, and the pattern is nearly monotonic. For the emerging markets, the low-volatility effect is not present when we only examine the quintile returns. When we include the Sharpe ratio term, the low-volatility puzzle is strong for both the developed and emerging market countries. We also note that when we eliminate the 1994–1998 sample period, which was characterized by unprecedented EM currency fluctuations, the low-volatility effects are statistically stronger. This pattern holds true for the global portfolios sorted using raw (unadjusted) volatilities, which we do not separately report. These results are consistent with what was reported by Blitz and van Vliet

[2007] and Frazinni and Pedersen [2011]. These results confirm that the low-volatility effect is robust globally and is not subsumed by the standard size and value anomalies or driven by country or industry differences.

Analyst Forecast Bias and Stock Volatility

In this section, we examine the portfolio characteristics associated with the various volatility decile portfolios. Table 3 reports the descriptive statistics such as book-to-price (B/P), earnings growth variability, average market capitalization, and so forth for the stocks in the decile portfolios. In addition, we report statistics on analyst earnings growth forecasts, subsequent realized growth, and analyst forecast bias. Again, we only report the statistics of portfolios formed on adjusted volatility, noting that the results are similar using raw volatilities.

Because the influences from countries, sectors, and firm characteristics are neutralized in the portfolio construction process, it is not surprising that the average market-cap and B/P characteristics are similar across the decile portfolios. The country and industry allocations are similar as well, but are not displayed in Table 3 for brevity. First, we observe that the earnings growth forecast biases, as measured by $(EPS_{\text{12-months-forward forecast}} - EPS_{\text{12-months-forward realized}})/BPS$, are positive on average for stocks, meaning that analysts are systematically over-optimistic regarding future corporate earnings growth. This is consistent with the literature on upward bias in sell-side analyst forecasts. Additionally, we observe that the low-volatility portfolios generally have lower forecasted earnings growth as measured by $(EPS_{\text{12-months-forward forecast}} - EPS_{\text{past-12-months realized}})/BPS$, but do not generally display lower realized earnings growth as measured by $(EPS_{\text{12-months-forward realized}} - EPS_{\text{past-12-months realized}})/BPS$. This observation suggests an interesting pattern of analyst bias in the cross-section—analysts seem to be more optimistic on the more volatile stocks!

A Model of Sell-Side Analyst Behavior

The observation that return volatility is cross-sectionally correlated with analyst bias in earnings growth forecasts is a new empirical finding, which contributes to the literature on analyst forecast bias as well as to the literature on the low-volatility premium. Because this paper is empirical in nature, we propose a plausible story to rationalize this finding, but do not propose testable implications of the story to ascertain its validity against competing hypotheses.

As we discussed earlier, sell-side analyst behaviors are thought to be influenced by their desire (1) to maintain good relationships with investment banking clients and prospects, (2) to avoid damaging their reputation with brokerage clients who subscribe to analyst research reports, and (3) to achieve high rankings against other analysts in published quality rankings.

Empirical evidence supports the fact that sell-side analysts have superior abilities to analyze public information and are adept at producing valuable private information on companies. It is not unreasonable to model analysts as skilled at estimating the distribution of next-period earnings growth, $\tilde{g}_t$, for firms they cover. Note that realized earnings growth, $\tilde{g}_t$, is a random variable drawn from a distribution with mean g_t and standard deviation σ_t. More formally, each analyst *i* produces a forecast of $\hat{g}_{t,i}$ and $\hat{\sigma}_{t,i}$. The true skill of an analyst is determined by the deviation over time between $\hat{g}_{t,i}$ and the unobserved true mean $g_{t,i}$. Since $g_{t,i}$ cannot be observed, the skill of analyst *i* can only be estimated by the average difference between his forecast $\hat{g}_{t,i}$ and the realized $\tilde{g}_{t,i}$ over time.[30] Finally, analysts report a biased forecast, $G_{t,i}$, instead of their true private information, $\hat{g}_{t,i}$.

We assume that the utility function of the analysts is (1) increasing in the "optimism of the reported growth forecast," or $G_{t,i} - \hat{g}_{t,i}$; (2) decreasing in the "detectability of the forecast bias," or $(G_{t,i} - \hat{g}_{t,i})/\hat{\sigma}_{t,i}$; and (3) decreasing in distortion in valuation accuracy of the forecast, or $|EPS(G_{t,i})/P_t - EPS(\hat{g}_{t,i})/P_t|$, where $EPS(G_{t,i})/P_t$ is the forward E/P based on the reported forecast $G_{t,i}$, and $EPS(\hat{g}_{t,i})/P_t$ is the forward E/P based on the true forecast $\hat{g}_{t,i}$. Although these assumptions are naïve and incomplete as descriptions of reality, they are consistent with the empirical evidence on analysts' behaviors and incentives.

If the variability of earnings growth, σ_t, for firm *i* is extremely low, then large bias, $G_{t,i} - \hat{g}_{t,i}$, would be easy for brokerage clients to detect. An econometrically savvy investor can detect whether an analyst has been "pumping" stock prices through highly inflated forecasts (over the last *T* periods) by testing if $\frac{1}{T}\sum\left(G_{t,i} - \tilde{g}_t\right)/\tilde{\sigma}_T$ is significantly larger than zero, where $\tilde{g}_t$ and $\tilde{\sigma}_T$ are the realized earnings growth and variability. Analyst stock recommendations are usually justified by valuation multiples based on forward earnings. As a result, analysts would not want to inflate reported $G_{t,i}$ and next year's earnings $EPS(G_{t,i})$ so significantly that an unattractive stock (with low $EPS(\hat{g}_{t,i})/P_t$ based on the analyst's true forecast) appears attractive.

Without writing a formal mathematical model, we simply state that a repeated game

30 For simplicity, we assume that each analyst covers only one firm.

equilibrium exists whereby all analysts inflate their reported earnings growth forecasts relative to their private unbiased growth estimates by k times earnings growth variability. The scalar k is determined by (1) the benefit to the analyst from improving/maintaining investment banking client/prospect relationships through "friendly" outlooks, (2) the risk of being accused of "pump and dump" by brokerage clients, and (3) the benefit from providing quality stock recommendations to brokerage clients. Intuitively, in this equilibrium, analysts inflate growth forecasts by a careful amount to avoid losing credibility outright and to ensure that their forecasts can still result in forward E/P ratios, which lead to good buy/hold/sell recommendations.

Theoretically, return volatility has a positive relationship with earnings growth variability, which we confirm empirically in Table 3. This then suggests that more volatile stocks are more likely to receive greater analyst inflation in earnings growth forecasts. Since investors are documented to overreact to analyst growth forecasts, our model predicts low returns for high-volatility stocks.

6. Forward E/P and Stock Returns

High Forward E/P = High Returns

Another prediction of our simple model is that stocks with analyst-forecasted high forward E/P ratios will outperform stocks with low forward E/P ratios. In Table 4a, we show that developed market stocks in the top decile, as sorted by analyst-forecasted forward E/P ratios, produce a 6% higher annualized return than those in the bottom decile. The Sharpe ratios for the top and bottom deciles are 0.48 and 0.19, respectively. Similarly, for emerging market stocks, the top quintile stocks outperform the bottom quintile by nearly 10% per annum (a Sharpe ratio of 0.73 versus 0.35).[31]

The forward E/P ratio can be interpreted as a tool for analysts to communicate the attractiveness of stocks.[32] In the bottom panel of Tables 4a and 4b, we show that the information contained in an analyst's forward E/P is not subsumed by the Fama–French return model; specifically, stocks that analysts find attractive (in three of the top four deciles for developed

[31] The emerging markets data are likely significantly more noisy than the developed markets data. This might contribute to the lack of monotonicity in the returns and the Sharpe ratios of the sorted portfolios.

[32] See Demirakos, Strong, and Walker [2004].

markets and in the top quintiles for emerging markets) display significant Fama–French alphas. Brokerage clients with advanced access to analyst research and recommendations appear to achieve better investment performance.

Tables 4a and 4b show that the analyst-earnings-growth-forecast bias is increasing in the forward E/P. This is another novel empirical fact that we introduce into the literature. This observation suggests that analysts inflate the earnings growth forecasts more aggressively for stocks that they find attractive from a forward E/P perspective and do not tend to inflate the earnings as aggressively for stocks they find to be less attractive. On average, for stocks that analysts find most attractive in the developed markets (top decile by forward E/P), the upward growth bias is 7%, and in the emerging markets (top quintile), the bias is 6%. This behavior is consistent with our simple model in which the analyst prefers to inflate earnings as much as possible without losing credibility with clients. For stocks that analysts believe are likely to produce great returns, inflating earnings aggressively is less likely to create a poor experience for clients who trade on analyst forecasts.

Volatility and Forward E/P Double-Sorted Portfolios

To summarize our findings and to explore any potential interactions, we perform an unconditional double sort on volatility and forward E/P. We report the portfolio statistics in Table 5a for developed markets and in Table 5b for emerging markets. The new discovery that we make is that the low-volatility effect is much more pronounced for the low forward E/P stocks. In the developed markets, for low forward E/P stocks, the lowest volatility portfolio has a Sharpe ratio of 0.42 and the highest volatility portfolio has a Sharpe ratio of 0.11, a difference of 74%. For high forward E/P stocks, the Sharpe ratios for the lowest and highest volatility portfolios are 0.63 and 0.45, respectively, a difference of 28%. In the emerging markets, we observe the same pattern. For low forward E/P stocks, the low volatility portfolio has s Sharpe ratio of 0.39 compared to a Sharpe ratio of 0.26 for the high-volatility portfolio, which is a 33% difference, and for high forward E/P stocks, the corresponding Sharpe ratios are 0.61 and 0.55, respectively, a 9% difference.

Table 6 reports the corresponding Fama–French alphas for the double-sorted portfolios. The results show a general pattern in which alphas are large for high forward E/P stocks and low-volatility stocks and are small for low forward E/P stocks and high-volatility stocks. This result can be interpreted in the following way. Forward E/P is a proxy for analysts' valuable private information, which is communicated only to their brokerage firm's clients. Empirical evidence also shows that investors underreact to analysts' stock recommendations, and this makes the forward E/P information from the I/B/E/S database valuable for creating outperformance.

Volatility is a proxy for analyst bias. Conventional wisdom indicates that investors have some awareness of the sell-side analyst bias, yet empirical evidence suggests that investors still substantially overreact to analyst optimism (or under-appreciate the size of the analyst bias). The degree to which investors over- or underreact to different aspects of the analyst research report is succinctly captured in the cross-sectional pattern of the Fama–French alphas presented in Table 6. We believe this particular finding is novel and contributes to the empirical literature on investor over/under-reaction to the release of analyst research.

5. Conclusions

The contributions of this paper are mainly empirical; we want to be careful not to overstate the significance of our theoretical contribution. Given our emphasis on the empirical results, we attempt to contribute to the literature by offering plausible explanations for the low-volatility puzzle and the sell-side analyst behaviors discussed throughout the paper.

Our empirical results both confirm and extend the work of other researchers. We confirm the findings of low-volatility returns in global developed and emerging markets. When we explore possible linkages between the low-volatility findings and analyst forecasts, we find several interesting results. We find evidence that sell-side analysts are strategic in how they inflate earnings growth forecasts for stocks. It is well accepted that sell-side analysts have incentives to provide optimistic forecasts, and their positive bias has a very specific cross-sectional pattern. First, they tend to inflate earnings growth forecasts for more volatile stocks. We hypothesize that this is because it is harder for clients to detect inflation in growth forecasts for stocks that have highly volatile growth. Second, analysts tend to more aggressively inflate growth forecasts for stocks that they have strong positive information on. We suspect that this is because clients are less likely to complain about overly optimistic growth forecasts for stock recommendations that prove to be profitable.

These strategic behaviors by analysts can explain, partially, the low-volatility premium. High-volatility stocks are more likely to receive more inflated earnings forecasts. Because investors are tend to overreact to analyst optimism and are generally willing to overpay for stocks with high analyst bias, this would predict low returns for high-volatility stocks. More interestingly, we find that analyst forecasts, while biased upward, do result on average in the correct stock picks for their clients. Specifically, stocks with forecasted high forward E/P ratios tend to outperform stocks with forecasted low forward E/P ratios. The high E/P stocks also produce sizeable positive Fama–French alphas. Finally, we document that the low-volatility effect is significantly stronger for low forward E/P stocks than for high forward E/P stocks.

Our empirical findings are novel and add to the literature on analyst behavior. They also provide greater richness to and expand on the known cross-sectional pattern of volatility premia. Finally, they provide insights into a plausible new mechanism that uses sell-side analyst behaviors to explain the low-volatility premium. .

REFERENCES

Ang, A., R. Hodrick, Y. Xing, and X. Zhang. “The Cross-Section of Volatility and Expected Returns.” *Journal of Finance*, vol. 61, no. 1 (2006), pp. 259–299.

——. “High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence.” *Journal of Financial Economics*, 91 (2009), pp. 1–23.

Arnott, R., F. Li, and K. Sherrerd. “Clairvoyant Value and the Value Effect.” *Journal of Portfolio Management*, vol. 35, no. 3 (2009), pp. 12–26.

Baker, M., B. Bradley, and J. Wurgler. “Benchmarks as Limits to Arbitrage: Understanding the Low-Volatility Anomaly.” NYU Working Paper No. FIN-10-002, 2010.

Barber, B., R. Lehavy, M. McNichols, and B. Trueman. “Can Investors Profit from the Prophets? Consensus Analyst Recommendations and Stock Returns.” *Journal of Finance*, vol. 56, no. 2 (2001), pp. 531–563.

Barberis, N., and M. Huang. “Stocks as Lotteries: The Implications of Probability Weighting for Security Prices.” *American Economic Review*, vol. 98, no. 5 (2008), pp. 2066–2100.

Bali, T., and N. Cakici. “Idiosyncratic Volatility and the Cross-Section of Expected Returns.” *Journal of Financial and Quantitative Analysis*, 43 (2008), pp. 29–58.

Blitz, D., and P. van Vliet. “The Volatility Effect: Lower Risk without Lower Return.” *Journal of Portfolio Management*, 34 (2007), pp. 102–113.

Black, F. “Capital Market Equilibrium with Restricted Borrowing.” *Journal of Business*, 45 (1972), pp. 444–454.

Black, F., N. Jensen, and M. Scholes. “The Capital Asset Pricing Model: Some Empirical Tests.” In *Studies in the Theories of Capital Markets*, M. Jensen, ed. New York: Praeger, 1972.

Boyer, B., T. Mitton, and K. Vorkink. “Expected Idiosyncratic Skewness.” *Review of Financial Studies*, vol. 23, no. 1 (2010), pp. 169–202.

Bradshaw, M. “The Use of Target Prices to Justify Sell-Side Analysts' Stock Recommendations.” *Accounting Horizons*, 16 (2002), pp. 27–40.

——. “How Do Analysts Use Their Earnings Forecasts in Generating Stock Recommendations?” *Accounting Review*, 79 (2004), pp. 25–50.

Brav, A., and R. Lehavy. “An Empirical Analysis of Analysts’ Target Prices: Short-Term Informativeness and Long-Term Dynamics.” *Journal of Finance*, 58 (2003), pp. 1933–1968.

Brennan, M., X. Cheng, and F. Li. “Agency and Institutional Investment.” *European Financial Management*, vol. 18, no. 1 (2012), pp. 1–27.

Brennan, M., and T. Chordia. “Brokerage Commission Schedules.” *Journal of Finance*, 48 (1993), pp. 1379–1402.

Cao, X., and Y. Xu. “Long-Run Idiosyncratic Volatilities and Cross-Sectional Stock Returns.” Working paper, February 2010.

Clarke, R., H. de Silva, and S. Thorley. “Know Your VMS Exposure.” *Journal of Portfolio Management*, 36 (2010), pp. 52–59.

Clarke, J., A. Khorana, A. Patel, and P. Rau. “Analyst Behavior at Independent Research Firms, Brokerages, and Investment Banks: Conflicts of Interest or Better Information?” Working paper, Georgia Institute of Technology, Wake Forest University, and Purdue University, 2004.

Clarke, J., and A. Subramanian. “Dynamic Forecasting Behavior by Analysts: Theory and Evidence.” *Journal of Financial Economics*, vol. 81, no. 1 (2006), pp. 81–113.

Conrad, J., K. Johnston, and S. Wahal. “Institutional Trading and Soft Dollars.” *Journal of Finance*, vol. 56, no. 1 (2001), pp. 397–416.

Dechow, P., A. Hutton, and R. Sloan. “An Empirical Assessment of the Residual Income Valuation Model.” *Journal of Accounting and Economics*, 26 (1999), pp. 1–34.

Dechow, P., and R. Sloan. “Returns to Contrarian Investment Strategies: Tests of Naïve Expectations Hypotheses.” *Journal of Financial Economics*, 43 (1997), pp. 3–27.

Demirakos, E., N. Strong, and M. Walker. “What Valuation Models Do Analysts Use?” *Accounting Horizons*, vol. 18, no. 4 (2004), pp. 221–240.

Dugar, A. and S. Nathan. “The Effect of Investment Banking Relationships on Financial Analysts’ Earnings Forecasts and Investments Recommendations.” *Contemporary Accounting Research* vol. 12, no. 1 (1995), pp. 131–160.

Fama, E., and K. French. “Common Risk Factors in the Returns on Stocks and Bonds.” *Journal of Financial Economics*, 33 (1993), pp. 2–56.

Francis, J., and D. Philbrick. “Analysts’ Decisions as Products of a Multi-Task Environment.” *Journal of Accounting Research*, 31 (1993), pp. 216–230.

Francis, J., and L. Soffer. “The Relative Informativeness of Analysts’ Stock Recommendations and Earnings Forecast Revisions.” *Journal of Accounting Research*, 35 (1997), pp. 193–211.

Frankel, R., and C. Lee. “Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns.” *Journal of Accounting and Economics*, 9 (1998), pp. 195–228.

Frazzini, A., and L. Pedersen. “Betting Against Beta.” NBER Working Paper Series No.16601, 2011.

Fu, F. “Idiosyncratic Risk and the Cross-Section of Expected Stock Returns.” *Journal of Financial Economics*, vol. 91, no. 1 (2009), pp. 24–37.

Haugen, R., and J. Heins. “Risk and the Rate of Return on Financial Assets: Some Old Wine in New Bottles.” *Journal of Financial and Quantitative Analysis*, vol. 10, no. 5 (1975), pp. 775–784.

Hayes, R. “The Impact of Trading Commission Incentives on Analysts' Stock Coverage Decisions and Earnings Forecasts.” *Journal of Accounting Research*, 36 (1998), pp. 299–320.

Hayes, R., and C. Levine. “An Approach to Adjusting Analysts’ Consensus Forecasts for Selection Bias.” *Contemporary Accounting Research*, vol. 17, no. 1 (2000), pp. 61–83.

Hong, H., J. Kubik, and D. Solomon. “Security Analysts' Career Concerns and Herding of Earnings Forecasts.” *RAND Journal of Economics*, 31 (2000), pp. 121–144.

Huang, W., Q. Liu, S. Rhee, and L. Zhang. “Return Reversals, Idiosyncratic Risk, and Expected Returns.’’ *Review of Financial Studies*, vol. 23, no. 1 (2010), pp. 147–168.

Irvine, P. “Do Analysts Generate Trade for Their Firms? Evidence from the Toronto Stock Exchange.” *Journal of Accounting and Economics*, 30 (2000), pp. 209–226.

Irvine, P. “Analysts’ Forecasts and Brokerage-Firm Trading.” *The Accounting Review*, 79:1 (2004), pp. 125–149.

Jiang, G., D. Xu, and T. Yao. “The Information Content of Idiosyncratic Volatility.” *Journal of Financial and Quantitative Analysis*, vol. 44, no. 1 (2009), pp. 1–28.

Kang, S., J. O’Brien, and K. Sivaramakrishnan. “Analysts’ Interim Earnings Forecasts: Evidence on the Forecasting Process.” *Journal of Accounting Research*, 32 (1994), pp. 103–112.

Kumar, A. “Who Gambles in the Stock Market?” *Journal of Finance*, vol. 64, no. 4 (2009), pp. 1–28.

La Porta, R. “Expectations and the Cross-Section of Stock Returns.” *Journal of Finance*, 51 (1996), pp. 1715–1742.

Lin, H., and M. McNichols. “Underwriting Relationship, Analysts’ Earnings Forecasts and Investment Recommendations.” *Journal of Accounting and Economics*, vol. 25, no. 1 (1998), pp. 101–127.

Loh, R., and M. Mian. "Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations?" *Journal of Financial Economics*, vol. 80, no. 2 (2006), pp. 455–483.

Malkiel, B., and Y. Xu. “Idiosyncratic Risk and Security Returns.” Working Paper, University of Texas at Dallas, 2002.

Michaely, R., and K. Womack. “Conflict of Interest and the Credibility of Underwriter Analyst Recommendations.” *Review of Financial Studies*, 12 (1999), pp. 653–686.

Mikhail, M., B. Walther, and R. Willis. “Do Security Analysts Exhibit Persistent Differences in Stock Picking Ability?” *Journal of Financial Economics*, 74 (2004), pp. 67–91.

Miller, M., and M. Scholes. “Rate of Return in Relation to Risk: A Reexamination of Some Recent Findings.” In *Studies in the Theory of Capital Markets*, M. Jensen, ed. New York: Praeger, 1972, pp. 47–78.

Mitton, T., and K. Vorkink. “Equilibrium Underdiversification and the Preference for Skewness.” *Review of Financial Studies*, vol. 20, no. 4 (2007), pp. 1255–1288.

Morgan, J., and P. Stocken. “An Analysis of Stock Recommendations.” *RAND Journal of Economics*, vol. 34, no. 1 (2003), pp. 183–203.

Purnanandam, A., and B. Swaminathan. “Are IPOs Really Underpriced?” *Review of Financial Studies*, 17 (2004), pp. 811–848.

Rajan, R., and H. Servaes. "Analyst Following of Initial Public Offerings." *Journal of Finance*, vol. 52, no. 2 (1997), pp. 507–529.

Ramnath, S., S. Rock, and P. Shane. “The Financial Analyst Forecasting Literature: A Taxonomy with Suggestions for Further Research.” *International Journal of Forecasting*, 24 (2008), pp. 34–75.

Spiegel, M., and X. Wang. “Cross-Sectional Variation in Stock Returns: Liquidity and Idiosyncratic Risk.” Working paper, Yale University, 2006.

Tversky, A., and D. Kahneman. “Advances in Prospect Theory: Cumulative Representation of Uncertainty.” *Journal of Risk and Uncertainty*, vol. 5, no. 4 (1992), pp. 297–323.

Womack, K. “Do Brokerage Analysts’ Recommendations Have Investment Value?” Working paper, University of Toronto, 1996.