How Does Prior Information Affect Analyst Forecast Herding?

Michele O'Neill
College of Business and Economics
The University of Idaho

Minsup Song *
College of Business and Administration
Sogang University

Judith Swisher
Department of Finance and Commercial Law
Haworth College of Business
Western Michigan University

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*Corresponding Author: College of Business Administration, Sogang University, Seoul, Korea. Phone: 82-2-705-8855. E-mail: msong@sogang.ac.kr. FAX: 82-2-705-8519.

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Abstract

This research uses four different measures of bold to investigate how prior information affects analyst herding decisions. Results for the more restrictive measures of bold suggest that the probability of herding is greater with large information shocks. Evidence also shows that analysts are more likely to herd in their forecast revisions when their current outstanding forecasts deviate more from the consensus mean and in the presence of strong observable signals. In general, analysts with current outstanding forecasts that are optimistic are more likely to issue revised forecasts that are also optimistic.

Keyword: Analyst Forecasts, Forecast Herding, Forecast Revisions, Bold Forecast

I. Introduction

Market response to analyst forecasts suggests that analysts are viewed by investors as knowledgeable information intermediaries. However, herding by analysts can reduce the information conveyed by their forecasts since analysts who herd may not fully use their private information.[1] The purpose of this study is to investigate the circumstances under which analysts herd in their earnings forecasts. In particular, this study examines how an analyst's herding decision in an annual earnings forecast is affected by prior observable signals released by other analysts and by uncertainty related to the analyst's current outstanding forecast.

Herding theories suggest that issuing a forecast that is inconsistent with the analyst's private information could be the optimal equilibrium for analysts who are concerned about their reputation (e.g., Graham 1999; Scharfstein and Stein 1990; Trueman 1994). For example, in the model of Scharfstein and Stein (1990), it could be better for an analyst (manager or decision maker) to simply follow the decision of other analysts because taking a similar action as others suggests to investors that the analyst has received a signal that is correlated with others, and therefore the analyst is more likely to look informed (or smart). Empirical evidence shows that analysts with weak forecasting ability are more likely to herd than analysts with strong forecasting ability. Hong, Kubik, and Solomon (2000) find that herding is negatively related with analyst experience. Clement and Tse (2005) show that herding is also related to other analyst characteristics such as brokerage size, forecast frequency, and the number of companies and industries that the analyst follows.

While previous empirical studies examine the cross-sectional differences in analyst characteristics as determinants of analysts' forecast herding, analytical studies suggest that prior

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[1] See Devenow and Welch (1996) and Bikhchandani and Sharma (2001) for a recent review of the literature.

observable signals released by other analysts are also important determinants for an analyst's herding decision. Bikhchandani and Sharma (2001) expect that an analyst's herding decision is sensitive to information shock related to other analyst forecasts because the analyst's strategy is to imitate other analyst forecasts regardless of her own private information. In particular, the characteristics of prior signals affect an analyst's incentive to discard her private information and instead mimic others, because an analyst's herding decision depends on the analyst's assessed risk to be regarded as incompetent by her clients if she issues a forecast inconsistent with prior signals. Graham (1999) and Trueman (1994) expect that analysts have more incentive to herd if they observe prior signals that are highly correlated or if the prior information is inconsistent with the analyst's private information. How prior information affects analysts' herding decisions, however, has not been rigorously investigated. We attempt to fill this gap by testing the empirical implications of the theoretical models with a sample of individual analysts' annual earnings forecasts.

We first examine how the information shock related to other analyst forecasts and the uncertainty of an analyst's current outstanding forecast affect herding in the analyst's subsequent forecast. Following Stickel (1990), we measure information shock by the change in the consensus forecast of other analysts since the date of an analyst's current outstanding forecast. The uncertainty of an analyst's current outstanding forecast is measured as the deviation of the forecast from the consensus forecast. We contend that the risk for an analyst to be regarded as uninformed or incompetent is high if the deviation of her current outstanding forecast from the consensus forecast is large, thus there is high uncertainty.

Next, we examine how the strength of prior signals affects analyst herding behavior. The strength of prior signals is measured by the change in analyst forecast dispersion and by the number of analyst forecasts issued since the date of an analyst's current outstanding forecast. We argue that the new information contains a strong signal about future earnings if there is convergence in other analyst forecasts or if the change in the consensus forecast is based upon a large number of analysts.

Our results show that analyst forecasts are more likely to converge when they observe a large magnitude consensus change, consistent with Bikhchandani and Sharma's (2001) expectation. In addition, we find that analysts are more likely to herd if the deviation of the analyst's current forecast from consensus is large or if the consensus forecast moves away from the analyst's current forecast. These results suggest that analysts feel greater pressure to herd when faced with greater risk of be regarded as uninformed or incompetent by investors. Finally, strong prior signals are more likely to lead analysts to move toward the consensus forecast. Our results are robust to controlling for characteristics of individual analyst forecast ability.

This study contributes to the herding literature in several ways. First, there is a need for a broader understanding of analyst herding. Hong et al. (2000) and Clement and Tse (2005) show analyst characteristics related to analyst forecast ability are strongly associated with herding. These studies conclude that weak forecast ability causes analysts to seek safety in forecasts that are close to the consensus, while strong analysts are less bounded by the consensus. While these studies find evidence regarding *who* herds in earnings forecasts, they are silent about *when* analysts herd. We extend our understanding of herding by showing that an analyst is more likely to herd when she observes prior signals that are inconsistent with her current outstanding forecast.

Second, our research also contributes to the general debate about herding behaviors. Theoretical studies posit that herding is conditional on prior observable signals inferred from actions taken by predecessors (Graham 1999; Trueman 1994). The results suggest that herding is positively associated with the information shock related to other analyst forecasts and the strength of prior signals. These prior signals and forecast uncertainty are public information available to all investors. Thus, prior public information contains predictive information about future herding behavior and can help market participants better evaluate the analysts' earnings forecast.

Third, we provide alternative measures of herding, which improve our understanding of analyst forecast revision behaviors. Previous empirical studies that examine analyst herding measure boldness in earnings forecasts (as opposed to herding) using either the position of the revised forecast relative to an analyst's current outstanding forecast and the consensus forecast (Clement and Tse 2005; Gleason and Lee 2003) or the distance of the analyst's new forecast from the consensus forecast (Clement and Tse 2005; Hong et al. 2000). By definition, herding implies the analyst's forecast moves toward the consensus forecast. Thus, we classify a forecast as bold if the analyst's new forecast moves further away from the consensus forecast than the analyst's current outstanding forecast was from the prior consensus forecast. In addition, we compare the directions of the change in the consensus and individual analyst forecast revisions. A forecast is classified as bold if the market expectation becomes pessimistic (optimistic) while an analyst's forecast becomes optimistic (pessimistic) and the analyst forecast diverges from the census forecast. We do not claim that our bold measures are better than previous measures. However, our bold measures are more restrictive than prior bold measures and provide additional insight into analyst forecast revision behaviors. We expect our measures of boldness can be used in future research examining analyst herding.

The remainder of the paper is organized as follows: Section II reviews prior literature; the sample selection process is described in Section III; our research methods are explained in Section IV; we present our results in Section V; and Section VI summarizes and concludes.

II. Prior Literature and Hypothesis Development

Analytical studies regarding herding behaviors suggest that managers (or analysts) attempt to take similar actions (or issue similar forecasts) in order to enhance their reputations by sending signals that they have private information correlated with market leaders' information. Scharfstein and Stein (1990) and Trueman (1994) show that there exists an equilibrium in which an analyst mimics other analyst forecasts or simply moves toward consensus forecast even though her private information tells her otherwise. The intuition of this behavior is that an analyst's deviation from other analysts' belief can lead market participants to believe the analyst uninformed (or incompetent). If the common decision turns out to be incorrect it will be attributed to an unlucky draw of the same signal realization from an informative distribution, and the analyst can share the blame instead of being regarded as uninformed analyst.

Hong et al. (2000) test the link between analyst career concerns and herding behaviors. They find that career concerns are important incentives for herding in analysts' earnings forecast by showing that less experienced analysts are more likely to issue herding forecasts and they are more likely to experience job termination. Clement and Tse (2005) extend Hong et al. by examining how analyst characteristics reflecting analyst forecasting ability, such as career experience, the number of firms and industries that an analyst follows, prior forecast accuracy, and brokerage firm size, are associated with herding behaviors in annual earnings forecasts.

They find analyst characteristics that represent strong forecasting ability are negatively associated with analyst herding behaviors.

Previous empirical studies, however, are silent about how prior information affects herding. Empirical evidence suggests that an analyst's next forecast can be predicted by using prior public information. Stickel (1990) documents that an analyst's forecast revision is significantly affected by the market expectation change, measured by the change in consensus forecast. In addition, he finds that the market pressure on analysts to revise, measured by the deviation of the analyst's outstanding forecast from the consensus forecast, leads analysts to move toward the consensus forecast. Stickel (1992) finds that members of the *Institutional Investor* All-American Research Team are less likely to be affected by the other analysts' forecast revisions. However, these studies do not examine analyst forecast revisions in the context of herding.

One focus of this study is to examine how new information released by other analysts affects an analyst's herding decision. Analytical studies suggest that an analyst herding decision depends on the prior signals observed as well as the analyst's private information (e.g., Graham 1999; Scharfstein and Stein 1990; Trueman 1994 among others). One empirical implication of Scharfstein and Stein's (1990) model is that an analyst who is uncertain about her forecasting ability is sensitive to the arrival of new information, because the analyst's strategy is to defer to the action of predecessors as soon as she believes that prior signals are more informative than her own information. Bikhchandani and Sharma (2001) predicts that herding is fragile and very sensitive to information shock, such as the arrival of informed investors or the release of new public information (p. 292). Thus, we predict that analysts are more likely to herd when they observe a large magnitude of new information.

H1: Analysts are more likely to herd when the magnitude of new information is large.

Another implication of Scharfstein and Stein's (1990) model is that an analyst will perceive higher pressure if her forecast deviates more from other analyst forecasts. Because an analyst's goal is to maximize her expectation of her client's end-of-period assessment of the probability that her ability is strong, the uncertainty that the analyst perceives is higher if her outstanding forecast is farther from consensus forecast. Stickel (1990) finds that analysts whose forecasts deviate more from the consensus are more likely to issue subsequent forecasts close to the consensus forecast. He concludes that analysts are under pressure to issue forecasts in line with the consensus. However, Stickel does not examine the deviation of analyst forecasts from the consensus in the context of herding. We expect that an analyst is more likely to herd if her current forecast has greater deviation from other analyst forecasts.

H2: Analysts are more likely to herd when their current outstanding forecast differs substantially from the previous consensus forecast.

We also examine how a change in market expectations affects analyst herding behavior. If an analyst observes prior signals that are inconsistent with her current belief, she will perceive higher pressure to herd. For example, if an analyst whose forecast is optimistic relative to the market consensus observes a negative consensus change, maintaining her current forecast implies that her private information is inconsistent with the market expectation. This will provide an incentive for the analyst to revise her forecast closer to the consensus forecast. Thus, we expect that analysts are more likely to herd when the market expectations move away from the analyst's current outstanding forecast.

H3: Analysts are more likely to herd when the consensus forecast moves away from their current outstanding forecasts.

Our fourth hypothesis tests the effect of the strength of prior signals on herding. Graham (1999) suggests that the effect of prior signals on herding increases with the strength of prior earnings expectations. The strength of prior information becomes strong if informative signals are highly correlated or prior signals are made by a large group of analysts. Similarly, Trueman (1994) suggests that analysts are more likely to herd when there is little uncertainty in prior forecasts by other analysts. Intuitively, this is because it would be risky for an analyst to reveal her private information that is inconsistent with other analysts if there is high consensus among analysts. If there is low consensus in analyst forecasts, an analyst would feel free to issue a forecast inconsistent with those of others. Thus, we expect that analyst forecast herding is negatively associated with the strength of prior signals.

H4: Analysts are more likely to herd in the presence of strong observable signals by other analysts.

III. Sample Selection

Annual earnings forecasts from 1990 to 2005 are obtained from I/B/E/S. Following Clement and Tse (2005), we require that forecasts are issued no earlier than 200 days before and no later than 30 days before the fiscal year-end. Like prior research, we use the last forecast that an analyst issues in a particular fiscal year (Clement and Tse 2005; O'Brien and Bushan 1990; Sinha et al. 1997). We require that a minimum of three analysts follow a firm so that two forecasts can be used in the calculation of the mean (consensus) forecast for comparison with another analyst's revised forecast. To facilitate comparison across companies, we deflate a forecast revision (or mean forecast revision) by the prior forecast (or prior mean forecast) so that it represents the percentage change in the forecast (or mean forecast). We eliminate observations for which the absolute value of the deflated analyst forecast revision and the mean forecast revision are greater than 2 (Agrawal, Chadha, and Chen 2006).

Table 1 reports the frequency of forecasts by year for the sample. The requirements outlined above yield a sample of 214,039 analyst-firm-year observations with 2,125 analysts per year, on average, and an average of 2,159 firms per year. The average number of analyst-firm-year observations during the sample period is 13,377.

IV. Research Design and Model Development

4.1. Measurement of Bold (Herding) Forecasts

Previous empirical studies that examine analyst earnings forecast herding use two approaches to measure herding forecasts. The first, employed by Gleason and Lee (2003) and Clement and Tse (2005), defines bold forecasts based on the position of a revised forecast relative to the analyst's current outstanding forecast and the mean consensus forecast immediately prior to forecast revision. More specifically, Gleason and Lee define a forecast as bold if an individual analyst forecast is larger (smaller) than both her own current forecast and the consensus forecast immediately prior to the forecast revision. Following these studies, our first measure of forecast boldness is defined as follows:

Bold1 = one if ($F_{i,j,t} > F_{i,j,t-v}$ and $F_{i,j,t} > \bar{F}_{i,j,t-1}$) or ($F_{i,j,t} < F_{i,j,t-v}$ and $F_{i,j,t} < \bar{F}_{i,j,t-1}$), zero otherwise.

The second approach is to use the devastation of an analyst's forecast from the consensus forecast. Prior research assumes that boldness in analyst forecasts increases with the distance of the analyst forecast from consensus forecast (Clement and Tse 2005; Graham 1999; Hong et al. 2000). Our second measure of bold forecast is based on the deviation of an analyst's forecast revision from the mean consensus forecast. If the distance of an analyst's revised forecast from the mean consensus forecast is larger than that of the analyst's current outstanding forecast relative to the prior consensus forecasts, we define it as a bold forecast. This bold forecast measure is intuitive, as herding implies that analyst simply moves toward to consensus forecast. Any forecast that moves away from the consensus forecast is defined as bold. Formally, bold is measured as follows:

Bold2 = one if $| F_{i,j,t-v} - \bar{F}_{i,j,t-v-1} | < | F_{i,j,t} - \bar{F}_{i,j,t-1} |$, zero otherwise.

Our third measure of boldness is determined by combining the two bold forecast measures defined above. For this new measure, we compute the distance of the current outstanding forecast from the consensus forecast immediately before the issuance of the current forecast. Under the definition of *Bold1*, an analyst's revised forecast is classified as bold as long as it is greater (smaller) than her current outstanding forecast and the consensus forecast, even if her forecast converges toward the mean consensus forecast. Requiring divergence from the consensus forecast is a more restrictive definition of boldness. A forecast revision is classified as bold if it is greater (less) than (i) both the current outstanding forecast and the mean consensus forecast, and (ii) the distance between the mean consensus forecast and the revised forecast is greater than the distance between the prior consensus forecast and the current outstanding forecast. Intuitively, this boldness measure implies that an analyst became more optimistic (or pessimistic) than her prior forecast as well as the consensus forecast. Thus:

$$Bold3 = \text{one if } \{(F_{i,j,t} > F_{i,j,t-v} \text{ and } F_{i,j,t} > \bar{F}_{i,j,t-1}) \text{ or } (F_{i,j,t} < F_{i,j,t-v} \text{ and } F_{i,j,t} < F_{i,j,t-1})\}$$

$$\text{and } |\bar{F}_{i,j,t-v-1} - F_{i,j,t-v}| < |\bar{F}_{i,j,t-1} - F_{i,j,t}|, \text{ zero otherwise.}$$

The fourth measure of boldness is based on the sign of the forecast revision and the distance from the mean consensus. Kandel and Pearson (1995) suggest that when two analysts observe the same information and have the same beliefs, their forecast revisions should be in the same direction and converge. If and only if two analysts have different beliefs (or different private information or differential likelihood functions) will their revisions be in different directions and move apart. In this case, an analyst becomes pessimistic (optimistic) while the market expectation becomes optimistic (pessimistic). In addition, since the analyst has different beliefs about future earnings, her new forecast deviates further from the market consensus. This is most extreme definition of boldness (herding). Formally, it is measured as follows:

$Bold4$ = one if $sign(F_{i,j,t-v} - F_{i,j,t}) \neq sign(\bar{F}_{i,j,t-v-1} - \bar{F}_{i,j,t-1})$ and $|F_{i,j,t-v} - \bar{F}_{i,j,t-v-1}| < |F_{i,j,t} - \bar{F}_{i,j,t-1}|$, zero otherwise.

By examining the four measures of boldness defined above, we extend the extant literature on herding. Results of our research provide greater insight into analyst herding behavior. The next section develops our model.

4.2. Model Development

We base our model on the one used by Stickel (1990), which predicts an analyst's forecast revision using information observed by the analyst. Stickel suggests that an analyst's forecast revision is a function of new information and market pressure for a forecast revision. He measures new information by the change in the mean consensus forecast since the date of the analyst's current outstanding forecast, and measures market pressure by the deviation of the analyst's current outstanding forecast from the mean consensus forecast.[2] However, Stickel does not examine how these factors affect the boldness of an analyst's forecast. Thus, we modify the model developed by Stickel to predict boldness in analyst forecasts as follows:

$$\begin{aligned} Bold_{i,j,t} = \beta_0 &+ \beta_1 AbsChgCon_{j,t-1} + \beta_2 AbsDeviation_{i,j,t-v} + \beta_3 lnCoverage_j \\ &+ \beta_4 DaysElapsed_{i,j,t} + \beta_5 ForHorizon_{i,j,t} + \varepsilon_{i,j,t} \end{aligned} \quad (1)$$

where,

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[2] Stickel (1990) also uses the cumulative stock returns as an additional measure of new information. However, he drops the cumulative stock returns from part of his analysis because the change in consensus forecast revision has a greater effect on individual analyst's next forecast.

$Bold_{i,j,t}$ = one (zero) if the forecast revision of analyst *i* for stock *j* on date *t* is classified as bold (herding);

$AbsChgCon_{j,t-1}$ = absolute value of the change in the consensus forecast of other analysts following firm *j* between the days *t* and day *t – v*. It is measured by $(\overline{F}_{j,t-1} - \overline{F}_{j,t-v-1}) / \overline{F}_{j,t-v-1}$ where $\overline{F}_{j,t-1}$ is the mean consensus forecast on day *t – 1*. The $Chg\,Rev_{j,t-1}$ is a proxy for new information to analysts since the issuance of analyst *i*'s forecasts on day *t – v;*

$AbsDeviation_{i,j,t-v}$ = difference between the consensus forecast for firm *j* and analyst *i*'s forecast on day *t – v,* measured by $(F_{i,j,t-v} - \overline{F}_{j,t-v-1}) / \overline{F}_{j,t-v-1}$ where $F_{i,j,t-v}$ is the individual analyst *i*'s annual earnings forecast at day *t-v*. It reflects uncertainty related the analyst's current outstanding forecast;

$lnCoverage_j$ = natural log of the number of analysts following firm *j* in a particular year;

$DaysElapsed_{i,j,t}$ = number of days elapsed since the last forecast by any analyst following firm *j* in a particular year, calculated as the days between analyst *i*'s forecast of firm *j*'s earnings and that of the last forecast*;*

$ForHorizon_{i,j,t}$ = number of days from the forecast of analyst *i* for stock *j* on date *t* to the end of the fiscal period.

The consensus forecast is calculated as the simple mean of the earnings forecasts of all other analysts as of day *t – 1*, excluding analyst *i*, for firm *j*. Only the most recent forecast issued by each analyst is used in the consensus forecast calculation. To avoid the stale forecast problem, only forecasts that are issued within 90 days before the forecast issuance day are used to compute the mean forecast and forecast revision. For the cross-sectional comparison, each variable is scaled by the prior forecast or by the prior mean forecast.

The model includes three control variables. Prior research suggests that competition among analysts can increase the private information production activities among analysts (Abarbanell, Lanen, and Verrecchia 1995; Lang and Lundholm 1996). Thus, a positive coefficient on *lnCoverage* would support the idea that analysts respond to greater competition by increasing their production of private information. Since Barron et al. (2002) and Cooper et al.

(2001) show that the timing of a forecast can affect analysts' private information production activities, we also include *DaysElapsed* and *ForHorizon* to control for the timing of the forecast.

Next, we extend the prediction model by examining the effect of the nature of new information on analyst forecast revisions. Hypothesis 3 predicts that an analyst have greater incentive to herd if she observes a market signal that is inconsistent with her current outstanding forecast. A change in the consensus may have different implications to analysts, depending on their current opinions on future earnings. For example, if analyst A's current forecast is optimistic (greater than mean consensus forecast), an upward consensus forecast revision means the other analysts' beliefs were revised toward analyst A's current forecast. In this case, analyst A may have little incentive to revise her forecast to imitate other analyst forecasts as she learns little from her observation of the consensus change. Or perhaps she will issue another forecast that is consistent with her own private information (Graham 1999). On the other hand, a downward consensus revision means a greater deviation of analyst A's forecast from other analysts' beliefs. This forecast revision means the market expectation has changed in a way that is inconsistent with the analyst's current belief. In this case, she may have a greater incentive to herd as she perceives greater pressure to revise her forecast.[3]

We explore the role of prior opinion and investigate how the characteristics of new information affect an analyst's response by dividing forecast revisions into two groups based on the sign of consensus revision: upward and downward consensus revisions. For each subgroup,

[3] Analysts may respond differently, depending on the characteristics of the new information. Analysts tend to issue favorable forecasts rather than unfavorable forecasts to maintain brokerage firm affiliation or to get information access to managers (e.g., Dugar and Nathan 1995; Lin and McNichols 1998; Das, Levine, and Sivaramakrishnan 1998; Womack 1996). This can lead analysts to differential reactions to bad news, such as self-selection in the coverage decision (McNichols and O'Brien 1997; Das, Guo, and Zhang 2006) or analysts' underreaction (overreaction) to bad (good) news (e.g.,Brown 2001; Easterwood and Nutt 1999; Abarbanell and Bernard 1992)).

we examine whether an individual analyst's current optimistic forecast is related to her revision by using a dummy variable to represent *Optimism.* The dummy variable *Optimism* has a value of one if the analyst's outstanding forecast is greater than the prior mean consensus forecast, zero otherwise. We also investigate the interaction of *Optimism* with the new information variable *AbsChgCon* and the market pressure variable *AbsDeviation* and estimate the following model:

$$\begin{aligned} Bold_{i,j,t} = {} & \beta_0 + \beta_1 AbsChgCon_{j,t-1} + \beta_2 AbsDeviation_{i,j,t-v} + \beta_3 Optimism_{i,j,t-v} \\ & + \beta_4 AbsChgCon_{j,t-1} \times Optimism_{i,j,t-v} + \beta_5 AbsDeviation_{i,j,t-v} \times Optimism_{i,j,t-v} \\ & + \beta_6 lnCoverage_j + \beta_7 DaysElapsed_{i,j,t} + \beta_8 ForHorizon_{i,j,t} + \varepsilon_{i,j,t} \end{aligned} \qquad (2)$$

Where,

$Optimism_{i,j,t-v}$ = one if an analyst's current outstanding forecast is greater than the prior mean consensus forecast, zero otherwise.

Our next prediction model includes the strength of prior information. We measure the strength of new information by the change in analyst forecast dispersion (*Convergence*) and the number of analyst forecasts that are used to compute the mean consensus forecast change (*NumIssues*). If analysts' private information is correlated, their forecast revisions will be highly correlated and the forecast dispersion will decrease. Therefore, we argue that there is strong new information if the change in consensus forecast is associated with lower forecast dispersion. In addition, given a large magnitude consensus change, we contend that the strength of the new information signal is greater if the change in consensus is made by a larger number of analysts. We further argue that there will be a lower probability of boldness in analyst forecasts if prior information has greater strength. We test our hypothesis by estimating the following model:

$$\begin{aligned}Bold_{i,j,t} &= \beta_0 + \beta_1 AbsChgCon_{j,t-1} + \beta_2 AbsDeviation_{i,j,t-v} + \beta_3 Optimism_{i,j,t-v} \\ &+ \beta_4 AbsChgCon_{j,t-1} \times Optimism_{i,j,t-v} + \beta_5 AbsDeviation_{i,j,t-v} \times Optimism_{i,j,t-v} \\ &+ \beta_6 ChgCon_{j,t-1} \times Convergence_{j,t-1} + \beta_7 ChgRev_{j,t-1} \times NumIssuer_{j,t-1} \\ &+ \beta_6 lnCoverage_j + \beta_7 DaysElapsed_{i,j,t} + \beta_8 ForHorizon_{i,j,t} + \varepsilon_{i,j,t}\end{aligned} \tag{3}$$

$Convergence_{j,t-1}$ = the change in the dispersion ($StdDev_{j,t-1} - StdDev_{j,t-v}$) of the forecasts used to determine the consensus forecast;

$NumIssuer_{j,t-1}$ = the number of analyst forecasts that are used to compute the mean consensus forecast change.

Our final prediction model examines the above variables while controlling for analyst characteristics. Clement and Tse (2005) show that various analyst characteristics are related to analyst forecasting ability. Model (4) controls for an analyst's firm and general experience, lagged forecast accuracy, the size of the brokerage that employs the analyst, and the frequency with which the analyst issues forecasts for the firm. Following Clement and Tse, all analyst characteristics are scaled and converted into values between zero and one for use in the regressions. To test the robustness of our results to inclusion of analyst characteristics, we estimate the following model:

$$\begin{aligned}Bold_{i,j,t} &= \beta_0 + \beta_1 AbsChgCon_{j,t-1} + \beta_2 AbsDeviation_{j,t-v} + \beta_3 Optimism_{j,t-v} \\ &+ \beta_4 AbsChgCon_{j,t-1} \times Optimism_{j,t-v} + \beta_5 AbsDeviation_{j,t-v} \times Optimism_{j,t-v} \\ &+ \beta_6 AbsChgCon_{j,t-1} \times Convergence_{j,t-1} + \beta_7 AbsChg\mathrm{Re}v_{j,t-1} \times NumIssuer_{j,t-1} \\ &+ \beta_8 LnCoverage_j + \beta_9 DaysElapsed_{i,j,t} + \beta_{10} ForHorizon_{i,j,t} \\ &+ \beta_{11} GeneralExperience_{i,j,t} + \beta_{12} FirmExperience_{i,j,t} + \beta_{13} LagForAccuracy_{i,j,t-1} \\ &+ \beta_{14} BrokerageSize_{i,j,t} + \beta_{15} Frequency_{i,j,t} + \beta_{16} FirmCoverage_{i,j,t} + \varepsilon_{i,j,t}\end{aligned} \tag{4}$$

where:

$GeneralExperience_{i,j,t}$ = a measure of analyst *i*'s analyst career experience. It is calculated as the number of quarters of analyst career experience for analyst *i* following firm *j* as of year *t* minus the minimum number of quarters of firm-specific experience for analysts following firm *j* in year *t*, with this difference scaled by the range of quarters of firm-specific experience for analysts following firm *j* in year *t*;

$FirmExperience_{i,j,t}$ = a measure of analyst *i*'s firm-specific experience. It is calculated as the number of quarters of firm-specific experience for analyst *i* following firm *j* as of year *t* minus the minimum number of quarters of firm-specific experience for analysts following firm *j* in year *t*, with this difference scaled by the range of quarters of firm-specific experience for analysts following firm *j* in year *t*;

$LagForAccuracy_{i,j,t-1}$ = a measure of analyst *i*'s prior forecast accuracy for firm *j*. It is calculated as the maximum absolute value of forecast error for analysts who follow firm *j* in year *t* – 1 minus the absolute value of forecast error for analyst *i* following firm *j* as of year *t – 1*, with this difference scaled by the range of forecast error for analysts following firm *j* as of year *t -1*;

$BrokerageSize_{i,j,t}$ = a measure of the analyst's broker size. It is calculated as the number of analysts employed by the broker employing analyst *i* following firm *j* in year *t* minus the minimum number of analysts employed by brokers for analysts following firm *j* in year *t*, with this difference scaled by the range of brokerage size for analysts following firm *j* in year *t*;

$Frequency_{i,j,t}$ = a measure of analyst *i*'s forecast frequency for firm *j*. It is calculated as the number of firm *j* forecasts made by analyst *i* following firm *j* as of year *t* minus the minimum number of firm *j* forecasts for analysts following firm *j* as of year *t*, with this difference scaled by the range of number of firm *j* forecasts issued by analysts following firm *j* as of year *t*;

$Firm\ Coverage_{i,j,t}$ = a measure of the number of companies analyst *i* follows in year *t*. It is calculated as the number of companies followed by analyst i following firm *j* in year *t* minus the minimum number of companies followed by analysts who follow firm *j* in year *t*, with this difference scaled by the range in the number of companies followed by analysts following firm *j* in year *t*.

We estimate the four models presented above to examine the determinants of boldness (herding) in analyst forecasts. Our analysis provides greater insight into analyst herding behavior. The next section presents the results of our research.

V. Results

5.1. Descriptive Statistics

Table 2 reports descriptive statistics on boldness and characteristics of analyst forecasts and the analyst characteristics. Based on the *Bold1* definition, 72.5% of the 214,046 analyst forecast revisions are classified as bold forecasts. This percentage of boldness in analyst forecast is close to that of Clement and Tse (2005), who find that 73.3% of forecasts are bold. The percentage of forecast revisions classified as bold decreases with the increasing requirements of *Bold2* (43.6%), *Bold3* (38.2%), and *Bold4* (10.1%). The low percentage of forecasts classified as boldness using the *Bold4* definition reflects the strong requirements of *Bold4*. Recall that for *Bold4*, a revision must (1) move in the opposite direction as the consensus revision (upward vs. downward), and (2) have a greater absolute difference from the consensus forecast than the current forecast to be classified as boldness.

Panel B of Table 2 presents descriptive statistics for the analyst forecast characteristics. Results show that the mean value of the mean consensus forecast changes (*ChgCon*) by a mean (median) value of -4.1% (-0.4%). The negative value of the mean consensus change implies that analysts who issue optimistic forecasts tend revise downward. When we examine the relation between the analysts' current outstanding forecasts and the prior mean consensus forecasts, 47.0% are classified as *Optimistic* forecasts, meaning they are greater than the prior mean consensus forecast. The mean (median) deviation between an analyst's forecast on day $t - v$ and the consensus forecast on day $t - v - 1$ (*Deviation*) is 2.5% (0.4%), which represents the pressure on the analyst to revise her forecast. Firms in our sample are covered, on average, by 18.9 (17.0) analysts. The average number of forecasts issued by other analysts since the date of the analyst's current outstanding forecast on day t-v (*NumIssuer*) is 15.6 (12.0). That means, on average, an analyst revises her forecast after observing about 16 forecasts issued by other analysts. The mean (median) value of the change in forecast dispersion (*Convergence*) is 0.072 (0.133), meaning analysts are more likely to converge over time. On average, 9.4 (5.0) days have elapsed since the last forecast by any analyst following the firm (*DaysElapsed*), and the average number of days until the fiscal yearend (*ForHorizon*) is 88.3 (71.0).

5.2. *The Association between Forecast Boldness and Prior Information*

Table 3 examines the effect of information shock on boldness or herding in analyst forecasts. Logistic regression results for equation (1) for the four measures of boldness are reported. Results in Table 3 are reported for the sample as a whole and for the two subsamples based on the sign of the mean consensus revision. If there is a positive (negative) change in mean consensus forecast immediately before an analyst's forecast revision, the analyst forecast revision is assigned to the 'upward (downward) consensus revision' group. A positive (negative) mean consensus change is classified as good (bad) news. For ease of interpretation, we use the absolute value of the change in consensus (*AbsChgCon*) and the deviation of current forecast from prior consensus (*AbsDeviation*).

Results for equation (1), which are presented in Table 3, show that for the whole sample and for both subsamples, the probability of a bold forecast revision defined as *Bold1* or *Bold2* is significantly greater with larger changes in the mean consensus forecast (*AbsChgCon*). Put another way, *AbsChgCon* represents the magnitude of new information observed by an analyst, and *Bold1* indicates that the analyst's revised forecast is more optimistic (pessimistic) than her current outstanding forecast and more optimistic (pessimistic) relative to the mean consensus. Therefore, the positive coefficient on *AbsChgCon* suggests that the analyst becomes more optimistic (pessimistic) than other analysts when he observes a large magnitude of new information. However, the negative coefficients on *AbsChgCon* in the regressions of *Bold3* and *Bold4* suggest that the analyst's new forecast moves closer to consensus forecast. Recall that *Bold4*, the most restrictive of the bold definitions, requires that an analyst revise her forecast in the opposite direction from the consensus revision and with greater deviation from consensus than the analyst's current forecast. Thus strong new information in terms of the change in the consensus forecast is associated with herding, based on *Bold3* and *Bold4*. This suggests that an analyst is more likely to converge to the mean forecast when there is large unexpected information, even though he maintains his optimistic (pessimistic) belief relative to that of the market.

For the whole sample and both subsamples, Table 3 shows that analysts are significantly less likely to issue bold forecasts (more likely to herd) when their current earnings forecasts are further away from prior consensus forecast (*AbsDeviation*). This result is consistent with the idea that analysts are under pressure to conform when their forecasts deviate substantially from the mean consensus forecast. The one exception is for *Bold4* for the upward consensus subsample, for which the estimated coefficient is not significantly different from zero.

Table 3 shows mixed results for the *lnCoverage* variable. Prior research suggests that greater competition among analysts results in greater generation of private information by analysts (Lang and Lundholm 1996; Abarbanell et al. 1995). Table 3 shows the probability of bold forecasts is greater for *Bold1* (whole sample and both subsamples), *Bold3* (whole sample and upward consensus subsample) and *Bold4* (downward consensus subsample). On the other hand, bold is negatively related to *lnCoverage* using *Bold2* (whole sample and both subsamples) and *Bold4* (whole sample and upward consensus subsample). A possible explanation for these mixed results is that more private information might not consistently lead to bold forecasts. In the aggregate, greater generation of private information by analysts could lead to more accurate consensus forecasts, which could lead to fewer bold forecasts.

The control variables *DaysElapsed* and *ForHorizon* have positive coefficients that are significantly different from zero for all regressions reported in Table 3. These results suggest that a bold forecast is more likely when a longer time has elapsed since the previous analyst forecast for a firm. In addition, the longer the forecast horizon (time until year end), the more likely a forecast is bold.

Results in Table 3 confirm Bikhchandani and Sharma's (2001) prediction that herding is sensitive to information shock. We find analyst forecasts are more likely to converge when there is large change in market expectations. In addition, analysts are more likely to move toward the consensus forecast when their current outstanding forecast deviates more from the consensus forecast. Our results also support the prediction by Scharfstein and Stein (1990) that analysts are subject to market pressure when their forecasts are inconsistent with the consensus forecast.

5.3. The Effect of Analyst Optimism on Forecast Revision Boldness

Table 4 reports the results of estimating equation (2), which includes an *Optimism* variable, along with two interactive variables (*AbsChgCon* × *Optimism* and *AbsDeviation* × *Optimism*). Equation (2) tests whether the probability of bold forecasts differs based on whether analysts' current outstanding forecasts are optimistic relative to the consensus forecast.

Results for *AbsChgCon* are similar to those reported in Table 3. The probability of a bold forecast revision defined as *Bold1* or *Bold2* is significantly greater with larger changes in the mean consensus forecast (*AbsChgCon*). However, when bold forecast revisions are defined based on *Bold3* or *Bold4*, the probability of a bold forecast revision is significantly lower with larger changes in the mean consensus forecast. The one difference from the results in Table 3 is that for the upward consensus revisions, bold forecasts are less likely (herding more likely) when bold forecasts are defined based on *Bold1*. However, the positive coefficient on *AbsChgCon* × *Optimism* suggests that an analyst's optimistic current forecast, when combined with a large upward consensus change, significantly increases the probability of a bold forecast revision.

Results for *AbsDeviation* are also similar to those reported in Table 3. Bold forecasts are less likely (herding more likely) with greater deviation of an analyst's current forecast from the day prior consensus forecast. This result is consistent with results in Table 3 that suggest market pressure to conform on analysts who deviate from consensus. The one exception is for upward consensus revisions using *Bold4* as the definition of boldness, in which case bold forecasts are more likely.

The *Optimism* variable tests whether analysts whose current outstanding forecasts are optimistic relative to the consensus estimate systematically issue bold forecasts. Results, reported in Table 4, generally show that analysts with optimistic current forecasts are more likely to issue bold forecasts. The probability of bold forecasts is greater for forecasts that are optimistic using *Bold1* (whole sample and upward consensus forecast revisions), *Bold2* (whole sample and downward consensus forecast revisions), *Bold3* (whole sample and both subsamples), and *Bold4* (only the downward consensus revision subsample). For the upward consensus forecast revisions, the probability of bold forecasts is greater for optimistic forecasts using *Bold1* and *Bold3*, and is lower for *Bold2* and *Bold4*. This suggests that when consensus forecast confirms the analyst's current forecast, analysts are more likely to become more optimistic (or pessimistic), but they converge to consensus forecast. For the downward consensus forecast revision, the probability of bold forecasts by optimistic analysts is lower (probability of herding is greater) for *Bold1* and greater for *Bold2*, *Bold3*, and *Bold4*, implying that analysts are more likely to diverge from consensus forecast when consensus forecast is inconsistent with the analyst's current forecast.

Results for the interactive variable *AbsChgCon* × *Optimism* show that for optimistic forecasts, the effect of *AbsChgCon* is greater relative to pessimistic forecasts for *Bold1* (upward consensus revision), *Bold2* (whole sample and downward consensus revision), *Bold 3* (whole sample and downward consensus revision), and *Bold4* (whole sample and upward consensus revision). The positive coefficients on *AbsChgCon* × *Optimism* for *Bold1* and *Bold3* in upward revisions suggests that analysts becomes more optimistic when consensus forecast revisions confirm the analyst's current forecast.

For the interactive variable *AbsDeviation* ×*Optimism*, the negative coefficients for *Bold1* (upward consensus subsample), *Bold2*(whole sample and both subsamples), *Bold3*(whole sample and both subsamples), and *Bold4* (upward consensus subsample) show that, in general, bold forecasts are less likely (herding more likely) when large deviations from consensus occur in conjunction with optimistic current forecasts. Only for the downward consensus subsample when bold is defined as *Bold1* or *Bold4* does *Optimism* have a significant positive interactive effect with *AbsDeviation*, suggesting that bold forecasts are more likely (herding less likely).

Finally, we examine the results in Table 4 for *lnCoverage*, *DaysElapsed*, and *ForHorizon*, which are similar to those reported in Table 3. The *lnCoverage* variable has mixed results, suggesting that competition among analysts does not have a clear effect on the probability of bold forecasts. As in Table 3, *DaysElapsed* and *ForHorizon* have positive coefficients that are significantly different from zero for all regressions reported in Table 4. Thus bold forecasts are more likely when a longer time has elapsed since the previous analyst forecast for a firm and when the forecast horizon is longer.

5.4. *The Effect of Signal Strength on Bold Forecasts*

Table 5 reports the results of estimating equation (4), which tests whether the impact of the change in the consensus is affected by the underlying strength of opinion among the analysts. Recall that equation (4) includes two additional interactive variables, *AbsChgCon* ×*Convergence* and *AbsChgCon* ×*NumIssuer*. *Convergence* is calculated as the change in the standard deviation of the forecasts used in computing the consensus forecast. Thus larger values of *Convergence* indicate greater uniformity of opinion among the analysts and greater strength in the consensus forecast. For *NumIssuer*, the number of analysts is an indication of the strength of the consensus forecast since a consensus forecast based on a small number of analysts would have less strength than the same consensus forecast that was backed by a large number of analysts.

As expected, results show that the probability of a bold forecast is lower with strong information. The negative coefficients of *AbsChgCon* × *Convergence* indicate that when there is a large magnitude change in the consensus in conjunction with lower dispersion of analyst forecasts, there is a lower probability of bold forecasts. The one exception is the significant positive coefficient for *Bold4* for the downward consensus subsample. The coefficients of *AbsChgCon* × *NumIssuer* are negative for all regressions in Table 5, indicating that the probability of a bold forecast is lower when a large magnitude change in consensus is based on a large number of analyst forecasts.

5.5. *Controlling for Analyst Characteristics*

Equation (4) examines the variables in equation (3), but also controls for several analyst characteristics. Results, which are reported in Table 6, are generally consistent with those reported in Table 5. Thus, our results are robust to inclusion of variables representing individual analyst ability, implying that prior information is an additional determinant of herding.

With respect to analyst characteristics, analysts with more years of experience (*GeneralExperience*) are generally less likely to make bold forecasts. The exceptions are for *Bold1* (downward consensus subsample), *Bold3* (downward consensus subsample), and *Bold4* (upward consensus subsample), for which the coefficients are not significantly different from zero. *FirmExperience* is positively related to bold forecasts, with the exception of *Bold2* (whole sample and upward consensus subsample) and *Bold4* (upward consensus subsample).

Larger values of *LagForAccuracy* represent more accurate prior forecasts. Table 6 shows that results for *LagForAccuracy* are mixed. *Bold1* (whole sample and both subsamples), *Bold2* (downward revision subsample), and *Bold3* (whole sample) have significant positive coefficients for *LagForAccuracy*. However, results show that for *Bold2* (whole sample) and *Bold4* (upward consensus subsample), *LagForAccuracy* is negatively related to bold forecasts. Results for the other six regressions show that *LagForAccuracy* is not a significant determinant of bold forecasts. These results provide only weak evidence that prior forecast accuracy in itself leads to bold forecasts.

Results in Table 6 for *BrokerageSize* are stronger, with evidence showing that for all regressions, analysts with larger brokerage firms are more likely to make bold forecasts. Similarly, all regressions show that the probability of bold forecasts is greater (herding is less likely) for analysts who make more frequent forecasts for a firm. The relation between bold forecasts and *FirmCoverage* is mixed. Results show that for *Bold1* (whole sample and downward consensus subsample) and *Bold4* (upward consensus subsample), firms with greater coverage have a lower probability of bold forecasts. However, for *Bold4* (downward consensus subsample), the probability of bold forecasts is significantly higher for firms with higher coverage. For the other nine regressions, there is not a statistically significant relation between bold and *FirmCoverage.*

VI. Summary and Conclusion

This paper investigates how prior information affects analyst herding decisions. We use four different measures of bold to provide greater insight into analyst herding behavior. Our analysis provides several key results. First, using the weaker measures of bold, the probability of a bold (herding) forecast revision is greater (smaller) with large information shocks. However, results using the more restrictive measures of bold suggest that the probability of a bold (herding) forecast revision is smaller (greater) with large information shocks. Second, analysts are more likely to herd in their forecast revisions when their current outstanding forecasts deviate more from the consensus mean. This result suggests that analysts yield to market pressure to conform. Additionally, analysts are more likely to herd in their forecast revisions in the presence of strong observable signals (convergence in the forecasts of a large number of analysts). Results also show that, in general, analysts with current outstanding forecasts that are optimistic are more likely to issue revised forecasts that are also optimistic. However, results vary under specific conditions such as upward or downward consensus revisions. Overall, this research adds to the existing body of evidence on analyst herding behavior.

References

Abarbanell, J. S., and V. L. Bernard. 1992. Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior. *Journal of Finance* 47 (3):1181-1207

Abarbanell, J. S., W. N. Lanen, and R. E. Verrecchia. 1995. Analysts' forecasts as proxies for investor beliefs in empirical research. *Journal of Accounting & Economics* 20 (1):31-60

Agrawal, A., S. Chadha, and M. A. Chen. 2006. Who is afraid of reg fd? The behavior and performance of sell-side analysts following the sec's fair disclosure rules. *Journal of Business* 79 (6):2811-2834

Barron, O. E., D. Byard, and O. Kim. 2002. Changes in analysts' information around earnings announcements. *Accounting Review* 77 (4):821-846

Bikhchandani, S., and S. Sharma. 2001. Herd behavior in financial markets. *IMF Staff Papers* 48 (3):279-310

Brown, L. D. 2001. A temporal analysis of earnings surprises: Profits versus losses. *Journal of Accounting Research* 39 (2):221-241

Clement, M. B., and S. Y. Tse. 2005. Financial analyst characteristics and herding behavior in forecasting. *Journal of Finance* 60 (1):307-341

Cooper, R. A., T. E. Day, and C. M. Lewis. 2001. Following the leader: A study of individual analysts' earnings forecasts. *Journal of Financial Economics* 61 (3):383-416

Das, S., R.-J. Guo, and H. Zhang. 2006. Analysts' selective coverage and subsequent performance of newly public firms. *Journal of Finance* 61 (3):1159-1185

Das, S., C. B. Levine, and K. Sivaramakrishnan. 1998. Earnings predictability and bias in analysts' earnings forecasts. *Accounting Review* 73 (2):277-294

Devenow, A., and I. Welch. 1996. Rational herding in financial economics. *European Economic Review* 40 (3-5):603-615

Dugar, A., and S. Nathan. 1995. The effect of investment banking relationships on financial analysts' earnings forecasts and investment recommendations. *Contemporary Accounting Research* 12 (1):131-160

Easterwood, J. C., and S. R. Nutt. 1999. Inefficiency in analyst's earnings forecasts: Systematic misreaction or systematic optimism? *Journal of Finance* 54 (5):1777-1797

Gleason, C. A., and C. M. C. Lee. 2003. Analyst forecast revisions and market price discovery. *Accounting Review* 78 (1):193-225

Graham, J. R. 1999. Herding among investment newsletters: Theory and evidence. *Journal of Finance* 54:237-268

Hong, H., J. D. Kubik, and A. Solomon. 2000. Security analysts' career concerns and herding of earnings forecasts. *RAND Journal of Economics* 31 (1):121-144

Lang, M. H., and R. J. Lundholm. 1996. Corporate disclosure policy and analyst behavior. *Accounting Review* 71 (4):467-492

Lin, H.-w., and M. F. McNichols. 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting & Economics* 25 (1):101-127

McNichols, M., and P. C. O'Brien. 1997. Self-selection and analyst coverage. *Journal of Accounting Research* 35 (3):167-199

Scharfstein, D. S., and J. C. Stein. 1990. Herd behavior and investment. *American Economic Review* 80 (3):465-479

Stickel, S. E. 1990. Predicting individual analyst earnings forecasts. *Journal of Accounting Research* 28 (2):409-417

———. 1992. Reputation and performance among security analysts. *Journal of Finance* 47 (5):1811-1836

Trueman, B. 1994. Analyst forecasts and herding behavior. *Review of Financial Studies* 7 (1):97-124

Womack, K. L. 1996. Do brokerage analysts' recommendations have investment value? *Journal of Finance* 51 (1):137-167

Table 1. Frequency of Analyst Forecasts by Year

Year	# of Analysts	# of Firms	# of Observations
1990	1,437	1,633	9,338
1991	1,710	1,672	12,391
1992	1,661	1,710	12,850
1993	1,629	1,796	12,726
1994	1,715	1,995	12,348
1995	1,841	2,173	12,862
1996	1,993	2,292	13,372
1997	2,229	2,502	13,907
1998	2,423	2,619	14,801
1999	2,571	2,512	14,415
2000	2,522	2,283	13,292
2001	2,399	2,170	12,649
2002	2,264	2,147	12,517
2003	2,355	2,192	13,628
2004	2,563	2,365	16,504
2005	2,693	2,476	16,439
Mean	2,125	2,159	13,377

Table 2. Descriptive Statistics on Forecast Boldness, Forecasts, and Analyst Characteristics

Panel A: Bold Forecasts for N = 214,046

Variable	Mean	Median	Std Dev
Bold1	0.725	1.000	0.447
Bold2	0.436	0.000	0.496
Bold3	0.382	0.000	0.486
Bold4	0.101	0.000	0.301

Panel B: Forecast Characteristics

ChgCon	-0.041	-0.004	0.216
Optimism	0.470	0.000	0.499
Deviation	0.025	0.004	0.337
Coverage	18.9	17.0	10.1
NumIssuer	15.6	12.0	13.7
Convergence	0.072	0.133	0.509
DaysElapsed	9.4	5.0	13.4
ForHorizon	88.3	71.0	42.6

Panel C: Raw Value of Analyst Characteristics

General Experience (# Qtrs.)	7.3	6.0	4.7
Firm Experience (# Qtrs.)	4.1	3.0	3.5
Lag Forecast Accuracy	0.6	0.0	77.9
Brokerage Size (# Brokers)	60.7	43.0	59.6
Forecast Frequency	4.3	4.0	2.0
Number of firms covered	20.1	17.0	16.4

Note:

Bold1 = one if ($F_{i,j,t} > F_{i,j,t-v}$ and $F_{i,j,t} > \bar{F}_{i,j,t-1}$) or ($F_{i,j,t} < F_{i,j,t-v}$ and $F_{i,j,t} < \bar{F}_{i,j,t-1}$), zero otherwise;

Bold2 = one if $| F_{i,j,t-v} - \bar{F}_{i,j,t-v-1} | < | F_{i,j,t} - \bar{F}_{i,j,t-1} |$, zero otherwise;

Bold3 = one if {($F_{i,j,t} > F_{i,j,t-v}$ and $F_{i,j,t} > \bar{F}_{i,j,t-1}$) or ($F_{i,j,t} < F_{i,j,t-v}$ and $F_{i,j,t} < \bar{F}_{i,j,t-1}$)} and $| \bar{F}_{i,j,t-v-1} - F_{i,j,t-v} | < | \bar{F}_{i,j,t-1} - F_{i,j,t} |$, zero otherwise;

Bold4 = one if $sign(F_{i,j,t-v} - F_{i,j,t}) \neq sign(\bar{F}_{i,j,t-v-1} - \bar{F}_{i,j,t-1})$ and $| F_{i,j,t-v} - \bar{F}_{i,j,t-v-1} | < | F_{i,j,t} - \bar{F}_{i,j,t-1} |$, zero otherwise;

$AbsChgCon_{j,t-1}$ = absolute value of change in the consensus forecast of other analysts following firm *j* between the days *t* and day *t* – *v*, deflated by absolute prior mean forecast;

$AbsDeviation_{i,j,t-v}$ = absolute value of difference between the consensus forecast for firm *j* and analyst *i*'s forecast on day *t* – *v*, deflated by absolute mean forecast;

$lnCoverage_j$ = log of number of analyst following the firm *j* in a particular year;

$NumIssuer_{j,t-1}$ = number of other analysts who issue forecast since the date of the analyst *i* current outstanding forecast on day *t-v;*

$Convergence_{j,t-1}$ = the change in the dispersion ($StdDev_{j,t-1} - StdDev_{j,t-v}$) of the forecasts used to determine the consensus forecast;

$DaysElapsed_{i,j,t}$ = days elapsed since the last forecast by any analyst following firm *j* in particular year; and

$ForHorizon_{i,j,t}$ = the number of days from the forecast date to the end of the fiscal period.

$Optimism_{i,j,t-v}$ = one if an analyst's current outstanding forecast is greater than the prior mean consensus forecast, zero otherwise;

General Experience = number of quarters of analyst career experience for analyst *i* following firm *j* as of year *t*;

Firm Experience = number of quarters of firm-specific experience for analyst *i* following firm *j* as of year *t*;

Lag Forecast Accuracy = absolute value of forecast error for analysts who follow firm *j* in year *t* – 1;

Broker Size = number of analysts employed by the broker employing analyst *i* following firm *j* in year *t*; and

$Frequency_{i,j,t}$ = number of firm *j* forecasts made by analyst *i* following firm *j* as of year *t*; and

Number of firms covered = number of firms followed by analyst *i*.

Table 3. Results of Logistic Regression of Boldness in Forecast

$$Bold_{i,j,t} = \beta_0 + \beta_1 ChgCon_{j,t-1} + \beta_2 Deviation_{i,j,t-v} + \beta_3 lnCoverage_j + \beta_4 DaysElapsed_{i,j,t} + \beta_5 ForHorizon_{i,j,t} + \varepsilon_{i,j,t}$$

	Bold1		Bold2		Bold3		Bold4	
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
All Revisions								
Intercept	0.6068	0.0001	0.0761	0.0302	-0.3346	0.0001	-1.7524	0.0001
AbsChgCon	0.3923	0.0001	1.0552	0.0001	-0.2916	0.0001	-5.0042	0.0001
AbsDeviation	-0.6938	0.0001	-4.7139	0.0001	-3.2435	0.0001	-0.5327	0.0001
lnCoverage	0.1100	0.0001	-0.0336	0.0001	0.0122	0.1530	-0.1592	0.0001
DaysElapsed	0.0031	0.0001	0.0033	0.0001	0.0045	0.0001	0.0170	0.0001
ForHorizon	0.0005	0.0001	0.0025	0.0001	0.0025	0.0001	0.0011	0.0001
Upward Consensus Revisions								
Intercept	0.3574	0.0001	-0.0522	0.3551	-0.5012	0.0001	-0.7215	0.0001
AbsChgCon	0.4349	0.0001	0.8485	0.0001	-0.9398	0.0001	-4.7731	0.0001
AbsDeviation	-0.8015	0.0001	-4.1841	0.0001	-2.6348	0.0001	-0.0273	0.6200
lnCoverage	0.1467	0.0001	-0.0164	0.1826	0.0424	0.0007	-0.3557	0.0001
DaysElapsed	0.0044	0.0001	0.0040	0.0001	0.0058	0.0001	0.0170	0.0001
ForHorizon	0.0003	0.1096	0.0018	0.0001	0.0016	0.0001	0.0007	0.0024
Downward Consensus Revisions								
Intercept	0.7795	0.0001	0.1134	0.0132	-0.2684	0.0001	-2.8830	0.0001
AbsChgCon	0.3222	0.0001	1.0535	0.0001	-0.1544	0.0012	-3.5409	0.0001
AbsDeviation	-0.6205	0.0001	-4.7435	0.0001	-3.3844	0.0001	-1.9601	0.0001
lnCoverage	0.0714	0.0001	-0.0446	0.0001	-0.0092	0.4297	0.1093	0.0001
DaysElapsed	0.0020	0.0005	0.0028	0.0001	0.0033	0.0001	0.0156	0.0001
ForHorizon	0.0008	0.0001	0.0031	0.0001	0.0032	0.0001	0.0015	0.0001

Note:

Bold1 = one if ($F_{i,j,t} > F_{i,j,t-v}$ and $F_{i,j,t} > \bar{F}_{i,j,t-1}$) or ($F_{i,j,t} < F_{i,j,t-v}$ and $F_{i,j,t} < \bar{F}_{i,j,t-1}$), zero otherwise;

Bold2 = one if $| F_{i,j,t-v} - \bar{F}_{i,j,t-v-1} | < | F_{i,j,t} - \bar{F}_{i,j,t-1} |$, zero otherwise;

Bold3 = one if {($F_{i,j,t} > F_{i,j,t-v}$ and $F_{i,j,t} > \bar{F}_{i,j,t-1}$) or ($F_{i,j,t} < F_{i,j,t-v}$ and $F_{i,j,t} < \bar{F}_{i,j,t-1}$)} and $| \bar{F}_{i,j,t-v-1} - F_{i,j,t-v} | < | \bar{F}_{i,j,t-1} - F_{i,j,t} |$, zero otherwise;

Bold4 = one if $sign(F_{i,j,t-v} - F_{i,j,t}) \neq sign(\bar{F}_{i,j,t-v-1} - \bar{F}_{i,j,t-1})$ and $| F_{i,j,t-v} - \bar{F}_{i,j,t-v-1} | < | F_{i,j,t} - \bar{F}_{i,j,t-1} |$, zero otherwise;

$AbsChgCon_{j,t-1}$ = absolute value of change in the consensus forecast of other analysts following firm *j* between the days *t* and day *t* – *v*, deflated by absolute prior mean forecast;

$AbsDeviation_{i,j,t-v}$ = absolute value of difference between the consensus forecast for firm *j* and analyst *i*'s forecast on day *t* – *v*, deflated by absolute mean forecast;

$lnCoverage_{j}$ = log of number of analyst following the firm *j* in a particular year;

$DaysElapsed_{i,j,t}$ = days elapsed since the last forecast by any analyst following firm *j* in particular year; and

$ForHorizon_{i,j,t}$ = the number of days from the forecast date to the end of the fiscal period.

Table 4: Current Optimistic Forecast and Boldness of Individual Analyst's Next Forecast

$$Bold_{i,j,t} = \beta_0 + \beta_1 AbsChgCon_{j,t-1} + \beta_2 AbsDeviation_{i,j,t-v} + \beta_3 Optimism_{i,j,t-v} + \beta_4 AbsChgCon_{j,t-1} \times Optimism_{i,j,t-v} + \beta_5 AbsDeviation_{i,j,t-v} \times Optimism_{i,j,t-v} + \beta_6 lnCoverage_j + \beta_7 DaysElapsed_{i,j,t} + \beta_8 ForHorizon_{i,j,t} + \varepsilon_{i,j,t}$$

	Bold1		Bold2		Bold3		Bold4	
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
All Revisions								
Intercept	0.5835	0.0001	0.0468	0.1867	-0.3669	0.0001	-1.7277	0.0001
AbsChgCon	0.7229	0.0001	0.7444	0.0001	-0.3572	0.0001	-5.4964	0.0001
AbsDeviation	-0.7231	0.0001	-4.2598	0.0001	-2.7832	0.0001	-0.5371	0.0001
Optimism	0.0541	0.0001	0.0705	0.0001	0.0812	0.0001	-0.0509	0.0056
AbsChgCon × *Optimism*	-0.9084	0.0001	0.7720	0.0001	0.0801	0.3422	1.1866	0.0001
AbsDeviation × *Optimism*	0.0227	0.6248	-1.0489	0.0001	-1.2489	0.0001	0.0160	0.9045
lnCoverage	0.1097	0.0001	-0.0340	0.0001	0.0115	0.1770	-0.1592	0.0001
DaysElapsed	0.0031	0.0001	0.0033	0.0001	0.0045	0.0001	0.0170	0.0001
ForHorizon	0.0005	0.0001	0.0025	0.0001	0.0025	0.0001	0.0011	0.0001
Upward Consensus Revisions								
Intercept	-0.1915	0.0021	-0.0399	0.4884	-0.6348	0.0001	-0.4404	<.0001
AbsChgCon	-0.8868	0.0001	2.4973	0.0001	-0.6921	0.0001	-5.2367	<.0001
AbsDeviation	-0.4604	0.0001	-2.9078	0.0001	-1.6298	0.0001	0.3155	<.0001
Optimism	0.9800	0.0001	-0.0731	0.0001	0.2059	0.0001	-0.5092	<.0001
AbsChgCon × *Optimism*	1.2929	0.0001	-1.7790	0.0001	-0.1894	0.3175	2.3907	<.0001
AbsDeviation × *Optimism*	-0.5418	0.0001	-2.1014	0.0001	-1.6268	0.0001	-1.7137	<.0001
lnCoverage	0.1427	0.0001	-0.0118	0.3401	0.0422	0.0008	-0.3535	<.0001
DaysElapsed	0.0041	0.0001	0.0043	0.0001	0.0057	0.0001	0.0175	<.0001
ForHorizon	0.0005	0.0025	0.0017	0.0001	0.0017	0.0001	0.0007	0.0058

Table 4. (Continued)

	Bold1		Bold2		Bold3		Bold4	
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Downward Consensus Revisions								
Intercept	1.0843	0.0001	-0.0135	0.7700	-0.2720	0.0001	-3.0344	0.0001
AbsChgCon	0.3752	0.0001	0.7390	0.0001	-0.3394	0.0001	-1.1806	0.0001
AbsDeviation	-0.7885	0.0001	-4.3551	0.0001	-3.0241	0.0001	-5.3403	0.0001
Optimism	-0.8367	0.0001	0.3250	0.0001	0.0391	0.0210	0.3875	0.0001
AbsChgCon × *Optimism*	-0.8950	0.0001	1.2983	0.0001	0.4641	0.0001	-3.5012	0.0001
AbsDeviation × *Optimism*	0.1860	0.0041	-0.3268	0.0294	-1.6344	0.0001	5.3035	0.0001
lnCoverage	0.0675	0.0001	-0.0401	0.0005	-0.0104	0.3721	0.1174	0.0001
DaysElapsed	0.0016	0.0070	0.0029	0.0001	0.0032	0.0001	0.0163	0.0001
ForHorizon	0.0013	0.0001	0.0029	0.0001	0.0033	0.0001	0.0012	0.0001

Note:

Bold1 = one if ($F_{i,j,t} > F_{i,j,t-v}$ and $F_{i,j,t} > \overline{F}_{i,j,t-1}$) or ($F_{i,j,t} < F_{i,j,t-v}$ and $F_{i,j,t} < \overline{F}_{i,j,t-1}$), zero otherwise;

Bold2 = one if $| F_{i,j,t-v} - \overline{F}_{i,j,t-v-1} | < | F_{i,j,t} - \overline{F}_{i,j,t-1} |$, zero otherwise;

Bold3 = one if {($F_{i,j,t} > F_{i,j,t-v}$ and $F_{i,j,t} > \overline{F}_{i,j,t-1}$) or ($F_{i,j,t} < F_{i,j,t-v}$ and $F_{i,j,t} < \overline{F}_{i,j,t-1}$)} and $| \overline{F}_{i,j,t-v-1} - F_{i,j,t-v} | < | \overline{F}_{i,j,t-1} - F_{i,j,t} |$, zero otherwise;

Bold4 = one if $sign(F_{i,j,t-v} - F_{i,j,t}) \neq sign(\overline{F}_{i,j,t-v-1} - \overline{F}_{i,j,t-1})$ and $| F_{i,j,t-v} - \overline{F}_{i,j,t-v-1} | < | F_{i,j,t} - \overline{F}_{i,j,t-1} |$, zero otherwise;

$AbsChgCon_{j,t-1}$ = absolute value of change in the consensus forecast of other analysts following firm *j* between the days *t* and day *t* – *v*, deflated by absolute prior mean forecast;

$AbsDeviation_{i,j,t-v}$ = absolute value of difference between the consensus forecast for firm *j* and analyst *i*'s forecast on day *t* – *v*, deflated by absolute mean forecast;

$lnCoverage_j$ = log of number of analyst following the firm *j* in a particular year;

$DaysElapsed_{i,j,t}$ = days elapsed since the last forecast by any analyst following firm *j* in particular year; and

$ForHorizon_{i,j,t}$ = the number of days from the forecast date to the end of the fiscal period; and

$Optimism_{i,j,t-v}$ = one if an analyst's current outstanding forecast is greater than the prior mean consensus forecast, zero otherwise.

Table 5. Strength of Prior Information and Boldness of Individual Analyst's Forecast Revision

$$Bold_{i,j,t} = \beta_0 + \beta_1 AbsChgCon_{j,t-1} + \beta_2 AbsDeviation_{i,j,t-v} + \beta_3 Optimism_{i,j,t-v} + \beta_4 AbsChgCon_{j,t-1} \times Optimism_{i,j,t-v}$$
$$+ \beta_5 AbsDeviation_{i,j,t-v} \times Optimism_{i,j,t-v} + \beta_6 AbsChgCon_{j,t-1} \times Convergence_{j,t-1} + \beta_7 AbsChgRev_{j,t-1} \times NumIssuer_{j,t-1}$$
$$+ \beta_6 lnCoverage_j + \beta_7 DaysElapsed_{i,j,t} + \beta_8 ForHorizon_{i,j,t} + \varepsilon_{i,j,t}$$

	Bold1		Bold2		Bold3		Bold4	
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
All Revisions								
Intercept	0.4752	0.0001	-0.1752	0.0001	-0.5821	0.0001	-1.9198	0.0001
AbsChgCon	1.8996	0.0001	3.8486	0.0001	2.8893	0.0001	-0.5194	0.1017
AbsDeviation	-0.7959	0.0001	-4.4701	0.0001	-2.9250	0.0001	-0.6856	0.0001
Optimism	0.0528	0.0001	0.0411	0.0003	0.0587	0.0001	-0.0550	0.0028
AbsChgCon × *Optimism*	-0.9600	0.0001	0.9203	0.0001	0.1191	0.2034	1.2395	0.0001
AbsDeviation × *Optimism*	0.0430	0.3694	-0.8555	0.0001	-1.0255	0.0001	0.0825	0.5440
AbsChgCon ×*Convergence*	-0.5847	0.0001	-1.6722	0.0001	-1.7481	0.0001	-0.2818	0.0618
AbsChgCon × *NumIssuer*	-0.3798	0.0001	-1.1153	0.0001	-1.2632	0.0001	-2.0267	0.0001
lnCoverage	0.1492	0.0001	0.0506	0.0001	0.0970	0.0001	-0.0810	0.0001
DaysElapsed	0.0030	0.0001	0.0036	0.0001	0.0047	0.0001	0.0172	0.0001
ForHorizon	0.0005	0.0001	0.0023	0.0001	0.0023	0.0001	0.0010	0.0001
Upward Consensus Revisions								
Intercept	-0.2611	0.0001	-0.2090	0.0006	-0.7967	0.0001	-0.5768	0.0001
AbsChgCon	0.5230	0.0211	6.4377	0.0001	3.0691	0.0001	-0.1578	0.7527
AbsDeviation	-0.4903	0.0001	-3.0632	0.0001	-1.7210	0.0001	0.2634	0.0001
Optimism	0.9783	0.0001	-0.0689	0.0001	0.2112	0.0001	-0.5043	0.0001
AbsChgCon × *Optimism*	1.5139	0.0001	-2.0924	0.0001	-0.0998	0.6245	2.7036	0.0001
AbsDeviation × *Optimism*	-0.6313	0.0001	-1.9692	0.0001	-1.5881	0.0001	-1.7729	0.0001
AbsChgCon ×*Convergence*	-0.9501	0.0001	-2.2070	0.0001	-2.2217	0.0001	-1.0570	0.0001
AbsChgCon × *NumIssuer*	-0.4886	0.0001	-1.2911	0.0001	-1.4491	0.0001	-2.2614	0.0001
lnCoverage	0.1690	0.0001	0.0495	0.0003	0.1037	0.0001	-0.2936	0.0001
DaysElapsed	0.0041	0.0001	0.0046	0.0001	0.0059	0.0001	0.0179	0.0001
ForHorizon	0.0006	0.0012	0.0016	0.0001	0.0016	0.0001	0.0005	0.0351

Table 5. (Continued)

	Bold1		Bold2		Bold3		Bold4	
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Downward Consensus Revisions								
Intercept	0.9446	0.0001	-0.2985	0.0001	-0.5500	0.0001	-3.3187	0.0001
AbsChgCon	1.5842	0.0001	3.8258	0.0001	2.9060	0.0001	4.0625	0.0001
AbsDeviation	-0.8843	0.0001	-4.5694	0.0001	-3.1712	0.0001	-5.5400	0.0001
Optimism	-0.8474	0.0001	0.2749	0.0001	-0.0074	0.6694	0.3683	0.0001
AbsChgCon × *Optimism*	-1.0621	0.0001	1.5193	0.0001	0.4780	0.0001	-3.4600	0.0001
AbsDeviation × *Optimism*	0.2696	0.0001	-0.2791	0.0680	-1.4462	0.0001	5.4127	0.0001
AbsChgCon ×*Convergence*	-0.5764	0.0001	-1.5387	0.0001	-1.5932	0.0001	0.3169	0.0649
AbsChgCon × *NumIssuer*	-0.3833	0.0001	-1.1156	0.0001	-1.2557	0.0001	-2.1171	0.0001
lnCoverage	0.1205	0.0001	0.0700	0.0001	0.1015	0.0001	0.2350	0.0001
DaysElapsed	0.0015	0.0142	0.0031	0.0001	0.0033	0.0001	0.0158	0.0001
ForHorizon	0.0011	0.0001	0.0027	0.0001	0.0031	0.0001	0.0010	0.0002

Note:

Bold1 = one if ($F_{i,j,t} > F_{i,j,t-v}$ and $F_{i,j,t} > \bar{F}_{i,j,t-1}$) or ($F_{i,j,t} < F_{i,j,t-v}$ and $F_{i,j,t} < \bar{F}_{i,j,t-1}$), zero otherwise;

Bold2 = one if $| F_{i,j,t-v} - \bar{F}_{i,j,t-v-1} | < | F_{i,j,t} - \bar{F}_{i,j,t-1} |$, zero otherwise;

Bold3 = one if {($F_{i,j,t} > F_{i,j,t-v}$ and $F_{i,j,t} > \bar{F}_{i,j,t-1}$) or ($F_{i,j,t} < F_{i,j,t-v}$ and $F_{i,j,t} < \bar{F}_{i,j,t-1}$)} and $| \bar{F}_{i,j,t-v-1} - F_{i,j,t-v} | < | \bar{F}_{i,j,t-1} - F_{i,j,t} |$, zero otherwise;

Bold4 = one if $sign(F_{i,j,t-v} - F_{i,j,t}) \neq sign(\bar{F}_{i,j,t-v-1} - \bar{F}_{i,j,t-1})$ and $| F_{i,j,t-v} - \bar{F}_{i,j,t-v-1} | < | F_{i,j,t} - \bar{F}_{i,j,t-1} |$, zero otherwise;

$AbsChgCon_{j,t-1}$ = absolute value of change in the consensus forecast of other analysts following firm *j* between the days *t* and day *t* – *v*, deflated by absolute prior mean forecast;

$AbsDeviation_{i,j,t-v}$ = absolute value of difference between the consensus forecast for firm *j* and analyst *i*'s forecast on day *t* – *v*, deflated by absolute mean forecast;

$lnCoverage_{j}$ = log of number of analyst following the firm *j* in a particular year;

$DaysElapsed_{i,j,t}$ = days elapsed since the last forecast by any analyst following firm *j* in particular year; and

$ForHorizon_{i,j,t}$ = the number of days from the forecast date to the end of the fiscal period;

$Optimism_{i,j,t-v}$ = one if an analyst's current outstanding forecast is greater than the prior mean consensus forecast, zero otherwise;

$Convergence_{i,j,t-v}$ = change in analyst forecast dispersion between day *t-v-1* and *t*-1; and

$NumIssuer_{j,t-1}$ = number of other analysts who issue forecast since the date of the analyst *i* current outstanding forecast on day *t-v;*

Table 6. Strength of Prior Information and Boldness of Individual Analyst's Next Forecast after Controlling for Analyst Characteristics

$$
\begin{aligned}
Bold_{i,j,t} = {} & \beta_0 + \beta_1 AbsChgCon_{j,t-1} + \beta_2 AbsDeviation_{j,t-v} + \beta_3 Optimism_{j,t-v} + \beta_4 AbsChgCon_{j,t-1} \times Optimism_{j,t-v} \\
& + \beta_5 AbsDeviation_{j,t-v} \times Optimism_{j,t-v} + \beta_6 AbsChgCon_{j,t-1} xConvergence_{j,t-1} + \beta_7 AbsChg\mathrm{Re}v_{j,t-1} \times NumIssuer_{j,t-1} \\
& + \beta_8 lnCoverage_j + \beta_9 DaysElapsed_{i,j,t} + \beta_{10} ForHorizon_{i,j,t} + \beta_{11} GeneralExperience_{i,j,t} \\
& + \beta_{12} FirmExperience_{i,j,t} + \beta_{13} LagForAccuracy_{i,j,t-1} + \beta_{14} Bro\mathrm{ker}ageSize_{i,j,t} + \beta_{15} Frequency_{i,j,t} \\
& + \beta_{16} FirmCoverage_{i,j,t} + \varepsilon_{i,j,t}
\end{aligned}
$$

	Bold1		Bold2		Bold3		Bold4	
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
All Revisions								
Intercept	0.1237	0.0120	-0.2950	0.0001	-0.8802	0.0001	-2.3309	0.0001
AbsChgCon	1.4066	0.0001	3.7789	0.0001	2.7218	0.0001	-0.9990	0.0022
AbsDeviation	-0.8278	0.0001	-4.4988	0.0001	-2.9823	0.0001	-0.7435	0.0001
Optimism	0.0533	0.0001	0.0413	0.0003	0.0583	0.0001	-0.0554	0.0027
AbsChgCon × *Optimism*	-0.9414	0.0001	0.9174	0.0001	0.1236	0.1853	1.2407	0.0001
AbsDeviation ×*Optimism*	0.0679	0.1586	-0.8427	0.0001	-0.9965	0.0001	0.1174	0.3944
AbsChgCon × *Convergence*	-0.5857	0.0001	-1.6668	0.0001	-1.7332	0.0001	-0.2649	0.0798
AbsChgCon ×*NumIssuer*	-0.3111	0.0001	-1.0785	0.0001	-1.1755	0.0001	-1.7534	0.0001
Coverage	0.1711	0.0001	0.0678	0.0001	0.1227	0.0001	-0.0374	0.0175
DaysElapsed	0.0026	0.0001	0.0034	0.0001	0.0043	0.0001	0.0167	0.0001
ForHorizon	0.0007	0.0001	0.0024	0.0001	0.0027	0.0001	0.0015	0.0001
GeneralExperience	-0.0236	0.2523	-0.0375	0.0270	-0.0359	0.0362	-0.0870	0.0014
FirmExperience	0.1114	0.0001	0.0262	0.1191	0.0617	0.0003	0.0898	0.0008
LagForAccuracy	0.1068	0.0001	-0.0324	0.0408	0.0280	0.0808	-0.0306	0.2229
BrokerageSize	0.3714	0.0001	0.0798	0.0001	0.1885	0.0001	0.1315	0.0001
Frequency	0.0933	0.0001	0.0981	0.0001	0.1945	0.0001	0.3695	0.0001
FirmCoverage	-0.0895	0.0001	0.0231	0.1699	-0.0177	0.3005	0.0205	0.4475

Table 6. (Continued)

	Bold1		Bold2		Bold3		Bold4	
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Upward Consensus Revision								
Intercept	-0.6353	0.0001	-0.3578	0.0001	-1.1104	0.0001	-0.8748	0.0001
AbsChgCon	0.4505	0.0470	6.2961	0.0001	2.8016	0.0001	-0.3768	0.4556
AbsDeviation	-0.5114	0.0001	-3.0874	0.0001	-1.7566	0.0001	0.2492	0.0001
Optimism	0.9697	0.0001	-0.0711	0.0001	0.2056	0.0001	-0.5064	0.0001
AbsChgCon × *Optimism*	1.4477	0.0001	-2.1180	0.0001	-0.1564	0.4396	2.5408	0.0001
AbsDeviation ×*Optimism*	-0.6123	0.0001	-1.9697	0.0001	-1.5878	0.0001	-1.7838	0.0001
AbsChgCon × *Convergence*	-0.9419	0.0001	-2.1989	0.0001	-2.1925	0.0001	-1.0228	0.0001
AbsChgCon ×*NumIssuer*	-0.4319	0.0001	-1.2081	0.0001	-1.2876	0.0001	-2.0299	0.0001
Coverage	0.1990	0.0001	0.0703	0.0001	0.1340	0.0001	-0.2618	0.0001
DaysElapsed	0.0037	0.0001	0.0043	0.0001	0.0054	0.0001	0.0174	0.0001
ForHorizon	0.0008	0.0001	0.0019	0.0001	0.0020	0.0001	0.0010	0.0002
GeneralExperience	-0.0532	0.0544	-0.0788	0.0016	-0.0820	0.0012	0.0074	0.8415
FirmExperience	0.1156	0.0001	0.0160	0.5145	0.0476	0.0552	0.0036	0.9228
LagForAccuracy	0.1075	0.0001	-0.0254	0.2817	0.0235	0.3258	-0.0584	0.0914
BrokerageSize	0.2961	0.0001	0.0923	0.0001	0.1744	0.0001	0.1923	0.0001
Frequency	0.1305	0.0001	0.1653	0.0001	0.2625	0.0001	0.2904	0.0001
FirmCoverage	-0.0364	0.1840	0.0167	0.5030	-0.0090	0.7208	-0.0939	0.0113

Table 6. (Continued)

	Bold1		Bold2		Bold3		Bold4	
Parameter	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Down Consensus Revision								
Intercept	0.6643	0.0001	-0.4651	0.0001	-0.8316	0.0001	-3.9736	0.0001
AbsChgCon	1.5429	0.0001	3.7772	0.0001	2.8036	0.0001	3.5422	0.0001
AbsDeviation	-0.9001	0.0001	-4.6044	0.0001	-3.2230	0.0001	-5.7517	0.0001
Optimism	-0.8348	0.0001	0.2801	0.0001	0.0009	0.9576	0.3728	0.0001
AbsChgCon × *Optimism*	-1.0475	0.0001	1.5129	0.0001	0.4725	0.0001	-3.4366	0.0001
AbsDeviation ×*Optimism*	0.2892	0.0001	-0.2454	0.1089	-1.3886	0.0001	5.6110	0.0001
AbsChgCon × *Convergence*	-0.5744	0.0001	-1.5346	0.0001	-1.5849	0.0001	0.3334	0.0521
AbsChgCon ×*NumIssuer*	-0.3633	0.0001	-1.0874	0.0001	-1.1993	0.0001	-1.8164	0.0001
Coverage	0.1382	0.0001	0.0875	0.0001	0.1238	0.0001	0.2972	0.0001
DaysElapsed	0.0014	0.0278	0.0030	0.0001	0.0030	0.0001	0.0153	0.0001
ForHorizon	0.0012	0.0001	0.0028	0.0001	0.0033	0.0001	0.0018	0.0001
GeneralExperience	0.0195	0.4383	-0.0066	0.7777	0.0012	0.9608	-0.2012	0.0001
FirmExperience	0.0776	0.0020	0.0463	0.0459	0.0740	0.0015	0.1974	0.0001
LagForAccuracy	0.0798	0.0006	-0.0066	0.7594	0.0305	0.1590	0.0549	0.1421
BrokerageSize	0.2865	0.0001	0.1272	0.0001	0.1891	0.0001	0.1731	0.0001
Frequency	0.0576	0.0283	0.0719	0.0032	0.1308	0.0001	0.5157	0.0001
FirmCoverage	-0.0769	0.0019	0.0089	0.6989	-0.0152	0.5122	0.0989	0.0131

Note:

Bold1 = one if ($F_{i,j,t} > F_{i,j,t-v}$ and $F_{i,j,t} > \bar{F}_{i,j,t-1}$) or ($F_{i,j,t} < F_{i,j,t-v}$ and $F_{i,j,t} < \bar{F}_{i,j,t-1}$), zero otherwise;

Bold2 = one if $| F_{i,j,t-v} - \bar{F}_{i,j,t-v-1} | < | F_{i,j,t} - \bar{F}_{i,j,t-1} |$, zero otherwise;

Bold3 = one if {($F_{i,j,t} > F_{i,j,t-v}$ and $F_{i,j,t} > \bar{F}_{i,j,t-1}$) or ($F_{i,j,t} < F_{i,j,t-v}$ and $F_{i,j,t} < \bar{F}_{i,j,t-1}$)} and $| \bar{F}_{i,j,t-v-1} - F_{i,j,t-v} | < | \bar{F}_{i,j,t-1} - F_{i,j,t} |$, zero otherwise;

Bold4 = one if $sign(F_{i,j,t-v} - F_{i,j,t}) \neq sign(\bar{F}_{i,j,t-v-1} - \bar{F}_{i,j,t-1})$ and $| F_{i,j,t-v} - \bar{F}_{i,j,t-v-1} | < | F_{i,j,t} - \bar{F}_{i,j,t-1} |$, zero otherwise;

$AbsChgCon_{j,t-1}$ = absolute value of change in the consensus forecast of other analysts following firm *j* between the days *t* and day *t* – *v*, deflated by absolute prior mean forecast;

$AbsDeviation_{i,j,t-v}$ = absolute value of difference between the consensus forecast for firm *j* and analyst *i*'s forecast on day *t – v*, deflated by absolute mean forecast;

$lnCoverage_{j}$ = log of number of analyst following the firm *j* in a particular year;

$DaysElapsed_{i,j,t}$ = days elapsed since the last forecast by any analyst following firm *j* in particular year; and

$ForHorizon_{i,j,t}$ = the number of days from the forecast date to the end of the fiscal period;

$Optimism_{i,j,t-v}$ = one if an analyst's current outstanding forecast is greater than the prior mean consensus forecast, zero otherwise;

$Convergence_{i,j,t-v}$ = change in analyst forecast dispersion between day *t-v-1* and *t*-1;

$NumIssuer_{j,t-1}$ = number of other analysts who issue forecast since the date of the analyst *i* current outstanding forecast on day *t-v;*

$GeneralExperience_{i,j,t}$ = number of quarters of analyst career experience for analyst *i* following firm *j* as of year *t* minus the minimum number of quarters of firm-specific experience for analysts following firm *j* in year *t*, with this difference scaled by the range of *General Experience* for analysts following firm *j* in year *t*;

$FirmExperience_{i,j,t}$ = number of quarters of firm-specific experience for analyst *i* following firm *j* as of year *t* minus the minimum number of quarters of firm-specific experience for analysts following firm *j* in year *t*, with this difference scaled by the range *Firm Experience* for analysts following firm *j* in year *t*;

$LagForAccuracy_{i,j,t-1}$ = the maximum absolute value of forecast error for analysts who follow firm *j* in year *t* – 1 minus the absolute value of forecast error for analyst *i* following firm *j* as of year *t – 1*, with this difference scaled by the range of *Lag Forecast Accuracy* for analysts following firm *j* as of year *t -1*;

$BrokerageSize_{i,j,t}$ = number of analysts employed by the broker employing analyst *i* following firm *j* in year *t* minus the minimum number of analysts employed by brokers for analysts following firm *j* in year *t*, with this difference scaled by the range of *Broker Size* for analysts following firm *j* in year *t*;

$Frequency_{i,j,t}$ = a number of firm *j* forecasts made by analyst *i* following firm *j* as of year *t* minus the minimum number of firm *j* forecasts for analysts following firm *j* as of year *t*, with this difference scaled by the range of number of firm *j* forecasts issued by analysts following firm *j* as of year *t*; and

$FirmCoverage_{i,j,t}$ = a number of firms followed by analyst *i* following firm *j* as of year *t* minus the minimum number of *Firm Coverage* for analysts following firm *j* as of year *t*, with this difference scaled by the range of *Firm Coverage* following firm *j* as of year *t*.