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Financial Analyst Characteristics and Herding Behavior in Forecasting

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ABSTRACT

This study classifies analysts' earnings forecasts as *herding* or *bold* and finds that (1) boldness likelihood increases with the analyst's prior accuracy, brokerage size, and experience and declines with the number of industries the analyst follows, consistent with theory linking boldness with career concerns and ability; (2) bold forecasts are more accurate than herding forecasts; and (3) herding forecast revisions are more strongly associated with analysts' earnings forecast errors (actual earnings—forecast) than are bold forecast revisions. Thus, bold forecasts incorporate analysts' private information more completely and provide more relevant information to investors than herding forecasts.

THE ASSOCIATION BETWEEN SECURITY RETURNS and analysts' forecast revisions suggests that investors extract relevant information about upcoming earnings from analyst forecasts. However, herding can reduce the information conveyed by individual analysts' forecasts if analysts do not fully use their private information when revising their forecasts or else revise their forecasts simply to be closer to the mean forecast and not because of new private information. The purpose of this study is to assess the causes and consequences of herding by analysts and to provide evidence that can help market participants better evaluate the information in analysts' earnings forecasts.

The first research question is whether analyst characteristics other than experience are associated with forecast boldness. We classify forecasts as *bold* if they are above both the analyst's own prior forecast and the consensus forecast immediately prior to the analyst's forecast, or else below both. We classify all other forecasts (i.e., those that move away from the analyst's own prior forecast and toward the consensus) as *herding* forecasts (Gleason and Lee (2003)).[1] Theoretical research suggests that forecasting boldness is related to the analyst's

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[1] The forecast boldness classification is illustrated in Figure 1. Gleason and Lee (2003) refer to forecasts that are above both the analyst's prior consensus and the mean forecast, or else below both, as *high-innovation* forecasts, and they refer to the remaining forecasts as *low-innovation* forecasts. For consistency with prior research on herding, we refer to high-innovation and low-innovation forecasts as *bold* and *herding* forecasts, respectively. This definition focuses on

reputation, career concerns, and self-assessed ability (Scharfstein and Stein (1990), Trueman (1994)).[2] Hong, Kubik, and Solomon (2000) find that (1) experienced analysts are more likely to provide bold forecasts than inexperienced analysts, and (2) inexperienced analysts are more likely than experienced analysts to lose their jobs after providing inaccurate or bold forecasts. This study extends Hong et al. (2000) by examining the relative importance of experience versus other analyst characteristics that proxy for analysts' self-assessed ability (e.g., the analyst's prior accuracy, brokerage size, forecast frequency, and the number of companies and industries the analyst follows) for explaining forecast boldness (Scharfstein and Stein (1990), Trueman (1994)).

The second research question is whether bold forecasts are, on average, more accurate than herding forecasts. Prior research finds that return responses are weaker for forecast revisions that herd toward a prior consensus than for forecast revisions that deviate from the consensus (Gleason and Lee (2003)). The reasons for this difference remain unexplored, but could be due to differences in forecast accuracy. Hong et al. (2000) explain that less experienced analysts are more likely to be discharged for making forecasts that deviate from the mean, and Hong and Kubik (2003) find that accurate forecasters are more likely to move to larger and more prestigious brokerages than less accurate forecasters. However, prior studies do not examine whether bold forecasts are on average more accurate than herding forecasts.

The third research question is motivated by Trueman's (1994) prediction that analysts revise their forecasts to a smaller extent than is warranted by their private information. This incomplete forecast revision results in a positive association between the analyst's forecast revision and the same analyst's earnings forecast error (actual earnings minus the analyst's earnings forecast). Trueman further predicts that small (positive or negative) forecast revisions are more likely to be incomplete than are extreme forecast revisions. We examine these predictions by comparing the association between forecast revisions and forecast errors for analysts providing bold and herding forecasts.

The results suggest a complex relation between analyst characteristics and herding behavior. First, we find that several analyst characteristics are associated with forecast boldness. Specifically, after controlling for the age of the forecast, we find that bold forecasts are *more* likely to be issued by (1) historically accurate analysts, (2) analysts employed by large brokerages, (3) frequent forecasters, and (4) analysts with more general (as opposed to firm-specific) experience. In contrast, bold forecasts are *less* likely to be issued by analysts who follow a large number of industries. Thus, the results confirm Hong et al.'s (2000) finding that forecast boldness is associated with the analyst's experience. We extend their results by showing that prior accuracy, brokerage size,

forecast revisions. We also define boldness as the distance of the analyst's forecast from the consensus forecast and report results based on this alternative definition.

[2] For example, Trueman (1994) predicts that forecast boldness depends on analysts' confidence in their own abilities, with more confident analysts providing bold forecasts and less confident analysts providing forecasts that are close to the prior mean.

forecast frequency, and the number of industries the analyst follows are also important for explaining forecast boldness.

Second, we find that bold forecasts are on average more accurate than herding forecasts, even after we control for analyst characteristics. With the exception of forecast horizon (the number of days between the forecast and the fiscal year-end), forecast boldness has at least as large an effect on forecast accuracy as any other analyst characteristic. Third, we find larger *improvements* in forecast accuracy for bold forecasts than for herding forecasts when we compare the forecast accuracy of original and revised forecasts. Thus, bold forecasts appear to reflect analysts' relevant private information to a greater extent than herding forecasts.

Fourth, we find evidence consistent with Trueman's (1994) predictions. Analyst forecast revisions are positively correlated with the analyst's forecast error, and the relation between forecast revisions and forecast errors is stronger for herding (small) forecast revisions than for bold (extreme) forecast revisions. Along with the finding that bold forecasts are more accurate than herding forecasts, this suggests that bold forecasts are based on relevant private information and reflect analysts' private information more completely than herding forecasts. In contrast, herding forecasts may simply result from uninformed (partial) mimicry of the mean forecast or other forecasters.

The study makes several contributions. First, we contribute to the growing literature on herding by financial analysts. Hong et al. (2000) find that more experienced analysts are less likely to herd. They conclude that career concerns cause less experienced analysts to seek safety in forecasts that are close to the consensus, while more experienced analysts are less bound by the consensus. Our results extend Hong et al. by showing that several other analyst characteristics are also strongly associated with herding (i.e., brokerage size, forecast frequency, and the number of industries followed).

Second, the study contributes to the more general debate about herding behavior. Theoretical studies posit that herding is inversely associated with a decision maker's (e.g., an analyst's or manager's) self-assessed ability (Scharfstein and Stein (1990), Trueman (1994)).[3] The results suggest that when measured using earnings forecasts, herding is inversely associated with several analyst characteristics (including prior accuracy, brokerage size, and forecast frequency) that prior research finds to be associated with forecast accuracy (and therefore, presumably with the analyst's self-assessed ability). This study is one of the first to empirically link herding with analyst characteristics associated with forecasting ability, so our results are relevant to the debate about the determinants of herding behavior.

[3] Cooper, Day, and Lewis (2001) construct a timeliness-based measure of analyst performance by exploiting analysts' tendency to herd following superior analysts' forecasts. Other studies on herding focus on mutual fund managers and investment advice, for example, Graham (1999) and Grinblatt, Titman, and Wermers (1995). Welch (2000, p. 391) finds similar herding for high- and low-quality analysts (measured using the number of recommendations by each brokerage), but reports that this result is not robust.

Third, we find that bold forecasts are more accurate than herding forecasts. This suggests that bold forecasts impound more private information about upcoming earnings than do herding forecasts, and, therefore, consensus earnings forecasts that are based on bold forecasts may be more accurate than consensus estimates based on all forecasts, whether bold or herding.

Fourth, the results suggest an explanation for the results documented by Gleason and Lee (2003) and Clement and Tse (2003). Those studies document greater return response coefficients for bold forecast revisions than for herding forecast revisions. The finding that bold forecasts are more accurate than herding forecasts could help explain these stronger return responses. We find that forecast revisions are positively correlated with forecast errors, but this correlation is weaker for bold forecast revisions. Gleason and Lee's (2003) finding that bold forecast revisions are correlated with returns around subsequent earnings announcements in spite of this weaker association between forecast revisions and forecast errors indicates that the delayed reaction to forecast revisions occurs because investors underreact to the forecast revision and not because the analyst underrevises.

The remainder of the article is organized as follows: We review prior literature in Section I. Section II explains the sample selection, and we summarize the research methods in Section III. We present the results in Section IV, and conclude with Section V.

I. Prior Literature

Scharfstein and Stein (1990) and Trueman (1994) provide the theoretical basis for the study. Scharfstein and Stein (1990) conclude that decision makers' (analysts' or managers') rational attempts to enhance their reputation may lead to herding. Focusing on financial analysts, Trueman (1994) suggests that analysts prefer to release an earnings forecast that is close to prior earnings expectations, even if their information justifies a more extreme (bold) forecast when the less extreme forecast enhances investors' assessment of the analyst's forecasting ability. Weak analysts are more concerned about reputation than strong analysts and are, therefore, more likely to herd. Trueman further predicts that the ex post forecast error is more highly correlated with small forecast revisions than with large forecast revisions because reputation concerns motivate herding analysts to release small positive (or negative) forecast revisions even when their information justifies larger positive (or negative) forecast revisions. We refer to this scenario as *informed herding*. An alternative view is that analysts who make small forecast revisions are uninformed (*uninformed herding*) and are simply moving toward the consensus (Gleason and Lee (2003)).

Hong et al. (2000) test the reputation and herding predictions in Scharfstein and Stein (1990). They find that more experienced analysts are more likely to issue bold forecasts than are less experienced analysts and that brokerage firms are more likely to discharge the less experienced analysts for inaccurate or bold forecasts. Their results are consistent with Scharfstein and Stein (1990) and Trueman (1994), suggesting that inexperienced analysts are *less* likely to provide extreme forecasts. That is, less experienced analysts are more concerned about their reputations and, therefore, tend to herd more frequently.[4]

Hong et al. (2000) focus on the analyst's years of experience and do not examine other measures of the analyst's ability. For example, Trueman (1994, p. 107) predicts that herding declines with the analyst's firm-specific experience, as well as with general experience. This study includes both experience measures. Furthermore, Hong et al. measure the boldness of forecasts using the deviation of each analyst's last forecast between January 1 and July 1 each year from the mean forecast by all other analysts. In contrast, we use the mean forecast at the time of the forecast as the benchmark toward which analysts may herd when revising their forecasts. We focus on forecast revisions because prior research finds that herding forecast revisions generate lower return responses than do bold forecast revisions (Gleason and Lee (2003)). However, the deviation of the analyst's forecast from the year-to-date consensus forecast is likely to contain useful information for analysts, investors, and employers, and we therefore use it as an alternative boldness measure. In addition, employers may release analysts whose forecasts deviate substantially from the year-end consensus, all else equal. We therefore use the deviation of the analyst's forecast from the year-end consensus to help explain forecast accuracy and employment outcomes.

Stickel (1990) finds that analysts' forecast revisions are correlated with changes in the prior consensus forecast, but that this correlation is weaker for members of the *Institutional Investor* All-American Research Team. Stickel concludes that members of the All-American Team are less likely to herd than are other analysts. We use a more direct measure of herding behavior, along with several analyst characteristics that reflect the analyst's forecast accuracy.

Prior research finds that forecast accuracy is related to several analyst and forecast characteristics (forecast horizon, past accuracy, brokerage size, forecast frequency, firm-specific and general experience, and the number of companies and industries the analyst follows: Mikhail, Walther, and Willis (1997), Clement (1999), Jacob, Lys, and Neale (1999), Brown (2001)). However, prior studies do not examine the relation between forecast boldness and accuracy. Gleason and Lee (2003) find that bold forecast revisions generate stronger return responses than do herding forecast revisions, and Clement and Tse (2003) find that analyst characteristics are associated with forecast accuracy for both bold and herding forecasts. Consistent with Gleason and Lee, Clement and Tse find that forecast revisions and analyst characteristics are only associated with returns for bold forecasts.[5]

[4] Cote and Sanders (1997) conduct a laboratory experiment examining implications of Trueman's (1994) theoretical analysis. They report that herding is less likely when the forecaster's self-perceived forecasting ability is high, consistent with Trueman's predictions. However, they do not link analysts' self-assessed ability with analyst characteristics that are associated with forecast accuracy.

[5] Stickel (1992) and Park and Stice (2000) find that return responses to analyst forecast revisions increase with the analyst's reputation and prior forecast accuracy, consistent with the theoretical predictions of Abarbanell, Lanen, and Verrecchia (1995).

Although Gleason and Lee (2003) conjecture that returns respond more strongly to bold forecasts because those forecasts provide investors with more new information than herding forecasts, neither their study nor Clement and Tse (2003) explains the difference in return responses. We investigate the empirical basis of this conjecture by examining the relative accuracy of bold versus herding forecasts, thereby determining whether some forecast types are more likely to provide new information to investors.

Abarbanell (1991) finds evidence that analysts do not fully exploit information in prior stock price changes about future earnings, suggesting that analysts underreact to available information. This finding motivates the examination of whether analysts' forecast revisions fully reflect their private information (Trueman (1994)).

Other studies examine analyst herding (Olsen (1996), DeBondt and Forbes (1999)), but they focus on a limited number of potential determinants of herding, and do not examine how herding affects forecast accuracy or whether herding forecast revisions are smaller than is warranted by the analyst's private information. This study addresses these issues.

II. Sample Selection

The analysis is based on I/B/E/S forecasts of annual earnings from 1989 to 1998.[6] Consistent with prior studies, we retain the last forecast an analyst issues in a particular year (O'Brien (1990), Sinha, Brown, and Das (1997), Clement (1999)). We include forecasts issued no earlier than 1 year ahead, and no later than 30 days before the fiscal year-end. Because we compare analysts providing forecasts for a particular firm within a year, we eliminate firm-years for which only one analyst provides a forecast. We eliminate all analyst forecasts with no prior year data on forecast accuracy. To facilitate comparisons across companies, we deflate forecast revisions and forecast errors by the firm's security price 2 days before the forecast revision date. We obtain security prices from CRSP, and we eliminate potential outliers by omitting observations with price-deflated forecast revisions above 0.10 or below -0.10. We also eliminate observations for which the price-deflated analyst forecast error is above 0.40 or below -0.40. These procedures yield a sample of 57,596 analyst–firm–year observations.[7]

[6] Prior to the early 1990s, forecast dates recorded by I/B/E/S sometimes differed from the actual forecast date by a few days (Cooper et al. (2001), Clement and Tse (2003)). Our results are unchanged when we restrict the sample to 1993 and later years.

[7] There are 58,384 observations before we apply the forecast revision and forecast error outlier screens. Firms reporting losses are disproportionately represented among the eliminated observations, suggesting that analysts have difficulty forecasting earnings for those firms. We obtain qualitatively similar results when we retain these observations in the sample, but forecast revision coefficients in the regression models are generally lower. We allow larger forecast errors than forecast revisions because analyst forecasts that are issued early in the year are typically less accurate, and requiring that forecast errors fall in too narrow an interval could eliminate a disproportionate number of early forecasts. We obtain similar results when we use the same limits for forecast revisions and forecast errors.

III. Research Methods

We first discuss the forecast boldness measure and highlight its primary properties. As Figure 1 illustrates, we classify forecasts as bold if they are above both the analyst's prior forecast and the prerevision consensus forecast, or else below both, and classify all other forecasts as herding. This definition focuses on forecast *revisions* because they convey analysts' information to investors, and prior research suggests that investors respond more strongly to bold forecast revisions than to herding forecast revisions. However, the (absolute) distance between a forecast and the consensus forecast may also be informative to decision makers, specifically, to analysts, investors, and employers. As Figure 2 shows, the consensus may be measured around an analyst's forecast revision (the year-to-date consensus) or at the end of the fiscal year (the fiscal year-end consensus). We define the distance measures in Figure 3. For a particular analyst, *YTD_Dist*1 measures the distance between the analyst's prerevision forecast and the prerevision consensus forecast; *YTD_Dist*2 measures the distance between the analyst's revised forecast and the prerevision consensus forecast; and *FYE_Dist* measures the distance between the analyst's revised forecast (the last forecast the analyst issues for the company that year) and the year-end consensus forecast. We use the distance of the revised forecast from the prerevision consensus (*YTD_Dist*2) as an alternative, cross-sectional, boldness measure. Employers' hiring and retention decisions may depend on forecast accuracy as well as on the forecast's distance from the year-end consensus, and we therefore use *FYE_Dist* to explain employment decisions.

The first research question concerns the determinants of forecast boldness. If analysts' self-assessed ability is correlated with the variables that predict forecast accuracy, then these analyst characteristics should be similarly associated with forecast boldness and forecast accuracy. Consequently, we examine the association between forecast boldness and several analyst and forecast characteristics that prior research has shown are associated with forecast accuracy. Specifically, we expect characteristics that are associated with increased forecast accuracy (e.g., lagged accuracy, brokerage size, forecast frequency, and firm-specific and general experience) to be positively associated with forecast boldness, and we expect characteristics that are inversely associated with forecast accuracy (e.g., the number of companies and industries the analyst follows) to be negatively associated with forecast boldness. Finally, we include

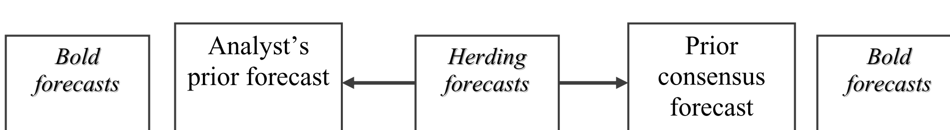
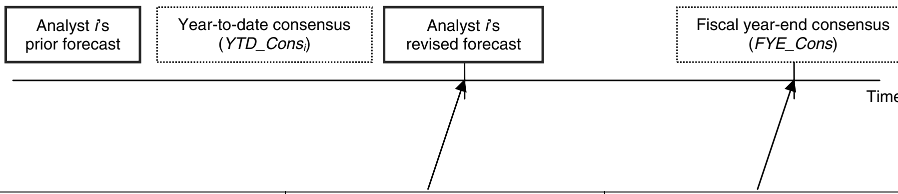


Figure 1. Bold and herding forecasts: Classification based on forecast revisions. Analysts may revise a prior forecast toward or away from the existing consensus forecast. Forecasts are classified as *bold* if they are above both the analyst's own prior forecast and the consensus forecast immediately prior to the analyst's forecast, or else below both. All other forecasts (i.e., those between the analyst's own prior forecast and the consensus forecast) are classified as *herding*.



Decision makers, their actions, and decision criteria	**Forecast revision date** Available information: analyst's prior forecast; mean forecast to date for all analysts; analyst characteristics (including prior year accuracy)	**End of fiscal period** Available information: all analysts' forecasts; analyst characteristics (including prior year accuracy)
Analysts Continually decide whether to issue a forecast.	Analysts decide whether to revise their own prior forecast away from or toward the current mean forecast (i.e., issue a bold or a herding forecast).	
Investors Respond to news in forecasts.	Investors evaluate the information content of analyst forecasts in light of available information.	
Employers Evaluate analysts on the information in their forecasts, their forecast accuracy, and other criteria.	Employers evaluate the information content of analyst forecasts.	Employers evaluate the analyst's forecast accuracy when earnings are announced.

Figure 2. Time line for forecast revisions and inputs to decisions by analysts, investors, and employers. This time line identifies possible decision criteria for analysts (in deciding whether to issue a forecast and what type of forecast to issue), investors (in responding to analysts' forecast revisions), and employers (in making employment and retention decisions on employees). The time line focuses on analyst i. Other analysts' forecasts are excluded from the time line, but are included in the consensus forecast immediately before analyst i's last forecast (YTD_Cons_i) and in the year-end consensus forecast (FYE_Cons).

days elapsed since the prior forecast because herding toward the prior mean may be more likely for revisions that are made soon after a prior forecast than for revisions that are made long after the previous forecast.

To allow comparisons of regression model coefficients, we scale each of the variables to range from 0 to 1 using a transformation that preserves the relative distances among each characteristic's measures for firm j in year t. The scaled independent variables for analyst i take the form

$$Characteristic_{ijt} = \frac{Raw\_Characteristic_{ijt} - Raw\_Characteristic\,\min_{jt}}{Raw\_Characteristic\,\max_{jt} - Raw\_Characteristic\,\min_{jt}}, \tag{1}$$

where $RawCharacteristic\max_{jt}$ and $RawCharacteristic\min_{jt}$ are the original maximum and minimum values, respectively, of a characteristic. A high value for $Characteristic_{ijt}$ indicates that analyst i scores high on that characteristic

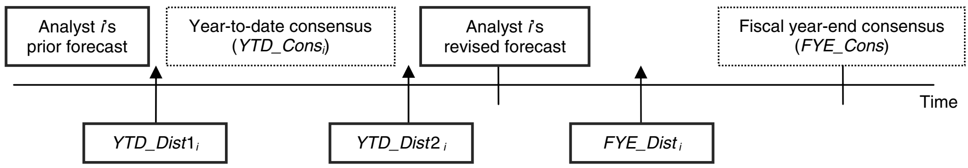


Figure 3. Measures of forecast deviations from the consensus forecast. This figure defines cross-sectional measures of forecast boldness, the absolute difference between the analyst's forecast and the consensus forecast. The absolute difference from the consensus is measured immediately prior to a forecast revision (*YTD_Dist*1, the difference between the analyst's prerevision forecast and the prerevision consensus forecast), immediately following the forecast revision (*YTD_Dist*2, the difference between the analyst's revised forecast and the prerevision consensus forecast), and at the fiscal year-end (*FYE_Dist*, the difference between the analyst's revised forecast and the fiscal year-end consensus forecast). This time line focuses on analyst i. Other analysts' forecasts are excluded from the time line, but are included in the consensus forecast immediately before analyst i's last forecast (YTD_Cons_i) and also in the year-end consensus forecast (*FYE_Cons*).

relative to other analysts who follow firm j in year t.[8] To ensure that the measures of forecasting performance increase with forecast accuracy, we scale the forecast accuracy measure to be 0 for the *least* accurate forecast (highest absolute forecast error) and 1 for the most accurate forecast (lowest absolute forecast error). The scaled accuracy measure for analyst i is

$$Accuracy_{ijt} = \frac{AFE\max_{jt} - AFE_{ijt}}{AFE\max_{jt} - AFE\min_{jt}}, \tag{2}$$

where $AFE\max_{jt}$ and $AFE\min_{jt}$ are the maximum and minimum absolute forecast errors, respectively, for analysts following firm j in year t. $Accuracy_{ijt}$, therefore, increases with forecast accuracy.

The first research question is whether analyst characteristics are associated with forecast boldness. We extend prior research (Hong et al. (2000)) by explaining forecast boldness using analyst characteristics (beyond experience) that we expect to be associated with forecast boldness because they are associated with forecast accuracy (and therefore presumably with the analyst's self-assessed ability). We estimate the following logit model:

$$\begin{aligned} Bold_{ijt} = {} & \alpha_0 + \alpha_1 DaysElapsed_{ijt} + \alpha_2 ForHorizon_{ijt} \\ & + \alpha_3 LagAccuracy_{ijt} + \alpha_4 BrokerSize_{ijt} + \alpha_5 ForFrequency_{ijt} \\ & + \alpha_6 FirmExperience_{ijt} + \alpha_7 GenExperience_{ijt} + \alpha_8 Companies_{ijt} \\ & + \alpha_9 Industries_{ijt} + \varepsilon_{ijt}, \end{aligned} \tag{3}$$

where

$Bold_{ijt}$ is an indicator variable for the boldness of analyst i's forecast for firm j in year t. It is equal to 1 if analyst i's forecast is above both the analyst's prior

[8] As an example, suppose analyst i's brokerage employs 25 analysts (that is, analyst i's brokerage size is 25), and the minimum and maximum brokerage sizes for analysts who follow firm j in year t are 10 and 50, respectively. Then, analyst i falls at the 37.5% level [(25 − 10)/(50 − 10)] of the range of brokerage sizes for analysts who followed firm j in year t.

forecast and the mean forecast immediately before the forecast revision, or else below both. It is set to 0 otherwise. The mean forecast is based on forecasts issued in the 90 days prior to analyst i's forecast revision.

$DaysElapsed_{ijt}$ is a measure of the days elapsed since the last forecast by any analyst following firm j in year t, calculated as the days between analyst i's forecast of firm j's earnings in year t and the most recent preceding forecast of firm j's earnings by any analyst, minus the minimum number of days between two adjacent forecasts of firm j's earnings by any two analysts in year t, with this difference scaled by the range of days between two adjacent forecasts of firm j's earnings in year t.

$ForHorizon_{ijt}$ is a measure of the time from the forecast date to the end of the fiscal period, calculated as the forecast horizon (days from the forecast date to the fiscal year-end) for analyst i following firm j in year t minus the minimum forecast horizon for analysts who follow firm j in year t, with this difference scaled by the range of forecast horizons for analysts following firm j in year t.

$LagAccuracy_{ijt}$ is a measure of analyst i's prior year forecast accuracy for firm j, calculated as the maximum *Accuracy* for analysts who follow firm j in year $t - 1$ minus the *Accuracy* for analyst i following firm j in year $t - 1$, with this difference scaled by the range of *Accuracy* for analysts following firm j in year $t - 1$.

$BrokerSize_{ijt}$ is a measure of the analyst's brokerage size, calculated as the number of analysts employed by the brokerage employing analyst i following firm j in year t minus the minimum number of analysts employed by brokerages 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.

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

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

$GenExperience_{ijt}$ is a measure of analyst i's general experience, calculated as the number of years of experience for analyst i following firm j in year t minus the minimum number of years of experience for analysts following firm j in year t, with this difference scaled by the range of years of experience for analysts following firm j in year t.

$Companies_{ijt}$ is a measure of the number of companies analyst i follows in year t, 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.

$Industries_{ijt}$ is a measure of the number of industries analyst i follows in year t, calculated as the number of two-digit SICs followed by analyst i following firm j in year t minus the minimum number of two-digit SICs followed by analysts who follow firm j in year t, with this difference scaled by the range in the number of two-digit SICs followed by analysts following firm j in year t.

The binary boldness measure in the logit model above is based on forecast revisions. We also report regression model results for the alternative (continuous) boldness measure, the distance of the revised forecast from the consensus forecast, *YTD_Dist*2. The model is

$$\begin{aligned} YTD\_Dist2_{ijt} = {} & \alpha_0 + \alpha_1 DaysElapsed_{ijt} + \alpha_2 ForHorizon_{ijt} + \alpha_3 LagAccuracy_{ijt} \\ & + \alpha_4 BrokerSize_{ijt} + \alpha_5 ForFrequency_{ijt} + \alpha_6 FirmExperience_{ijt} \\ & + \alpha_7 GenExperience_{ijt} + \alpha_8 Companies_{ijt} + \alpha_9 Industries_{ijt} + \varepsilon_{ijt}, \end{aligned} \tag{4}$$

where

YTD_Dist2_{ijt} is a measure of the distance of analyst i's revised forecast for firm j from the prerevision (year-to-date) consensus forecast in year t, calculated as the absolute distance of the revised forecast from the year-to-date consensus for analyst i following firm j in year t minus the minimum absolute distance for analysts who follow firm j in year t, with this difference scaled by the range in absolute distances for analysts following firm j in year t.[9]

The second research question examines the relation between forecast boldness and forecast accuracy. If analysts base bold forecasts on relevant private information, then forecast boldness should be associated with more accurate forecasts, after controlling for other determinants of forecast accuracy. On the other hand, if bold forecasts were issued by overconfident but poorly informed analysts, then forecast boldness would have no incremental association with forecast accuracy. We examine this issue by regressing forecast accuracy on forecast boldness after controlling for other forecast and analyst characteristics:

$$\begin{aligned} Accuracy_{ijt} = {} & \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForHorizon_{ijt} + \beta_3 LagAccuracy_{ijt} \\ & + \beta_4 BrokerSize_{ijt} + \beta_5 ForFrequency_{ijt} + \beta_6 FirmExperience_{ijt} \\ & + \beta_7 GenExperience_{ijt} + \beta_8 Companies_{ijt} + \beta_9 Industries_{ijt} \\ & + \beta_{10} FYE\_Dist_{ijt} + \beta_{11} YTD\_Dist2_{ijt} + \beta_{12} Bold_{ijt} + \varepsilon_{ijt}, \end{aligned} \tag{5}$$

[9] The year-to-date consensus is based on forecasts issued within 90 days of the forecast revision. We obtain similar results without this restriction.

where

Accuracy$_{ijt}$ is a measure of analyst i's forecast accuracy for firm j in year t, calculated as the maximum absolute forecast error for analysts who follow firm j in year t minus the absolute forecast error of analyst i following firm j in year t, with this difference scaled by the range of absolute forecast errors for analysts following firm j in year t.

FYE_Dist$_{ijt}$ is a measure of the distance of analyst i's forecast for firm j from the fiscal-year-end consensus forecast in year t, calculated as the absolute distance of the forecast from the fiscal-year-end consensus for analyst i following firm j in year t minus the minimum absolute distance for analysts who follow firm j in year t, with this difference scaled by the range in absolute distances for analysts following firm j in year t.[10]

If analysts provide bold forecasts when they possess relevant private information, then the coefficient on *Bold* will be positive. Similarly, if analysts provide forecasts that deviate from the prerevision consensus when they have relevant information, then the coefficient on *YTD_Dist*2 will be positive. A positive coefficient on the fiscal year-end distance, *FYE_Dist*, would suggest that analysts who deviate from the year-end consensus incorporate information in their forecasts that other analysts omit. However, the fiscal year-end distance may be a less reliable indicator of useful private information than the year-to-date distance because much of a firm's earnings information is publicly available by the end of the year. In addition, unrevised forecasts may deviate from the year-end consensus because the consensus shifts over time. Thus, the *FYE_Dist* coefficient could be negative if analysts who deviate from the year-end consensus are poorly informed. Consistent with prior research, we expect forecast accuracy to increase with prior accuracy, brokerage size, forecast frequency, and firm and general experience. We expect forecast accuracy to decline with days elapsed since the prior forecast, forecast horizon, and the number of companies and industries the analyst follows.

The forecast boldness measures, *Bold* and *YTD_Dist*2, are explanatory variables in the forecast accuracy equation and dependent variables in the equation to determine whether analyst characteristics are associated with boldness. Neither analysis predicts the other. For example, experienced analysts may be more likely than inexperienced analysts to issue bold forecasts (Hong et al. (2000)) and accurate forecasts (Mikhail et al. (1997), Clement (1999), Jacob et al. (1999)). However, forecast boldness may have no incremental association with forecast accuracy beyond experience. The boldness analysis also provides information that cannot be derived from the forecast accuracy model. Prior research finds that several analyst characteristics are related to forecast accuracy (Clement (1999), Jacob et al. (1999)), and theory predicts that herding is related to analysts' self-assessed ability (Scharfstein and Stein (1990), Trueman (1994)). However, individuals' perceptions of their abilities could be inconsistent

[10] Consistent with the year-to-date consensus, the fiscal-year-end consensus is based on forecasts issued within 90 days of the fiscal year-end. We obtain similar results without this restriction.

with the forecast accuracy model's predictions of those abilities. It is therefore an empirical question whether analysts herd as if their self-assessed ability is consistent with the forecast accuracy model's predictions of that ability. The empirical tests address these questions.

The third research question is whether the association between forecast revisions and forecast errors differs for bold and herding forecasts. Trueman (1994) predicts that the association between forecast revisions and forecast errors is stronger for herding forecasts than for bold forecasts. We examine this possibility by regressing the earnings forecast error on both the forecast revision and the interaction of the forecast revision with the forecast boldness dummy variable, after controlling for interactions between the forecast revision and each of the analyst characteristics. We also include the interaction of the forecast revision with each of the forecast boldness measures (*Bold* and *YTD_Dist*2) as explanatory variables. The model is[11]

$$\begin{aligned} ERRP_{ijt} = {} & \delta_0 + \gamma_0 REVP_{ijt} + \gamma_1 REVP_{ijt} \times DaysElapsed_{ijt} + \gamma_2 REVP_{ijt} \\ & \times ForHorizon_{ijt} + \gamma_3 REVP_{ijt} \times LagAccuracy_{ijt} + \gamma_4 REVP_{ijt} \\ & \times BrokerSize_{ijt} + \gamma_5 REVP_{ijt} \times ForFrequency_{ijt} + \gamma_6 REVP_{ijt} \\ & \times FirmExperience_{ijt} + \gamma_7 REVP_{ijt} \times GenExperience_{ijt} + \gamma_8 REVP_{ijt} \\ & \times Companies_{ijt} + \gamma_9 REVP_{ijt} \times Industries_{ijt} + \gamma_{10} REVP_{ijt} \\ & \times YTD\_Dist2_{ijt} + \gamma_{11} REVP_{ijt} \times Bold_{ijt} + \varepsilon_{ijt}, \end{aligned} \tag{6}$$

where

$ERRP_{ijt}$ (forecast error scaled by price) is analyst *i*'s forecast error for firm *j* in year *t* scaled by the end-of-day stock price two days prior to the revision. The forecast error equals firm *j*'s year-*t* earnings minus analyst *i*'s forecast of firm *j*'s year-*t* earnings.

$REVP_{ijt}$ (revision scaled by price) is analyst *i*'s forecast revision for firm *j* in year *t* scaled by the end-of-day stock price 2 days prior to the revision. The revision equals analyst *i*'s forecast of firm *j*'s earnings in year *t*, less analyst *i*'s prior forecast of firm *j*'s earnings in year *t*.

We expect the coefficient of *REVP* to be positive because herding forecast revisions should be positively correlated with forecast errors. We expect the co-

[11] The goal is to evaluate the completeness of analysts' response to their private information when they revise their forecasts. Evidence of incomplete response by analysts to their private information need not imply that returns at the earnings announcement date are correlated with the analyst's revision. That is, incomplete forecast revision by the analyst need not imply incomplete price adjustment to earnings-related news. First, investors may realize that some analysts tend to revise their forecasts conservatively and may infer (and respond to) the correct forecast revision from the publicized revision (Trueman (1994, p. 98). Second, subsequent forecast revisions may more fully incorporate the new information in security prices, so that security prices correctly reflect analysts' private information at the earnings announcement date. And third, herding forecasts may occur with little or no private information, meaning that return responses to the forecast revisions should be relatively small.

efficients of *REVP* × *Bold* and *REVP* × *YTD_Dist*2 to be negative, indicating that the positive association between *REVP* and *ERRP* is *lower* for bold forecast revisions.

IV. Results

A. Descriptive Statistics

We report descriptive statistics in Table I. Panel A shows the distribution of several analyst characteristics before they are scaled to range from 0 to 1. The distributions are similar to those in prior studies (Clement (1999), Jacob et al. (1999)). For example, the mean brokerage size is about 30 analysts, and each analyst follows a mean of 21 firms in six industries.[12] We report distributions for the scaled variables in Panel B. Recall that the variables are scaled to range from 0 to 1, but preserve the relative positions of each observation within a firm-year. The mean scaled values range from 0.36 for firm experience to 0.58 for accuracy, indicating that the distributions of the variables are skewed.[13]

We compare means of current period forecast accuracy and analyst characteristics for bold and herding forecasts in Table I, Panel C. With the exception of days elapsed since the prior forecast, all of the variables differ significantly across bold and herding forecasts (1% significance level). Most importantly, current period bold forecasts are significantly more accurate than herding forecasts, suggesting that bold forecasts tend to be based on relevant information. In addition, analysts issuing bold forecasts are (on average) employed by larger brokerages, issue more frequent forecasts, and have greater firm-specific and general experience. All of these characteristics are associated with greater forecast accuracy (Clement (1999)). In contrast, analysts issuing herding forecasts tend to cover more companies and industries, suggesting that those analysts are less inclined to stake out bold positions than analysts who specialize in fewer companies or industries. Bold forecasts on average have longer forecast horizons, so analysts are more likely to issue bold forecasts early in the year. Analysts may feel less constrained by the consensus forecast early in the year because it includes relatively few forecasts.

Before the revision occurs, analysts who issue bold forecast revisions are closer to the prerevision consensus than are analysts who issue herding revisions (*YTD_Dist*1 is significantly smaller for bold forecast revisions than for herding forecast revisions). These positions are reversed after the revisions, with analysts who issue bold forecast revisions moving relatively far from the

[12] These are sample-wide means for the analyst–firm–year observations. Each analyst appears once in the sample for each firm that analyst follows in each year. Thus, analysts who follow multiple firms appear in the sample multiple times, and those observations contribute disproportionately to the mean number of firms the analyst follows. When each analyst is included once in the sample each year, the mean number of firms the analyst follows is 14. Similarly, when each brokerage firm appears once in the sample each year, the mean number of analysts per brokerage is 13. Distributions of the remaining analyst characteristics do not change substantially when we restrict each analyst to one observation per year or include a separate observation for each firm the analyst follows.

[13] Symmetric distributions would yield means and medians of 0.5 for each of the scaled variables.

Table I

Descriptive Statistics on Analyst Characteristics

This table reports descriptive statistics for 57,596 analyst forecast observations from 1989 to 1998. Analyst and forecast characteristics are derived from detailed I/B/E/S data. We restrict the sample to forecasts issued no earlier than 1 year and no later than 30 days before the fiscal year-end, and include the last forecast issued by the analyst for a particular firm in each sample year. The characteristics are *DaysElapsed*, the number of days since any analyst's prior forecast; *ForHorizon*, the number of days from the forecast date to the fiscal year-end; *BrokerSize*, the number of analysts in the analyst's brokerage in each year; *FirmExperience*, the analyst's years of experience forecasting a particular firm's earnings; *GenExperience*, the analyst's overall years of forecasting experience; *Companies*, the number of companies the analyst follows in each year; and *Industries*, the number of two-digit SIC industries the analyst follows in each year. Panel A reports the descriptive statistics for raw (unscaled) forecast and analyst characteristics. Panel B reports the descriptive statistics for forecast and analyst characteristics, including current year and prior year absolute forecast accuracy (*Accuracy* and *LagAccuracy*), that are scaled to range from 0 to 1 for each firm-year. Panel C compares mean scaled characteristics for bold forecast revisions (forecasts that are above both the analyst's prior forecast and the consensus, or else below both) and herding forecast revisions (forecasts that are between the analyst's own prior forecast and the consensus forecast). Statistics are also provided for the distance of the analyst's prerevision forecast from the year-to-date consensus forecast (*YTD_Dist*1), the distance of the revised forecast from the prerevision consensus forecast (*YTD_Dist*2), and the distance of the forecast from the year-end consensus forecast (*FYE_Dist*), all scaled to range from 0 to 1 within each firm-year. Panel D reports correlations among the scaled characteristics.

Panel A: Distribution of Selected Raw (Unscaled) Forecast and Analyst Characteristics

Characteristic and Raw Units of Measurement	Mean	25th Percentile	Median	75th Percentile
DaysElapsed: Days since the prior forecast	13.6	2	7	15
ForHorizon: Days to fiscal year-end	97.9	55	71	134
BrokerSize: Number of analysts in the brokerage	29.8	11	24	43
ForFrequency: Number of forecasts made	3.8	2	3	5
FirmExperience: Years of firm experience	3.8	2	3	5
GenExperience: Years of general experience	5.7	3	5	8
Companies: Number of companies followed	21.2	12	17	24
Industries: Number of two-digit SICs followed	5.9	3	5	7

(continued)

Table I—*Continued*

Panel B: Distribution of Scaled Forecast and Analyst Characteristics

Characteristic	Mean	25^{th} Percentile	Median	75^{th} Percentile
Accuracy	0.580	0.033	0.709	1.000
DaysElapsed	0.379	0.000	0.212	0.833
ForHorizon	0.394	0.027	0.212	0.857
LagAccuracy	0.565	0.000	0.667	1.000
BrokerSize	0.433	0.047	0.349	0.831
ForFrequency	0.406	0.000	0.333	0.800
FirmExperience	0.364	0.000	0.200	0.750
GenExperience	0.448	0.000	0.400	0.857
Companies	0.406	0.043	0.292	0.765
Industries	0.399	0.000	0.286	0.750

Panel C: Comparison of Scaled Forecast and Analyst Characteristics for Bold and Herding Forecast Revisions

	Bold Forecast Revisions ($N = 42{,}223$)	Herding Forecast Revisions ($N = 15{,}373$)	t-Value for Difference	Significance
Accuracy	0.6009	0.5210	21.03	<0.001
DaysElapsed	0.3776	0.3845	−1.83	0.068
ForHorizon	0.4023	0.3703	8.65	<0.001
LagAccuracy	0.5720	0.5457	6.91	<0.001
BrokerSize	0.4426	0.4068	9.92	<0.001
ForFrequency	0.4142	0.3847	7.88	<0.001
FirmExperience	0.3669	0.3568	2.70	0.008
GenExperience	0.4521	0.4368	4.12	<0.001
Companies	0.4022	0.4187	−4.59	<0.001
Industries	0.3900	0.4224	−8.81	<0.001
*YTD_Dist*1	0.3213	0.5868	−76.04	<0.001
*YTD_Dist*2	0.4545	0.2672	56.04	<0.001
FYE_Dist	0.3359	0.3947	−15.63	<0.001

Panel D: Correlations among Scaled Forecast and Analyst Characteristics (Significance Levels Are in Parentheses)

	Accuracy	*Days Elapsed*	*For Horizon*	*Lag Accuracy*	*Broker Size*	*For Frequency*	*Firm Experience*	*Gen Experience*	*Companies*	*Industries*	*YTD_Dist*1	*YTD_Dist*2
DaysElapsed	−0.038											
	(<0.001)											
ForHorizon	−0.277	0.054										
	(<0.001)	(<0.001)										
LagAccuracy	0.082	−0.035	−0.048									
	(<0.001)	(<0.001)	(<0.001)									
BrokerSize	0.024	0.024	0.019	0.022								
	(<0.001)	(<0.001)	(<0.001)	(<0.001)								
ForFrequency	0.154	0.015	−0.340	0.041	0.020							
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.002)							
FirmExperience	0.021	0.002	−0.023	0.009	0.012	0.022						
	(<0.001)	(0.693)	(<0.001)	(0.039)	(0.005)	(<0.001)						
GenExperience	0.006	0.002	−0.014	0.002	0.034	−0.006	0.524					
	(0.138)	(0.666)	(<0.001)	(0.628)	(<0.001)	(0.132)	(<0.001)					
Companies	−0.041	0.030	−0.005	−0.062	−0.023	−0.014	0.129	0.203				
	(<0.001)	(<0.001)	(0.275)	(<0.001)	(<0.001)	(0.001)	(<0.001)	(<0.001)				
Industries	−0.048	0.016	0.014	−0.054	−0.135	−0.045	0.080	0.137	0.570			
	(<0.001)	(0.001)	(0.004)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)			
*YTD_Dist*1	−0.130	−0.015	0.088	−0.084	−0.052	−0.165	−0.011	0.004	0.067	0.083		
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.006)	(0.329)	(<0.001)	(<0.001)		
*YTD_Dist*2	−0.065	0.051	0.218	−0.012	0.067	−0.060	0.005	0.015	0.008	−0.016	0.044	
	(<0.001)	(<0.001)	(<0.001)	(0.004)	(<0.001)	(<0.001)	(0.191)	(<0.001)	(0.045)	(< 0.001)	(<0.001)	
FYE_Dist	−0.395	0.022	0.423	−0.071	−0.023	−0.204	−0.015	−0.002	0.029	0.049	0.167	0.201
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.646)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

prerevision consensus (*YTD_Dist*2 is significantly larger for bold forecast revisions than for herding forecast revisions). However, other analysts subsequently revise their forecasts, and by year-end, the bold analysts are again closer to the fiscal-year-end consensus than are herding analysts, albeit by a smaller margin than for the year-to-date distances (*FYE_Dist* is significantly smaller for bold forecast revisions than for herding forecast revisions).

We report correlations among the current period's forecast accuracy and analyst and forecast characteristics in Panel D. Consistent with prior research, forecast accuracy is positively correlated with prior accuracy, brokerage size, forecast frequency, and firm experience, and is negatively correlated with days since the prior forecast, forecast horizon, and the number of companies and industries the analyst follows. Forecast accuracy is more strongly (negatively) correlated with the distance of the forecast from the year-end consensus than with any other measure. The correlations among the analyst characteristics are below 0.25, except for those between forecast horizon and forecast frequency; firm-specific and general experience; and the number of companies and industries the analyst follows. However, the results below are not sensitive to multicollinearity—we obtain essentially the same results when we omit either member of the highly correlated pairs of variables from the analysis.

Panel C of Table I shows that forecast boldness is related to analyst characteristics. We provide further evidence on analysts' tendency to issue bold forecasts by examining whether their average boldness is correlated across years. We compute mean boldness measures for all the firms an analyst follows in a particular year, along with mean forecast horizon, forecast accuracy, and forecast frequency (results are not reported in the tables). Then, we compute the correlation between the means in successive years for 7,072 analysts with sufficient data to calculate successive year means. The correlations are 0.064 for boldness, 0.112 for forecast horizon, 0.095 for accuracy, and 0.272 for forecast frequency, all significant at better than the 1% level. This suggests that an analyst's mean forecast boldness over all of the firms the analyst follows is stable enough to be significantly correlated across years.[14]

B. The Association between Forecast Boldness and Analyst Characteristics

Panel A of Table II reports the results of estimating a logit model explaining the incidence of forecast boldness using analyst characteristics. Consistent with Hong et al. (2000), we find that general experience is significantly positively associated with forecast boldness. The odds of observing a bold forecast from an analyst with the highest general experience level are 1.124 times larger than the odds of observing a bold forecast from an analyst with the lowest general

[14] The correlation between successive year means of the distance between the revised forecast and the prerevision consensus for individual analysts (*YTD_Dist*2) is 0.089, significant at better than the 1% level. This further suggests that boldness may be a stable analyst characteristic.

experience level.[15] In addition to the general experience effect documented by Hong et al. we find that several other variables are associated with forecast boldness. The odds of observing a bold forecast increase with forecast horizon, prior accuracy, brokerage size, and forecast frequency. The odds of observing a bold forecast decrease with days elapsed since the last forecast and the number of industries an analyst follows. Except for days elapsed since the prior forecast, these other variables are *at least as* strongly associated with the likelihood of a bold forecast as is general experience. For example, the odds ratio of forecast frequency is 1.318, compared with 1.124 for general experience.[16]

Panel B of Table II reports regression model results for boldness defined as the distance of the analyst's revised forecast from the prerevision consensus forecast, *YTD_Dist*2. The results are consistent with the Panel A results. Consistent with Hong et al. (2000), *YTD_Dist*2 increases with general experience; *YTD_Dist*2 also increases with days elapsed since the prior forecast, forecast horizon, brokerage size, forecast frequency, and the number of companies the analyst follows; and declines with the number of industries the analyst follows. The positive coefficient on the number of companies appears to be due to multicollinearity, since it is insignificant when we exclude the number of industries from the model. Thus, most variables are significant *and* have the same sign with both boldness measures (forecast horizon, brokerage size, forecast frequency, general experience, and the number of industries the analyst follows) or are insignificant with both (firm experience).

Hong et al. (2000) show that inexperienced analysts are more likely to leave the sample after providing inaccurate or bold forecasts, and they conclude that analysts herd in response to their career concerns. The results above extend Hong et al. (2000) by showing that several analyst characteristics beyond experience are associated with boldness, and they suggest two possibilities. The first is that analyst characteristics that are associated with forecast boldness are also associated with analyst turnover such that career concerns fully explain herding behavior. The second possibility is that some characteristics that are associated with increased herding are *not* associated with increased analyst turnover, suggesting that herding behavior is partly driven by factors other than career concerns. This possibility is important because theory proposes that analysts' self-assessed ability is an alternative motivator to career concerns for boldness. We investigate whether analysts' self-assessed ability as well as their career concerns motivate boldness by estimating a logit model of

[15] We base this inference on the fact that experience and the other explanatory variables are scaled to range from 0 for the lowest level of a particular characteristic among all analysts providing a forecast for a given firm in a particular year, to 1 for the highest level of the characteristic among all analysts providing a forecast for that firm-year. The odds ratio is the difference in odds for one unit of the explanatory variable (analyst characteristic), which by construction corresponds to the difference between the lowest and the highest levels of the characteristic.

[16] Trueman (1994, p. 107) predicts that both firm-specific and general experience are associated with increased forecast boldness—specifically that an analyst who has not been providing forecasts long or who has recently changed the set of firms covered is more likely to herd. The univariate comparisons in Table I, Panel B show that bold forecasters on average have more firm-specific and general experience. However, firm-specific experience is only significantly (positively) associated with forecast boldness in the logistic analysis when general experience is excluded from the model.

Table II

The Association between Forecast Boldness and Analyst Characteristics

This table reports the association between forecast boldness and analyst characteristics. The characteristics, all scaled to range from 0 to 1 within each firm-year, are *DaysElapsed*, the number of days since any analyst's prior forecast; *ForHorizon*, the number of days from the forecast date to the fiscal year-end; *LagAccuracy*, the analyst's prior year absolute forecast accuracy for the firm; *BrokerSize*, the number of analysts in the analyst's brokerage in each year; *FirmExperience*, the analyst's years of experience forecasting a particular firm's earnings; *GenExperience*, the analyst's overall years of forecasting experience; *Companies*, the number of companies the analyst follows in each year; and *Industries*, the number of two-digit SIC industries the analyst follows in each year. Panel A reports the estimation results for a logit model of the association between forecast boldness and analyst and forecast characteristics. Forecasts in Panel A are classified as bold ($Bold = 1$) if they are above both the analyst's prior forecast and the consensus, or else below both. All other forecasts (i.e., forecasts that are between the analyst's own prior forecast and the consensus forecast) are classified as herding ($Bold = 0$). In Panel B, boldness is measured using the distance of the analyst's revised forecast from the prerevision consensus forecast (*YTD_Dist*2). This measure is scaled to range from 0 to 1 for each firm-year. Panel B reports regression model results for the association between *YTD_Dist*2 and analyst and forecast characteristics. $N = 57{,}596$.

Panel A: Logit Model Estimates with Forecast Boldness Measured Using Forecast Revisions

$$\begin{aligned} Bold_{ijt} &= \alpha_0 + \alpha_1 DaysElapsed_{ijt} + \alpha_2 ForHorizon_{ijt} + \alpha_3 LagAccuracy_{ijt} \\ &\quad + \alpha_4 BrokerSize_{ijt} + \alpha_5 ForFrequency_{ijt} + \alpha_6 FirmExperience_{ijt} \\ &\quad + \alpha_7 GenExperience_{ijt} + \alpha_8 Companies_{ijt} + \alpha_9 Industries_{ijt} + \varepsilon_{ijt}. \end{aligned}$$

				Odds Ratio Estimates		
	Parameter	Chi-Square	Significance	Point Estimate	95% Confidence Limits	
Intercept	0.6540	456.26	<0.001			
DaysElapsed	−0.0591	6.28	0.013	0.943	0.900	0.987
ForHorizon	0.3107	146.96	<0.001	1.364	1.298	1.435
LagAccuracy	0.1483	39.82	<0.001	1.160	1.108	1.214
BrokerSize	0.2030	65.40	<0.001	1.225	1.166	1.287
ForFrequency	0.2765	117.18	<0.001	1.318	1.254	1.386
FirmExperience[a]	0.0171	0.38	0.540	1.017	0.963	1.074
GenExperience	0.1168	16.59	<0.001	1.124	1.062	1.189
Companies[b]	−0.0134	0.19	0.664	0.987	0.929	1.048
Industries	−0.1803	36.27	<0.001	0.835	0.787	0.885
Likelihood ratio chi-square		423.2	<0.001			

(*continued*)

analysts' continued employment that extends the Hong et al. (2000) model by including additional potential explanatory variables for the analyst's continued employment after issuing a bold forecast:

$$\begin{aligned} Employ_{it+1} &= \varphi_0 + \varphi_1 Accuracy_{it} + \varphi_2 Bold_{it} + \varphi_3 Bold_{it} \times IAccuracy_{it} \\ &\quad + \varphi_4 Bold_{it} \times IBrokerSize_{it} + \varphi_5 Bold_{it} \times IForFrequency_{it} \\ &\quad + \varphi_6 Bold_{it} \times IFirmExperience_{it} + \varphi_7 Bold_{it} \times IGenExperience_{it} \\ &\quad + \varphi_8 Bold_{it} \times ICompanies_{it} + \varphi_9 Bold_{it} \times IIndustries_{it} \\ &\quad + \varphi_{10} ForHorizon_{it} + \varphi_{11} FYE\_Dist_{it} + \varepsilon_{it}, \end{aligned} \tag{7}$$

Table II—*Continued*

Panel B: Regression Model Estimates with Forecast Boldness Measured Using the Distance of the Revised Forecast from the Prerevision Consensus Forecast

$$YTD\_Dist2_{ijt} = \alpha_0 + \alpha_1 DaysElapsed_{ijt} + \alpha_2 ForHorizon_{ijt} + \alpha_3 LagAccuracy_{ijt} + \alpha_4 BrokerSize_{ijt} + \alpha_5 ForFrequency_{ijt} + \alpha_6 FirmExperience_{ijt} + \alpha_7 GenExperience_{ijt} + \alpha_8 Companies_{ijt} + \alpha_9 Industries_{ijt} + \varepsilon_{ijt}.$$

	Parameter (t-Statistics)
Intercept	0.2724*
	(53.11)
DaysElapsed	0.0357*
	(9.11)
ForHorizon	0.2134*
	(50.79)
LagAccuracy	−0.0021
	(−0.55)
BrokerSize	0.0588*
	(14.24)
ForFrequency	0.0114*
	(2.73)
FirmExperience[c]	0.0010
	(0.22)
GenExperience	0.0147*
	(3.11)
Companies[d]	0.0210*
	(4.12)
Industries	−0.0248*
	(−4.98)
R^2	0.054

Panel A: Percent concordant 54.7; Percent discordant 43.8; Percent tied 1.5.
[a]When either *FirmExperience* or *GenExperience* is excluded from the model, the coefficient of the remaining variable is positive and significant at the 1% level.
[b]When either *Companies* or *Industries* is excluded from the model, the coefficient of the remaining variable is positive and significant at the 1% level.
[c]When either *FirmExperience* or *GenExperience* is omitted from the model, the coefficient of the remaining variable is significantly positive at the 5% level.
[d]When *Companies* is excluded from the model, the coefficient of *Industries* is significantly negative at the 1% level. When *Industries* is excluded from the model, the coefficient of *Companies* is statistically insignificant.
*Significant at the 1% level.

where

$Employ_{it+1}$ is an indicator variable for continued employment in year $t+1$. It is equal to 1 if analyst i remains in the I/B/E/S sample in year $t+1$ after providing a forecast in year t, and is 0 otherwise.

$Accuracy_{it}$ is the mean of analyst i's forecast accuracy measure, $Accuracy_{ijt}$, over all firms j for which the analyst provides a forecast in year t.

$Bold_{it}$ is the mean of analyst i's boldness measure, $Bold_{ijt}$, over all firms j for which the analyst provides a forecast in year t.

$ICharacteristic_{it}$ is an indicator variable for analyst characteristics, $Characteristic_{ijt}$ ($Accuracy_{ijt}$, $BrokerSize_{ijt}$, $ForFrequency_{ijt}$, $FirmExperience_{ijt}$, $GenExperience_{ijt}$, $Companies_{ijt}$, and $Industries_{ijt}$). $Characteristic_{ijt}$ is scaled to range from 0 to 1 within each firm-year for each variable. $ICharacteristic_{ijt}$ is equal to 1 if the mean value of the characteristic over all firms j for which analyst i provides a forecast in year t exceeds 0.5, and is 0 otherwise.

$ForHorizon_{it}$ is the mean amount of time between analyst i's forecast and the fiscal year-end, $ForHorizon_{ijt}$, over all firms j for which the analyst provides a forecast in year t.

FYE_Dist_{it} is the mean absolute distance of analyst i's forecast from the fiscal-year-end consensus forecast, FYE_Dist_{ijt}, over all firms j for which the analyst provides a forecast in year t.

Based on Hong et al. (2000) finding that the likelihood that an analyst leaves the sample (i.e., $Employ_{it+1} = 0$) declines with forecast accuracy and increases with boldness, we expect the forecast accuracy coefficient (φ_1) to be positive and the forecast boldness coefficient (φ_2) to be negative.[17] Furthermore, Hong et al. find that among bold forecasters, inexperienced analysts are more likely to leave the sample than are experienced analysts, and we therefore expect the differential coefficients for bold forecasters with high levels of firm-specific and general experience (φ_6 and φ_7) to be positive. We include the mean amount of time between the analyst's last forecast and the end of the fiscal period (*ForHorizon*) to control for the possibility that some analysts exit the sample during the year and stop providing forecasts, and also because analysts who do not update their forecasts may be more likely to exit the sample. We expect this coefficient to be negative. We include the distance of the analyst's forecast from the fiscal-year-end consensus (*FYE_Dist*) in the model because analysts whose forecasts deviate from the year-end consensus may face adverse career consequences, all else equal. We expect the coefficient on *FYE_Dist* (φ_{11}) to be negative.

The forecast boldness analysis shows that the likelihood that a forecast is bold increases with brokerage size and general experience, and it declines with the number of industries the analyst follows. If career concerns fully explain analysts' herding behavior, then the likelihood that they remain in the sample after issuing a bold forecast should also increase with brokerage size and general experience, and decline with the number of industries followed. We report estimation results for the employment model in Table III, Panel A. The sample includes 9,200 analyst–year observations, compared with 57,596 analyst–firm–year observations in the original sample. Consistent with Hong et al. (2000), we find a significant positive coefficient on forecast accuracy and a significantly

[17] Mikhail, Walther, and Willis (1999) also report that analyst turnover increases as the analyst's forecast accuracy declines.

positive interaction coefficient for forecast boldness with general experience (6% significance level), indicating that experienced analysts are less likely to exit the sample after issuing a bold forecast.[18] We find significant negative coefficients on forecast horizon and the distance of the forecast from the fiscal-year-end consensus.[19]

The results also suggest motivations other than career concerns for boldness. Analysts employed by big brokerages are *more* likely to issue bold forecasts than others, but they appear to face similar separation prospects after issuing a bold forecast (the coefficient on bold forecasts for big-brokerage analysts in the employment model is statistically insignificant). And analysts who cover a large number of firms or industries are *more* likely to remain in the sample after issuing a bold forecast than other analysts. However, the results in Table II show that the tendency to issue bold forecasts is unrelated to the number of companies the analyst follows (Panel A), but analysts who follow a large number of industries are *less* likely to issue bold forecasts than others. Thus, bold analysts who follow large numbers of firms or industries appear to enjoy greater job security than other bold analysts, but this greater job security does not appear to increase the frequency with which those analysts issue bold forecasts. Instead, analysts who follow large numbers of industries appear to issue *fewer* bold forecasts than other analysts. This phenomenon is more readily explained by the analyst's self-assessed ability (Scharfstein and Stein (1990), Trueman (1994)) than by career concerns. Specifically, prior research finds that forecast accuracy declines with the number of companies and industries analysts follow, perhaps due to analysts' inability to develop and use specialized knowledge when they follow many companies or industries. Those analysts may be more reticent to issue bold forecasts even though they are less likely to be penalized for doing so than more specialized analysts. In sum, the results suggest that the association between analyst characteristics and forecast boldness is more complex than is suggested by Hong et al. (2000). In particular, both career concerns and the analyst's self-assessed ability appear to contribute to boldness.

In Table III, Panel B, we report results for the employment model with the mean distance of forecasts from the year-to-date consensus over all the firms the analyst follows, YTD_Dist2_{it}, in place of the boldness indicator variable. The results are consistent with the Panel A results. The likelihood that the

[18] The forecast boldness coefficient is not statistically significant in this model, but is significantly negative when we define forecast boldness based on the distance from the year-to-date consensus forecast below.

[19] When we exclude forecast horizon from the model, the boldness-interaction coefficients for forecast frequency and distance from the year-end consensus are significantly positive and negative, respectively. In addition, the forecast boldness coefficient becomes significantly negative. As Table I shows, bold forecast revisions tend to occur earlier in the year than herding forecast revisions. These results suggest that low forecast frequency and deviation from the consensus are sometimes due to analysts leaving the sample during the year and issuing no forecasts near the fiscal year-end. A second possibility is that analysts leave the sample in part because they are slow to update their forecasts.

Table III

The Association between Analyst Characteristics and Analyst Retention: Logit Model Estimates for Individual Analysts

The logit models in Panels A and B investigate whether analyst characteristics affect the employment consequences of issuing bold forecasts. There are 9,200 analyst–year observations. The dependent variable, *Employ*, is one if the analyst remains in the sample in year $t + 1$ and zero otherwise. In Panel A, individual forecasts revisions are classified as bold ($Bold = 1$) if they are above both the analyst's prior forecast and the consensus, or else below both, and zero otherwise. The boldness measure in the model is the mean of *Bold* for all the firms the analyst follows each year. This mean *Bold* measure is interacted with indicator variables for scaled analyst and forecast characteristics: Forecast accuracy, brokerage size, forecast frequency, firm experience, general experience, and the number of companies and industries the analyst follows. The indicator variable is one if the mean scaled characteristic across the firms the analyst follows in a particular year exceeds 0.5, and zero otherwise. For example, $Bold_{it} \times IGenExperience_{it}$ equals analyst i's average boldness measure in year t if that analyst's mean scaled general experience over all the firms j the analyst follows ($GenExperience_{ijt}$) is above 0.5 in year t (i.e., $IGenExperience_{it} = 1$), and is zero otherwise ($IGenExperience_{it} = 0$). In Panel B, forecast boldness is measured as the scaled distance of the analyst's forecast from the prerevision mean forecast (YTD_Dist2_{ijt}). This distance measure is then averaged over all the firms the analyst follows in each year to derive YTD_Dist2_{it}. Similar to Panel A, the boldness measure is interacted with indicator variables for forecast accuracy, brokerage size, forecast frequency, firm experience, general experience, and the number of companies and industries the analyst follows. In addition to the interactions, the explanatory variables in both panels include the mean scaled values over all the firms the analyst follows in year t for forecast accuracy, forecast boldness, forecast horizon (the number of days from the forecast date to the fiscal year-end), and the distance of the analyst's forecast from the fiscal year-end consensus forecast estimate.

Panel A: Forecast Boldness Is Measured Using Forecast Revisions

$$\begin{aligned} Employ_{it+1} = {} & \varphi_0 + \varphi_1 Accuracy_{it} + \varphi_2 Bold_{it} + \varphi_3 Bold_{it} \times IAccuracy_{it} \\ & + \varphi_4 Bold_{it} \times IBrokerSize_{it} + \varphi_5 Bold_{it} \times IForFrequency_{it} + \varphi_6 Bold_{it} \\ & \times IFirmExperience_{it} + \varphi_7 Bold_{it} \times IGenExperience_{it} + \varphi_8 Bold_{it} \times ICompanies_{it} \\ & + \varphi_9 Bold_{it} \times IIndustries_{it} + \varphi_{10} ForHorizon_{it} + \phi_{11} FYE\_Dist_{it} + \varepsilon_{it}. \end{aligned}$$

				Odds Ratio Estimates		
	Parameter	Chi-Square	Significance	Point Estimate	95% Confidence Limits	
Intercept	2.7316	398.92	<0.001			
Accuracy	0.3167	5.60	0.018	1.373	1.056	1.784
Bold	−0.0757	0.42	0.517	0.927	0.738	1.165
Bold × *IAccuracy*	0.1705	3.81	0.051	1.186	0.999	1.407
Bold × *IBrokerSize*	0.1166	2.46	0.117	1.124	0.971	1.300
Bold × *IForFrequency*	0.1666	3.49	0.062	1.181	0.992	1.407
Bold × *IFirmExperience*[a]	−0.0663	0.47	0.495	0.936	0.774	1.132
Bold × *IGenExperience*	0.1757	3.78	0.052	1.192	0.999	1.423
Bold × *ICompanies*[b]	0.7702	50.68	<0.001	2.160	1.747	2.670
Bold × *IIndustries*	0.4633	21.80	<0.001	1.589	1.308	1.930
ForHorizon	−0.0153	635.99	<0.001	0.985	0.984	0.986
FYE_Dist	−0.5753	23.15	<0.001	0.563	0.445	0.711
Likelihood ratio chi-square		1698.58	<0.001			

(*continued*)

Table III—*Continued*

Panel B: Forecast Boldness Is Measured Using the Distance of the Revised Forecast from the Prerevision Consensus Forecast

$$Employ_{it+1} = \varphi_0 + \varphi_1 Accuracy_{it} + \varphi_2 YTD\_Dist2_{it} + \varphi_3 YTD\_Dist2_{it} \times Accuracy_{it} + \varphi_4 YTD\_Dist2_{it} \times IBrokerSize_{it} + \varphi_5 YTD\_Dist2_{it} \times IForFrequency_{it} + \varphi_6 YTD\_Dist2_{it} \times IFirmExperience_{it} + \varphi_7 YTD\_Dist2_{it} \times IGenExperience_{it} + \varphi_8 YTD\_Dist2_{it} \times ICompanies_{it} + \varphi_9 YTD\_Dist2_{it} \times IIndustries_{it} + \varphi_{10} ForHorizon_{it} + \phi_{11} FYE\_Dist_{it} + \varepsilon_{it}.$$

				Odds Ratio Estimates		
	Parameter	Chi-Square	Significance	Point Estimate	95% Confidence Limits	
Intercept	2.9061	543.13	<0.001			
Accuracy	0.3608	7.28	0.007	1.434	1.104	1.864
YTD_Dist2	−0.3320	5.14	0.024	0.717	0.539	0.956
YTD_DiST2 × *IAccuracy*	0.2198	2.69	0.102	1.246	0.958	1.620
YTD_Dist2 × *IBrokerSize*	0.1183	1.07	0.302	1.126	0.899	1.409
YTD_Dist2 × *IForFrequency*	0.1156	0.66	0.419	1.123	0.849	1.485
YTD_Dist2 × *IFirmExperience*[c]	−0.0885	0.35	0.554	0.915	0.683	1.227
YTD_Dist2 × *IGenExperience*	0.3132	5.13	0.024	1.368	1.043	1.793
YTD_Dist2 × *ICompanies*[d]	1.1646	47.27	<0.001	3.205	2.299	4.467
YTD_Dist2 × *IIndustries*	0.7474	22.71	<0.001	2.111	1.553	2.871
ForHorizon	−0.0156	650.58	<0.001	0.985	0.983	0.986
FYE_Dist	−0.6248	27.01	<0.001	0.535	0.423	0.678
Likelihood ratio chi-square		1691.89	<0.001			

Panel A: Percent concordant 75.1; Percent discordant 24.5; Percent tied 0.4.
Panel B: Percent concordant 74.8; Percent discordant 24.8; Percent tied 0.4.

[a]When *Bold* × *IFirmExperience* is excluded from the model, the coefficient of *Bold* × *IGenExperience* is positive and significant at better than the 7% level. When *Bold* × *IGenExperience* is excluded from the model, the coefficient of *Bold* × *IFirmExperience* is not statistically significant.

[b]When either *Bold* × *ICompanies* or *Bold* × *IIndustries* is excluded from the model, the coefficient of the remaining variable is positive and significant at better than the 1% level.

[c]When *YTD_Dist*2 × *IFirmExperience* is excluded from the model, the coefficient of *YTD_Dist*2 × *IGenExperience* is positive and significant at better than the 3% level. When *YTD_Dist*2 × *IGenExperience* is excluded from the model, the coefficient of *YTD_Dist*2 × *IFirmExperience* is not statistically significant.

[d]When either *YTD_Dist*2 × *ICompanies* or *YTD_Dist*2 × *IIndustries* is excluded from the model, the coefficient of the remaining variable is positive and significant at better than the 1% level.

analyst remains in the sample increases with forecast accuracy and declines with forecast horizon. Consistent with Hong et al. (2000), the boldness coefficient is significantly negative under this definition of forecast boldness. Analysts employed by big brokerages and frequent forecasters tend to issue bold forecasts more frequently than other analysts (Table II), but appear to face similar separation prospects to other analysts after issuing bold forecasts. The likelihood that analysts who issue bold forecasts remain in the sample increases with general experience and with the number of companies or industries the analyst follows.

Table IV

The Association between Forecast Accuracy and Analyst Characteristics, Including Forecast Boldness

$$\begin{aligned} Accuracy_{ijt} = {} & \beta_0 + \beta_1 DaysElapsed_{ijt} + \beta_2 ForHorizon_{ijt} + \beta_3 LagAccuracy_{ijt} + \beta_4 BrokerSize_{ijt} \\ & + \beta_5 ForFrequency_{ijt} + \beta_6 FirmExperience_{ijt} + \beta_7 GenExperience_{ijt} + \beta_8 Companies_{ijt} \\ & + \beta_9 Industries_{ijt} + \beta_{10} FYE\_Dist_{ijt} + \beta_{11} YTD\_Dist2_{ijt} + \beta_{12} Bold_{ijt} + \varepsilon_{ijt}. \end{aligned}$$

This table reports the association between forecast accuracy and analyst and forecast characteristics, along with two alternative measures of forecast boldness. The characteristics, all scaled to range from 0 to 1 within each firm-year, are *DaysElapsed*, the number of days since any analyst's prior forecast; *ForHorizon*, the number of days from the forecast date to the fiscal year-end; *LagAccuracy*, the analyst's prior-year absolute forecast accuracy for the firm; *BrokerSize*, the number of analysts in the analyst's brokerage in each year; *FirmExperience*, the analyst's years of experience forecasting a particular firm's earnings; *GenExperience*, the analyst's overall years of forecasting experience; *Companies*, the number of companies the analyst follows in each year; and *Industries*, the number of two-digit SIC industries the analyst follows in each year. The boldness measures are *Bold*, which is one if the analyst's forecast revision is above both the analyst's prior forecast and the consensus, or else below both, and zero otherwise, and *YTD_Dist2*, the scaled distance of the analyst's revised forecast from the prerevision consensus forecast. The model includes the scaled distance of the analyst's forecast from the overall consensus (*FYE_Dist*) as a control. Coefficient t-statistics are in parentheses.

	All Observations $N = 57{,}596$		Bold Forecasts $N = 42{,}223$	Herding Forecasts $N = 15{,}373$
Intercept	0.7019**	0.6664**	0.7220**	0.6688**
	(135.24)	(118.30)	(118.90)	(66.83)
DaysElapsed	−0.0245**	−0.0234**	−0.0261**	−0.0183*
	(−6.44)	(−6.14)	(−5.92)	(−2.46)
ForHorizon	−0.1258**	−0.1291**	−0.1499**	−0.0738**
	(−28.13)	(−28.90)	(−28.94)	(−8.36)
LagAccuracy	0.0482**	0.0468**	0.0479**	0.0430**
	(12.66)	(12.33)	(10.81)	(5.86)
BrokerSize	0.0141**	0.0129**	0.0140**	0.0085
	(3.48)	(3.20)	(2.99)	(1.08)
ForFrequency	0.0435**	0.0411**	0.0393**	0.0431**
	(10.64)	(10.08)	(8.27)	(5.46)
FirmExperience[a]	0.0151**	0.0150**	0.0143**	0.0161
	(3.39)	(3.37)	(2.78)	(1.81)
GenExperience	0.0014	0.0003	0.0000	0.0009
	(0.30)	(0.06)	(0.01)	(0.10)
Companies[b]	−0.0246**	−0.0242**	−0.0251**	−0.0222*
	(−4.95)	(−4.89)	(−4.35)	(−2.32)

(*continued*)

C. Forecast Accuracy, Forecast Boldness, and Analyst Characteristics

We report estimates of the forecast accuracy model in Table IV for the full sample, both including and excluding a dummy variable to indicate forecast boldness. We also report results separately for bold and herding forecasts. The

Table IV—*Continued*

	All Observations $N = 57{,}596$		Bold Forecasts $N = 42{,}223$	Herding Forecasts $N = 15{,}373$
Industries	−0.0113*	−0.0099*	−0.0123*	−0.0028
	(−2.34)	(−2.05)	(−2.18)	(−0.30)
FYE_Dist	−0.3413**	−0.3335**	−0.3222**	−0.3612**
	(−79.15)	(−77.01)	(−63.87)	(−42.68)
*YTD_Dist*2	0.0344**	0.0195**	0.0375**	−0.0379**
	(8.42)	(4.65)	(7.92)	(−4.22)
Bold		0.0569**		
		(16.02)		
R-squared	0.178	0.181	0.174	0.183

*Significant at the 5% level.
**Significant at the 1% level.
[a]When *FirmExperience* is excluded from the model, the coefficient of *GenExperience* is positive and statistically significant in the full sample without the bold dummy variable and in the full sample with the bold dummy variable (5% significance level). The coefficient is statistically insignificant in the remaining models. When *GenExperience* is excluded from the model, the coefficient of *FirmExperience* is positive and significant at better than the 1% level in the full sample and in the bold subsample and at the 5% level in the herding subsample.
[b]When *Companies* or *Industries* is excluded from the model, the coefficient of the remaining variable is significantly negative at the 1% level except in the herding subsample, where the *Industries* coefficient is significant at the 10% level when *Companies* is excluded from the model.

regression model results are consistent with the univariate comparisons in Table I, Panel C. Most notably, the coefficient of the bold forecast dummy variable is significantly positive, indicating that bold forecast revisions tend to be significantly more accurate than herding forecast revisions. Furthermore, the coefficient of the alternate boldness measure, distance of the forecast from the year-to-date consensus (*YTD_Dist*2), is also significantly positive except in the herding subsample, where it is significantly negative. Thus, forecast accuracy increases with the distance of the forecast from the prerevision consensus, except for herding forecast revisions, where accuracy *declines* with distance from the consensus.

The distance from the year-end consensus (*FYE_Dist*) is significantly negatively related to forecast accuracy. The remaining coefficient estimates are generally consistent with prior research (Clement (1999), Clement and Tse (2003)). Lagged forecast accuracy, brokerage size, forecast frequency, and firm experience are significantly associated with increased forecast accuracy, while days elapsed since the prior forecast, forecast horizon, and the number of companies and industries the analyst follows are associated with lower forecast accuracy. Firm-specific experience appears to be more closely related to forecast accuracy than is general experience. In summary, forecast boldness is associated with increased forecast accuracy even after we control for analyst characteristics that prior research finds to be associated with forecast accuracy.

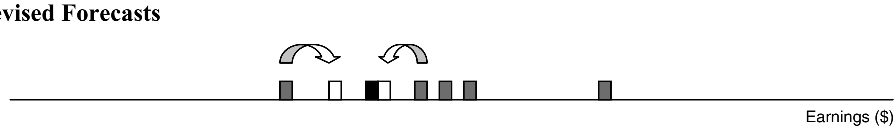
D. The Association between Analysts' Forecast Errors and Forecast Boldness

We next provide evidence both on whether analysts revise their forecasts to a smaller extent than is warranted by their private information and whether this tendency is different for bold and herding forecasts. The descriptive statistics in Table I (Panel C) suggest that herding analysts' prerevision forecasts are on average farther from the prerevision consensus than are bold analysts' prerevision forecasts. In Figure 4, we illustrate a possible scenario for forecast revisions in which (1) prerevision forecasts differ, (2) forecast revisions are positively associated with forecast errors, and (3) this association differs for bold and herding forecast revisions. This scenario is consistent with Trueman's (1994) prediction. To examine this issue empirically, we regress forecast errors on the forecast revision and its interaction with analyst and forecast characteristics, including boldness, and report the results in Table V. The forecast revision coefficient is positive and significant, suggesting that individual analysts' forecast errors are to some extent predictable from their forecast revisions. When forecast boldness is included in the model, the forecast revision coefficient (which is the coefficient for herding forecasts when the model includes a slope dummy for bold forecasts) increases from its level in the original overall sample estimation.

Original Forecasts

The analyst with the lowest forecast issues a herding forecast revision, and the analyst with the second-lowest forecast issues a bold forecast revision. Actual earnings (denoted by the solid rectangle) are closer to the bold analyst's forecast than to the herding analyst's forecast. Each analyst's forecast error is the difference between actual earnings and the analyst's revised forecast.

Revised Forecasts



In this case, both analysts' forecast errors are positively related to their forecast revisions. That is, the lowest analyst's forecast revision is positive, as is the forecast error. The second-lowest analyst's forecast revision and forecast error are both negative. However, the bold analyst's forecast revision is large in relation to the forecast error. In contrast, the herding analyst's forecast revision is small relative to that analyst's forecast error.

Figure 4. Bold and herding forecast revisions and forecast errors. Analyst forecast revisions may be associated with the analysts' forecast errors based on reported earnings. This figure illustrates one possible scenario for the association between analysts' forecast revisions and their forecast errors.

Table V

The Association between Analysts' Forecast Revisions and Their Forecast Errors

$$\begin{aligned} ERRP_{ijt} = {} & \delta_0 + \gamma_0 REVP_{ijt} + \gamma_1 REVP_{ijt} \times DaysElapsed_{ijt} + \gamma_2 REVP_{ijt} \times ForHorizon_{ijt} \\ & + \gamma_3 REVP_{ijt} \times LagAccuracy_{ijt} + \gamma_4 REVP_{ijt} \times BrokerSize_{ijt} + \gamma_5 REVP_{ijt} \\ & \times ForFrequency_{ijt} + \gamma_6 REVP_{ijt} \times FirmExperience_{ijt} + \gamma_7 REVP_{ijt} \times GenExperience_{ijt} \\ & + \gamma_8 REVP_{ijt} \times Companies_{ijt} + \gamma_9 REVP_{ijt} \times Industries_{ijt} + \gamma_{10} REVP_{ijt} \times YTD\_Dist2_{ijt} \\ & + \gamma_{11} REVP_{ijt} \times Bold_{ijt} + \varepsilon_{ijt}. \end{aligned}$$

This table investigates the effect of analyst characteristics on the association between analysts' forecast revisions and the analysts' earnings forecast errors. The dependent variable is the analyst's forecast error deflated by the per-share security price 2 days before the forecast revision date. The explanatory variables are the price-deflated forecast revision, the product of the forecast revision and scaled analyst and forecast characteristics, and the product of the forecast revision and two alternative proxies for forecast boldness. The characteristics, all scaled to range from 0 to 1 within each firm-year, are *DaysElapsed*, the number of days since any analyst's prior forecast; *ForHorizon*, the number of days from the forecast date to the fiscal year-end; *LagAccuracy*, the analyst's prior year absolute forecast accuracy for the firm; *BrokerSize*, the number of analysts in the analyst's brokerage in each year; *FirmExperience*, the analyst's years of experience forecasting a particular firm's earnings; *GenExperience*, the analyst's overall years of forecasting experience; *Companies*, the number of companies the analyst follows in each year; and *Industries*, the number of two-digit SIC industries the analyst follows in each year. The boldness measures are *Bold*, which is one if the analyst's forecast revision is above both the analyst's prior forecast and the consensus, or else below both, and zero otherwise, and *YTD_Dist2*, the scaled distance of the analyst's revised forecast from the prerevision consensus forecast. Coefficient t-statistics are in parentheses.

	All Observations $N = 57{,}596$		Bold Forecasts $N = 42{,}223$	Herding Forecasts $N = 15{,}373$
Intercept	−0.0032**	−0.0032**	−0.0030**	−0.0037**
	(−27.30)	(−27.90)	(−22.58)	(−16.83)
REVP	0.5488**	0.8019**	0.4463**	0.7835**
	(21.11)	(26.45)	(15.60)	(12.17)
REVP × *DaysElapsed*	0.0375	0.0298	0.0869**	−0.1999**
	(1.91)	(1.52)	(4.11)	(−3.88)
REVP × *ForHorizon*	0.4018**	0.4136**	0.4277**	0.3638**
	(19.06)	(19.66)	(18.88)	(6.57)
REVP × *LagAccuracy*	−0.0684**	−0.0521**	−0.0352	−0.1353**
	(−3.55)	(−2.71)	(−1.69)	(−2.73)
REVP × *BrokerSize*	0.0202	0.0205	0.0504*	−0.1310*
	(1.00)	(1.02)	(2.33)	(−2.48)
REVP × *ForFrequency*	0.0349	0.0619**	0.0782**	0.0041
	(1.56)	(2.78)	(3.27)	(0.07)
REVP × *FirmExperience*[a]	−0.0246	−0.0339	−0.0121	−0.1021
	(−1.09)	(−1.50)	(−0.49)	(−1.76)
REVP × *GenExperience*	−0.0204	−0.0134	0.0246	−0.2640**
	(−0.89)	(−0.59)	(1.00)	(−4.35)
REVP × *Companies*[b]	0.0756**	0.0676**	0.0205	0.4233**
	(3.10)	(2.78)	(0.78)	(6.46)

(*continued*)

Table V—*Continued*

	All Observations $N = 57{,}596$		Bold Forecasts $N = 42{,}223$	Herding Forecasts $N = 15{,}373$
$REVP \times Industries$	0.0565*	0.0438	0.0327	0.0075
	(2.34)	(1.82)	(1.26)	(0.12)
$REVP \times YTD\_Dist2$	−0.5950**	−0.5041**	−0.6240**	0.3326**
	(−29.75)	(−24.31)	(−28.31)	(5.53)
$REVP \times Bold$		−0.3722**		
		(−16.13)		
R^2	0.067	0.071	0.061	0.116

*Significant at the 5% level.
**Significant at the 1% level.
[a]When $REVP \times FirmExperience$ is excluded from the model, the coefficient of $REVP \times GenExperience$ is negative and significant in the overall sample without the bold dummy (10% significance level) and in the herding subsample (1% level), but is statistically insignificant in the remaining models. When $REVP \times GenExperience$ is excluded from the model, the coefficient of $REVP \times FirmExperience$ is negative and significant in the overall sample without the bold dummy (10% significance level) and with the bold dummy (5% significance level). The coefficient is negative and significant at better than the 1% level in the herding subsample, but is statistically insignificant in the bold subsample.
[b]When $REVP \times Companies$ is excluded from the model, the coefficient of $REVP \times Industries$ is positive and significant at better than the 1% level in all models except the bold subsample, where it is positive and significant at the 5% level. When $REVP \times Industries$ is excluded from the model, the coefficient of $REVP \times Companies$ is positive and significant at better than the 1% level in all models except the bold subsample, where it is positive and significant at the 10% level.

The forecast boldness coefficients ($REVP \times Bold$ and $REVP \times YTD\_Dist2$) are negative and statistically significant, suggesting that forecast boldness reduces the association between forecast revisions and forecast errors.[20]

The results for bold and herding forecast samples are consistent with the overall sample results. The forecast revision coefficient is 0.446 for bold forecasts and 0.784 for herding forecasts. The model explanatory power is 0.06 for the bold forecasts, but is 0.12 for the herding forecasts. Interestingly, the coefficient of $REVP \times YTD\_Dist2$ is significantly positive in the herding subsample, but is significantly negative in the other samples. The forecast accuracy model (Table IV) also shows a different sign for YTD_Dist2 in the herding subsample than in the bold and overall samples, suggesting that the distance from the year-to-date consensus forecast has different implications for bold versus herding forecast *revisions*. Specifically, bold forecast revisions that are far from

[20] The coefficient of the forecast revision is 0.802, and the differential coefficients for *Bold* and YTD_Dist2 are −0.372 and −0.504, respectively. Therefore, the coefficient of the forecast revision for bold forecast revisions that result in the farthest forecasts relative to the prerevision consensus is −0.074, and is statistically significant. This negative coefficient is consistent with Trueman's (1994) prediction that extreme forecast revisions are negatively associated with forecast errors because the forecast revision is larger than is warranted by the analyst's information (Prendergast and Stole (1996)). By comparison, the coefficient for herding forecasts is 0.802.

the year-to-date consensus are associated with increased accuracy (Table IV) and with smaller association between forecast revisions and forecast errors (Table V), but the opposite is true for herding forecast revisions—for analysts who issue herding forecast revisions, distance from the mean is associated with lower accuracy and greater association between forecast revisions and forecast errors. Thus, the implications of a forecast's distance from the consensus differ for bold versus herding forecast revisions.

Collectively, analyst characteristics are statistically significant in Table V. Most notably, the coefficient for forecast horizon is significantly positive—analysts appear more likely to provide forecasts that fully reflect their private information as the fiscal year progresses. However, the coefficient estimates are small and insignificant for most of the characteristics, indicating that analyst characteristics play a relatively minor role in explaining the extent to which analysts incorporate their private information in their forecasts.[21]

The results above suggest that bold analysts are more likely to incorporate new information in their forecasts than herding analysts. We investigate differences in the information underlying forecast revisions by estimating the association between improvements in analysts' forecast accuracy and analyst characteristics:

$$\begin{aligned} Improve_{ijt} = {} & \phi_0 + \phi_1 DaysElapsed_{ijt} + \phi_2 ForHorizon_{ijt} + \phi_3 LagAccuracy_{ijt} \\ & + \phi_4 BrokerSize_{ijt} + \phi_5 ForFrequency_{ijt} + \phi_6 FirmExperience_{ijt} \\ & + \phi_7 GenExperience_{ijt} + \phi_8 Companies_{ijt} + \phi_9 Industries_{ijt} \\ & + \phi_{10} YTD\_Dist1_{ijt} + \phi_{11} YTD\_Dist2_{ijt} + \phi_{12} Bold_{ijt} + \varepsilon_{ijt}, \end{aligned} \tag{8}$$

where

$Improve_{ijt}$ is the difference between the absolute forecast error for analyst *i*'s revised forecast for firm *j* in year *t* and the absolute forecast error for the prerevision forecast, scaled by the end-of-day stock price 2 days prior to the revision.

If bold analysts are more likely to provide useful new information in their revisions than herding analysts, then the coefficients of *Bold* and *YTD_Dist2* should be significantly positive. We include analyst characteristics as explanatory variables, along with the year-to-date distance measure for the prerevision forecast. The results, reported in Table VI, show a positive coefficient on the forecast horizon (early forecasts show greater improvement than later forecasts) and a negative coefficient on forecast frequency (frequent forecasters

[21] The estimated effects of other analyst characteristics (such as prior forecast accuracy) on the association between forecast revisions and forecast errors further support Trueman's (1994) predictions. In the full-sample model (excluding the forecast boldness variable), the revision-interaction coefficient for prior accuracy is significantly negative (1% level), while the interaction coefficients for the number of companies and industries the analyst follows are positive and significant at better than the 5% level. Therefore, the association between forecast revisions and forecast errors is smaller for analysts with high prior accuracy and who follow relatively few companies and industries—all characteristics that are associated with increased forecast accuracy.

Table VI

The Association between Improvements in Forecast Accuracy and Analyst Characteristics, Including Forecast Boldness

$$\begin{aligned} Improve_{ijt} = {} & \phi_0 + \phi_1 DaysElapsed_{ijt} + \phi_2 ForHorizon_{ijt} + \phi_3 LagAccuracy_{ijt} \\ & + \phi_4 BrokerSize_{ijt} + \phi_5 ForFrequency_{ijt} + \phi_6 FirmExperience_{ijt} \\ & + \phi_7 GenExperience_{ijt} + \phi_8 Companies_{ijt} + \phi_9 Industries_{ijt} + \phi_{10} YTD\_Dist1_{ijt} \\ & + \phi_{11} YTD\_Dist2_{ijt} + \phi_{12} Bold_{ijt} + \varepsilon_{ijt}. \end{aligned}$$

This table reports the association between the improvement in forecast accuracy from the analyst's forecast revision (*Improve*) and two proxies for forecast boldness, along with analyst and forecast characteristics. *Improve* is the difference between the absolute forecast errors for the revised forecast and the prerevision forecast, with this difference scaled by the stock price 2 days before the forecast revision. The characteristics, all scaled to range from 0 to 1 within each firm-year, are *DaysElapsed*, the number of days since any analyst's prior forecast; *ForHorizon*, the number of days from the forecast date to the fiscal year-end; *LagAccuracy*, the analyst's prior year absolute forecast accuracy for the firm; *BrokerSize*, the number of analysts in the analyst's brokerage in each year; *FirmExperience*, the analyst's years of experience forecasting a particular firm's earnings; *GenExperience*, the analyst's overall years of forecasting experience; *Companies*, the number of companies the analyst follows in each year; and *Industries*, the number of two-digit SIC industries the analyst follows in each year. The boldness measures are *Bold*, which is one if the analyst's forecast revision, is above both the analyst's prior forecast and the consensus, or else below both, and zero otherwise, and *YTD_Dist*2, the scaled distance of the analyst's revised forecast from the prerevision consensus forecast. Coefficient *t*-statistics are in parentheses.

	All Observations $N = 57{,}596$	
Intercept	0.2208**	0.0279
	(12.44)	(1.40)
DaysElapsed	−0.0250*	−0.0182
	(−2.01)	(−1.47)
ForHorizon	0.0792**	0.0747**
	(5.81)	(5.50)
LagAccuracy	−0.0018	−0.0032
	(−0.15)	(−0.25)
BrokerSize	0.0016	−0.0008
	(0.12)	(−0.06)
ForFrequency	−0.0900**	−0.0899**
	(−6.70)	(−6.72)
FirmExperience	0.0005	0.0010
	(0.03)	(0.07)
GenExperience	−0.0031	−0.0078
	(−0.21)	(−0.52)
Companies	0.0015	0.0003
	(0.09)	(0.02)
Industries	0.0257	0.0287
	(1.62)	(1.82)
*YTD_Dist*1	0.4553**	0.5467**
	(34.57)	(39.53)
*YTD_Dist*2	0.0982**	0.0382*
	(7.42)	(2.42)
Bold		0.2523**
		(20.91)
R-squared	0.027	0.035

*Significant at the 5% level.
**Significant at the 1% level.
Coefficients in this table are multiplied by 100.

show less improvement on their last forecast revision). The coefficient for forecast boldness is significantly positive for both measures (*YTD_Dist*2 and *Bold*), indicating that bold analysts have greater improvements in their forecast accuracy than herding analysts. Forecast improvements also increase with the distance of the prerevision forecast from the consensus (*YTD_Dist*1), but both boldness measures remain significantly positive when the prerevision distance measure is excluded from the model. Thus, bold analysts appear more likely to incorporate relevant new information in their forecasts than herding analysts.

V. Conclusion

Prior research suggests that analysts' herding behavior when forecasting earnings is influenced by their career concerns. Compared to inexperienced analysts, experienced analysts are more likely to provide bold forecasts and less likely to be discharged afterward (Hong et al. (2000)). However, the association between forecast boldness and other forecast characteristics has remained unexplored. Theory predicts that both career concerns and analysts' self-assessed ability explain forecast boldness, and we therefore examine the association between herding behavior and analyst characteristics other than experience that may be related to self-assessed forecasting ability. The study is also motivated by prior research that finds that the return response to a given forecast revision is stronger for bold forecasts than for herding forecasts (Gleason and Lee (2003), Clement and Tse (2003)). The difference in return responses suggests that investors view bold forecasts as more informative than herding forecasts, but the reasons for this have not previously been examined. Our empirical tests provide evidence on these questions by examining differences in the forecast accuracy of bold versus herding forecasts and by examining whether bold forecasts are more likely to reflect analysts' private information than herding forecasts.

We find that the likelihood that an analyst's forecast revision is bold increases with forecast horizon, prior accuracy, brokerage size, forecast frequency, and general experience, and declines with days elapsed since the prior forecast and the number of industries the analyst follows. Furthermore, some analyst characteristics are at least as closely associated with the incidence of forecast boldness as is experience (e.g., brokerage size, forecast frequency, and the number of industries the analyst follows). These results extend Hong et al. (2000) by demonstrating that other analyst characteristics beyond experience are associated with forecast boldness. We examine career concerns in additional tests and find that boldness is consistent with career concerns as well as with other motivations, most likely analysts' self-assessed forecasting ability. For example, analysts who follow large numbers of industries appear to face *lower* likelihood of adverse career outcomes from issuing bold forecasts, but those analysts are nevertheless *less* likely than other analysts to issue bold forecasts.

The second major finding is that bold forecasts are more accurate than herding forecasts, even after we control for other analyst characteristics. Prior research finds stronger return responses to bold forecast revisions than to herding forecast revisions, and the results suggest that investors may be aware of the superior accuracy of bold forecasts. The results suggest that consensus forecasts that are restricted to bold forecasts may be more accurate than consensus forecasts that weight all forecasts equally.

The third major finding is that herding forecast revisions are more strongly associated with the analyst's forecast error than are bold forecast revisions. This evidence is consistent with Trueman's (1994) conjecture that large (bold) forecast revisions reflect the analyst's private information more completely than do small (herding) forecast revisions. Additional analysis shows that bold forecast revisions are associated with greater improvements in the analyst's forecast accuracy than herding forecast revisions. In summary, bold forecasters appear to possess relevant private information and to incorporate their information in their forecast revisions. In contrast, herding forecasters appear to revise their forecasts with relatively little information—and to revise their forecasts incompletely in light of what little private information they possess.

Future research might focus on analysts who tend to provide bold forecasts across companies and over time. To the extent that forecast boldness indicates that the analyst possesses relevant private information, analysts who consistently provide bold forecasts may be more likely than others to develop and act upon useful private information.

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