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Synopsis

Studying the determinants of management forecast precision is important because a better understanding of the factors affecting management's choice of forecast precision can provide investors and other users with cues about the characteristics of the information contained in the forecasts. In addition, as regulators assess the regulation of voluntary management disclosures, they need to better understand how managers choose among forecast precision disclosure alternatives. Using 16,872 management earnings forecasts collected from 1995 through 2004, we provide strong evidence that forecast precision is negatively associated with the magnitude of the forecast surprise and that this negative association is stronger when the forecast is bad news than when it is good news. We also find that forecast precision is negatively associated with the absolute magnitude of the forecast error that proxies for the forecast uncertainty that managers face when they issue forecasts, and that the negative association is stronger when forecast errors are negative. These results are consistent with greater liability concerns related to bad news forecasts and negative forecast errors, respectively. Our study provides educators and researchers with important insights into management's choice of earnings forecast precision, which is a component of the voluntary disclosure process that is not well understood.

INTRODUCTION

In this study, we extend prior research on the determinants of the precision of management forecasts by examining the association between management forecast precision and the forecast surprise, and between management forecast precision and the forecast error. The forecast surprise can be thought of as the amount (i.e., the sign and magnitude) of the "news" in the management forecast, and the forecast error can be thought of as a measure of management's uncertainty regarding the future earnings realization.

The practice of earnings guidance, and in particular the issuance of management forecasts of earnings, has grown significantly since the Private Securities Litigation Reform Act (PSLRA) was passed by Congress in 1995.[1] Although policy makers provided the "Safe Harbor Rule" in 1979 and the PSLRA in 1995 to protect managers and to induce them to release more forward-looking information (Hirst et al. 2008), evidence suggests that litigation concerns affect management disclosure choices (Baginski et al. 2002). At the time this legislation was adopted, the primary goal of policy makers was to increase broad disclosures of forward-looking information. In addition, forecast precision and accuracy were expected to improve as managers gained experience with providing forward-looking information. Moreover, as the Financial Accounting Standards Board and the International Accounting Standards Committee move to more principles-based standards, there is an expectation that firms will provide more transparent disclosures.

Even with these changes, managers can be expected to act strategically to enhance their reputations and to minimize perceived litigation risk. Thus, to promote more *precise* disclosures in the United States, policy makers should consider the effect of management incentives on management's choice of forecast precision. Moreover, although some forecasts are imprecise, allowing managers to select their forecast precision can help them to convey their level of uncertainty regarding future earnings realizations.

Given that management forecasts of earnings have important consequences,[2] understanding managers' choices regarding forecast attributes is important for investors, regulators, and educators. Baginski et al. (2004) point out that the incentives that cause managers to choose among various forecast characteristics have not been extensively studied, and Hirst et al. (2008, 2) state that "given that managers have substantially greater control over forecast characteristics than they have over forecast antecedents and consequences, it is striking that the decisions managers make about such characteristics are comparatively less understood." Understanding management's choice of forecast precision is important because the choice of precision can provide investors and other users with cues about the characteristics of the information contained in the forecasts. Moreover, understanding the determinants of forecast precision should allow regulators to better evaluate policies related to voluntary management disclosures. Finally, as Hirst et al. (2008, 2) point out, "gaining a better understanding of the choices that managers make once they decide to issue an earnings forecast is an important direction for both theory development and empirical research." Although we are not able to observe the decision process underlying the choice of precision, we can empirically examine some of the tradeoffs that likely underlie management's choice of forecast precision to gain a better understanding of how management chooses forecast precision. This has implications for other voluntary disclosures where managers can exercise significant discretion in the choice of disclosure characteristics.

A small body of the extant accounting literature investigates the determinants of management forecast precision. Although this literature documents that forecast precision varies as expected with the amount of private information (as proxied by analyst following) and public information (as proxied by firm size) (Baginski and Hassell 1997), with product market concentration and forecast venue (Bamber and Cheon 1998), and with forecast horizon (Baginski and Hassell 1997; Bamber and Cheon 1998), prior studies are unable to document an association between the sign of the forecast surprise and forecast precision.[3] Note that this prior research focuses on the difference in forecast precision between good and bad news forecasts, but does not consider the magnitude of the news in the forecast (i.e., the forecast surprise). Furthermore, these studies examine relatively small samples of hand-collected forecasts (and thus have low power) that were made during an earlier period (i.e., the 1980s) when management concerns regarding litigation were likely different from those in more recent periods.

We extend prior studies on forecast precision by focusing on the roles of forecast surprise and forecast uncertainty. We define forecast precision as whether forecasts are point estimates, ranges, minimums or maximums, or qualitative statements. We measure forecast surprise as the absolute value of the difference between management's earnings forecast and the consensus analyst forecast or as the absolute value of the cumulative abnormal returns at the management forecast date. We use the forecast error, which we measure as the absolute value of the difference between management's earnings forecast and actual (*ex post*) earnings, to proxy for management's uncertainty about the eventual earnings realization.[4]

Both the forecast surprise and the forecast uncertainty should be important in management's decision regarding forecast precision because both could be important in any potential litigation. For example, decisions to litigate by the plaintiffs bar would certainly be a function of the price reactions surrounding both the issuance of the forecast and the subsequent earnings realization. The magnitudes of the price reactions can be affected by the choice of precision and management's defence can appeal to "uncertainty" if the issued forecast has low precision.

We expect managers to issue less-precise forecasts when their forecasts include more surprising news (e.g., when their earnings expectations are further from analysts' current expectations), because the magnitude of the surprise will be less evident to investors when management forecasts are less precise. Similarly, we expect that managers will issue less-precise forecasts when they have greater uncertainty about future earnings realizations. Thus, we expect a negative association between forecast precision and forecast surprise, and a negative association between forecast precision and forecast error. Moreover, because we expect managers to be more concerned about a decrease in stock prices (and resultant legal liability) that results from the release of bad news or the release of news with negative signed forecast errors (Skinner 1994, 1997; Atiase et al. 2006),[5] we expect that the negative association between forecast precision and forecast surprise and the negative association between forecast precision and the forecast error will be stronger for bad-news forecasts and for forecasts with negative signed forecast errors. Using a larger sample of more recent management earnings forecasts than used in prior work (i.e., 16,872 firm-year observations collected from the First Call database for the years 1995 through 2004), we perform extensive empirical analyses and find evidence consistent with our expectations. In addition, our inferences are invariant whether we conduct the analyses using our full sample of forecasts or using a restricted sample of only those forecasts with higher precision (i.e., point and range forecasts). Furthermore, our inferences are robust to whether we use a discrete or continuous variable for the level of forecast precision, and to different measures of the magnitude of the forecast surprise. These findings suggest that managers act strategically when choosing the precision of their earnings forecasts, presumably to enhance their reputations and to minimize perceived litigation risk.

In the next section, we discuss the prior literature and present our hypotheses. We describe our methodology and models in the section that follows, and then present our empirical results. The final section concludes by summarizing our results and inferences.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

When issuing an earnings forecast, managers must choose the precision of the forecast (King et al. 1990). A point forecast (such as "earnings per share of $1.00") provides the highest level of precision, while a range forecast (such as "earnings per share between $0.50 and $1.50") provides the next level of precision. Although the midpoint of a range can be viewed as the most probable amount, interpreting a range forecast probably involves some weighting of the distribution. For example, a forecast with a relatively small range (such as "earnings per share between $0.90 and $1.10") is likely viewed as being much more precise than is a forecast with a relatively greater range (such as "earnings per share between $0.50 and $1.50"). That is, although the midpoints of these two ranges are the same, the level of precision varies dramatically. Minimum forecasts (such as "earnings per share of at least $0.50") or maximum forecasts (such as "earnings per share of at most $1.50") are even less precise than are point or range forecasts. Finally, the least-precise form of forecast consists of qualitative statements such as "earnings will be better next year." In our empirical analyses, we combine minimum and maximum forecasts with other qualitative statements because the distinction between minimum/maximum forecasts and qualitative statements requires coder judgment. For example, forecasts such as "we expect a loss" and "we may not meet expectations" can be interpreted as either maximum forecasts or as qualitative statements. However, our results are qualitatively similar when we consider these categories separately.

Following prior research (Skinner 1994; Kasznik and Lev 1995; Soffer et al. 2000; Field et al. 2005), we expect that managers have incentives to issue forecasts to reduce legal liability. That is, if managers do not disclose material information on a timely basis, investors could have a basis for lawsuits. However, the issuance of management forecasts, per se, does not necessarily decrease legal liability (Francis et al. 1994; Skinner 1997; Healy and Palepu 2001). Rather, the issuance of management forecasts could increase legal liability in two ways. First, if managers issue forecasts containing surprising news (i.e., with greater forecast surprise), investors can litigate on the basis that management failed to disclose material information on a more timely basis. Second, if the forecasted information turns out to be inaccurate (i.e., results in a greater forecast error), investors can litigate on the basis that management disclosed erroneous information.[6] The first possibility is related to our Hypotheses 1 and 2, whereas the second possibility is related to our Hypotheses 3 and 4.

Given the potential legal consequences of issuing very surprising forecasts, we expect managers to issue less-precise forecasts when their forecasts include more surprising news (e.g., when their earnings expectations are further from analysts' current expectations) because the magnitude of the surprise will be less evident to investors when management forecasts are less precise.[7] More-precise forecasts could have a greater impact on stock prices (Baginski et al. 1993; Libby et al. 2006; Han and Tan 2007), because the implications of precise forecasts are more readily discernable (Baginski et al. 1993).[8] This potential for a differential response can give managers incentives to release more or less precise forecasts depending on their intentions (Titman and Trueman 1986; Hughes and Pae 2004). As a result, we expect that management's choice of forecast precision is systematically related to the forecast surprise. Specifically, we predict that managers have incentives to release less-precise forecasts when the forecast surprise is large to influence the magnitude of the market's reaction and to avoid potential legal liability. This leads us to our first hypothesis (stated in the alternative form).

H1: Forecast precision will be negatively related to the degree of forecast surprise.

Next, we expect the association between forecast precision and forecast surprise to be stronger for bad-news forecasts (i.e., when forecast surprise is negative, so that the forecasted earnings are smaller than the market's expectation or the market's reaction to the forecast disclosure is negative) than for good-news forecasts (i.e., when forecast surprise is positive). Prior studies find that bad news precipitates litigation more often than does good news (Skinner 1994; Kasznik and Lev 1995; Field et al. 2005) or experience large negative returns (Alexander 1992). Thus, managers should be more cautious in their choice of forecast precision when making bad-news forecasts (relative to when making good-news forecasts) as the magnitude of the forecast surprise increases because the likelihood of potential litigation is greater the worse the news. Consistent with this prediction, Graham et al. (2005, 65) report that "some CFOs admit that they do not mind 'fuzziness' in bad news disclosures." Hughes and Pae (2004) also show that managers issue imprecise forecasts to dampen the adverse market reaction to bad news. Accordingly, we predict that bad-news forecasts will be less precise than good-news forecasts when the forecasts contain more surprising news. We test this prediction with our second hypothesis (stated in the alternative form).

H2: The negative relationship between forecast precision and the degree of forecast surprise will be stronger for bad-news forecasts than for good-news forecasts.

As discussed earlier, litigation can also result when earnings realizations differ greatly from forecasted earnings. Consistent with this, Francis et al. (1994) report that 28 of 45 litigations in their sample are because of misleading earnings forecasts or preemptive earnings disclosures. Because a lawsuit is costly to the firm even if the defendant prevails (Graham et al. 2005), managers have incentives to attempt to avoid litigation by strategically choosing the level of forecast precision. One strategy for reducing the probability of litigation is to release only accurate information. Another strategy for reducing litigation exposure resulting from inaccurate news is to release imprecise information because the more imprecise the information, the less likely the forecast can be construed to be inaccurate. Thus, when managers are more uncertain about future earnings realizations, we expect them to issue less-precise forecasts.

In general, a range forecast is less likely than a point forecast to be inaccurate (all else equal) because a range forecast contains more possible outcomes and is more likely to include the realization. Similarly, because a forecast with a larger range encompasses more possible outcomes, a larger range forecast is more likely to include the realization. Thus, because the probability that a forecast will turn out to be inaccurate increases as precision increases, management forecast precision can provide information about the degree of management's confidence in the accuracy of their forecasts (King et al. 1990). However, managers do not know the future earnings realization with certainty, so they likely form expectations of future earnings, as well as expectations about the precision of their estimates. Therefore, we expect managers to issue more (less) precise forecasts when the forecast uncertainty is smaller (greater), and we posit that the realized (or *ex post*) magnitude of the forecast error is a suitable empirical proxy for this forecast uncertainty. Our hypothesis, stated in the alternative form, follows.

H3: Forecast precision will be negatively related to the forecast error.

Recall that U.S. firms are more likely to be sued when they report large negative earnings surprises or experience large negative returns at the time of earnings announcements. Prior optimistic management forecasts could contribute to these negative earnings surprises or negative returns. Choi and Ziebart (2004) suggest that this asymmetric loss function induces managers to issue slightly less optimistic or more pessimistic forecasts than they would in the absence of litigation concerns. Moreover, when managers face uncertainties in making their forecasts, they are likely to issue more imprecise forecasts because such forecasts are less likely to be inaccurate *ex post*. Given this, when managers perceive that the likelihood of negative forecast errors (i.e., forecasted earnings are greater than realized *ex post* earnings) is greater than the likelihood of positive forecast errors (i.e., forecasted earnings are smaller than realized *ex post* earnings), we predict that managers are more likely to issue imprecise forecasts to decrease their exposure to legal liability. We test this prediction with our fourth hypothesis (stated in the alternative form).

> **H4**: The negative relationship between forecast precision and forecast error will be stronger when forecast errors are negative than when they are positive.

In summary, we expect that forecast precision will be inversely related to the magnitude of the forecast surprise and to the magnitude of the absolute forecast error, and that the inverse relationships will be stronger for bad-news forecasts and for forecasts with negative errors, respectively.

METHODOLOGY

Sample Selection and Distributions

We obtain management forecasts of annual earnings per share (EPS) for the period 1995 through 2004 from First Call. Our sample period begins in 1995 because management earnings forecasts became more prevalent with the passage of the PSLRA and because the First Call data became more comprehensive at this point (Anilowski et al. 2007). The First Call database includes both qualitative and quantitative management forecasts of earnings, and it has been widely used in the extant management forecast literature. This yielded 27,841 management forecast observations. To minimize possible confounding effects when multiple forecasts (i.e., forecasts for multiple fiscal periods) were made on the same date, we eliminated 5,764 observations containing multiple forecasts.[9] Because we need a measure of extant expectations to calculate the forecast surprise, and because we need actual earnings to calculate the subsequent earnings surprise, we removed an additional 3,053 forecasts with either no preceding analyst consensus forecast available for the corresponding fiscal year or no actual earnings in the First Call database.[10] To remove forecasts that may have been erroneously added to the database after the actual earnings release, we further deleted 56 forecasts made more than 110 calendar days after fiscal year-end.[11, 12] Finally, we removed forecasts for which we were unable to obtain the requisite data for our analyses on COMPUSTAT (1,582 observations) or CRSP (514 observations). Our final sample comprises 16,872 management forecast observations made by 2,735 firms. Table 1 summarizes our sample selection procedure.

Insert <Table 1>

Descriptive statistics, by year and overall, regarding the number and percentage of sample observations with each type of forecast precision are provided in Table 2, Panel A.

Clearly, the number of management forecasts is increasing substantially over time, as is the number of each type of management forecast. Point and range forecasts are more common than are qualitative forecasts. Furthermore, the proportion of point forecasts is declining over time, from a high of 49.4 percent in 1995 to a low of 11.7 percent in 2004, while the proportion of range forecasts is generally increasing over time, from 42.1 percent in 1995 to 82.3 percent in 2004 (with a low of 30 percent in 1997). This tendency could be related to the stringent disclosure-related legal liability that U.S. firms face. Interestingly, the proportion of qualitative forecasts increased from 8.5 percent in 1995 to a high of 36 percent in 1999, and then declined to 6 percent in 2004.

Insert < Table 2>

Though not tabulated, we examine whether those firms making multiple forecasts during our sample period issue multiple types of forecasts with different precision. That is, we investigate whether the forecast type is "sticky." We find that the number of forecast types increases as the number of forecasts issued increases, confirming that firms issue forecasts with different precision at different points in time. For example, for the 379 firms issuing two forecasts during the sample period, 45.9 percent (174 firms) issued forecasts with different precision. At the extreme (when 15 or more forecasts were issued), 55.9 percent of firms issued all three types of forecasts.

We next stratify the total sample of observations into either good news or bad news observations and test whether the sign of the news is related to the forecast precision. Following Baginski and Hassell (1997) and Bamber and Cheon (1998), Table 2, Panel B classifies as good (bad) news those observations with a forecast surprise variable (*FS1*) measured by cumulative abnormal return (*CAR*) greater (less) than zero. *CAR* is measured as the summation of the market-adjusted daily returns over the three-day window centered on the management forecast issue date, using standard market model procedures. Here, we find that managers are more likely to issue a range forecast regardless of the sign of news (good or bad), and that the preponderance of point forecasts is about the same across both good news and bad news (22.8 percent for good news and 21.4 percent for bad news). Similarly, the proportion of qualitative forecasts is 11.3 percent for good news and 12.9 percent for bad news.

Next, we classify point and range forecasts by the sign of an alternative forecast surprise variable (*FS2*) in Table 2, Panel C. We measure *FS2* as (management forecast – the most recent median analyst forecast) / stock price. Consistent with prior studies (Bamber and Cheon 1998; Baginski et al. 2004), we classify the observation as good news if *FS2* is greater than or equal to zero, and classify the observation as bad news otherwise. When considering range forecasts, we use the midpoint of the range as the management forecast. Because no meaningful midpoint can be calculated from the qualitative forecasts, we focus only on point and range forecasts for this analysis. Accordingly, the number of observations falls from 16,872 in Panel B to 14,831 in Panel C. Once again, we find that managers are more likely to issue a range forecast, but the proportion differs depending on whether the forecast is good or bad news. Specifically, when the news is good, 28.7 percent of forecasts are point forecasts and 71.3 percent are range forecasts, but when the news is bad, only 18.7 percent of forecasts are point forecasts and 81.3 percent are range forecasts.

We test whether the proportions based on forecast precision are independent of the sign of news. When we use the *FS1* to classify news (in Panel B), the chi-square statistic for independence is 13.00 (p-value = 0.0015, df = 2), and when we use *FS2* to classify news (in Panel C), the chi-square statistic for independence is 184.50 (p-value < 0.0001, df = 1). This indicates that the difference in proportion for good versus bad news is significant, suggesting that the choice of precision *is* related to the sign of the news. However, the difference in the proportion is much more significant, both statistically and economically, for *FS2* than for *FS1*.[13]

We next perform multivariate analyses to confirm that this result holds when we control for other factors likely to affect management's choice of forecast precision.

Empirical Models

To examine hypotheses H1 and H2, we use the following equation, Eq. (1), which models the relationship between forecast precision, forecast surprise, and a set of control variables.

$$\begin{aligned} PRECISION = {} & b_0 + b_1\, BAD\_FS1 \text{ (or } BAD\_FS2) + b_2\, ABS\_FS1 \text{ (or } ABS\_FS2) \\ & + b_3\, BAD\_FS1{*}ABS\_FS1 \text{ (or } BAD\_FS2{*}ABS\_FS2) + b_4\, HORIZON + b_5\, SDRES \\ & + b_6\, CON\_OWN + b_7\, LN(NANAL) + b_8\, MB + b_9\, LN(SIZE) + b_{10}\, CONC + b_{11}\, YEAR + \varepsilon \end{aligned} \quad (1)$$

where:

PRECISION	=	the precision of the management forecast, measured by either *PRECISION1* or *PRECISION2*;
PRECISION1	=	2 for point forecasts, 1 for range forecasts, and 0 for qualitative statements;
PRECISION2	=	0 for point forecasts, and for range forecasts, is the negative of (the absolute value of [the upper limit minus the lower limit] deflated by the share price at day –2);
FS1	=	forecast surprise measured as the summation of market-adjusted returns over the three-day window centered on the forecast announcement date;
FS2	=	forecast surprise measured as the management forecast minus the most recent median analyst forecast preceding the management forecast, deflated by the share price at day –2;
BAD_FS1	=	1 if *FS1* < 0, and 0 otherwise;
BAD_FS2	=	1 if *FS2* < 0, and 0 otherwise;
ABS_FS1	=	the degree of forecast surprise, measured as the absolute value of *FS1*;

ABS_FS2 = the degree of forecast surprise, measured as the absolute value of *FS2;*

HORIZON = the forecast horizon, measured by the natural logarithm of the number of calendar days between forecast and end of the fiscal year to which the forecast pertains plus 111 days;[14]

SDRES = the standard deviation of market model residuals estimated over a 200-day period ending 31 trading days before the management forecast announcement;

CON_OWN = concentrated ownership, defined as one minus the relative number of common shareholders to common shares outstanding (= 1 – [1000*(the number of common shareholders / the number of common shares outstanding)]);

LN(NANAL) = the natural logarithm of the number of First Call analysts following the firm during the month immediately preceding the management forecast;

MB = the ratio of market to book value of the firm's common equity at the beginning of the fiscal year;

LN(SIZE) = the natural logarithm of the market value of common equity at the beginning of the fiscal year;

CONC = the firm's product-market concentration ratio, measured as the sales of the top-five firms in the firm's two-digit *SIC* code industry in that year, divided by total sales in that industry during the year;

YEAR = the year in which the management forecast is issued (1 = 1995, 2 = 1996, … , 10 = 2004).

We measure the precision of the forecasts using either *PRECISION1* or *PRECISION2*. *PRECISION1* is a discrete variable and tests using this dependent measure include all three forecast types (point, range, and qualitative), while *PRECISION2* is a continuous variable and tests using this dependent measure include only point and range forecasts. All tests on *PRECISION1* use an ordered logit model, while all tests on *PRECISION2* use ordinary least squares. The degree of the forecast surprise is measured by *ABS_FS1* and by *ABS_FS2*,[15] and the sign of the forecast surprise is measured by *BAD_FS1* and *BAD_FS2*, respectively. If H1 is descriptive, so that forecast precision is lower the greater the forecast surprise, we expect the coefficient on *ABS_FS1* (or *ABS_FS2*) to be negative. Similarly, if H2 is descriptive, so that the negative relation between forecast precision and forecast surprise is stronger for bad-news firms than for good-news firms, we expect the coefficient on *BAD_FS1 * ABS_FS1* (or *BAD_FS2 * ABS_FS2*) to be negative.

Among the control variables, we expect *HORIZON* to be negative because forecasts made later in the period should be subject to less earnings uncertainty (and thus, should be more precise). Because rapid changes in the business environment should make it difficult for managers to issue accurate, precise forecasts, and because managers' beliefs should be more precise the lower the variability in expected economic earnings, we follow Baginski and Hassell (1997) and include *SDRES*, which we expect to be negative.[16] We expect *CON_OWN* to be negative because monitoring and litigation concerns are likely to be higher when ownership is more concentrated (Ashbaugh-Skaife et al. 2007), leading managers to issue less-precise forecasts (Bamber and Cheon 1998). We use analyst following (*LN(NANAL)*) to proxy for private information production (Bhushan 1989) and/or the informativeness of firm disclosures (Lang and Lundholm 1996), and expect firms with greater analyst following to issue more-precise forecasts. We expect growth potential (*MB*) to be positive because high-growth firms have stronger incentives to avoid negative earnings surprises (Skinner and Sloan 2002) and more-precise forecasts could be used to guide the market's expectation downward to the beatable level.[17] We expect firm size (*LN(SIZE)*) to be positive because larger firms provide more disclosure and their disclosure is of higher quality (Waymire 1986; Lang and Lundholm 1993, 1996; Botosan and Plumlee 2002), presumably because larger firms have stronger incentives to build reputations for good disclosure and could issue more precise forecasts in response (King 1996). Alternatively, firm size could proxy for diversified operations, implying smoother and more predictable earnings, which could cause more-precise earnings forecasts as well as less forecast error. Finally, we expect firms with large proprietary costs related to concentrated product-markets (*CONC*) to issue less-precise forecasts (Bamber and Cheon 1998). We include *YEAR* to control for any time-series trend in forecast precision.[18] We do not form expectations about the sign on this coefficient estimate because Bamber and Cheon (1998) document an increase in forecast precision over their (prior) sample period while, alternatively, increases in legal liability related to missed forecasts over time suggest a decrease in forecast precision over time.[19]

To test hypotheses H3 and H4, we extend Eq. (1) as follows:[20]

$$\begin{aligned} PRECISION2 = {} & b_0 + b_1\, BAD\_FS1 \text{ (or } BAD\_FS2) + b_2\, ABS\_FS1 \text{ (or } ABS\_FS2) \\ & + b_3\, BAD\_FS1*ABS\_FS1 \text{ (or } BAD\_FS2*ABS\_FS2) + b_4\, FERROR + b_5\, DNFE \\ & + b_6\, DNFE*FERROR + b_7\, HORIZON + b_8\, SDRES + b_9\, CON\_OWN \\ & + b_{10}\, LN(NANAL) + b_{11}\, MB + b_{12}\, LN(SIZE) + b_{13}\, CONC + b_{14}\, YEAR + \varepsilon \end{aligned} \tag{2}$$

Eq. (2) adds three additional variables of interest ─ *FERROR, DNFE* and *DNFE*FERROR* ─ to Eq. (1). We use the *ex post* accuracy of the forecasts, *FERROR* (measured as the absolute value of the difference between the management forecast and the actual *ex post* earnings per share, deflated by stock price at day -2), to proxy for management's forecast uncertainty about the eventual earnings realization. *DNFE* is an indicator variable set to 1 if the forecast error is negative (i.e., if the management forecast exceeds the actual *ex post* earnings per share), and 0 otherwise. If H3 is descriptive, so that forecast precision is lower the greater the absolute forecast error, we expect the coefficient on *FERROR* to be negative. Similarly, if H4 is descriptive, so that the negative relation between forecast precision and the absolute forecast error is stronger when forecast errors are negative than when they are positive, we expect the coefficient on *DNFE* * *FERROR* to be negative.

In Table 3, we report descriptive statistics for the variables we use in our analyses. The statistics are similar to those reported in prior studies.[21]

Insert <Table 3>

Although not separately tabulated, we checked the correlations among variables used in the study. As expected, *PRECISION1* and *PRECISION2* are positively correlated (with a Pearson correlation coefficient of 0.3376, $p < 0.001$). The correlation between *ABS_FS2* and *FERROR* is 0.7531 ($p < 0.001$), but the correlation between *ABS_FS1* and *FERROR* is relatively low (r = 0.0832). Among the control variables, only the correlations between *SDRES* and *LN(SIZE)* (r = -0.4603) and between *LN(NANAL)* and *LN(SIZE)* (r = 0.7821) are greater than 0.3. In our regression analyses, no variance inflation factors exceed 3.75, confirming that multicollinearity is not a concern in our regression tests.

EMPIRICAL RESULTS

Before testing our hypotheses, we first attempt to replicate the main findings in prior studies using our sample. Our study differs from prior studies that find weak evidence that managers tend to issue more (less) precise forecasts when news is good (bad) (e.g., Baginski and Hassell 1997; Bamber and Cheon 1998) in two important ways. First, our sample size is much larger, giving us greater power to detect a relation if one does, in fact, exist. Second, our sample is drawn from a more recent period where management's concerns over litigation are likely to be greater. Here, we use a simplified version of Eq. (1), similar to the model used in those studies and examine whether the coefficients on *BAD_FS1* and/or *BAD_FS2* are significantly negative:

$$PRECISION1 = b_0 + b_1\, BAD\_FS1\ (or\ BAD\_FS2) + b_2\, HORIZON + b_3\, SDRES + b_4\, CON\_OWN + b_5\, LN(NANAL) + b_6\, MB + b_7\, LN(SIZE) + b_8\, CONC + b_9\, YEAR + \varepsilon \qquad (3)$$

Untabulated results on the indicator variables (*BAD_FS1* and *BAD_FS2*) are consistent with the theory in Baginski and Hassell (1997) and Bamber and Cheon (1998). Specifically, we find that the coefficients on *BAD_FS1* and *BAD_FS2* are negative and statistically significant, revealing that managers *do* issue more (less) precise forecasts when news is good (bad). That is, bad-news forecasts are less precise while good-news forecasts are more precise. Our results on the other variables are generally consistent with prior studies and with expectations. Specifically, we find evidence suggesting that managers issue more precise forecasts when expected earnings variability (*SDRES*) is smaller and when their firms are followed by a larger number of analysts (*LN(NANAL)*). Furthermore, consistent with Bamber and Cheon (1998), we are unable to document the predicted association between forecast precision and growth opportunities (*MB*) or between forecast precision and ownership concentration (*CON_OWN*). Interestingly, the coefficient on *LN(SIZE)* (*HORIZON*) is not significant using the full sample, but is positive (negative) and significant when we restrict the sample to point and range forecasts. These results suggest that firm size is not related to management's choice between issuing a qualitative statement, a range forecast, or a point forecast, but when only point and range forecasts are considered, large firms tend to release point forecasts more often than small firms. Similarly, forecast horizon is not related to management's choice of forecast precision in the full sample, but managers tend to release less-precise forecasts the longer the forecast horizon when only point and range forecasts are considered.[22] Contrary to results in Bamber and Cheon (1998), we find that forecast precision has declined over time (*YEAR*), but this could be because of our different sample selection criteria and time periods[23] and could be related to litigation resulting from missed forecasts in recent years (Wagner 2006). Finally, unlike Bamber and Cheon (1998), we do not find that firms in highly concentrated product markets (*CONC*) issue less-precise forecasts.

In Table 4, we test hypotheses H1 and H2, using Eq. (1). The coefficients on *ABS_FS1* and on *ABS_FS2* test H1, and coefficients on *BAD_FS1 * ABS_FS1* and on *BAD_FS2 * ABS_FS2* test H2. We perform our analyses using a clustering procedure that accounts for serial dependence across years for a given firm.

Insert <Table 4>

We present the results from six models. The first two models include all forecasts and classify bad versus good news based on *FS1*. The next four models include only point and range forecasts and classify news based on *FS1* (models 3 and 4) or on *FS2* (models 5 and 6). We use this restricted sample because most management forecasts are either point or range forecasts and these forms are easier to interpret than qualitative statements. All models include the sign of the news and the magnitude of the forecast surprise, and three of the models (models 2, 4, and 6) interact these variables.[24]

In all models, the coefficients on the forecast surprise (*ABS_FS1* and *ABS_FS2*) are significantly negative, confirming that as forecast surprise increases, forecasts become more imprecise, consistent with H1. Moreover, the coefficients on the interaction terms, *BAD_FS1* ABS_FS1* and *BAD_FS2*ABS_FS2* are significantly negative, revealing that the negative association between forecast precision and forecast surprise is stronger for bad news, consistent with H2. Finally, note that management forecasts are less precise, on average, when the earnings news is bad (i.e., the coefficients on *BAD_FS1* and *BAD_FS2* are negative). Results for the control variables are largely consistent with those discussed previously in our replication of prior studies.

In Table 5, we report the results using Eq. (1), restricting the sample to only point and range forecasts. Here, precision is a continuous variable where the value of *PRECISION2* is 0 for a point forecast, negative and close to 0 for a narrow range forecast, and more negative for a wide range forecast; that is, it is the negative of the absolute value of the upper limit minus the lower limit deflated by the share price at day –2. Thus, *PRECISION2* is not defined if we include qualitative statements. In essence, Table 5 replicates the analyses reported in Table 4 but considers the size of the range for range forecasts.

Insert <Table 5>

Again, we estimate various models, classifying good versus bad news using *FS1* (models 1 and 2) and *FS2* (models 3 and 4), and we consider both the sign and the magnitude of the forecast surprise, as well as the interaction of the sign and magnitude. The results are consistent across Tables 4 and 5; as the magnitude of the forecast surprise increases, forecasts become less precise (i.e., the coefficients on *ABS_FS1* and *ABS_FS2* are significantly negative). This imprecision is manifested in management moving from making a point forecast, to a range forecast with a small range, and then to a range forecast with a large range as the forecast surprise increases. The results also indicate that this effect is more pronounced for bad-news forecasts than for good-news forecasts (i.e., the coefficients on the interaction variables, *BAD_FS1*ABS_FS1* and *BAD_FS2*ABS_FS2,* are significantly negative).

Finally, in Table 6, we report the results from extending our analyses by focusing on point and range forecasts and including the realized (*ex post*) absolute forecast error. The results regarding H1 and H2 are consistent with those reported in Table 5. Specifically, forecast precision is negatively associated with forecast surprise, and this effect is more pronounced for bad-news forecasts than for good-news forecasts. However, results on the absolute forecast error are mixed. When we use *FS1* to classify the forecasts as good or bad news (i.e., in models 1 and 2), the coefficient on the forecast error (*FERROR*) is significantly negative, consistent with management considering the magnitude of the forecast uncertainty when choosing the level of forecast precision, and making less-precise forecasts the larger the forecast error. In addition, this effect is more pronounced when the signed forecast error is negative, as evidenced by the significantly negative coefficient on *DNFE*FERROR* (in model 2). When we use *FS2* to classify forecasts as good or bad news (i.e., in models 3 and 4), the coefficient on the forecast error is not significantly different from zero. However, for bad-news forecast errors, the coefficient on *DNFE*FERROR* is again significantly negative, and a joint test on *DNFE*FERROR* and *FERROR* reveals that bad-news forecasts are significantly less precise the larger the forecast error ($F = 8.15$, $p = 0.004$). Overall, these results suggest that management's decision regarding forecast precision is related to both the forecast surprise and the forecast error, especially when the signed forecast error is negative. These findings are consistent with H3 and, in the case of negative forecast errors, H4.

Insert <Table 6>

The insignificant coefficients on *FERROR* reported in models 3 and 4 of Table 6 could be because of the high correlation ($r = 0.7531$) between absolute forecast error (*FERROR*) and forecast surprise (*ABS_FS2*).[25] To check whether the insignificant coefficients on *FERROR* are attributable to this high correlation, we use Eq. (4), which can be viewed as a shortened version of Eq. (2) that does not contain any variables related to forecast surprise and re-perform the analyses.

$$PRECISION2 = b_0 + b_1\,FERROR + b_2\,DNFE + b_3\,DNFE{*}\,FERROR + b_4\,HORIZON + b_5\,SDRES + b_6\,CON\_OWN + b_7\,LN(NANAL) + b_8\,MB + b_9\,LN(SIZE) + b_{10}\,CONC + b_{11}\,YEAR + \varepsilon \tag{4}$$

The results from estimating Eq. (4) are reported in model 5. Both b_1 and b_3 are highly significant. Specifically, the coefficient on *FERROR* is -1.878 ($p < 0.001$) and that on *DNFE*FERROR* is -8.028 ($p < 0.001$), consistent with H3 and H4, respectively.

In Table 2, Panel A, we note substantial changes in forecast properties from the pre-Reg FD period to the post-Reg FD period. Specifically, our results show that the number of forecasts increased and the forecast precision decreased, consistent with prior findings (Heflin et al. 2003; Ajinkya et al. 2005).[26] As a robustness check that controls for structural changes around the issuance of Reg FD, we replace the *YEAR* variable in Eqs. (1) and (2) with a Reg FD indicator variable that is set to 1 if the forecast is issued in the post-Reg FD period (i.e., after October 2000), and 0 otherwise. Our results (not tabulated) show that the coefficients on this indicator variable in all models are negative and significant at the 1 percent level, consistent with findings in Ajinkya et al. (2005) and with their argument that after Reg FD, firms issued forecasts with less precision (thus reducing the cost of disclosure). More importantly, however, our empirical findings on H1 through H4 are unchanged by the addition of the Reg FD indicator variable. That is, in all models, we continue to find that forecast precision is negatively associated with the magnitudes of forecast surprise and absolute forecast error, and that the negative association is stronger for bad-news forecasts and for forecasts with negative forecast errors.

To further examine whether our main results differ between the Pre- and the Post-Reg FD periods, we also interacted the Reg FD indicator variable and the variables of interest (i.e., *ABS_FS1, BAD_FS1*ABS_FS1, FERROR, DNFE*FERROR*) and added these and the Reg FD indicator variable to Eqs. (1) and (2). The coefficients on the interactions are generally insignificant, suggesting that the associations reported did not change between the Pre- and Post-Reg FD periods.[27]

CONCLUSION

In this study, we reexamine whether the sign of the news (good versus bad) is associated with the precision of management earnings forecasts (i.e., point, range, or qualitative forecasts). Prior studies hypothesize such an association, but the evidence is mixed. Using a larger sample of more recent forecasts than used in these prior studies, we provide strong evidence that bad-news forecasts *are* less precise than are good-news forecasts. We also show that the precision of range forecasts is related to the sign of the news and to the magnitude of the forecast surprise (i.e., the difference between the management earnings forecast and the market's extant expectations for future earnings). Specifically, forecasts become less precise and ranges (for range forecasts) become larger the greater the forecast surprise, and the relationship is stronger for bad-news forecasts than for good-news forecasts. Furthermore, we find evidence consistent with management considering forecast uncertainty (measured by the absolute difference between the management earnings forecast and management's expectations for future earnings) when choosing the level of forecast precision, even after controlling for the sign and magnitude of the forecast surprise. In addition, we find that the relationship between forecast precision and forecast uncertainty is stronger when the management forecast exceeds *ex post* earnings (so that the realized forecast error is negative). We posit that this could result from management's litigation concerns.

In sum, the findings in our study are consistent with management acting strategically when choosing forecast precision. In developing policies to encourage managers to issue earnings guidance, it is important for policy makers to consider this strategic behavior. For example, over the last ten years, we observe a significant shift away from point forecasts, toward range forecasts. Because the precision of range forecasts also varies with the sign of the news, the magnitude of the forecast surprise, and the magnitude of the absolute forecast error, we posit that precision may have deteriorated and the "quality" of information may have declined even though more management forecasts are issued. Thus, further research to understand the factors affecting management's choice of forecast precision should be an important input to disclosure regulation.

This study is subject to a number of limitations. First, management's choice of forecast precision may be influenced by omitted factors. Although our models include various control variables, our proxies may not be sufficient to fully control for other omitted latent variables. Second, managers have the ability to use forecast precision and other forecast characteristics simultaneously. Although we control for forecast timing (*HORIZON*) in our analyses, other factors such as forecast venue and the announcement of supplementary information (see Hutton et al. 2003 among others) are beyond the scope of this study and are not considered here. Finally, managers may intentionally issue biased forecasts to influence the market's perception. We consider the forecast bias in our empirical analyses only in a limited sense, because we believe that the bias would have a second-order impact (if any) on the precision of the forecasts. Future research on the interaction between the choice of precision and other factors is warranted.

REFERENCES

Ajinkya, B., S. Bhojraj, and P. Sengupta. 2005. The association between outside directors, institutional investors and the properties of management earnings forecasts. *Journal of Accounting Research* 43 (June): 343–76.

Alexander, J. C. 1992. Do the merits matter? A study of settlements of securities class actions. *Securities Law Review*:25–126.

Anilowski, C., M. Feng, and D. J. Skinner. 2007. Does earnings guidance affect market returns? The nature and information content of aggregate earnings guidance. *Journal of Accounting and Economics* 44 (September): 36–63.

Ashbaugh-Skaife, H., D. Collins, and W. Kinney. 2007. The discovery and reporting of internal control deficiencies prior to SOX-mandated audits. *Journal of Accounting and Economics* 44 (September): 166–92.

Atiase, R. A., S. Supattarakul, and S. Tse. 2006. Market reaction to earnings surprise warnings: The incremental effect of shareholder litigation risk on the warning effect. *Journal of Accounting, Auditing and Finance* 21 (Spring): 191–222.

Baginski, S. P., E. J. Conrad, and J. M. Hassell. 1993. The effects of management forecast precision on equity pricing and on the assessment of earnings uncertainty. *The Accounting Review* 68 (October): 913–27.

Baginski, S. P., and J. M. Hassell. 1990. The market interpretation of management earnings forecasts as a predictor of subsequent financial analyst forecast revision. *The Accounting Review* 65 (January): 175–190.

———. 1997. Determinants of management forecast precision. *The Accounting Review* 72 (April): 303–12.

Baginski, S. P., J. M. Hassell, and M. D. Kimbrough. 2002. The effect of legal environment on voluntary disclosure: Evidence from management earnings forecasts issued in U.S. and Canadian markets. *The Accounting Review* 77 (January): 25–50.

———. 2004. Why do managers explain their earnings forecasts? *Journal of Accounting Research* 42 (March): 1–29.

Bamber, L. S., and Y. S. Cheon. 1998. Discretionary management earnings forecast disclosure: Antecedents and outcomes associated with forecast venue and forecast specificity choices. *Journal of Accounting Research* 36 (Autumn): 167–90.

Behn, B. K., J-H Choi, and T. Kang. 2008. Audit quality and properties of analysts' earnings forecasts. *The Accounting Review* 83 (March): 327–49.

Bhushan, R. 1989. Firm characteristics and analyst following. *Journal of Accounting and Economics* 11 (July): 255–74.

Botosan, C. A., and M. A. Plumlee. 2002. A re-examination of disclosure level and the expected cost of equity capital. *Journal of Accounting Research* 40 (March): 21–40.

Bushee, B. J., D. A. Matsumoto, and G. S. Miller. 2004. Managerial and investor responses to disclosure regulation: The case of Reg FD and conference calls. *The Accounting Review* 79 (July): 617–43.

Choi, J. -H. and D. Ziebart. 2004. Management earnings forecasts and the market's reaction to predicted bias in the forecast. *Asia-Pacifc Journal of Accounting and Economics* 11 (December): 167–92.

Coller, M., and T. L. Yohn. 1997. Management forecasts and information asymmetry: An examination of bid-ask spreads. *Journal of Accounting Research* 35 (March): 181–91.

Field, L., M. Lowry, and S. Shu. 2005. Does disclosure deter or trigger litigation? *Journal of Accounting and Economics* 39 (September): 487–507.

Francis, J., D. Philbrick, and K. Schipper. 1994. Shareholder litigation and corporate disclosures. *Journal of Accounting Research* 32 (Autumn): 137–64.

Graham, J. R., C. R. Harvey, and S. Rajgopal. 2005. The economic implications of corporate financial reporting. *Journal of Accounting and Economics* 40 (December): 3–73.

Han, J., and H. -T. Tan. 2007. Investors' reaction to management guidance forms. *The Accounting Review* 82 (March): 521–43.

Healy, P., and K. Palepu. 2001. Information asymmetry, corporate disclosure, and the capital markets: A review of empirical disclosure literature. *Journal of Accounting and Economics* 31 (September): 405–40.

Heflin, F., K. R. Subramanyam, and Y. Zhang. 2003. Regulation FD and the financial information environment: Early evidence. *The Accounting Review* 78 (January): 1–37.

Hirst, E., L. Koonce, and S. Venkataraman. 2008. Management earnings forecasts: A review and framework. *Accounting Horizons* 22 (September): 1–24.

Hughes, J. S., and S. Pae. 2004. Voluntary disclosure of precision information. *Journal of Accounting and Economics* 37 (June): 261–89.

Hutton, A., G. Miller, and D. Skinner. 2003. The role of supplementary statements with management earnings forecasts. *Journal of Accounting Research* 41 (December): 867-90.

Kasznik, R. and B. Lev. 1995. To warn or not to warn: Management disclosures in the face of an earnings surprise. *The Accounting Review* 70 (January): 113–34.

King, R. R. 1996. Reputation formation for reliable reporting: An experimental investigation. *The Accounting Review* 71 (July): 375–96.

King, R. R., G. Pownall, and G. Waymire. 1990. Expectations adjustment via timely management forecasts: Review, synthesis, and suggestions for future research. *Journal of Accounting Literature* 9: 113–44.

Lang, M., and R. Lundholm. 1993. Cross-sectional determinants of analyst ratings of corporate disclosures. *Journal of Accounting Research* 31 (Autumn): 246–71.

———. 1996. Corporate disclosure policy and analyst behavior. *The Accounting Review* 71 (October): 467–92.

Libby, R., H-T. Tan, and J. Hunton. 2006. Does the form of management's earnings guidance affect analysts' earnings forecasts? *The Accounting Review* 81 (January): 207–25.

Pownall, G., C. Wasley, and G. Waymire. 1993. The stock price effects of alternative types of management earnings forecasts. *The Accounting Review* 68 (October): 896–912.

Skinner, D. J. 1994. Why firms voluntarily disclose bad news. *Journal of Accounting Research* 32 (Spring): 38–60.

———. 1997. Earnings disclosures and stockholder lawsuits. *Journal of Accounting and Economics* 23 (November): 249–282.

Skinner, D. J., and R. Sloan. 2002. Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. *Review of Accounting Studies* 7 (June/September): 289–312.

Soffer, L. C., S. R. Thiagarajan, and B. R. Walther. 2000. Earnings preannouncement strategies. *Review of Accounting Studies* 5 (March): 5–26.

Titman, S., and B. Trueman. 1986. Information quality and the valuation of new issues. *Journal of Accounting and Economics* 8 (June): 159–72.

Wagner, J. 2006. Earnings: To guide or not to guide. *Directorship* (July-August): 22–3.

Waymire, G. 1986. Additional evidence on the accuracy of analyst forecasts before and after voluntary management earnings forecasts. *The Accounting Review* (January): 129–42.

White, H. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48 (May): 817–38.

Endnotes

1. Management forecasts of earnings are voluntary disclosures so managers have significant discretion in terms of the forecast precision, the timing of their forecasts, the time horizon of forecasts (e.g., quarterly or annual), the level of forecast disaggregation, and a number of other attributes such as the provision of supplementary information.

2. These consequences include, but are not limited to, effects on stock prices (Pownall et al. 1993), analyst forecasts (Baginski and Hassell 1990), the cost of capital (Lang and Lundholm 1993; Healey and Palepu 2001; Botosan and Plumlee 2002), and bid-ask spread (Coller and Yohn 1997).

3. For example, Baginski and Hassell (1997) use the sign of the stock price reaction measured over the three days surrounding the management forecast to classify the news as good or bad, and find no significant association between the sign of the stock price reaction and forecast precision. Alternatively, Bamber and Cheon (1998) characterize good versus bad news based on whether the management forecast exceeds extant analyst forecasts and on the sign of the stock price reaction to the management forecast. They find weak evidence that bad news forecasts are less precise, but this result is not significant when they control for the multiple observations per sample firm. The exception is Skinner (1994) who studies 374 disclosures made by 93 NASDAQ firms between 1981 and 1990, and finds that good-news disclosures are more precise than bad-news disclosures.

4. Here, forecasted earnings proxies for management's rational expectation for future earnings. A larger forecast error implies that management had greater difficulty in forecasting earnings, suggesting that managers faced greater uncertainty at the time of the forecast issuance.

5. Negative (positive) signed forecast errors occur when forecasts exceed (fall short of) the actual *ex post* earnings. In other words, negative (positive) forecast errors occur when forecasts are optimistic (pessimistic).

6. Graham et al. (2005) find that more than 46 percent of managers surveyed agree with the litigation cost hypothesis – that firms can avoid potential lawsuits when actual earnings outcomes do not match forward-looking disclosures by limiting these disclosures. Alternatively, Baginski et al. (2002) report that U.S. firms tend to release more imprecise, short-term forecasts and more bad-news forecasts, while Canadian firms release more-precise, long-term forecasts and more good-news forecasts. They explain that their findings are consistent with higher potential legal liability costs of U.S. firms versus Canadian firms.

7. Alternatively, managers could choose to overstate the magnitude of bad news in their earnings forecasts (which would create a positive earnings surprise at the earnings announcement) in an attempt to manage litigation risk. However, this strategy would induce excessive stock price volatility (because of the initial excessive stock price decrease at the time of the forecast issuance and the successive stock price increase at the time of the earnings announcement), and managers are still responsible for making overly pessimistic disclosures. Although we do not formally test whether managers manage litigation risk by issuing biased forecasts, we do perform separate analyses on positive and negative signed forecast errors (i.e., forecast bias) to determine whether their association with forecast precision differs.

8. Note, however, that Pownall et al. (1993) do not find a stronger market reaction to more precise management forecasts.

9. We eliminated these observations rather than attempting to control for the confounding effect statistically, because when forecasts for multiple fiscal periods are made on the same date, we cannot determine the amount of the forecast surprise that is related to each of the forecasts.

10. For a discussion of the benefits of using the First Call actual EPS, see footnote 15 in Ajinkya et al. (2005).

11. The cutoff of 110 days is based on Baginski and Hassell (1997), where forecasts made more than 110 days after period-end (but before the earnings release) are deleted from their sample of 922 annual management forecasts. Removing this restriction does not materially affect our results.

12. Among our 16,872 sample observations, 803 observations are issued after fiscal year-end (but within 110 calendar days from the fiscal year-end). Our results are robust to the exclusion of these preannouncement observations.

13. Note that our test results are generally stronger when we measure the forecast surprise based on the *FS2* rather than *FS1.* We suggest that using analyst forecasts allows us to form a cleaner proxy for the magnitude of the news in the forecast because stock market returns likely reflect other confounding factors.

14. We add 111 to avoid taking the logarithm of a negative number. See endnote 20 for further details.

15. To measure the magnitude of the surprise, we also use the rank of the variable rather than the continuous variable. Because the results are not qualitatively different, we do not separately report results using the rank.

16. In untabulated analyses, we also use the dispersion of analyst forecasts (*DISP*) to control for earnings variability, where we require at least four analyst forecasts (Behn et al. 2008). The Pearson correlation between *DISP* and *FERROR* (n = 11,153) is not very high ($r = 0.1462$, $p < 0.001$), suggesting that the variables capture different information, presumably because the information available to analysts and management differs. While our results *are* robust to this alternative measure, we tabulate the results using *SDRES* because this measure is used in related studies (e.g., Baginski and Hassell 1997) and because the use of *DISP* requires that sample observations have a minimum number of analysts following, skewing our sample composition toward very large firms.

17. In contrast, Bamber and Cheon (1998) expect a negative sign on growth potential because growth firms may have larger proprietary costs. However, Bamber and Cheon (1998) fail to find a significant relationship between forecast precision and growth.

18. As defined below Eq. (1), for the comparability with Bamber and Cheon (1998, 178), *YEAR* is a discrete year variable rather than a series of dummy variables for individual years. Sensitivity analysis using separate dummy variables for each year yields qualitatively identical inferences.

19. According to Wagner (2006, 22), "navigating the Securities and Exchange Commission rules regarding guidance can be tricky. And companies have seen millions worth of market capitalization vaporize when performance didn't exactly match predictions. So, rather than hazard a stock sell-off—not to mention the occasional spurious class action—after missing their earnings per share estimate by even a penny, corporate leaders are more often deciding to give investors actual business news rather than magic numbers."

20. Here, we measure forecast precision using *PRECISION2* because *FERROR* is measureable only when forecasts are point estimates or ranges.

21. The *DAYSPRIOR* variable in Table 3 is the unlogged value of the number of calendar days from the management forecast date to fiscal year-end. When the variable is converted to the logged value, and relabelled *HORIZON*, for our multivariate analyses (as reported in Tables 4, 5, and 6), we add 111 days (following prior literature) because some forecasts are made as late as 110 days after fiscal year-end (but before the earnings announcement date). For example, if a forecast is made on January 10 (10 days after the end of the fiscal year), the variable is converted to log(-10 + 111) = log(101). As a robustness check, we re-perform all of the analyses after removing 792 observations where the forecast was released after fiscal year-end (but before the earnings announcement). The results are qualitatively similar and all inferences remain the same.

22. When the dependent variable is defined as *PRECISION2* in subsequent analyses (as reported in Tables 5 and 6), we still find that the coefficient on *LN(SIZE)* (*HORIZON*) is significantly positive (negative). These results, combined with those above, indicate that larger firms (firms with a shorter forecast horizon) tend to release point forecasts or forecasts with narrower ranges rather than wider ranges when only point and range forecasts are considered.

23. Specifically, Bamber and Cheon (1998) study an earlier time period (1981 through 1991) and require that sample firms have at least eight years of analyst disclosure ratings available from the Association for Investment Management and Research over the period 1981 through 1991. Because of this, we expect that their sample firms are likely larger than ours, on average.

24. In additional analyses, rather than combining the good and bad news subsamples, we divided the samples and perform regressions with good and bad news subsamples separately. All the

results are qualitatively similar to those in Tables 4, 5, and 6, so we do not tabulate these results. These results can be obtained from the authors on request.

25. Recall that the coefficients on *FERROR* are significant (in models 1 and 2) when we use *ABS_FS1* rather than *ABS_FS2*, and that the correlation between *FERROR* and *ABS_FS1* is not high (0.0832).

26. Interestingly, Bushee et al. (2004) find that managers were significantly less likely to hold conference calls following the implementation of Reg FD. Thus, it may be that managers substituted earnings forecasts for conference calls, but that the overall quality of information did not increase during the post-Reg FD period.

27. For example, the coefficients on *FD, FD*ABS_FS1,* and *FD*BAD_FS1*ABS_FS1* are -0.741 ($p < 0.001$), 0.043 ($p = 0.191$), and -0.175 ($p = 0.325$) respectively when *FD* and the interaction variables are added to Model 2 in Table 5. The coefficients on *FD*, *FD*FERROR*, and *FD*DNFE*FERROR* are -0.146 ($p < 0.001$), -0.116 ($p = 0.235$), and -1.036 ($p = 0.197$) respectively when *FD* the interaction variables are added to Model 5, Table 6. Because management concerns about legal liability may have been magnified after the passage of the Sarbanes-Oxley Act of 2002 (SOX), we also examine whether there are structural changes in our main results by including a post-SOX indicator variable and interactions between this indicator and our variables of interest into Eqs. (1) and (2). Untabulated analyses reveal that the coefficients on these interaction variables are insignificant, while the coefficient on SOX is significantly negative. This is similar to the results using our post-Reg FD variable. These results suggest that while management forecast precision is lower, all else equal, in the post-SOX period, our main results were not significantly altered with the passage of SOX.

TABLE 1
Sample Selection

Management forecasts of annual earnings per share (EPS) from the First Call database from 1995 through 2004	27,841
(-) Observations with forecasts for more than one period	(5,764)
(-) Forecasts missing a preceding consensus analyst forecast or corresponding actual earnings in First Call	(3,053)
(-) Forecasts made more than 110 days after the fiscal-year end	(56)
(-) Forecasts missing COMPUSTAT data	(1,582)
(-) Forecasts missing CRSP data	(514)
Number of management forecasts in the final sample	**16,872**
Number of firms in final sample	**2,735**

TABLE 2
Sample Distributions

Panel A: Precision of Management Forecasts by Forecast Year - Number and (Percentage)

	Point	Range	Qualitative	Total
1995	116 (49.4)	99 (42.1)	20 (8.5)	235 (100.0)
1996	131 (42.3)	127 (41.0)	52 (16.8)	310 (100.0)
1997	222 (46.6)	143 (30.0)	111 (23.3)	476 (100.0)
1998	371 (44.5)	247 (29.7)	215 (25.8)	833 (100.0)
1999	340 (32.8)	324 (31.2)	374 (36.0)	1,038 (100.0)
2000	382 (35.0)	442 (39.3)	300 (26.7)	1,124 (100.0)
2001	547 (22.5)	1,605 (66.1)	276 (11.4)	2,428 (100.0)
2002	618 (20.0)	2,250 (72.8)	223 (7.2)	3,091 (100.0)
2003	535 (15.8)	2,624 (77.4)	232 (6.8)	3,391 (100.0)
2004	462 (11.7)	3,246 (82.3)	238 (6.0)	3,946 (100.0)
Total	3,724 (22.1)	11,107 (65.8)	2,041 (12.1)	16,872 (100.0)

Table 2 (Continued)

Panel B: Precision of Management Forecast by the Sign of News (Good or Bad) Where the Sign is Measured Based on the Sign of *FS1* - Frequency and (Percentage)

Forecast Type	Point	Range	Qualitative	Total
Good News	1,903 (22.8)	5,509 (65.9)	942 (11.3)	8,354 (100.0)
Bad News	1,821 (21.4)	5,598 (65.7)	1,099 (12.9)	8,518 (100.0)
Total	3,724 (22.1)	11,107 (65.8)	2,041 (12.1)	16,872 (100.0)

Note: We classify forecasts as good news if *FS1* (which is measured using cumulative abnormal returns) > 0, and as bad news if *FS1*< 0.

Panel C: Precision of Management Forecast by the Sign of News (Good or Bad) Where the Sign is Measured Based on the Sign of *FS2* - Frequency and (Percentage)

Forecast Type	Point	Range	Total
Good News	2,727 (28.7)	6,762 (71.3)	9,489 (100.0)
Bad News	997 (18.7)	4,345 (81.3)	5,342 (100.0)
Total	3,724 (25.1)	11,107 (74.9)	14,831 (100.0)

Note: We classify forecasts as good news if *FS2* (which is measured as [(management forecast - median analyst forecast) / stock price] ≥ 0, and as bad news if *FS2* < 0.

TABLE 3
Descriptive Statistics

	N	Mean	Std. Dev.	5%	Median	95%
FS1	16,872	-0.0095	0.1045	-0.1875	-0.0001	0.1280
ABS_FS1	16,872	0.0656	0.0819	0.0031	0.0391	0.2162
BAD_FS1	16,872	0.5049	0.5000	0	1	1
FS2	14,831	0.0180	0.0642	-0.0171	0.0004	0.1060
ABS_FS2	14,831	0.0254	0.0617	0	0.0031	0.1123
BAD_FS2	14,831	0.3602	0.4801	0	0	1
FERROR	14,831	0.0325	0.0736	0.0002	0.0081	0.1283
DNFE	14,831	0.5443	0.4981	0	1	1
DAYSPRIOR	16,872	204.0	195.5	4.0	210.0	377.0
SDRES	16,872	0.0271	0.0141	0.0107	0.0239	0.0541
CON_OWN	16,872	0.8103	0.4183	0.3522	0.9222	0.9957
NANAL	16,872	8.623	6.587	1.000	7.000	22.000
MB	16,872	3.115	11.689	0.719	2.329	10.031
SIZE	16,872	8,245	29,293	77	1,132	33,267
CONC	16,872	0.422	0.168	0.185	0.384	0.746

Notes:

FS1 = forecast surprise measured as the summation of market-adjusted daily returns over the three-day window centered on the management forecast date using standard market model procedures (*CAR*);

ABS_FS1 = the degree of forecast surprise, measured as the absolute value of *FS1*;

BAD_FS1 = an indicator variable which equals one if *FS1* < 0 and zero if *FS1* > 0;

FS2 = forecast surprise measured as the management forecast minus the most recent median analyst forecast preceding the management forecast, deflated by stock price at day -2;

ABS_FS2 = the degree of forecast surprise, measured as the absolute value of *FS2*;

BAD_FS2 = an indicator variable which equals one if *FS2* < 0 and zero if *FS2* ≥ 0;

FERROR = unsigned forecast error measured by the absolute value of (the actual earnings per share minus management forecast, deflated by stock price at day -2);

DNFE = an indicator variable that equals one if the signed forecast error is negative (i.e., management forecast exceeds the actual earnings per share) and zero otherwise;

DAYSPRIOR = the number of calendar days between the forecast and the end of fiscal year to which the forecast pertains;

SDRES = standard deviation of market model residuals estimated over a 200-day period, ending 31 trading days before the management forecast;

CON_OWN = concentrated ownership defined as one minus the relative number of common shareholders to common shares outstanding (= 1 – [1000*(the number of common shareholders / the number of common shares outstanding)]);

NANAL = the number of First Call analysts following for the month immediately preceding the management forecast;

MB	= the ratio of market to book value of the firm's common equity at the beginning of the forecast fiscal year;
SIZE	= the market value of common equity at the beginning of the forecast fiscal year (in millions);
CONC	= the firm's product-market concentration ratio, measured as the sales of the top-five firms in the two digit *SIC* industry in that year, divided by total sales in that industry during the year.

Table 4
The Association between Forecast Precision and the Magnitude of Forecast Surprise Considering Good versus Bad News

$$PRECISION1 = b_0 + b_1\,BAD\_FS1\ (or\ BAD\_FS2) + b_2\,ABS\_FS1\ (or\ ABS\_FS2) + b_3\,BAD\_FS1{*}ABS\_FS1\ (or\ BAD\_FS2{*}ABS\_FS2) + b_4\,HORIZON + b_5\,SDRES + b_6\,CON\_OWN + b_7\,LN(NANAL) + b_8\,MB + b_9\,LN(SIZE) + b_{10}\,CONC + b_{11}\,YEAR + \varepsilon$$

Variable	Expected Sign	All Forecasts		Point and Range Forecasts Only			
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
BAD_FS1	(-)	-0.100 (0.001)***	-0.013 (0.328)	-0.112 (0.003)***	0.006 (0.548)	-	-
BAD_FS2	(-)	-	-	-	-	-0.654 (0.000)***	-0.657 (0.000)***
ABS_FS1	(-)	-1.191 (0.000)***	-0.209 (0.063)*	-1.236 (0.000)***	-0.017 (0.037)**	-	-
ABS_FS2	(-)	-	-	-	-	-1.424 (0.002)***	-1.445 (0.007)***
*BAD_FS1 * ABS_FS1*	(-)	-	-1.432 (0.001)***	-	-1.898 (0.000)***	-	-
*BAD_FS2 * ABS_FS2*	(-)	-	-	-	-	-	-0.243 (0.045)**
HORIZON	(-)	0.016 (0.648)	0.014 (0.629)	-0.124 (0.008)***	-0.126 (0.007)***	-0.131 (0.006)***	-0.131 (0.006)***
SDRES	(-)	-1.353 (0.255)	-1.714 (0.202)	10.071 (0.937)	9.639 (0.921)	8.797 (0.920)	8.769 (0.913)
CON_OWN	(-)	0.060 (0.741)	0.061 (0.742)	-0.010 (0.459)	-0.009 (0.463)	-0.002 (0.491)	-0.002 (0.492)
LN(NANAL)	(+)	0.123 (0.003)***	0.125 (0.003)***	0.045 (0.246)	0.047 (0.233)	0.020 (0.381)	0.020 (0.379)
MB	(+)	-0.003 (0.842)	-0.003 (0.155)	-0.002 (0.242)	-0.003 (0.238)	-0.003 (0.194)	-0.003 (0.194)
LN(SIZE)	(+)	-0.012 (0.684)	-0.012 (0.681)	0.108 (0.001)***	0.108 (0.001)***	0.113 (0.001)***	0.113 (0.001)***
CONC	(-)	0.064 (0.686)	0.063 (0.685)	0.118 (0.722)	0.120 (0.725)	0.153 (0.773)	-0.153 (0.227)
YEAR	(?)	-0.094 (0.000)***	-0.095 (0.000)***	-0.331 (0.000)***	-0.333 (0.000)***	-0.338 (0.000)***	-0.338 (0.000)***
N		16,872	16,872	14,831	14,831	14,831	14,831
Log-likelihood Ratio (Chi-square)		214.67 (0.000)***	225.93 (0.000)***	1572.07 (0.000)***	1585.04 (0.000)***	1760.85 (0.000)***	1760.89 (0.000)***
Pseudo R^2		0.015	0.016	0.149	0.150	0.166	0.166

Table 4 (Continued)

Notes:
Models 1and 2 are the ordered-response logit analysis of the management forecast precision, where the dependent variable, *PRECISION1* is set to 2 for point forecasts, 1 for range forecasts, and 0 for qualitative forecasts. Models 3, 4, 5 and 6 are the binary logit analysis of the management forecast precision which equals one for point forecasts, and zero for range forecasts. A positive coefficient in all models is associated with more precise (i.e., specific) forecasts. Intercepts are not tabulated for parsimony.
YEAR is the year in which the management forecast is issued (1 = 1995, 2 = 1996, … , 10 = 2004). Please refer to Table 3 for the definitions of other variables.
When estimating the coefficients' standard errors, we use a White (1980) procedure to correct for heteroskedasticity and a clustering procedure that accounts for serial dependence across years for a given firm. One-tailed *p*-values are presented in the parentheses when a directional prediction is made. Otherwise, *p*-values are two-tailed.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5
The Association between a Continuous Measure of Forecast Precision and the Magnitude of Forecast Surprise Considering Good versus Bad News

$$PRECISION2 = b_0 + b_1\ BAD\_FS1\ (or\ BAD\_FS2) + b_2\ ABS\_FS1\ (or\ ABS\_FS2) + b_3\ BAD\_FS1{*}ABS\_FS1\ (or\ BAD\_FS2{*}ABS\_FS2) + b_4\ HORIZON + b_5\ SDRES + b_6\ CON\_OWN + b_7\ LN(NANAL) + b_8\ MB + b_9\ LN(SIZE) + b_{10}\ CONC + b_{11}\ YEAR + \varepsilon$$

Variable	Expected Sign	Model 1	Model 2	Model 3	Model 4
Intercept	(?)	0.496 (0.000)***	0.502 (0.000)***	0.751 (0.000)***	0.768 (0.000)***
BAD_FS1	(-)	-0.015 (0.118)	-0.008 (0.319)	-	-
BAD_FS2	(-)	-	-	-0.075 (0.000)***	-0.028 (0.033)**
ABS_FS1	(-)	-0.237 (0.013)**	-0.183 (0.037)**	-	-
ABS_FS2	(-)	-	-	-3.549 (0.000)***	-3.056 (0.000)***
*BAD_FS1 * ABS_FS1*	(-)	-	-0.176 (0.036)**	-	-
*BAD_FS2 * ABS_FS2*	(-)	-	-	-	-3.621 (0.004)***
HORIZON	(-)	-0.166 (0.000)***	-0.165 (0.000)***	-0.160 (0.000)***	-0.168 (0.000)***
SDRES	(-)	-6.008 (0.000)***	-5.921 (0.000)***	-6.282 (0.000)***	-5.720 (0.000)***
CON_OWN	(-)	0.010 (0.717)	0.010 (0.714)	0.014 (0.809)	0.013 (0.788)
LN(NANAL)	(+)	0.061 (0.000)***	0.060 (0.000)***	0.066 (0.000)***	0.061 (0.000)***
MB	(+)	0.001 (0.021)**	0.001 (0.021)**	0.001 (0.044)**	0.001 (0.046)**
LN(SIZE)	(+)	0.043 (0.000)***	0.043 (0.000)***	0.033 (0.000)***	0.033 (0.000)***
CONC	(-)	0.015 (0.597)	0.015 (0.596)	0.062 (0.856)	0.057 (0.838)
YEAR	(?)	-0.030 (0.000)***	-0.030 (0.000)***	-0.047 (0.000)***	-0.047 (0.000)***
N		14,831	14,831	14,831	14,831
F-value		126.39 (0.000)***	115.54 (0.000)***	298.61 (0.000)***	294.03 (0.000)***
R^2		0.079	0.079	0.168	0.179

Table 5 (Continued)

Notes:
The dependent variable, *PRECISION2*, is set to 0 for point forecasts, and for range forecasts is the negative of (the absolute value of [the upper limit minus the lower limit] deflated by the share price at day –2). A positive coefficient is associated with more precise forecasts. All models are estimated by OLS and all coefficients are multiplied by 100 for presentation purposes.
YEAR is the year in which the management forecast is issued (1 = 1995, 2 = 1996, … , 10 = 2004) and *DNFE* is an indicator variable which equals one if signed management forecast error is negative and zero otherwise. Please refer to Table 3 for the definitions of other variables.
When estimating the coefficients' standard errors, we use a White (1980) procedure to correct for heteroskedasticity and a clustering procedure that accounts for serial dependence across years for a given firm. One-tailed *p*-values are presented in the parentheses when a directional prediction is made. Otherwise, *p*-values are two-tailed.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6
The Association between a Continuous Measure of Forecast Precision and Forecast Surprise and Forecast Error, Considering Good versus Bad News

$$PRECISION2 = b_0 + b_1\,BAD\_FS1\ (\text{or}\ BAD\_FS2) + b_2\,ABS\_FS1\ (\text{or}\ ABS\_FS2) + b_3\,BAD\_FS1{*}ABS\_FS1\ (\text{or}\ BAD\_FS2{*}ABS\_FS2) + b_4\,FERROR + b_5\,DNFE + b_6\,DNFE{*}\,FERROR + b_7\,HORIZON + b_8\,SDRES + b_9\,CON\_OWN + b_{10}\,LN(NANAL) + b_{11}\,MB + b_{12}\,LN(SIZE) + b_{13}\,CONC + b_{14}\,YEAR + \varepsilon$$

Variable	Expected Sign	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	(?)	0.495 (0.000)***	0.366 (0.000)***	0.748 (0.000)***	0.621 (0.000)***	0.357 (0.000)***
BAD_FS1	(-)	-0.001 (0.493)	-0.001 (0.472)	-	-	-
BAD_FS2	(-)	-	-	-0.026 (0.087)*	-0.048 (0.021)**	-
ABS_FS1	(-)	-0.191 (0.040)**	-0.196 (0.044)**	-	-	-
ABS_FS2	(-)	-	-	-2.715 (0.000)***	-2.719 (0.000)***	-
*BAD_FS1 * ABS_FS1*	(-)	-0.056 (0.067)*	-0.016 (0.070)*	-	-	-
*BAD_FS2 * ABS_FS2*	(-)	-	-	-3.738 (0.004)***	-1.564 (0.032)**	-
FERROR	(-)	-2.221 (0.000)***	-1.868 (0.000)***	-0.037 (0.117)	-0.023 (0.298)	-1.878 (0.000)***
DNFE	(?)	-	-0.140 (0.015)***	-	-0.104 (0.003)***	-0.139 (0.001)***
DNFE FERROR*	(-)	-	-8.027 (0.001)***	-	-5.056 (0.004)***	-8.028 (0.001)***
HORIZON	(-)	-0.130 (0.000)***	-0.113 (0.000)***	-0.163 (0.000)***	0.144 (0.000)***	-0.124 (0.000)***
SDRES	(-)	-5.430 (0.000)***	-4.337 (0.001)***	-5.590 (0.000)***	-5.105 (0.000)***	-4.620 (0.000)***
CON_OWN	(-)	0.009 (0.715)	0.005 (0.603)	0.013 (0.781)	0.009 (0.713)	0.004 (0.596)
NANAL	(+)	0.064 (0.000)***	0.053 (0.000)***	0.061 (0.000)***	0.055 (0.000)***	0.053 (0.000)***
MB	(+)	0.001 (0.035)**	0.001 (0.046)**	0.001 (0.047)**	0.001 (0.071)*	0.001 (0.071)*
LN(SIZE)	(+)	0.033 (0.000)***	0.034 (0.000)***	0.033 (0.000)***	0.033 (0.000)***	0.034 (0.000)***
CONC	(-)	0.050 (0.802)	0.049 (0.816)	0.059 (0.845)	0.059 (0.849)	0.048 (0.801)
YEAR	(?)	-0.042 (0.000)***	-0.043 (0.000)***	-0.049 (0.000)***	-0.047 (0.000)***	-0.042 (0.000)***
N		14,831	14,831	14,831	14,831	14,831
F-value		183.86 (0.000)***	207.37 (0.000)***	270.62 (0.000)***	252.89 (0.000)***	203.53 (0.000)***
R^2		0.130	0.164	0.180	0.193	0.159

Table 6 (Continued)

Notes:
The dependent variable, *PRECISION2*, is set to 0 for point forecasts, and for range forecasts is the negative of (the absolute value of [the upper limit minus the lower limit] deflated by the share price at day –2). A positive coefficient is associated with more precise forecasts. All models are estimated by OLS and all coefficients are multiplied by 100 for presentation purposes.
YEAR is the year in which the management forecast is issued (1 = 1995, 2 = 1996, … , 10 = 2004). Please refer to Table 3 for the definitions of other variables.
When estimating the coefficients' standard errors, we use a White (1980) procedure to correct for heteroskedasticity and a clustering procedure that accounts for serial dependence across years for a given firm. One-tailed *p*-values are presented in the parentheses when a directional prediction is made. Otherwise, *p*-values are two-tailed.
* Significant at 10%; ** significant at 5%; *** significant at 1%.