The Effect of Issuing Biased Earnings Forecasts on Analysts' Access to Management and Survival

by

Bin Ke*
Smeal College of Business
Pennsylvania State University

and

Yong Yu
McCombs School of Business
University of Texas at Austin

Abstract

This study offers evidence on the earnings forecast bias analysts use to please firm management and the associated benefits they obtain from issuing such biased forecasts in the years prior to Regulation Fair Disclosure. Analysts who issue initial optimistic earnings forecasts followed by pessimistic earnings forecasts before the earnings announcement produce more accurate earnings forecasts and are less likely to be fired by their employers. The effect of such biased earnings forecasts on forecast accuracy and firing is stronger for analysts who follow firms with heavy insider selling and hard-to-predict earnings. The above results hold regardless of whether a brokerage firm has investment banking business or not. These results are consistent with the hypothesis that analysts use biased earnings forecasts to curry favor with firm management in order to obtain better access to management's private information.

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*Corresponding author
Bin Ke
Pennsylvania State University
354 Business Building
University Park, PA 16802
814-865-0572 (phone)
814-863-8393 (fax)
bxk127@psu.edu (email)

1. Introduction

Prior research finds that financial analysts often issue biased earnings forecasts to please firm management (see e.g., Richardson et al., 2004; Francis and Philbrick, 1993; Das et al., 1998; Lim, 2001; Matsumoto, 2002), but it is not well understood why analysts have incentives to do so. In addition, the form of the forecast bias analysts are assumed to use to please management varies across studies. Some studies assume managers prefer optimistic earnings forecasts (e.g., Francis and Philbrick, 1993) while others assume managers prefer pessimistic forecasts (e.g., Matsumoto, 2002). Recently Richardson et al. (2004) argue that managers prefer initial optimistic forecasts followed by pessimistic forecasts immediately before the earnings announcement.

The objective of this study is to identify the form of the earnings forecast bias analysts use to please management and the associated benefits analysts receive from such biased earnings forecasts. We consider both annual and quarterly earnings forecast biases because analysts often issue both forecasts. To our knowledge, we are the first study that simultaneously examines annual and quarterly earnings forecast biases at the individual analyst level. Because earnings forecast accuracy is important to analysts and their brokerage firms (Mikhail et al., 1999; Leone and Wu, 2002), we hypothesize that analysts issue biased earnings forecasts to curry favor with management so that they can obtain more private information from management to improve their earnings forecast accuracy relative to other analysts (H1). In addition, we hypothesize that analysts who issue biased earnings forecasts are less likely to be fired by their employers (H2).

In light of previous research's conflicting results on the form of the forecast bias analysts use to please management, we consider four possible forms of earnings forecast biases that capture the intertemporal pattern of each analyst's earnings forecasts (denoted OP, OO, PO, PP). For annual earnings forecasts, the four forecast biases are defined using each analyst's first and last one-year ahead annual earnings forecasts issued between two consecutive annual earnings announcement dates. OP denotes the analysts whose first one-year ahead annual earnings forecast issued after the prior fiscal year's earnings announcement is optimistic (i.e., forecast is greater than the realized earnings), but whose last one-year ahead annual earnings forecast issued before the current year's earnings announcement is pessimistic (i.e., forecast is less than or equal to the realized earnings); OO denotes the analysts whose first and last annual earnings forecasts are always optimistic; PP denotes the analysts whose first and last annual earnings forecasts are always pessimistic; finally, PO represents the analysts whose annual earnings forecasts switch from initial pessimism to later optimism. For quarterly earnings forecasts, the four forecast biases for each analyst are defined similarly except that the first earnings forecast for the current quarter is defined as the first two-quarters ahead earnings forecast issued after the announcement of the quarterly earnings two quarters prior and the last earnings forecast is defined as the last one-quarter ahead earnings forecast issued before the current quarter's earnings announcement. The difference in the definitions of the four forecast biases for annual and quarterly earnings forecasts reflects the reality that the majority of analysts issue at least two one-year-ahead annual earnings forecasts between two consecutive annual earnings announcements while only one one-quarter-ahead quarterly earnings forecast between two consecutive quarterly earnings announcements.[1]

We test our hypotheses over the period January 1, 1983-June 30, 2000.[2] For both annual and quarterly earnings forecasts, we find that OP analysts are associated with more accurate earnings

[1] For all the stocks with nonmissing data included in the IBES database over calendar years 1983-1999, 73% of the analyst firm years issue at least two one-year ahead annual earnings forecasts between two consecutive annual earnings announcement dates, while only 23% of the analyst firm year quarters issue at least two one-quarter ahead quarterly earnings forecasts between two consecutive quarterly earnings announcement dates.

[2] Our sample ends on June 30, 2000 because Regulation Fair Disclosure (FD) became effective on October 23, 2000, which prohibits firm management from disclosing material nonpublic information to select individuals, and our variable definitions are measured from July 1, year t to June 30, year t+1. We leave to future research to study the effect of the regulation on the private communication between firm management and analysts.

forecasts and a smaller likelihood of being fired by their employers than other analysts, suggesting that it is the OP bias that analysts use to obtain better access to firm management.

Richardson et al. (2004) find that the OP bias based on consensus earnings forecasts is more severe for firms whose managements wish to sell their personal equity holdings in the firm. Das et al. (1998) argue that access to management is more valuable to analysts when a firm's earnings are difficult to forecast. Therefore, we conjecture that analysts who cover firms with heavy insider trading or hard-to-forecast earnings benefit more from issuing OP earnings forecasts. Consistent with this conjecture, we find that the predicted effect of OP on forecast accuracy and firing is stronger for firms whose earnings are more difficult to forecast and whose managements engage in heavy insider selling. Overall, these results are consistent with the hypothesis that analysts use OP earnings forecasts to gain better access to managers' private information.

Further analyses indicate that the predicted effects of H1 and H2 exist for analysts employed by both investment banks and pure brokerage firms (i.e., those without investment banking businesses). Thus, our results cannot be solely driven by the alleged investment banking incentive. However, we cannot rule out the possibility that the predicted effects for H1 and H2 for the investment bank analysts are partially driven by the investment banking incentive.

Given the documented benefits from issuing OP earnings forecasts, why don't all analysts issue OP forecasts for all firms? We believe there are several reasons. First, as Hong and Kubik (2003) argue, some analysts may not be willing to issue biased forecasts given their good conscience and what they know. Second, firm managers do not have incentives to play the biased earnings forecast game. For example, as we have shown above, managers who do not plan to sell stocks in their own firms do not have as strong an incentive as managers who do to pressure analysts to issue biased forecasts. Furthermore, even if both analysts and managers have incentives to play the biased forecast game, it seems reasonable to assume that managers prefer to cooperate with analysts who have a significant influence on capital market investors (hereafter referred to as the "bang for the buck" hypothesis). We find empirical support for this hypothesis. Specifically, relative to other analysts, we find that OP analysts are more experienced, employed by larger brokerage firms, and more likely to be an All-Star as determined by the Institutional Investor magazine, all indicators of influential analysts.

The results from our study should be of interest to investors and securities regulators who wish to understand the causes of biased earnings forecasts. Our results are also relevant to future researchers who wish to investigate analysts' forecasting behavior. It is common for researchers to require an analyst to be in the sample for several years. Since less biased analysts do not survive, analyses based on surviving analysts could be biased and should be interpreted with caution.

Our study is not the first to recognize the potential influence of firm management on analysts' biased earnings forecasts. For example, Francis and Philbrick (1993) argue that analysts issue optimistic earnings forecasts in order to maintain good relations with management (see also Das et al., 1998; Lim, 2001).[3] However, those studies do not examine the benefits of biased forecasts to individual analysts (i.e., improved forecast accuracy and job security) nor simultaneously consider the various earnings forecast biases.

Chen and Matsumoto (2006) study how revisions in stock recommendations affect analysts' access to management and forecast accuracy. They find that analysts who upgrade a stock experience a significant increase in forecast accuracy relative to analysts who downgrade a stock prior to the passage of regulation FD but not after. They do not study earnings forecast biases or analyst firing.

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3 A recent study by Eames and Glover (2003) raises questions on the robustness of Das et al. (1998).

Hong and Kubik (2003) and Leone and Wu (2002) examine the impact of forecast optimism on analyst turnover (including promotion) but do not consider the other bias measures. More importantly, neither study considers the fear of losing access to management as an explanation for analysts' biased earnings forecasts.

The rest of the paper is organized as follows. Section 2 develops the research hypotheses. Section 3 describes the sample selection and data. Section 4 discusses the variable definitions and presents the regression models. Section 5 reports the test results. We conclude in Section 6.

2. Hypothesis Development

2.1. Benefits from Issuing Biased Earnings Forecasts

Prior research on earnings forecast biases often focus on managerial incentives (see e.g., Matsumoto, 2002; Richardson et al., 2004). Those studies assume that analysts have incentives to issue biased earnings forecasts preferred by managers. We directly test this assumption by demonstrating the benefits individual analysts receive from issuing biased earnings forecasts. Specifically, we examine whether analysts who issue biased earnings forecasts gain better access to management's private information so that their earnings forecast accuracy and job security can be improved relative to other analysts. The possible forms of earnings forecast biases analysts could use to please managers are discussed in section 2.2.

It is well recognized that earnings forecast accuracy is an important determinant of an analyst's reputation, annual compensation, and career success. For example, Mikhail et al. (1999) and Hong et al. (2000) find that analysts whose earnings forecasts are more accurate relative to others are less likely to be fired. The reason forecast accuracy is important to analysts and their brokerage firms is that brokerage firms want analysts who are influential among the buy-side (especially institutional investors) and this influence is directly determined by an analyst's ability to make accurate earnings forecasts. Leone and Wu (2002) document that earnings forecast accuracy is an important determinant of the All-Star analyst ranking in the Institutional Investor magazine's annual survey of buy-side investors. Influential analysts can significantly raise the reputation and influence of their brokerage firms among Wall Street investors and corporate executives, which in turn can bring many tangible and intangible benefits, such as stimulating more trading by their firms' investing clients, helping their firms win more lucrative investment-banking businesses, etc.

Both anecdotal evidence and academic research also suggest that management is an important source of analysts' private information (see Schipper, 1991). One important form of private communication between management and analysts is closed conference calls (before Regulation FD took effect). Bowen et al. (2002) find that conference calls significantly increase analysts' earnings forecast accuracy. Furthermore, Solomon and Frank (2003) report that analysts who issue unfavorable earnings forecasts are often punished in subtle ways by firm management, especially before Regulation FD took effect. Therefore, we hypothesize that analysts have an incentive to use biased earnings forecasts to please management so that they can gain better access to management's private information to improve their earnings forecast accuracy relative to other analysts. This prediction is stated in the following hypothesis:

H1: analysts who issue biased earnings forecasts have more accurate earnings forecasts relative to other analysts.

In addition to suffering a decrease in current earnings forecast accuracy, analysts who do not issue biased earnings forecasts are likely to lose the privileged access to management and their *future* earnings forecast accuracy is expected to deteriorate as a result. Since analysts' forecast accuracy is critical to brokerage firms' reputation and influence, we expect brokerage firms to fire those analysts who do not issue biased earnings forecasts, even after controlling for those analysts' current earnings forecast accuracy. This discussion leads to the following hypothesis:

H2: analysts who issue biased earnings forecasts are less likely to be fired.[4]

Given the hypothesized benefits in H1 and H2, why would not all analysts issue biased earnings forecasts preferred by management? We believe there are several reasons. First, as Hong and Kubik (2003, p. 339) argue, some analysts may not, out of good conscience, be willing to play the biased earnings forecast game with management given what they know. However, good conscience is unobservable and thus cannot be directly tested. Second, even if analysts are interested in playing the biased earnings forecast game, some firm managers may lack incentives. For example, Richardson et al. (2004) find that managers' preference for biased earnings forecasts is stronger for firms whose managers wish to sell a portion of their personal equity holdings in the firm. Thus, if a manager does not plan to sell shares, he should have little incentives to play the biased forecast game, ceteris paribus. Section 5.2.3 reports evidence consistent with this argument. Third, even if both analysts and managers have incentives to play the biased forecast game, it is reasonable to assume that managers prefer to cooperate with analysts who can exert a significant influence on both other analysts and equity investors (referred to as the "bang for the buck" hypothesis).[5] Cooperation with obscure analysts will be less beneficial to managers because these analysts will be less effective in affecting stock investors' expectations. Furthermore, the strategy of giving all analysts who are willing to issue biased forecasts the same private information may not be optimal because it would make no single analyst better off relative to his peers and thus

[4] Although an analyst who issues biased forecasts may be able to move up to a more prestigious brokerage firm, we expect this move-up effect to be weaker than the firing effect in H2 because the analyst's current employer will try to offer monetary incentives to retain him. Empirically, we find only weak evidence that analysts who issue biased forecasts are more likely to move up to more prestigious brokerage firms.

[5] This hypothesis has support from both academic research (see e.g., Gintschel and Markov, 2004; Krigman et al., 2001) and anecdotal news reports (see e.g., Smith and Cauley, 1999; Levitt, 1998).

would reduce all analysts' incentives to play the biased forecast game. In section 5.2.6 we provide evidence on the characteristics of the analysts who issue biased forecasts that are consistent with the "bang for the buck" hypothesis.

2.2. Definitions of Earnings Forecast Biases

Although the idea that analysts use biased earnings forecasts to win favor from firm management has been advanced in many studies, the form of the earnings forecast bias analysts are assumed to use to please management varies across studies. Many studies assume that managers prefer optimistic earnings forecasts (see e.g., Francis and Philbrick, 1993) while others assume that managers prefer pessimistic forecasts (see e.g., Matsumoto, 2002). Richardson et al. (2004) reconcile the conflicting assumptions in prior research by analyzing the intertemporal patterns of consensus earnings forecasts. They show that managers prefer initial optimistic consensus earnings forecasts followed by pessimistic consensus earnings forecasts immediately before the earnings announcement.

Richardson et al. (2004) further show that one important reason that managers prefer initial optimism and later pessimism is their desire to sell a portion of their equity holdings in the firm at a higher price. To avoid the perception of illegal insider trading and investor litigations, corporate executives are usually allowed to sell their equity holdings only after the earnings announcement (see Bettis et al., 2000; Roulstone, 2003). In addition, Bartov et al. (2002) find that for firms with similar earnings forecast errors at the beginning of a quarter, firms that can meet or beat analysts' latest earnings forecasts before the earnings announcement enjoy a higher stock return than firms that cannot. Therefore, corporate executives prefer analysts to issue pessimistic earnings forecasts immediately before the earnings announcement and optimistic earnings forecasts immediately after the earnings announcement, both of which lead to higher stock prices.[6]

In addition to different assumptions on the form of the earnings forecast bias preferred by managers, prior research does not differentiate annual versus quarterly earnings forecast biases nor study how individual analysts, if issuing multiple earnings forecasts for the same fiscal period, adjust their forecast biases over the forecast horizon. Because a typical analyst issues both annual and quarterly earnings forecasts, it is important to understand whether analysts issue biased annual or biased quarterly earnings forecasts or both to win favor from management. In this study we consider both annual and quarterly earnings forecasts at the individual analyst level. To our knowledge, we are the first study that examines the intertemporal pattern of individual analysts' annual and quarterly forecast biases.

Although the evidence in Richardson et al. (2004) and our discussion above suggest that analysts should issue OP earnings forecasts to win favor from management, we also investigate the other three earnings forecast biases (i.e., PP, OO, and PO) as well because prior research has argued that managers prefer pure forecast optimism or pure forecast pessimism. By considering the four possible forecast biases simultaneously, we can determine the exact form of the forecast bias preferred by managers. For example, if managers are only interested in meeting or beating analysts' latest earnings forecasts, analysts who issue either OP or PP should have more accurate earnings forecasts and are less likely to be fired. In contrast, if managers prefer the OP bias only, OP analysts should have more accurate earnings forecasts and be less likely fired than other analysts.

3. Data and Sample Selection Procedures

[6] We refer interested readers to Richardson et al. (2004) for a detailed discussion of managers' preferences for biased earnings forecasts.

Our analyst forecast sample comes from the merged IBES actual/detail file over the period January 1, 1983-June 30, 2000. Our sample starts from 1983 because there are very few earnings forecast observations before 1983 in IBES. The sample ends on June 30, 2000 because Regulation FD became effective on October 23, 2000, which significantly changed the communications between firm management and analysts, and our variables are measured from July 1, year t to June 30, t+1 (see section 4 below for the details). We retain only those analysts that work for a U.S.-based brokerage firm and have non-missing values for the following variables in IBES: annual and quarterly earnings forecasts, actual earnings, earnings announcement date, IBES ticker, analyst code, and broker code. We eliminate late annual (quarterly) earnings announcements by deleting the top one percent of the distribution of the distance between the annual (quarterly) earnings announcement and the fiscal year (quarter) end. In addition, we require each firm to have at least 3 analysts following for the quarterly and annual earnings forecasts separately because some of our regression variables cannot be defined or are unreliable for thinly covered stocks. We obtain similar results if each stock is required to have a minimum of 5 analysts following. For annual earnings forecasts, we further require each analyst to issue at least two one-year ahead annual earnings forecasts between two consecutive annual earnings announcement dates; for quarterly earnings forecasts, we require each analyst to issue at least one one-quarter ahead and one two-quarters ahead quarterly earnings forecast for the same fiscal quarter. Our final annual earnings forecast sample contains a maximum of 228,904 firm-analyst-year observations over the period January 1, 1983-June 30, 2000, representing 32,303 analyst-year observations and 7,871 unique analysts. Our final quarterly earnings forecast sample contains a maximum of 114,075 firm-analyst-year-quarter observations over January 1, 1983-June 30, 2000, representing 15,278 analyst-year observations and 4,359 unique analysts. Note that we do not require each analyst to have both annual and quarterly earnings forecasts for the same fiscal year. The significantly smaller sample size for quarterly earnings forecasts is due to the fact that analysts typically do not issue multiple earnings forecasts for the same fiscal quarter before the quarterly earnings announcement. Note our quarterly forecast sample includes earnings forecasts for all four fiscal quarters.

Data on executive insiders' stock sales and purchases, which are required for some of our analyses, come from First Call/Thomson Financial Insider Research Services Historical Files. The insider trading data are available for only calendar years 1985-2000. Data on brokerage firm classification come from the Securities Data Company over the period 1980-2002.

4. Research Design

4.1. Variable Definitions

Because earnings forecast accuracy is measured at the firm-analyst level, H1 is tested at the firm-analyst level. Similarly, because analyst turnover is defined at the analyst level, H2 is tested at the analyst level. As a sensitivity check, we also test H1 using the average values of the regression variables at the analyst level and obtain similar conclusions. We follow Hong and Kubik (2003) for most of our variable definitions. Below we describe the construction of our regression variables. The role of each variable is discussed in Section 4.2.

Figure 1 depicts the timeline we use to construct our variables for the annual earnings forecasts. Because the majority of our sample firms end their fiscal years on December 31, we define analysts' firing over a one-year period from July 1, year t+1 to June 30, year t+2 (denoted year t+1) to ensure that an analyst's firing is based on his performance in the year immediately before July 1, year t+1 (denoted year t).[7] All the other regression variables are constructed using

[7] The percentage of our sample firms whose fiscal year end falls in December, January, February, and March are 66%, 3.5%, 1.3%, and 6.4%, respectively.

data before July 1, t+1. Hong and Kubik (2003) also use July 1 as the cutoff for their analysis of analyst turnover. Our results are robust to alternative cutoffs (e.g., April 1, or January 1).

$Fire_{i,t+1}$ is equal to 1 if analyst i works for a large brokerage house during the year from July 1, t to June 30, t+1, and moves to a small brokerage house during the year from July 1, t+1 to June 30, t+2 (i.e., demotion), or if analyst i permanently leaves the IBES database during the year from July 1, t+1 to June 30, t+2 (i.e., termination); and zero otherwise. Following Hong and Kubik (2003), a brokerage house is large if it employs at least 25 analysts in year t. Because we are interested in how biased forecasts affect analysts' chance of being fired, analysts who move from a small brokerage firm to a large one (i.e., promotion) or move between equal-status brokerage firms (i.e., parallel moves) are coded zero in $Fire_{i,t+1}$. However, we obtain similar conclusions if parallel moves or promotions are coded one in $Fire_{i,t+1}$.[8] We use $Fire_{i,t+1}$ for both the annual and quarterly earnings forecast analyses. Our definition of $Fire_{i,t+1}$ is consistent with Hong et al. (2000) and Leone and Wu (2002).

An important limitation of $Fire_{i,t+1}$ is that we do not know the real causes of an analyst's job change. We assume that demotion and termination are due to current or expected future poor performance, but it is possible that these analysts left their current employers for better opportunities. However, we show below that $Fire_{i,t+1}$ is negatively associated with current earnings forecast accuracy, suggesting that $Fire_{i,t+1}$ represents a reasonable (though noisy) proxy for the true unobservable incidence of firing.

Variables Related to Annual Earnings Forecasts

[8] The percentages of analysts who experience demotion, termination, promotion and parallel moves in our sample are 1.2, 13.9, 1.4 and 4.9, respectively.

A_{jt} denotes firm j's annual earnings for year t that is announced immediately before July 1, year t+1. A_{jt-1} denotes firm j's annual earnings for year t-1. F_{ijt}^{last} is analyst i's latest forecast of annual earnings A_{jt}, issued in the second half of the period from the earnings announcement date of A_{jt-1} to the earnings announcement date of A_{jt}. F_{ijt}^{first} is analyst i's earliest forecast of annual earnings A_{jt} issued in the first half of the period from the earnings announcement date of A_{jt-1} to the earnings announcement date of A_{jt}.

$OP_{i,t}$ denotes analyst's i's optimism-to-pessimism bias in year t and is defined as follows. First, we define a dummy OP_{ijt} that is equal to 1 if F_{ijt}^{first} is greater than A_{jt} (i.e., initial optimism), and F_{ijt}^{last} is less than or equal to A_{jt} (i.e., later pessimism), and zero otherwise.[9] $OP_{i,t}$ is the average of OP_{ijt} for all the firms covered by analyst i in year t. The other annual earnings forecast biases (i.e., OO_{ijt}, PP_{ijt}, PO_{ijt} at the firm-analyst level and $OO_{i,t}$, $PP_{i,t}$, $PO_{i,t}$ at the analyst level) are defined similarly.

$Accuracy_{i,t}$ is the average accuracy of analyst i's earnings forecasts in year t and is defined following Hong and Kubik (2003). Specifically, we first calculate analyst i's absolute forecast error in year t as $FE_{ijt} = | F_{ijt}^{last} - A_{jt} |$. Second, we rank all analysts based on the absolute forecast errors for firm j in year t (denoted $rank_{ijt}$). The most accurate analyst receives a rank of 1, and the least accurate analyst receives the highest rank. If analysts are equally accurate, we assign those analysts the midpoint of the ranks they take up. Third, we develop a ranking score that adjusts for the difference in analyst coverage across different firms:

$$Accuracy_{ijt} = 100 - \frac{rank_{ijt} - 1}{number\ of\ analysts_{j,t} - 1} \times 100. \qquad (1)$$

9 Inference is similar if the observations whose F_{ijt}^{last} is equal to A_{jt} (6.5% of the sample) are deleted.

Thus, $Accuracy_{ijt}$ ranges from zero to 100. $Accuracy_{i,t}$ is the average of $Accuracy_{ijt}$ for all the firms covered by analyst i in year t, representing the average relative forecast accuracy of analyst i in year t.

An alternative measure of forecast accuracy is the absolute forecast accuracy, defined as the absolute forecast error scaled by lagged stock price. We use $Accuracy_{i,t}$ and $Accuracy_{ijt}$ because they are more consistent with our hypotheses and prior research (e.g., Hong et al., 2000; Jacob et al., 1999; Leone and Wu, 2002; Mikhail et al. 1999). For example, both Mikhail et al. (1999) and Hong et al. (2000) show that it is the relative forecast accuracy rather than the absolute forecast accuracy that determines analyst firing. However, as Hong et al. (2000) acknowledge, the relative accuracy measures could be less reliable for analysts who cover few firms or cover thinly followed firms. In addition, analysts who cover fewer firms may be able to spend more time on each firm and thus produce more accurate earnings forecasts. We control for these effects by including $FirmsCovered_{ijt}$ and $Follow_{ijt}$ in the regression model for H1. $FirmsCovered_{ijt}$ is the number of firms (including firm j) followed by analyst i in year t. $Follow_{ijt}$ is the total number of analysts (including analyst i) who follow firm j in year t.

Consistent with prior research (e.g., O'Brien, 1990; Clement, 1999; Jacob et al., 1999; Mikhail et al., 1999; Hong and Kubik, 2003), relative forecast accuracy is defined using F_{ijt}^{last} rather than F_{ijt}^{first}. We believe using F_{ijt}^{last} to define relative forecast accuracy is preferred for several reasons. First, because management is likely to communicate their private earnings information to favored analysts throughout the year, forecast accuracy defined using F_{ijt}^{last} will more completely reflect the effect of issuing biased earnings forecasts on analysts' access to management. Second, the evidence in Mikhail et al. (1999) suggests that analysts' earnings forecast accuracy before earnings announcements (i.e., $Accuracy_{i,t}$) is important to brokerage firms and their investors. Leone and Wu (2002) also find that $Accuracy_{i,t}$ is a significant determinant of institutional investors' All-Star analyst ranking. Finally, even if analysts obtain more private information from management at the beginning of the year, they may not wish to reveal this private information immediately in F_{ijt}^{first} because doing so will erode their competitive advantage later in the year when they issue F_{ijt}^{last}. Arya et al. (2005) further demonstrate that investors may also prefer this strategy because it reduces other analysts' incentive to herd and thus increases the total information available to investors. In untabulated regression analysis we find forecast accuracy defined using F_{ijt}^{last} is a more important determinant of $Fire_{i,t+1}$ than that defined using F_{ijt}^{first}, suggesting F_{ijt}^{last} is the earnings forecast that analysts care the most.

$Bold_{i,t}$ denotes the average boldness of analyst i's earnings forecasts in year t and is defined similarly to $Accuracy_{i,t}$. First, we calculate the consensus earnings forecast (excluding analyst i) as follows:

$$\bar{F}_{-i,j,t}^{first} = \frac{\sum_{m \neq i} F_{m,j,t}^{first}}{number\ of\ analysts_{j,t} - 1}, \tag{2}$$

where -i is the set of analysts other than analyst i. Second, we calculate analyst i's deviation from the consensus, $deviation_{i,j,t} = | F_{i,j,t}^{first} - \bar{F}_{-i,j,t}^{first} |$. Third, we rank all the analysts who cover firm j in year t based on $deviation_{i,j,t}$. Fourth, we use equation (1) to develop a ranking score (denoted $Bold_{ijt}$) that adjusts for the difference in analyst coverage across firms. Finally, $Bold_{i,t}$ is the average of $Bold_{ijt}$ over all the firms covered by analyst i in year t. Intuitively, $Bold_{i,t}$ captures analyst i's deviation from his peers in earnings forecasts.

$Experience_{i,t}$ is the number of years analyst i appears in the IBES annual earnings forecast database as of year t. $FirmExperience_{ijt}$ is the number of years analyst i follows stock j as of year t. $FirmExperience_{i,t}$ is the average of $FirmExperience_{ijt}$ across all the stocks followed by analyst i in year t. GAP_{ijt} is the distance between the earnings announcement date for A_{jt} and the forecast date for F_{ijt}^{last}. $GAP_{i,t}$ is the average GAP_{ijt} for all the firms covered by analyst i in year t. Because $Accuracy_{ijt}$ is expressed in ranking, we also create a similar ranking variable for $FirmsCovered_{ijt}$, $FirmExperience_{ijt}$ and GAP_{ijt}, denoted $R\_FirmsCovered_{ijt}$, $R\_FirmExperience_{ijt}$, and R_GAP_{ijt}, respectively. Similar to $Accuracy_{i,t}$, $FirmExperience_{i,t}$ and $GAP_{i,t}$ are converted into ranking and denoted $R\_FirmExperience_{i,t}$ and $R\_GAP_{i,t}$, respectively.

Variables Related to Quarterly Earnings Forecasts

Note that the analyst turnover definition ($Fire_{i,t+1}$) is identical for the annual and quarterly forecast analyses. To compute the other regression variables needed for the quarterly earnings forecast analysis, we first identify the quarterly earnings announcements made between the two annual earnings announcement dates for A_{jt-1} and A_{jt} in Figure 1, including the earnings announcement for the last fiscal quarter (i.e., announcement date for A_{jt}). Then, for each quarterly earnings announcement (say fiscal quarter 2 of 1998), we identify all the one-quarter ahead and two-quarters ahead quarterly earnings forecasts that are issued after the announcement of the quarterly earnings two quarters prior (i.e., fiscal quarter 4 of 1997) but before the announcement of the current quarterly earnings announcement (i.e., fiscal quarter 2 of 1998). We do not consider three or more quarters ahead quarterly earnings forecasts because there are very few in IBES. Finally, we retain the first (last) quarterly earnings forecast that is issued in the first (second) half of the period between the announcement of the quarterly earnings two quarters prior (i.e., fiscal quarter 4 of 1997) and the announcement of the current quarterly earnings (i.e., fiscal quarter 2 of 1998).

The quarterly equivalents of $Accuracy_{ijt}$, $Bold_{ijt}$, $FirmsCovered_{ijt}$, $FirmExperience_{ijt}$, GAP_{ijt}, $R\_FirmsCovered_{ijt}$, $R\_FirmExperience_{ijt}$, R_GAP_{ijt}, and $Follow_{ijt}$ are computed for each of the quarterly earnings announcements that fall between the two annual earnings announcement dates for A_{jt-1} and A_{jt} in Figure 1. To obtain the yearly equivalents of $OP_{i,t}$, $OO_{i,t}$, $PP_{i,t}$, $PO_{i,t}$, $Accuracy_{i,t}$, $Bold_{i,t}$, and $Experience_{i,t}$, we first compute the mean of each quarterly equivalent across all quarters in year t for each firm-analyst, followed by the averaging of the mean quarterly equivalent across all firms followed by analyst i in year t.

4.2. Regression Models

We use the following OLS regression model to test H1:

$$Accuracy_{ijt} = \alpha_k + \alpha_t + \alpha_1 Bias_{ijt} + Control\ variables_{ijt} + \varepsilon_{ijt} \tag{3}$$

The model is estimated using annual earnings forecasts at the firm-analyst-year level and quarterly earnings forecasts at the firm-analyst-year-quarter level. Therefore, the subscript ‘t’ in the model refers to either yearly or quarterly observations. α_k and α_t are brokerage firm and year fixed effects, controlling for systematic differences in $Accuracy_{ijt}$ across time and brokerage firms. The control variables are $Bold_{ijt}$, $R\_FirmExperience_{ijt}$, $R\_FirmsCovered_{ijt}$, R_GAP_{ijt}, and $\ln(Follow_{ijt})$. $Bold_{ijt}$ controls for the potential effect of forecast boldness on forecast accuracy because Hong et al. (2000) find that bold but inexperienced analysts are more likely to be fired. $R\_FirmExperience_{ijt}$, $R\_FirmsCovered_{ijt}$, and R_GAP_{ijt} control for the effect of analyst i’s firm-specific forecasting experience, number of firms covered, and forecast timing, respectively, on forecast accuracy. Because the dependent variable is a relative measure, these three variables are also defined on relative terms.[10] Because $Follow_{ijt}$ is identical for all the analysts who follow the same firm j, it is not converted to a ranking variable. We use $\ln(Follow_{ijt})$ to allow for a possible nonlinear effect of $Follow_{ijt}$. $Bias_{ijt}$ refers to OP_{ijt}, OO_{ijt}, PP_{ijt}, or PO_{ijt} for both annual and quarterly earnings forecasts. To avoid multicollinearity, the coefficient on PO_{ijt} is suppressed in model (3). If a forecast bias is used to win favor from management, H1 predicts the coefficient on that forecast bias to be larger than the coefficients on the other forecast biases.

We do not include any firm-specific control variables in regression model (3) because $Accuracy_{ijt}$ is relative forecast accuracy for all analysts covering the same firm and thus automatically controls for firm-specific differences. For example, relative forecast accuracy controls for variations in earnings forecast difficulty across companies and time. As another example, firm size may be a determinant of *absolute* forecast accuracy because large firms tend to have a richer information environment. However, firm size should not have an effect on *relative* forecast accuracy because all analysts who cover the firm face the same information environment. Likewise, regression model (3) does not need to control for management's earnings management incentives or public information disclosures (e.g., quarterly earnings announcements) between the annual earnings announcement dates for A_{jt-1} and A_{jt} because such events are common to all analysts who follow the same firm and thus has been controlled for in $Accuracy_{ijt}$.

Because the definitions of $Accuracy_{ijt}$ and $Bias_{ijt}$ use information in the last earnings forecast, the regression model (3) implicitly assumes that an analyst who receives privileged access

[10] Because R_GAP_{ijt} is an important determinant of forecast accuracy, we also allow the effect of R_GAP_{ijt} to differ for each value of R_GAP_{ijt} and obtain similar inference.

to management's private information before issuing his last earnings forecast can credibly commit to firm management that his last earnings forecast will be biased. This seems a reasonable assumption given the intimate and frequent interactions between firm management and financial analysts.

As argued in section 2.2, $Bias_{ijt}$ is also expected to affect $Accuracy_{ijt+1}$. Unfortunately, such effect is not observable for the analysts who do not issue biased forecasts and thus are fired (see H2).[11] Thus, we do not use $Accuracy_{ijt+1}$ in regression model (3). However, as a sensitivity check, we also report the Heckman (1976) regression result of $Accuracy_{ijt+1}$ on $Bias_{ijt}$ in section 5.2.4.

We use the following logit regression model to test H2:

$$Fire_{i,t+1} = \beta_k + \beta_t + \beta_1 Bias_{i,t} + \beta_2 Accuracy_{i,t} + \beta_3 Bold_{i,t} + \beta_4 \ln(Experience_{i,t}) + \varepsilon_{it} \quad (4)$$

The model is estimated using annual and quarterly earnings forecasts aggregated at the analyst year level. β_k and β_t are brokerage firm and year fixed effects. $Accuracy_{i,t}$ controls for the effect of past forecast accuracy on $Fire_{i,t+1}$, while $\ln(Experience_{i,t})$ controls for an analyst's tenure in the profession. $Bold_{i,t}$ controls for the effect of forecast boldness on analyst turnover. Hong et al. (2000) find that bold but inexperienced analysts are more likely to leave the analyst profession. $Bias_{i,t}$ refers to $OP_{i,t}$, $OO_{i,t}$, $PP_{i,t}$, or $PO_{i,t}$. Again, to avoid multicollinearity, the coefficient on PO_{ijt} is suppressed in model (4). If a forecast bias is used to win favor with management, H2 predicts the coefficient on that forecast bias to be smaller than the coefficients on the other forecast biases. Note that regression model (4) controls for the current period earnings

[11] For our sample, 20% of the analysts who were terminated (i.e., disappeared from the IBES database) did so only after one year of employment.

forecast accuracy $Accuracy_{i,t}$, thus the coefficient on $Bias_{i,t}$ captures the effect of a forecast bias on the probability of firing above and beyond the current period forecast accuracy.

5. Descriptive Statistics and Regression Results

5.1. Descriptive Statistics

Table 1 reports the descriptive statistics for the variables used in regression models (3) and (4). Panels A and B show the variables used in model (3) for the annual and quarterly earnings forecasts, respectively, while Panels C and D show the variables used in model (4) for the annual and quarterly earnings forecasts, respectively.

The unit of observation in Panel A is a firm-analyst-year. The mean values of OP, OO, PP, and PO indicate that the most common annual earnings forecast bias is OO, followed by PP, OP, and PO. Although it is difficult to assess whether the frequencies of the four biases are normal or abnormal in the absence of a clear benchmark, it is striking to observe that the PO bias is the rarest in the sample. The mean analyst has 4.3 years of stock-specific forecasting experience ($FirmExperience_{ijt}$), follows 25.29 stocks ($FirmsCovered_{ijt}$), and covers stocks with 21.07 analysts following ($Follow_{ijt}$).[12] The mean GAP of 78.89 days suggests that the last annual earnings forecast is on average issued after the 3rd fiscal quarter's earnings announcement date. Panel A also reports the distribution of the ranked variables. The mean of each of those ranked variables is 50 by construction.

[12] The distribution of $FirmsCovered_{ijt}$ at the firm-analyst-year level is distorted because the values of $FirmsCovered_{ijt}$ are identical for all the firms covered by analyst i in year t. The mean (median) of $FirmsCovered_{ijt}$ at the analyst-year level is 13.91 (11). This problem also applies to $FirmsCovered_{ijt}$ in Panel B.

The unit of observation in Panel B is a firm-analyst-year-quarter. Had all analysts who are included in Panel A issued at least two quarterly earnings forecasts for each fiscal quarter, the sample size for Panel B should be four times the size in Panel A (i.e., 228,904*4). The smaller sample size of 114,075 in Panel B reflects the fact that analysts issue either zero or only one quarterly earnings forecast for many fiscal quarters. Despite the significant difference in the sample size between Panel A and Panel B, the frequencies of the four forecast biases in Panel B are close to those in Panel A except that the PP bias has the highest frequency. The mean values of $FirmExperience_{ijt}$, $Follow_{ijt}$, and $FirmsCovered_{ijt}$ are similar to those in Panel A. The mean GAP of 48.67 days suggests that the last quarterly earnings forecast is on average issued in the middle of two consecutive quarterly earnings announcement dates.

The unit of observation in Panel C is an analyst-year. The mean $Fire_{i,t+1}$ indicates that 15% of the analysts are fired over our sample period, a nontrivial percentage. Untabulated analyses further indicate that among the fired analysts in our sample, 20.2% of them are fired in the second year of their career, 22.47% in the third year of their career, 14.59% in the fourth year of their career, and 9.49% in the fifth year of their career. Clearly, the majority of the firing occurs in an analyst's early stage of his career. The distributions of the four forecast biases are similar to those in Panel A. The mean analyst has been in the analyst profession for 5.01 years ($Experience_{i,t}$).

The unit of observation in Panel D is an analyst-year. Due to the sample size difference, the mean $Fire_{i,t+1}$ is slightly smaller than that in Panel C. The distributions of the four forecast biases are similar to those in Panel B. The distribution of $Experience_{i,t}$ is approximately one year higher than that in Panel C.

Table 2 reports the Spearman (top diagonal) and Pearson (bottom diagonal) correlations for the key regression variables in models (3) and (4) using observations at the analyst-year level.

Because the correlations are similar for both Spearman and Pearson, we focus on the Pearson correlations (bottom diagonal) in the following discussion.

$Accuracy_{i,t}^{A}$ is the relative earnings forecast accuracy ($Accuracy_{i,t}$) using annual earnings forecasts while $Accuracy_{i,t}^{Q}$ is the relative earnings forecast accuracy ($Accuracy_{i,t}$) using quarterly earnings forecasts. The other variables in Table 2 are similarly defined. The correlation between $Accuracy_{i,t}$ and $OP_{i,t}$ is significantly positive for both annual and quarterly forecasts, but the correlation between $Accuracy_{i,t}$ and any of the other three biases is either significantly negative or insignificant. These univariate correlations are consistent with the hypothesis that analysts use $OP_{i,t}$ forecasts to gain better access to management's private information. In addition, the significantly positive correlation between $OP_{i,t}^{A}$ and $OP_{i,t}^{Q}$ suggests that analysts often issue both annual and quarterly OP earnings forecasts to please management.

$Fire_{i,t+1}$ is significantly negatively correlated with $OP_{i,t}$ for both annual and quarterly forecasts. Except for the marginally significantly negative correlation between $Fire_{i,t+1}$ and $PP_{i,t}^{A}$, the correlation between $Fire_{i,t+1}$ and any of the other forecast biases is either insignificant or significantly positive. These univariate correlations are consistent with the hypothesis that analysts who issue annual and quarterly OP earnings forecasts are less likely to be fired. This evidence is consistent with the univariate correlations for $Accuracy_{i,t}$.

5.2 Regression Results

5.2.1. H1

Table 3 reports the OLS regression results for H1. Panel A reports the results for annual earnings forecasts while Panel B shows the results for quarterly earnings forecasts. The standard errors are adjusted for heteroskedasticity and correlations for observations of the same stocks using the method of Rogers (1993).

Results for Annual Earnings Forecasts

Column (1) of Panel A shows that relative to PO analysts' forecast accuracy, OP analysts' annual earnings forecasts are more accurate while OO analysts' forecasts are less accurate and PP analysts' forecasts are equally accurate. In addition, the coefficient on OP is significantly larger than those of OO and PP (two-tailed p<0.001). These results are consistent with the hypothesis that analysts use OP forecasts to gain better access to management's private information. The significantly negative coefficient on OO and the insignificant coefficient on PP are inconsistent with the hypothesis that analysts issue consistently optimistic or pessimistic annual earnings forecasts to gain better access to management.[13]

The negative coefficient on $Bold_{ijt}$ suggest that bolder analysts produce less accurate earnings forecasts. The coefficient on $FirmExperience_{ijt}$ is significantly positive, suggesting that experienced analysts produce more accurate forecasts, a finding consistent with Clement (1999). As expected, forecasts issued closer to the earnings announcement date are more accurate. We do not offer any economic interpretation on the coefficients on $R\_FirmsCovered_{ijt}$ and $\ln(Follow_{ijt})$ because they mainly control for the limitations of $Accuracy_{ijt}$ for analysts who follow few firms or thinly covered firms.

[13] An alternative earnings forecast optimism definition used in prior research is defined relative to the consensus earnings forecast of the other analysts who follow the same firm (see e.g., Hong and Kubik, 2003). Including this alternative optimism definition in models (3) and (4) does not alter any of our inferences. In addition, the coefficient on this alternative optimism is significantly negative in model (3) and significantly positive in model (4), suggesting that optimistic analysts produce less accurate earnings forecasts and are more likely to be fired, inconsistent with the hypothesis that analysts use optimistic earnings forecasts to please firm management for more private information.

Because only the coefficient on OP in column (1)'s regression is consistent with H1, column (2) of Panel A reports the regression in column (1) after dropping OO and PP. As expected, the coefficient on OP continues to be significantly positive. The result in column (3) is discussed in section 5.2.3.

Results for Quarterly Earnings Forecasts

Column (1) of Panel B reports the regression coefficients of model (3) for quarterly earnings forecasts. The coefficients on both the control variables and the four forecast biases are consistent with those in column (1) of Panel A. Column (2) of Panel B reports the regression result without OO and PP. As expected, the coefficient on OP remains significantly positive. Overall, the evidence in Panels A and B is consistent with Richardson et al. (2004) who find that managers prefer OP consensus earnings forecasts. The result in column (3) is discussed in section 5.2.3.[14]

5.2.2. H2

Table 4 reports the logit regression results for H2. Panel A reports the results for annual earnings forecasts while Panel B shows the results for quarterly earnings forecasts. Panel C combines the regression variables in Panels A and B into one regression. The standard errors in table 4 are adjusted for heteroskedasticity and correlations for observations of the same brokers using the method of Rogers (1993).

Results for Annual Earnings Forecasts

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14 Including the relative earnings forecast accuracy defined using the initial earnings forecast F_{ijt}^{first} in regression model (3) does not affect the coefficient on OP in Table 3, suggesting that the positive coefficient on OP is not because OP analysts are inherently more accurate than other analysts. In addition, the coefficient on OP is robust to controlling for the ranked signed difference between the reported earnings and an individual analyst's initial or last earnings forecast (defined in the same way as $Accuracy_{ijt}$).

Column (1) of Panel A reports the regression coefficients of model (4) using annual earnings forecasts. Consistent with prior research, more accurate and more experienced analysts are less likely to be fired. The coefficient on $Bold_{i,t}$ is insignificant. The coefficient on OP is significantly negative but the coefficients on OO and PP are insignificant. In addition, the coefficient on OP is significantly larger in magnitude than those on OO and PP (two-tailed p=0.01 or lower). Because model (4) controls for current forecast accuracy, the significant regression coefficient on OP suggests that OP analysts are less likely to be fired presumably because of their improved <u>future</u> earnings forecast accuracy relative to other analysts (see section 5.2.4 for direct evidence). The insignificant coefficients on OO and PP further suggest that consistently issuing optimistic or pessimistic annual earnings forecasts alone is not sufficient to reduce the probability of firing. As a sensitivity check, column (2) of Panel A reports the coefficients of model (4) after dropping OO and PP. Not surprisingly, the coefficient on OP remains significantly negative. The result in column (3) is discussed in section 5.2.3.

Results for Quarterly Earnings Forecasts

Column (1) of Panel B reports the regression coefficients of model (4) for quarterly earnings forecasts. The coefficients on the control variables are consistent with those in column (1) of Panel A. Consistent with the coefficients in Panel A, the coefficients on OP and OO are significantly negative and insignificant, respectively. There is weak evidence at the 10% two-tailed significance level that PP analysts are less likely to be fired relative to the benchmark PO analysts. However, the coefficient on PP is significantly smaller in magnitude than that on OP (two-tailed p=0.05). In addition, as shown in column (2) of Panel B, the effect of OP dominates the other three biases as the coefficient on OP remains significantly negative after the omission of OO and PP in the regression. Overall, the results for the quarterly forecasts are consistent with those for the annual forecasts. The result in column (3) is discussed in section 5.2.3.

Results for Annual and Quarterly Earnings Forecasts Combined

To determine the incremental effect of $OP_{i,t}^{A}$ and $OP_{i,t}^{Q}$ on the probability of firing, Panel C of Table 4 reports the coefficients of model (4) by combining the independent variables in column (1) of Panels A and B. The sample size in this regression is smaller than that in Panel A or Panel B because not all analysts issue both annual and quarterly earnings forecasts for the same fiscal year. The coefficients on the control variables remain in the same directions as those in Panels A and B and significant except for the insignificant coefficient on $Accuracy_{i,t}^{Q}$. Thus, once controlling for the annual earnings forecast accuracy, the quarterly earnings forecast accuracy matters little in the probability of firing. The coefficients on $OP_{i,t}^{A}$ and $OP_{i,t}^{Q}$ are both significantly negative but are not significantly different from each other (two-tailed p=0.59), suggesting that both the annual and quarterly OP biases are associated with the probability of firing.

5.2.3. Further Tests of H1 and H2

Regression models (3) and (4) assume that analysts have incentives to use biased earnings forecasts to please managements of all firms. However, as discussed in section 2.2, the preference for biased earnings forecasts should be stronger for managers who need to sell significant amounts of their personal equity holdings in the firm regularly. Thus, these managers should have a stronger incentive to trade their private information for analysts' biased earnings forecasts. In addition, we also expect the predicted effect of biased forecasts on relative forecast accuracy and the probability of firing to be stronger for firms with difficult-to-forecast earnings. This is because when earnings are easy to predict and thus all analysts' earnings forecasts are already very accurate, having management's private information will not enable an analyst to significantly improve his relative forecast accuracy. The converse is true when earnings are difficult to predict.

The last column of Table 3 reports the regression results of model (3) allowing the coefficient on OP_{ijt} (annual forecasts in Panel A and quarterly forecasts in Panel B) to vary with the insider trading intensity (denoted $InsiderSell_{ijt}$) and the degree of earnings forecasting difficulty (denoted $Dispersion_{ijt}$). For both the annual and quarterly samples, $InsiderSell_{ijt}$ is a dummy that is equal to 1 if the average net insider selling (expressed in 1982 dollars) by all corporate officers and directors for firm j followed by analyst i during the calendar year immediately before the earnings announcement date for $Accuracy_{ijt}$ is larger than the 75th percentile of our sample. For the annual sample, $InsiderSell_{i,t}$ is the average of $InsiderSell_{ijt}$ over all the firms covered by analyst i in year t. For the quarterly sample, $InsiderSell_{i,t}$ is defined as the mean of $InsiderSell_{ijt}$ across all quarters in year t for each firm-analyst, followed by the averaging of the above mean across all firms covered by analyst i in year t.[15]

Because we wish to capture the ex ante effect of insider selling, $InsiderSell_{i,t}$ is measured before $Accuracy_{i,t}$ and $Fire_{i,t+1}$ (the dependent variables for H1 and H2 respectively). Using insider sales after the measurement of the dependent variables is problematic because insiders tend to sell (buy) after positive (negative) earnings surprises. In addition, insiders should continue to have an incentive to report earnings increases immediately after their stock sales in order to avoid the perception of illegal insider trading. Therefore, $InsiderSell_{i,t}$ should be a reasonable proxy for

15 Aboody and Kasznik (2000) find that corporate executives manage voluntary disclosures to depress stock prices immediately before new stock option grants. Because new option grants are unavailable for all of our sample firms, they are not included in $InsiderSell_{ijt}$. As a result, our insider selling measure likely understates the true effect of the insider selling incentive.

insiders' ex ante preference for biased earnings forecasts. The correlation between $InsiderSell_{i,t}$ and $InsiderSell_{i,t+1}$ is very high (the Pearson correlation is 62% for our sample).

$Dispersion_{ijt}$ is a dummy that is equal to 1 if the forecast dispersion (defined as the standard deviation of the earnings forecasts scaled by the magnitude of the realized earnings) is greater than the 75th percentile of our sample.[16] For both the annual and quarterly samples, $Dispersion_{ijt}$ is computed using each analyst's first earnings forecast, although results are similar if each analyst's last earnings forecast is used instead. $Dispersion_{i,t}$ is the average of $Dispersion_{ijt}$ over all the firms covered by analyst i in year t and defined similarly to $InsiderSell_{i,t}$.

Note that $InsiderSell_{ijt}$ and $Dispersion_{ijt}$ are not defined as continuous variables because the effects of insider selling and forecast difficulty are likely nonlinear. In addition, continuous measures of $InsiderSell_{i,t}$ and $Dispersion_{i,t}$ could be unduly influenced by a few of the stocks followed by analysts i in year t. Untabulated sensitivity checks indicate that the interaction results for $InsiderSell_{i,t}$ and $Dispersion_{i,t}$ are robust to alternative cutoffs (e.g., 66th, 70th, or 80th percentile), but become insignificant when $InsiderSell_{ijt}$ and $Dispersion_{ijt}$ are defined as continuous variables.

Consistent with our predictions, the coefficients on $OP_{ijt} \times InsiderSell_{ijt}$ and $OP_{ijt} \times Dispersion_{ijt}$ in both Panels A and B of Table 3 are significantly positive with the exception of the positive but insignificant coefficient on $OP_{ijt} \times Dispersion_{ijt}$ in Panel B. The results suggest

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16 Because of zero realized earnings, $Dispersion_{ijt}$ is not defined for 298 firm-analyst-year observations in the annual forecast sample and 462 firm-analyst-year-quarter observations in the quarterly forecast sample. $Dispersion_{ijt}$ is set equal to 1 in those cases.

that the positive effect of issuing OP annual and quarterly earnings forecasts on relative forecast accuracy is stronger for firms with heavy insider sales and hard-to-predict earnings.

The negative coefficients on $InsiderSell_{ijt}$ and $Dispersion_{ijt}$ in Table 3 are expected and consistent with H1 because they reflect the effect of these two variables for only analysts who do not issue OP forecasts. For example, for a low forecast dispersion firm, management's private information should matter less in determining the ranking of the analysts who follow the firm; therefore analysts who do not issue OP forecasts are not going to suffer significantly in forecast accuracy relative to those who issue OP forecasts. In contrast, for a high dispersion firm, management's private information matters more in the ranking and therefore those analysts who do not issue OP forecasts are going to suffer more in forecast accuracy relative to the OP analysts who cover the same firm. Therefore, we should expect non-OP analysts' relative earnings forecast accuracy to be lower for high dispersion firms than for low dispersion firms. A similar reasoning applies to $InsiderSell_{ijt}$. The negative coefficients on $InsiderSell_{ijt}$ and $Dispersion_{ijt}$ do not conflict with our argument in section 4.2 that firm-specific variables should not affect $Accuracy_{ijt}$ when included alone. We have verified that the coefficients on $InsiderSell_{ijt}$ and $Dispersion_{ijt}$ are insignificant when OP_{ijt}, $OP_{ijt} \times InsiderSell_{ijt}$ and $OP_{ijt} \times Dispersion_{ijt}$ are omitted from the interaction model in Table 3.

The last column of Table 4 reports the regression results of model (4) allowing the coefficients on $OP_{i,t}$ to vary with $InsiderSell_{i,t}$ and $Dispersion_{i,t}$. As predicted, the coefficients on $OP_{i,t} \times InsiderSell_{i,t}$ and $OP_{i,t} \times Dispersion_{i,t}$ in Panels A and B of Table 4 are significantly negative except for the insignificant coefficient on $OP_{i,t} \times Dispersion_{i,t}$ in Panel B. These results suggest that the negative effect of issuing annual and quarterly OP forecasts on the probability of firing is stronger for firms with heavy insider sales and hard-to-predict earnings. Overall, the results from the interaction models in Tables 3 and 4 provide further support for our hypotheses.

Because we find little evidence in column (1) of tables 3 and 4 (panels A and B) that OO and PP are associated with improved forecast accuracy and a smaller probability of firing, the interaction models in column (3) of tables 3 and 4 do not allow the coefficients on OO and PP to vary with the insider selling and forecast dispersion variables. As a sensitivity check, we rerun the interaction models in tables 3 and 4 by allowing the coefficients on OO and PP to vary with the insider selling and forecast dispersion variables (results not tabulated). For the annual sample in panel A of table 3, the coefficient on $OP_{ijt} \times InsiderSell_{ijt}$ is larger (i.e., consistent with H1) than the coefficients on $OO_{ijt} \times InsiderSell_{ijt}$ and $PO_{ijt} \times InsiderSell_{ijt}$ but not different from the coefficient on $PP_{ijt} \times InsiderSell_{ijt}$ at the 10% one-tailed level or better; the coefficient on $OP_{ijt} \times Dispersion_{ijt}$ is larger than the coefficient on $PP_{ijt} \times Dispersion_{ijt}$ but not different from the coefficients on $OO_{ijt} \times Disperson_{ijt}$ and $PO_{ijt} \times Dispersion_{ijt}$ at the 10% one-tailed level or better. For the quarterly sample in panel B of table 3, the coefficient on $OP_{ijt} \times InsiderSell_{ijt}$ is significantly larger than the coefficients on $OO_{ijt} \times InsiderSell_{ijt}$, $PP_{ijt} \times InsiderSell_{ijt}$, and $PO_{ijt} \times InsiderSell_{ijt}$ at the 10% one-tailed level or better, but the coefficient on $OP_{ijt} \times Dispersion_{ijt}$ is never significantly larger than any of the other three dispersion interactions at the 10% one-tailed level.

For the annual sample in panel A of table 4, the coefficient on $OP_{i,t} \times InsiderSell_{i,t}$ is significantly smaller (i.e., consistent with H2) than the coefficients on $OO_{i,t} \times InsiderSell_{i,t}$ and $PP_{i,t} \times InsiderSell_{i,t}$ but not different from the coefficient on $PO_{i,t} \times InsiderSell_{i,t}$ at the 10% one-tailed level or better; the coefficient on $OP_{i,t} \times Dispersion_{i,t}$ is smaller than the coefficients on

$OO_{i,t} \times Disperson_{i,t}$ and $PP_{i,t} \times Dispersion_{i,t}$ but not different from the coefficient on $PO_{i,t} \times Dispersion_{i,t}$ at the 10% one-tailed level or better. For the quarterly sample in panel B of table 4, the coefficient on $OP_{i,t} \times InsiderSell_{i,t}$ is significantly smaller than the coefficients on $OO_{i,t} \times InsiderSell_{i,t}$ and $PP_{i,t} \times InsiderSell_{i,t}$ but not different from the coefficient on $PO_{i,t} \times InsiderSell_{i,t}$ at the 10% one-tailed level or better; but the coefficient on $OP_{i,t} \times Dispersion_{i,t}$ is not different from any of the other dispersion interactions at the 10% one-tailed level. Overall, the results from above sensitivity checks are broadly consistent with the reported interaction models in tables 3 and 4 but weaker in significance because of the separation of the control group into three subgroups.[17]

To gauge the economic significance of issuing OP earnings forecasts on analysts' forecast accuracy and job security, we compute the marginal effects of OP for the annual earnings forecast regressions in Panel A of Tables 3 and 4. The coefficient on OP_{ijt} in Panel A, column (2) of Table 3 (6.530) indicates that a one standard deviation increase in OP_{ijt} is associated with an increase in relative forecast accuracy of 2.86 (i.e., 6.530*0.438). For analysts who cover stocks with heavy insider selling and difficult-to-forecast earnings (defined as observations whose values of $InsiderSell_{ijt}$ and $Dispersion_{ijt}$ are equal to one), a one standard deviation increase in OP_{ijt} is associated with an increase in relative forecast accuracy of 3.33 (i.e., [6.079+0.781+0.736]*0.438). As a comparison, a one standard deviation increase in $R\_FirmExperience_{i,t}$ in Panel A, column (2) of Table 3 is associated with an increase in relative forecast accuracy of only 0.41 (i.e., 0.013*31.43).

[17] As a sensitivity check, we also replaced OP in the regressions of columns (2) and (3) of tables 3 and 4 with either OO, PP, or PO. We found no evidence consistent with H1 and H2 for any of those biases.

The coefficient on $OP_{i,t}$ in Panel A, column (2) of Table 4 indicates that a one standard deviation increase in $OP_{i,t}$ is associated with a decrease in the probability of firing by 0.99% evaluated at the mean values of the independent variables. For analysts who cover stocks with heavy insider selling and difficult-to-forecast earnings (defined as observations whose values of $InsiderSell_{i,t}$ and $Dispersion_{i,t}$ exceed the 75th percentile of the sample), a one standard deviation increase in $OP_{i,t}$ is associated with a decrease in the probability of firing by 1.45% evaluated at the mean values of the independent variables. Because the mean unconditional probability of firing is 15% (see Table 1, Panel C), increasing $OP_{i,t}$ by one standard deviation will reduce the probability of firing by 9.7% (i.e., 1.45/15). As a comparison, the coefficient on $Accuracy_{i,t}$ in Panel A, column (2) of Table 4 indicates that a one standard deviation increase in $Accuracy_{i,t}$ is associated with a decrease in the probability of firing by 3.91% evaluated at the mean values of the independent variables. It should be noted that the effect of $Accuracy_{i,t}$ partially reflects the effect of $OP_{i,t}$ because OP analysts also produce more accurate contemporaneous earnings forecasts.

5.2.4. The Effect of Issuing Biased Earnings Forecasts on Future Earnings Forecast Accuracy

As part of the motivation for H2 in section 2.1, we assume that analysts who do not issue biased earnings forecasts will suffer in their future earnings forecast accuracy, even after controlling for current forecast accuracy. We use the following regression model to offer direct evidence on this hypothesis for the annual and quarterly earnings forecasts separately:

$$\begin{aligned} Accuracy_{i,t+1} &= \alpha_k + \alpha_{t+1} + \alpha_1 Bias_{i,t} + \alpha_2 Accuracy_{i,t} + \alpha_3 Bold_{i,t+1} + \alpha_4 \ln(Follow_{i,t+1}) \\ &+ \alpha_5 R\_FirmsCovered_{i,t+1} + \alpha_6 R\_FirmExperience_{i,t+1} + \alpha_7 R\_GAP_{i,t+1} + \varepsilon_{i,t+1} \end{aligned} \tag{5}$$

The above model is similar to model (3) except for the addition of $Accuracy_{i,t}$. In addition, model (5) can only be estimated using the surviving analysts because analysts who do not issue biased earnings forecasts are more likely to be fired. To produce consistent estimates of the regression coefficients of model (5), we use regression model (4) without the year and broker fixed effects to correct for the sample selection bias (see Heckman, 1976). Because regression model (4) is estimated at the analyst year level, the unit of observation for model (5) is also an analyst year. $Bias_{i,t}$ refers to the $OP_{i,t}$ bias and is predicted to be positive. The other variables are defined in section 4.1.

Table 5 reports the regression coefficients of model (5) for annual (Panel A) and quarterly (Panel B) earnings forecasts. The standard errors are adjusted for heteroskedasticity and correlations for observations of the same brokers using the method of Rogers (1993).

For both the annual and quarterly earnings forecasts, the coefficients on the control variables are consistent with those in Table 3 and generally significant. As expected, the coefficient on $Accuracy_{i,t}$ is significantly positive in both panels. The coefficient on $OP_{i,t}$ is significantly positive for the annual earnings forecasts in Panel A but insignificant (though positive) for the quarterly earnings forecasts in Panel B (two-tailed p=0.13). The weaker coefficient on $OP_{i,t}$ in Panel B could be caused by the smaller sample size. Another reason is that not all analysts issue multiple quarterly earnings forecasts for every fiscal quarter (see footnote 1) and thus the values of $OP_{i,t}$ and $Accuracy_{i,t+1}$ could be computed for different mixes of firms, which should weaken the association between $OP_{i,t}$ and $Accuracy_{i,t+1}$. Overall, the results in Table 5 are consistent with the hypothesis that OP analysts produce more accurate future earnings forecasts, even after controlling for the current earnings forecast accuracy. This evidence offers one rationale for why the coefficient on $OP_{i,t}$ in model (4) is negative even after controlling for current forecast accuracy.

5.2.5. Investment Banking Incentive As an Alternative Explanation

Popular press (see e.g., Gasparino, 2002) alleges that analysts use biased earnings forecasts to help their employers win more investment banking businesses. The record settlement between U.S. government regulators and the ten largest securities firms in 2003 directly targets securities firms' alleged abuses of using biased analyst research to win investment-banking business. While several studies (e.g., Michaely and Womack, 1999; Dugar and Nathan, 1995; Lin and McNichols, 1998; Bradshaw et al., 2003) finds evidence supporting the above allegation, a few recent studies (e.g., Cowen et al., 2006; Jacob et al., 2003) find no such evidence.

Because analysts who work for investment banks may have better access to management's private information during the underwriting process of existing clients or during the competition for new clients, our H1 and H2 are potentially consistent with the investment banking incentive. However, such associations are spurious (not causal) because an analyst's primary purpose for issuing biased earnings forecasts is not to obtain management's private information to improve forecast accuracy. Instead, improved forecast accuracy is merely a byproduct of analysts' effort to use biased earnings forecasts to win more investment banking deals.

To determine whether the hypothesized effects of H1-H2 are solely motivated by the investment banking incentive, we rerun regression models (3) and (4) for both annual and quarterly earnings forecasts by allowing the coefficient on OP to vary with $Bookrunner_{i,t}$, a dummy variable that is equal to 1 if a brokerage house served as an equity offering book runner in at least 11 out of the 23 years from 1980 to 2002 (denoted book runner), and 0 if a brokerage house never derived any revenues from investment banking over 1980-2002 (denoted pure brokerage firm). We also tried 15 years and 23 years as cutoffs and obtained similar results. Brokerage firms who served as book runners for fewer than 11 years or only as syndicates over 1980-2002 are excluded from this analysis because the influence of investment banking business is unclear for these firms, although inference is similar if those brokerage firms are combined with the book runners or pure brokerage firms.

If the investment banking incentive is the driver of biased earnings forecasts, the predicted effects of H1 and H2 should not exist for analysts who work for pure brokerage firms. Untabulated regression results find no evidence that the predicted effects of H1 and H2 are stronger for analysts who work for investment banks than for those who work for pure brokerage firms. Thus, the documented results for H1 and H2 cannot be solely explained by the investment banking incentive. However, we cannot rule out the possibility that the predicted effects of H1 and H2 for the investment bank analysts are partially related to the investment banking incentive.

5.2.6. Who Are the OP Analysts?

The results in the previous sections show that analysts who issue OP forecasts produce more accurate earnings forecasts and are less likely to be fired. Thus, a natural question to ask is why not all analysts issue OP forecasts. Section 2.1 offers several plausible explanations. One testable explanation is the “bang for the buck” hypothesis. This hypothesis states that managers will play the biased earnings forecast game only with analysts who can exert a significant influence on investors’ expectations. Prior research (see e.g., Jacob et al., 1999; Mikhail et al., 1997; Stickel, 1992) indicates that analysts that are more experienced, from large brokerage houses, and an All-

Star as rated by the Institutional Investor magazine are more influential among investors. Thus, we expect those analysts to be more likely to issue OP forecasts.

Table 6 reports test results consistent with this hypothesis based on the larger annual earnings forecast sample. The unit of observation is an analyst year. Panel A reports the univariate statistics of analyst characteristics by high and low OP using a cutoff of the median OP, while Panel B reports the regression of OP on the multiple analyst characteristics. The regression model also controls for year fixed effects and adjusts the coefficient standard errors for heteroskedasticity and dependence of observations of the same brokerage firms per Rogers (1993). The dependent variable OP is multiplied by 100 in Panel B to increase the precision of the reported regression coefficients. $FirmExperience_{i,t}$ is defined as before. $Bro\ker size_{i,t}$ is defined as the number of unique analysts that belong to brokerage firm i in year t. $AllStar_{i,t}$ is a dummy variable that is coded one if an analyst is an All-Star as ranked by the Institutional Investors magazine in the prior year, and zero otherwise. Consistent with the hypothesis, Panel A of Table 6 shows that high OP analysts are more experienced, employed by larger brokerage firms, and more likely to be an All-Star. The results from the multiple variable regression in Panel B of Table 6 are consistent with the descriptive statistics in Panel A.

6. Conclusion

Analysts are often alleged to use biased earnings forecasts to please management, but the form of the earnings forecast bias analysts use and the benefits analysts receive from issuing biased forecasts are not clearly identified. We hypothesize that analysts use biased earnings forecasts to gain better access to management's private information to improve their earnings forecast accuracy and job security. Based on prior research, we consider four earnings forecast biases that analysts could use to please firm management (denoted OP, OO, PP, and PO). OP denotes individual analysts whose initial earnings forecasts are optimistic (i.e., forecast is greater than the realized earnings) but whose last earnings forecasts before the earnings announcement are pessimistic (i.e., forecast is no greater than the realized earnings); OO denotes analysts whose initial and last forecasts are both optimistic while PP denotes analysts whose initial and last forecasts are both pessimistic; finally PO denotes analysts whose initial earnings forecasts are pessimistic but whose last forecasts are optimistic. We test our research questions using both annual and quarterly earnings forecasts because individual analysts often issue both annual and quarterly earnings forecasts and thus it is interesting to examine whether the forecast bias analysts use to please management varies across forecast horizon.

We find that analysts who issue both annual and quarterly OP forecasts have more accurate current and future earnings forecasts relative to other analysts and are less likely to be fired by their employers. These effects are stronger for firms with heavy insider sales and hard-to-predict earnings. In addition, we find that those results hold for analysts employed by both investment banks and pure brokerage firms without investment banking business. Taken together, these empirical results are consistent with the hypothesis that analysts use the OP bias to please firm management to gain better access to management's private information. Further analyses indicate that OP analysts are more experienced, employed by larger brokerage firms and more likely to be an All-Star. The characteristics of the OP analysts are consistent with the hypothesis that management is more willing to play the biased earnings forecast game with analysts who have more influence on capital market investors.

Despite the robust and consistent empirical results for H1 and H2, our results should be interpreted with caution because we merely document associations and thus our results could be subject to unknown alternative explanations. In addition, the regression results for H2 should be interpreted with caution because the construct validity of the dependent variable (Firing) cannot be independently verified.

Regulation FD has significantly changed the private communication between firm management and financial analysts. Future research may study how Regulation FD affects analysts' incentives to use biased earnings forecasts to gain better access to management's private information. Although recent research (see e.g., Gintschel and Markov, 2004) shows that Regulation FD significantly reduces the amount of private information analysts receive from firm management, it remains unclear whether the private communication between management and analysts has been completely cut off. For instance, Regulation FD still allows managers to disclose nonmaterial nonpublic information to analysts. As the SEC recognizes, such nonmaterial information could be combined with analysts' own private information to generate material new insights. As a result, firm management may still have substantial leverage in pressing analysts to issue biased earnings forecasts to gain access to their private information.

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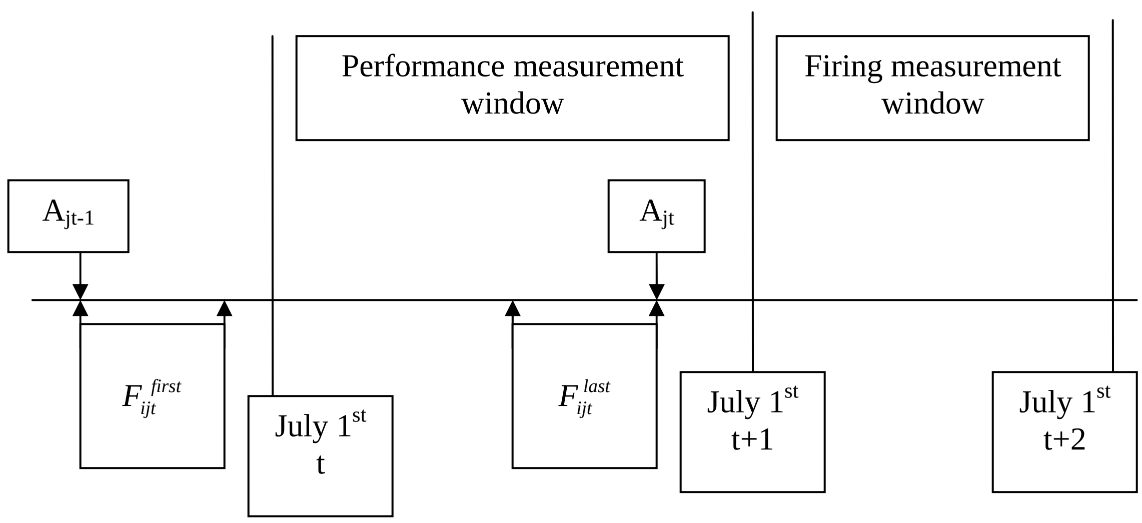
Figure 1. Timeline for the construction of regression variables



Variable definitions:

A_{jt} denotes firm j's annual earnings for year t that is announced immediately before July 1, year t+1;

A_{jt-1} denotes firm j's annual earnings for year t-1;

F_{ijt}^{last} is analyst i's latest forecast of annual earnings $A_{jt,}$ issued in the second half of the period from the earnings announcement date of A_{jt-1} to the earnings announcement date of A_{jt}; and

F_{ijt}^{first} is analyst i's earliest forecast of annual earnings A_{jt} issued in the first half of the period from the earnings announcement date of A_{jt-1} to the earnings announcement date of A_{jt}.

Table 1. Descriptive Statistics over January 1, 1983-July 1, 2000

Panel A. Variables used in model (3) for annual earnings forecasts[a]

variable	*N*	*Mean*	*25%*	*median*	*75%*	*S.D.*
OP_{ijt}	228,904	0.260	0	0	1	0.438
OO_{ijt}	228,904	0.343	0	0	1	0.475
PP_{ijt}	228,904	0.306	0	0	1	0.461
PO_{ijt}	228,904	0.091	0	0	0	0.287
$Accuracy_{ijt}$	228,904	50.00	23.53	50.00	76.19	31.67
$Bold_{ijt}$	228,904	50.00	21.43	50.00	77.78	32.44
$FirmExperience_{ijt}$	228,904	4.30	2	3	6	3.15
$R\_FirmExperience_{ijt}$	228,904	50.00	22.73	50.00	76.67	31.43
$Follow_{ijt}$	228,904	21.07	11	19	29	12.62
$FirmsCovered_{ijt}$	228,904	25.29	14	20	29	22.56
$R\_FirmsCovered_{ijt}$	228,904	50.00	21.15	50.00	78.57	33.13
GAP_{ijt}	228,904	78.89	43	81	104	43.81
R_GAP_{ijt}	228,904	50.00	21.43	50.00	78.57	32.97

Panel B. Variables used in model (3) for quarterly earnings forecasts[b]

variable	*N*	*Mean*	*25%*	*median*	*75%*	*S.D.*
OP_{ijt}	114,075	0.291	0	0	1	0.454
OO_{ijt}	114,075	0.298	0	0	1	0.458
PP_{ijt}	114,075	0.365	0	0	1	0.481
PO_{ijt}	114,075	0.045	0	0	0	0.208
$Accuracy_{ijt}$	114,075	50.00	25.00	50.00	75.00	33.03
$Bold_{ijt}$	114,075	50.00	21.42	50.00	80.00	34.33
$FirmExperience_{ijt}$	114,075	4.89	2	4	7	3.71
$R\_FirmExperience_{ijt}$	114,075	50.00	21.42	50.00	78.57	33.51
$Follow_{ijt}$	114,075	23.96	15	22	32	11.91
$FirmsCovered_{ijt}$	114,075	20.15	13	18	24	11.98
$R\_FirmsCovered_{ijt}$	114,075	50.00	21.00	50.00	80.00	35.39
GAP_{ijt}	114,075	48.67	23	46	76	28.48
R_GAP_{ijt}	114,075	50.00	20.00	50.00	80.00	34.87

Panel C. Variables used in model (4) for annual earnings forecasts[c]

variable	*N*	*Mean*	*25%*	*median*	*75%*	*S.D.*
$Fire_{i,t+1}$	32,303	0.15	0	0	0	0.36
$OP_{i,t}$	32,303	0.25	0.00	0.22	0.38	0.25
$OO_{i,t}$	32,303	0.35	0.13	0.33	0.50	0.29
$PP_{i,t}$	32,303	0.30	0.00	0.25	0.50	0.28
$PO_{i,t}$	32,303	0.09	0.00	0.00	0.13	0.16
$Accuracy_{i,t}$	32,303	49.85	41.33	50.00	58.77	14.70
$Bold_{i,t}$	32,303	50.32	42.09	50.00	58.18	14.18
$Experience_{i,t}$	32,303	5.01	2	4	7	3.76

Panel D: Variables used in model (4) for quarterly earnings forecasts[d]

variable	*N*	*Mean*	*25%*	*median*	*75%*	*S.D.*
$Fire_{i,t+1}$	15,278	0.12	0	0	0	0.32
$OP_{i,t}$	15,278	0.30	0.00	0.25	0.50	0.29
$OO_{i,t}$	15,278	0.32	0.00	0.25	0.50	0.31
$PP_{i,t}$	15,278	0.34	0.00	0.33	0.50	0.31
$PO_{i,t}$	15,278	0.04	0.00	0.00	0.00	0.13
$Accuracy_{i,t}$	15,278	49.65	37.50	50.00	62.50	21.67
$Bold_{i,t}$	15,278	50.28	37.50	50.00	62.50	22.17
$Experience_{i,t}$	15,278	6.22	3	5	9	4.10

[a] The subscript i refers to analyst i; the subscript j refers to stock j; and the subscript t refers to year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). OP_{ijt} is optimism-to-pessimism forecast bias for analyst i who follows firm j in year t. OO_{ijt} is optimism-to-optimism forecast bias for analyst i who follows firm j in year t. PP_{ijt} is pessimism-to-pessimism forecast bias for analyst i who follows firm j in year t. PO_{ijt} is pessimism-to-optimism forecast bias for analyst i who follows firm j in year t. The four forecast biases are defined using each analyst's first and last annual earnings forecasts over two consecutive annual earnings announcement dates. $Accuracy_{ijt}$ is the standardized earnings forecast accuracy ranking (based on the last earnings forecast) of analyst i relative to other analysts who follow the same firm j in year t. $Bold_{ijt}$ is the standardized ranking of the deviation of analyst i's first annual earnings forecast relative to other analysts' forecasts for the same firm j in year t. $FirmExperience_{ijt}$ is the number of years analyst i follows stock j as of year t. $Follow_{ijt}$ is the total number of analysts (including analyst i) who follow firm j in year t. $FirmsCovered_{ijt}$ is the number of firms (including firm j) followed by analyst i in year t. GAP_{ijt} is the distance in days between the earnings announcement date for A_{jt} and the forecast date for F_{ijt}^{last} for

analyst i in year t. $R\_FirmExperience_{ijt}$, $R\_FirmsCovered_{ijt}$, and R_GAP_{ijt} are the standardized ranking of $FirmExperience_{ijt}$, $FirmsCovered_{ijt}$, and GAP_{ijt}, respectively.

[b] The subscript i refers to analyst i; the subscript j refers to stock j; and the subscript t refers to any of the quarters that fall within year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). OP_{ijt} is optimism-to-pessimism forecast bias for analyst i who follows firm j in quarter t. OO_{ijt} is optimism-to-optimism forecast bias for analyst i who follows firm j in quarter t. PP_{ijt} is pessimism-to-pessimism forecast bias for analyst i who follows firm j in quarter t. PO_{ijt} is pessimism-to-optimism forecast bias for analyst i who follows firm j in quarter t. The four forecast biases are defined using each analyst's first and last quarterly earnings forecasts issued between the quarterly earnings announcement two quarters prior and the current quarter's earnings announcement. The other variables in Panel B are defined in the same way as the annual definitions in Panel A, using quarterly earnings forecasts.

[c] The subscript i refers to analyst i; the subscript j refers to stock j; and the subscript t refers to year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). $Fire_{i,t+1}$ is equal to one if analyst i is demoted from a large brokerage firm to a small brokerage firm or permanently leaves the profession during the year from July 1, t+1 to June 30, t+2, and zero otherwise. $Experience_{i,t}$ is the number of years analyst i appears in the IBES annual earnings forecast database as of year t. The other variables in Panel C are the average of the respective variables in Panel A across all stocks j followed by analyst i in year t.

[d] The subscript i refers to analyst i; the subscript j refers to stock j; and the subscript t refers to any of the quarters that fall within year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). $Experience_{i,t}$ is defined in Panel C above. The other variables in Panel D are the average of the same variables in Panel B across all stocks j followed by analyst i in year t and are defined as the mean of each quarterly variable across all quarters in year t for each firm-analyst, followed by the averaging of the mean quarterly variable across all firms j followed by analyst i in year t.

Table 2. Correlations for Key Regression Variables over January 1, 1983-July 1, 2000[a]

	$OP^A_{i,t}$	$OO^A_{i,t}$	$PP^A_{i,t}$	$PO^A_{i,t}$	$OP^Q_{i,t}$	$OO^Q_{i,t}$	$PP^Q_{i,t}$	$PO^Q_{i,t}$	$Accuracy^A_{i,t}$	$Accuracy^Q_{i,t}$	$Fire_{i,t+1}$
$OP^A_{i,t}$		-0.292***	-0.293***	-0.150***	0.257***	-0.011	-0.189***	-0.090***	0.118***	0.030***	-0.107***
$OO^A_{i,t}$	-0.378***		-0.548***	-0.125***	-0.044***	0.352***	-0.296***	-0.032***	-0.062***	-0.020**	0.033***
$PP^A_{i,t}$	-0.372***	-0.570***		-0.033***	-0.122***	-0.290***	0.386***	0.039***	-0.033***	-0.017**	-0.050***
$PO^A_{i,t}$	-0.219***	-0.227***	-0.138***		-0.131***	-0.065***	0.126***	0.140***	-0.014**	0.010	0.016***
$OP^Q_{i,t}$	0.297***	-0.049***	-0.112***	-0.130***		-0.419***	-0.440***	-0.170***	0.021**	0.180***	-0.029***
$OO^Q_{i,t}$	0.030***	0.350***	-0.295***	-0.037***	-0.336***		-0.547***	-0.154***	-0.001	-0.147***	0.009
$PP^Q_{i,t}$	-0.177***	-0.316***	0.402***	0.125***	-0.359***	-0.504***		-0.105***	-0.022**	-0.018**	0.012
$PO^Q_{i,t}$	-0.076***	-0.055***	0.071***	0.191***	-0.102***	-0.090***	0.030***		0.006	-0.006	0.016*
$Accuracy^A_{i,t}$	0.123***	-0.038***	-0.022***	-0.014**	0.022**	0.001	-0.027**	0.003		0.232***	-0.147***
$Accuracy^Q_{i,t}$	0.032***	-0.020**	-0.012	0.011	0.170***	-0.137***	-0.017**	0.007	0.199***		-0.036***
$Fire_{i,t+1}$	-0.064***	0.062***	-0.014*	0.013**	-0.044***	-0.009	-0.001	0.002	-0.137***	-0.037***	

[a] $Accuracy^A_{i,t}$ is $Accuracy_{i,t}$ using annual earnings forecasts, while $Accuracy^Q_{i,t}$ is $Accuracy_{i,t}$ using quarterly earnings forecasts. See Table 1 for other variable definitions. Spearman correlations are reported in the top diagonal and Pearson correlations are reported in the bottom diagonal. The sample size for the correlations among the annual earnings forecast variables is 32,303; the sample size for the correlations among the quarterly earnings forecast variables is 15,278; the sample size for the correlations across annual and quarterly earnings forecast variables is 14,511. *, **, *** denote two-tailed significance levels of 10%, 5%, and 1%, respectively.

Table 3. OLS Regression Results of Analyst Forecast Accuracy (H1)

Panel A. Regression results using annual earnings forecasts [a]

Dependent variable = $Accuracy_{ijt}$	(1)	(2)	(3)
	Coefficient (standard error)		
OP_{ijt}	5.059	6.530	6.079
	(0.296)***	(0.162)***	(0.235)***
OO_{ijt}	-3.106		
	(0.255)***		
PP_{ijt}	-0.105		
	(0.308)		
$Bold_{ijt}$	-0.018	-0.017	-0.017
	(0.002)***	(0.002)***	(0.002)***
$R\_FirmExperience_{ijt}$	0.013	0.013	0.013
	(0.003)***	(0.003)***	(0.003)***
$\ln(Follow_{ijt})$	-0.054	0.058	0.018
	(0.049)	(0.049)	(0.050)
$R\_FirmsCovered_{ijt}$	-0.006	-0.006	-0.006
	(0.003)**	(0.003)**	(0.003)**
R_GAP_{ijt}	-0.108	-0.111	-0.108
	(0.003)***	(0.003)***	(0.003)***
$InsiderSell_{ijt}$			-0.185
			(0.098)*
$OP_{ijt} \times InsiderSell_{ijt}$			0.781
			(0.332)**
$Dispersion_{ijt}$			-0.646
			(0.115)***
$OP_{ijt} \times Dispersion_{ijt}$			0.736
			(0.362)**
Brokerage firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	228,904	228,904	220,734
R^2	0.038	0.037	0.036

Panel B. Regression results using quarterly earnings forecasts [b]

Dependent variable = $Accuracy_{ijt}$	(1)	(2)	(3)
		Coefficient (standard error)	
OP_{ijt}	8.533	10.740	10.252
	(0.594)***	(0.224)***	(0.291)***
OO_{ijt}	-5.464		
	(0.519)***		
PP_{ijt}	0.125		
	(0.573)		
$Bold_{ijt}$	-0.015	-0.014	-0.014
	(0.003)***	(0.003)***	(0.003)***
$R\_FirmExperience_{ijt}$	0.008	0.008	0.008
	(0.004)**	(0.004)**	(0.004)**
$\ln(Follow_{ijt})$	-0.006	0.009	0.005
	(0.004)	(0.005)**	(0.005)
$R\_FirmsCovered_{ijt}$	-0.009	-0.009	-0.009
	(0.003)**	(0.004)**	(0.004)**
R_GAP_{ijt}	-0.102	-0.105	-0.105
	(0.004)***	(0.004)***	(0.004)***
$InsiderSell_{ijt}$			-0.231
			(0.167)
$OP_{ijt} \times InsiderSell_{ijt}$			1.153
			(0.468)**
$Dispersion_{ijt}$			-1.044
			(0.173)***
$OP_{ijt} \times Dispersion_{ijt}$			0.511
			(0.470)
Brokerage firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	114,075	114,075	113,000
R^2	0.049	0.044	0.044

[a] The subscript i refers to analyst i; the subscript j refers to stock j; and the subscript t refers to year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). $InsiderSell_{ijt}$ is a dummy that is equal to 1 if the average net

insider selling (expressed in 1982 dollars) by all corporate officers and directors for firm j followed by analyst i during the calendar year immediately before the earnings announcement date for $Accuracy_{ijt}$ is larger than the 75th percentile of our sample. $Dispersion_{ijt}$ is a dummy that is equal to 1 if the forecast dispersion (defined as the standard deviation of the earnings forecasts scaled by the magnitude of the realized earnings) is greater than the 75th percentile of our sample. $Dispersion_{ijt}$ is computed using each analyst's first earnings forecast F_{ijt}^{first}, although results are similar if each analyst's last earnings forecast F_{ijt}^{last} is used instead. See Table 1 for other variable definitions. The standard errors are computed using Rogers' (1993) method, which allows heteroskedasticity and any type of correlation for observations of the same stocks but assumes independence for observations of different stocks. *, **, *** denote two-tailed significance levels of 10%, 5%, and 1%, respectively.

[b] The subscript i refers to analyst i; the subscript j refers to stock j; and the subscript t refers to any of the quarters that fall within year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). $InsiderSell_{ijt}$ and $Dispersion_{ijt}$ are defined similarly to Panel A above. See Table 1 for other variable definitions. The standard errors are computed using Rogers' (1993) method, which allows heteroskedasticity and any type of correlation for observations of the same stocks but assumes independence for observations of different stocks. *, **, *** denote two-tailed significance levels of 10%, 5%, and 1%, respectively.

Table 4. Logit Regression Results of Analyst Firing (H2)

Panel A. Regression results using annual earnings forecasts [a]

Dependent variable = $Fire_{i,t+1}$	(1)	(2)	(3)
		Coefficient (standard error)	
$Accuracy_{i,t}$	-0.027	-0.028	-0.028
	(0.001)***	(0.001)***	(0.001)***
$OP_{i,t}$	-0.371	-0.366	0.001
	(0.117)***	(0.069)***	(0.158)
$OO_{i,t}$	0.142		
	(0.109)		
$PP_{i,t}$	-0.158		
	(0.126)		
$Bold_{i,t}$	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)*
$\ln(Experience_{i,t})$	-0.223	-0.222	-0.214
	(0.036)***	(0.036)***	(0.035)***
$InsiderSell_{i,t}$			-0.280
			(0.109)**
$OP_{i,t} \times InsiderSell_{i,t}$			-0.620
			(0.271)**
$Dispersion_{i,t}$			0.404
			(0.093)***
$OP_{i,t} \times Dispersion_{i,t}$			-0.617
			(0.284)**
Brokerage firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	32,303	32,303	30,650

Panel B. Regression results using quarterly earnings forecasts [b]

Dependent variable = $Fire_{i,t+1}$	(1)	(2)	(3)
		Coefficient (standard error)	
$Accuracy_{i,t}$	-0.004	-0.004	-0.004
	(0.001)***	(0.001)***	(0.001)***
$OP_{i,t}$	-0.527	-0.297	-0.110
	(0.184)***	(0.105)***	(0.154)
$OO_{i,t}$	-0.191		
	(0.173)		
$PP_{i,t}$	-0.292		
	(0.173)*		
$Bold_{i,t}$	0.002	0.002	0.001
	(0.001)	(0.001)	(0.001)
$\ln(Experience_{i,t})$	-0.081	-0.081	-0.073
	(0.038)**	(0.038)**	(0.037)*
$InsiderSell_{i,t}$			0.109
			(0.115)
$OP_{i,t} \times InsiderSell_{i,t}$			-0.738
			(0.392)*
$Dispersion_{i,t}$			-0.049
			(0.116)
$OP_{i,t} \times Dispersion_{i,t}$			-0.011
			(0.263)
Brokerage firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	15,278	15,278	14,942

Panel C. Regression results using both annual and quarterly earnings forecasts [c]

Dependent variable = $Fire_{i,t+1}$	(1)
	Coefficient (standard error)
$Accuracy^{A}_{i,t}$	-0.036
	(0.003)***
$Accuracy^{Q}_{i,t}$	-0.002
	(0.002)
$OP^{A}_{i,t}$	-0.308
	(0.140)**
$OP^{Q}_{i,t}$	-0.197
	(0.114)*
$Bold^{A}_{i,t}$	-0.003
	(0.002)
$Bold^{Q}_{i,t}$	0.003
	(0.001)**
$\ln(Experience_{i,t})$	-0.121
	(0.041)***
Brokerage firm fixed effects	Yes
Year fixed effects	Yes
N	14,511

[a] The subscript i refers to analyst i; the subscript j refers to stock j; and the subscript t refers to year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). $InsiderSell_{i,t}$ is the average of $InsiderSell_{ijt}$ over all the firms j covered by analyst i in year t. $Dispersion_{i,t}$ is the average of $Dispersion_{ijt}$ over all the firms j covered by analyst i in year t. See Tables 1 and 3 for other variable definitions. The standard errors are computed using Rogers' (1993) method, which allows heteroskedasticity and any type of correlation for observations of the same brokerage houses but assumes independence for observations of different brokerage houses. *, **, *** denote two-tailed significance levels of 10%, 5%, and 1%, respectively.

[b] The subscript i refers to analyst i; the subscript j refers to stock j; and the subscript t refers to any of the quarters that fall within year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). $InsiderSell_{i,t}$ and $Dispersion_{i,t}$

are defined as the mean of the same quarterly variable across all quarters in year t for each firm-analyst, followed by the averaging of the mean quarterly variable across all firms j followed by analyst i in year t. See Tables 1 and 3 for other variable definitions. The standard errors are computed using Rogers' (1993) method, which allows heteroskedasticity and any type of correlation for observations of the same brokerage houses but assumes independence for observations of different brokerage houses. *, **, *** denote two-tailed significance levels of 10%, 5%, and 1%, respectively.

[c] The subscript i refers to analyst i; the subscript j refers to stock j; and the subscript t refers to year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). $Bold_{i,t}^{A}$ and $Bold_{i,t}^{Q}$ are $Bold_{i,t}$ for annual earnings forecasts and quarterly earnings forecasts, respectively. $OP_{i,t}^{A}$ and $OP_{i,t}^{Q}$ are $OP_{i,t}$ for annual earnings forecasts and quarterly earnings forecasts, respectively. See Tables 1, 2, and 3 for other variable definitions. The standard errors are computed using Rogers' (1993) method, which allows heteroskedasticity and any type of correlation for observations of the same brokerage houses but assumes independence for observations of different brokerage houses. *, **, *** denote two-tailed significance levels of 10%, 5%, and 1%, respectively.

Table 5: Heckman Regression Results of Future Earnings Forecast Accuracy

Panel A. Regression results using annual earnings forecasts [a]

Dependent variable = $Accuracy_{i,t+1}$	(1)
	Coefficient (standard error)
$OP_{i,t}$	0.968
	(0.344)***
$Accuracy_{i,t}$	0.068
	(0.008)***
$Bold_{i,t+1}$	-0.036
	(0.009)***
$R\_FirmExperience_{i,t+1}$	-0.001
	(0.005)
$\ln(Follow_{i,t+1})$	0.023
	(0.013)*
$R\_FirmsCovered_{i,t+1}$	-0.001
	(0.003)
$R\_GAP_{i,t+1}$	-0.178
	(0.008)***
Brokerage firm fixed effects	Yes
Year fixed effects	Yes
N	23,289

Panel B. Regression results using quarterly earnings forecasts [b]

Dependent variable = $Accuracy_{i,t+1}$	(1)
	Coefficient (standard error)
$OP_{i,t}$	1.330
	(0.881)
$Accuracy_{i,t}$	0.043
	(0.011)***
$Bold_{i,t+1}$	-0.007
	(0.013)
$R\_FirmExperience_{i,t+1}$	-0.002
	(0.008)
$\ln(Follow_{i,t+1})$	0.032
	(0.026)
$R\_FirmsCovered_{i,t+1}$	-0.002
	(0.007)
$R\_GAP_{i,t+1}$	-0.115
	(0.013)***
Brokerage firm fixed effects	Yes
Year fixed effects	Yes
N	9,737

[a] The subscript i refers to analyst i; the subscript j refers to stock j; and the subscript t refers to year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). $Follow_{i,t+1}$ is the average of $Follow_{ijt+1}$ across all firms j covered by analyst i in year t. $R\_FirmExperience_{i,t}$ and $R\_GAP_{i,t}$ are the averages of $R\_FirmExperience_{ijt}$ and R_GAP_{ijt}, respectively, across all firms j covered by analyst i in year t. See Table 1 for other variable definitions. The standard errors are computed using Rogers' (1993) method, which allows heteroskedasticity and any type of correlation for observations of the same brokerage houses but assumes independence for observations of different brokerage houses. *, **, *** denote two-tailed significance levels of 10%, 5%, and 1%, respectively.

[b] The subscript i refers to analyst i; the subscript j refers to stock j; and the subscript t refers to any of the quarters that fall within year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). All the variables in Panel B are the

mean of their quarterly equivalents across all firms j covered by analyst i in year t and are defined as the mean of each quarterly variable across all quarters in year t for each firm-analyst, followed by the averaging of the mean quarterly variable across all firms j followed by analyst i in year t. The standard errors are computed using Rogers' (1993) method, which allows heteroskedasticity and any type of correlation for observations of the same brokerage houses but assumes independence for observations of different brokerage houses. *, **, *** denote two-tailed significance levels of 10%, 5%, and 1%, respectively.

Table 6: Characteristics of Analysts Who Issue annual OP Forecasts

Panel A. Descriptive statistics (N=32,303)[a]

Mean (median)[standard Deviation]

Variable	OP>median	OP≤median	P Value from a Ranksum Test of the Difference
$FirmExperience_{i,t}$	3.320 (2.750) [2.082]	2.975 (2.416) [1.949]	<0.001
$Broker\,size_{i,t}$	43.570 (32.000) [42.857]	41.011 (28.000) [41.498]	<0.001
$AllStar_{i,t}$	0.133 (0.000) [0.340]	0.104 (0.000) [0.306]	<0.001

Panel B. Regression of OP on analyst characteristics[b]

Dependent variable = $OP_{i,t}$ *100	(1)
	Coefficient (standard error)
$FirmExperience_{i,t}$	0.225
	(0.087)***
$Broker\,size_{i,t}$	0.013
	(0.003)***
$AllStar_{i,t}$	1.865
	(0.400)***
Year fixed effects	Yes
N	32,303

[a] The subscript i refers to analyst i; and the subscript t refers to year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). $Broker\,size_{i,t}$ is the number of unique analysts that belong to brokerage firm i in year t. $AllStar_{i,t}$ is coded one if an analyst is an All-Star as determined by the Institutional Investor magazine in year t-1, and zero otherwise. The All-Star data are available for only 1995-2000. See Panel C of Table 1 for other variable definitions.

[b] The subscript i refers to analyst i; and the subscript t refers to year t, defined as the period from July 1, t to July 1, t+1 (see Figure 1). See Panel A above for other variable definitions. The standard errors are computed using Rogers' (1993) method, which allows heteroskedasticity and any type of correlation for observations of the same brokerage houses but assumes independence for observations of different brokerage houses. *, **, *** denote two-tailed significance levels of 10%, 5%, and 1%, respectively.