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Credibility of Management Forecasts

Jonathan L. Rogers
Phillip C. Stocken

07-02

The Wharton School
University of Pennsylvania

The Rodney L. White Center for Financial Research

The Wharton School
University of Pennsylvania
3254 Steinberg Hall-Dietrich Hall
3620 Locust Walk
Philadelphia, PA 19104-6367

(215) 898-7616
(215) 573-8084 Fax
http://finance.wharton.upenn.edu/~rlwctr

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Credibility of Management Forecasts*

Jonathan L. Rogers and Phillip C. Stocken

The Wharton School
University of Pennsylvania
Philadelphia
PA 19104-6365

February 2002

Abstract

This paper examines the credibility of management earnings forecasts. With regard to how forecast bias varies with manager incentives, we establish that when it is more difficult for market participants to detect forecast bias, financially distressed firms are more optimistic than healthy firms and firms in concentrated industries are more pessimistic than those in less concentrated industries. With regard to the stock price response to forecasts, we find that the market's immediate response varies with the predicted bias in good news but not in bad news forecasts. The market's subsequent response, however, is consistent with it eventually identifying the bias in bad news forecasts and modifying its valuation of the firm in the appropriate direction.

*We thank Brian Bushee, Phil Berger, John Core, Gus De Franco, Chris Ittner, Dave Larker, Christian Leuz, Ro Verrecchia and workshop participants at The Wharton School for helpful comments. We also gratefully acknowledge support from the Rodney L. White Center for Financial Research and thank First Call for providing data used in this study. Please address all correspondence to: Phillip Stocken, The Wharton School, University of Pennsylvania, Philadelphia, PA 19104. Telephone: (215) 898-4942. Fax: (215) 573-2054. E-mail: pstocken@wharton.upenn.edu.

Credibility of Management Forecasts

1 Introduction

This paper examines the credibility of management earnings forecasts. Policy-makers, equity analysts and investors have long been concerned with the credibility of this form of voluntary disclosure. For instance, the Securities and Exchange Commission (SEC) traditionally argued that market forces were insufficient to induce managers to forecast truthfully and thus prohibited the inclusion of forward-looking statements in SEC filings. Investors, however, regarded forward-looking information as being useful and called for firms to provide it. Hence, in 1973, the SEC reversed its long-standing exclusionary policy and subsequently issued several pronouncements encouraging the release of forward-looking information. In 1979, it adopted a "safe-harbor" provision to shelter managers from litigation arising from unattained projections in SEC filings (Penman [1980], and Pownall and Waymire [1989]). More recently, Congress enacted the Private Securities Litigation Reform Act of 1995, which extended these provisions to any forward-looking statements that management offered in good faith. Opponents of the legislation vigorously contested it, claiming that it would provide a "license to lie" (Grundfest and Perino, 1997, ii).

The "expectation adjustment hypothesis" predicts that managers will truthfully reveal their private information to align investors' expectations with their own (Ajinkya and Gift [1984]). While managers may typically aim to align the market's expectations with their own and therefore offer unbiased forecasts, from time to time they may have incentives to issue biased forecasts. Even though managers may have such incentives, market participants can often use the subsequent earnings report, which is audited, and information from other sources, such as financial analysts, to detect and punish biased forecasting. Since this institutional feature constrains a manager's forecasting behavior, forecast bias should vary with both a manager's incentives to issue a self-serving forecast and market participants' ability to detect deviant forecasting. Forecast bias is the systematic difference between a management earnings forecast and the earnings realization.

In this study, we first consider how forecast bias varies with the managers' incentives. We find the association between forecast errors and management incentives to issue misleading forecasts varies with how difficult it is for the market to detect biased forecasting. We consider specifically identifiable management incentives to misrepresent private information. We find that when it is more difficult for the market to detect forecast bias, financially distressed firms are more optimistic than healthy firms, and firms in concentrated industries are more pessimistic than those in less concentrated industries. An optimistic (pessimistic) forecast is one where the management forecast is greater (less) than the earnings realization. We also consider managers' incentives that are not specifically identifiable but nevertheless are implicitly revealed through their observable actions. We find that forecast errors are associated with managers' incentives that are implicitly revealed when a good news forecast is released. A good (bad) news forecast is one that is greater (less) than the prevailing consensus analyst forecast.

Second, we examine the stock price response to management forecasts. When the market is capable of identifying managements' incentives, the market's response is positively associated with the forecast news, but the efficiency of its response varies with the news. With regard to good news forecasts, the market's immediate response is consistent with the market viewing these forecasts with skepticism and adjusting for the predicted bias in the forecast. Further, the market's immediate adjustment for the predicted bias seems to be complete because we find that the subsequent risk-adjusted returns are not associated with the predicted bias in these forecasts. With regard to bad news forecasts, in contrast, the market initially takes them at face value even though these forecasts are predictably biased. Subsequently, however, the risk-adjusted returns are consistent with the market identifying the predicted bias in the forecasts and modifying its valuation of the firm in the appropriate direction.

This study makes several contributions to the literature on management forecasting behavior. First, the extant evidence regarding the presence of forecast bias is mixed. For instance, early research suggested that management forecasts in the late 1960s and early 1970s were optimistic on average (e.g., Penman [1980]); in contrast, research examining more recent time periods documents that forecasts are unbiased on average (e.g., McNichols [1989], Kasznik [1999], Johnson, Kasznik, and Nelson [2001]). Choi and Ziebart [2000] find mixed evidence of average forecast bias but observe a temporal trend in forecast bias when they separate long-term forecasts and short-term forecasts. In this paper, we find that management earnings forecasts are not only biased, but managers strategically distort their forecasts in response to their incentives and the market's capability to detect biased forecasting.

Second, we develop a prediction model that allows us to evaluate whether or not the market's assessment of a forecast's credibility is appropriate. Prior studies have used the stock price response to a forecast or analyst forecast revisions to infer the credibility of the forecast (see, for instance, Jennings [1987] and Williams [1996]). These studies have concluded that bad news is more credible than good news based on observing that the market or analysts are more responsive to bad news than good news. These studies have not established, however, whether bad news is more precise, or less biased, than good news. In this paper, we develop a measure of forecast bias, and thus, are capable of evaluating the appropriateness of the market's response to a forecast. We find that investors interpret bad news as being more credible than good news even though we do not find evidence that bad news is unbiased or even less biased than good news. Our results suggest that investors also should skeptically interpret bad news forecasts and not simply take them at face value.

Last, we find evidence that the market's ability to detect dissembling, at least imperfectly, dampens managements' incentives to bias their forecasts. Despite this forecasting constraint, managers bias their earnings forecasts in a predictable fashion. Thus it appears that the extant market forces are insufficient to deter managers from offering self-serving forecasts in the period after the enactment of the Private Securities Litigation Reform Act of 1995.

The rest of the paper proceeds as follows: Section 2 develops the hypotheses; Section 3 describes the sample; Section 4 specifies the research design and discusses the results; and Section 5 concludes.

2 Hypothesis Development

Managers may benefit from issuing forecasts that manipulate market participants' beliefs about the firm's value. For instance, issuing an optimistic forecast may discourage or delay investors (or directors) from replacing the firm's management; conversely, issuing a pessimistic forecast may delay or deter competitors from entering the firm's product market.

Although managers may have incentives to misrepresent their private information, they nevertheless are constrained, at least partially, from misleading market participants because these participants can use the audited earnings report and information from other sources to assess the forecast's veracity.[1] If a plaintiff can establish in court that a management forecast (either written or oral) was made with actual knowledge that it was false or misleading, then the safe-harbor provisions in the Private Securities Litigation Reform Act of 1995 do not apply. In this case, a misleading forecast will expose the manager to criminal penalties under the anti-fraud provisions of Section 10(b) of the Securities Exchange Act of 1934 and the SEC promulgated Rule 10b-5. In addition to legal censure, the firm may suffer what stock traders call a "liar's discount": this is the discounting of a firm's stock price below that of its competitors when analysts refuse to trust a firm's management after its prior voluntary disclosure is exposed to be misleading (King, 1988).

The usefulness of an audited earnings report and information from other sources for assessing the truthfulness of a management forecast varies, in part, with the difficulty of accurately predicting earnings. A manager should be able to predict earnings more accurately when earnings are stable or when there is little uncertainty about the firm's earnings as evidenced by low variation in equity analysts' earnings forecasts. On the other hand, if the firm's earnings vary significantly as circumstances change, then it is more difficult for the manager to forecast earnings and therefore more difficult for the market to evaluate the manager's forecasting accuracy. In this light, we develop an empirical measure that reflects market participants' ability to assess the veracity of the manager's forecast.

Theoretical studies have examined whether a manager will dissemble when investors can use a subsequent earnings report to assess the truthfulness of the manager's forecast. For instance, Sansing [1992] studies a single-period signaling model

[1] Indeed, Lev and Penman [1990] argue that management forecasts are credible because investors can *ex post* verify a manager's forecast by comparing it with the audited earnings report.

containing a manager and a representative investor. The manager privately observes the firm's value and whether the accounting system will reveal his private information. The investor, in contrast, is uncertain about the firm's value and whether the accounting system will reveal the manager's information. Sansing shows that the existence of an accounting system is sufficient to ensure that the manager will partially reveal his information. Stocken [2000] considers a repeated cheap-talk game and establishes that a manager will almost always truthfully report his non-verifiable private information provided several conditions are satisfied, including the earnings report being sufficiently useful for assessing the veracity of the manager's voluntary disclosure.[2]

Market participants can more cogently assess the credibility of a manager's forecast if they can unambiguously compare it to the realized earnings report. Earnings forecasts, however, are offered with varying levels of specificity.[3] It may be easier for market participants to assess the veracity of point and range estimates than qualitative estimate of earnings.[4] In light of our emphasis on investors' ability to assess managements' forecasting credibility, we focus our attention on point and range earnings forecasts. We acknowledge, however, that these types of forecasts exclude a substantial proportion of management forecasts.[5]

[2] The other two sufficient conditions are that the manager is sufficiently patient and his forecasting performance is evaluated over a sufficiently long time horizon. Stocken [2000] establishes that these conditions are sufficient to guarantee that the manager will truthfully reveal his private information even though the earnings report might be a noisy monitor of the manager's forecasting behavior.

[3] For example, earnings forecast might be in the form of a point estimate (e.g., we expect earnings to be $1.00 this year), a range estimate (e.g., we expect earnings to be between $.90 and $1.10 this year), a minimum estimate (e.g., we expect earnings to be greater that $.90 this year), a maximum estimate (e.g., we expect earnings to be less than $1.10 this year), or some qualitative forecast where the earnings are not quantified or bounded in any sense (e.g., we are bullish about earnings this year).

[4] In an experimental study, Hirst, Koonce, and Miller [1999] find that forecast specificity and management prior forecast accuracy affect the confidence of investors' judgement about a firm's earnings.

[5] See, for instance, Pownall, Wasley, and Waymire [1993] and Bamber and Cheon [1998].

2.1 Management incentives and forecasting bias

Against this background, we expect forecast bias to be related to managements' incentives to manipulate market participants' beliefs coupled with the participants' ability to assess the forecast's integrity. Management forecasts are useful to both capital market and product market participants.[6] In this study, we address the capital market effects on the managers' incentives by examining firms' forecasting behavior when they are financially distressed and consider the product market effect by considering how firms' disclosure varies with the level of industry concentration.[7]

The first two hypotheses consider specific incentives to issue misleading forecasts that the capital market and product market induce.

Financial Distress A manager's incentive to issue a misleading forecast varies with the firm's financial health, holding constant the market's ability to detect a misleading forecast. For instance, when a firm has performed poorly, we expect a manager to be more inclined to issue an optimistic forecast and provide encouraging news about the firm's future prospects. Such a disclosure is aimed at convincing investors that they should continue to employ the manager because he is executing a business plan that will restore the ailing company to financial health.[8] Whether or not the manager of a distressed firm actually issues an optimistic forecast, however, is affected by the market's ability to assess the credibility of the manager's forecast. Hence, our directional hypothesis (stated in the alternative form) is:

[6] Newman and Sansing [1993] and Gigler [1994] examine how the presence of these two audiences theoretically affect the credibility of a manager's voluntary disclosure.

[7] We do not consider managers' incentives to dissemble when they approach the capital market for financing because Frankel, McNichols, and Wilson [1995] find that in these circumstances, where the threat of litigation is severe, forecasts are unbiased.

[8] Other incentives encouraging managers of financial distressed firms to issue optimistic forecasts include reducing the probability of bankruptcy, acquisition, or hostile takeover. See Frost [1997] for further details.

H1a: Managers of financially distressed firms issue more optimistic forecasts when it is more difficult for the market to detect misrepresentation.

Industry Concentration Industries become concentrated when some firms enjoy a competitive advantage over their competitors: this advantage may be attributable to economies of scale, barriers to entry, product brand awareness, proprietary technology, and the like (see Besanko, Dranove, and Shanley, 2000). Firms in more concentrated industries are more profitable than firms in less concentrated industries.[9] Further, when a new firm enters an industry, the profits of firms in more concentrated industries decline by a larger amount than the profits of firms in less concentrated industries.[10] Consequently, the manager of a firm in a concentrated industry has a greater incentive than a manager of a firm in a less concentrated industry to discourage competitors from entering the industry.[11] Therefore, such a manager may be more inclined to release pessimistic information, holding constant the market's ability to detect a misleading forecast. Whether or not a firm releases a pessimistic forecast, however, is affected by the market's ability to assess the truthfulness of the manager's forecast. Thus, our directional hypothesis (stated in the alternative form) is:

H1b: Managers of firms in concentrated industries issue more pessimistic forecasts when it is more difficult for the market to detect misrepresentation.

[9] Tirole [1993, 221-223] notes that most empirical analyses, consistent with theoretical predictions, find a positive relation between concentration and profitability.

[10] See Tirole's [1993, 218-223] analysis of an imperfectly competitive market showing that firm's profits decline when new firms enter the market and the magnitude of this decline is proportional to firm profitability, which, in turn as noted earlier, is proportional to industry concentration. Bresnahan and Reiss [1991] find empirical evidence consistent with this relation.

[11] Darrough and Stoughton [1990] and Wagenhofer [1990] examine the incentives for firms to voluntary disclose proprietary information when the disclosure affects the entry decision of a prospective competitor.

In addition to the incentives that a firm's financial distress and its industry concentration induce, managers have other incentives to bias their forecasts.[12] Many of these incentives, however, are not empirically observable. Consequently, we consider two proxies that implicitly reveal managers' unobserved incentives to misrepresent their private information.

Lagged Forecast Error Managers develop reputations over time for offering accurate forecasts. Williams (1996), for instance, finds a significant association between the usefulness of prior forecasts and analyst earnings revisions following a subsequent management forecast. To the extent that a manager's unobserved incentives and the ability of the market to detect misrepresentation remain constant over time, we would expect the sign and magnitude of previous forecast errors to be associated with future forecast errors. The previous forecast error represents an optimizing choice the manager made in response to his incentives and the market participants' ability to detect misrepresentation existing in that period. Therefore, our directional hypothesis (stated in the alternative form) is:

H1c: Forecast errors are positively associated with previous forecast errors.

Forecast News Management's expectation of earnings often differ from the market's prevailing expectation of earnings. Under the expectations adjustment hypothesis, managers issue forecasts to align the market's expectations with their own (Ajinkya and Gift [1984] and Hassell and Jennings [1986]). They reveal their private information to reduce information asymmetry in the market and thus reduce the fir-

[12]Managers may have incentives to misrepresent their private information induced by their personal circumstances, such as age and financial interest in the firm. We expect the market to consider these factors when evaluating forecast bias. We leave consideration of these manager idiosyncratic factors to future research.

m's cost of capital (See, for instance, King, Pownall, and Waymire [1990], Coller and Yohn [1997], and Verrecchia [2001]).[13] If managers truthfully reveal their private information and analysts' forecasts are unbiased, then forecast errors should not be correlated with forecast news.[14]

Managers, however, may opportunistically issue forecasts to manipulate investors' beliefs. Their incentives to issue forecasts are influenced by the litigation environment. Skinner [1994] and Kasznik and Lev [1995] suggest that managers release bad news to prepare investors for disappointing earnings and thereby reduce the probability of litigation. Given the litigation environment, managers may feel compelled to release bad news irrespective of their other incentives to manipulate investors' beliefs (see Baginski and Hassell, 1997). Conversely, managers may feel less compelled to release good news. If managers have incentives to push investors' beliefs about earnings downward, then they may choose to withhold good news or may even iniquitously issue bad news. Thus, bad news forecasts might be issued by managers who privately observed bad news and feel compelled to disclose it, or by those who observed good news but chose to depress investors' beliefs. In contrast, the decision to release a good news forecast is more likely to implicitly reveal a manager's other incentives to manipulate investors' beliefs upward. Hence, to the extent that analysts' forecasts are unbiased, forecast errors should be positively associated with forecast news, and this association should be weaker for bad news forecasts.

These arguments yield the following directional hypothesis (stated in the alterna-

[13]Other reasons for providing forecasts include signaling a manager's superior ability to anticipate changes in the firm's economic environment (Trueman [1986]) and disclosing bad news to reduce expected litigation costs (e.g., Skinner [1994]).

[14]Keane and Runkle [1998] find that analysts' earnings forecasts are unbiased. They attribute the earlier findings that forecasts are biased (see Brown [1993] for an extensive survey) to correlation across analyst forecast errors and observable discretionary asset write-downs that analysts intentionally ignore.

tive form):

H1d: Forecast errors are positively associated with forecast news and this association is weaker for bad news forecasts than for good news forecasts.

Next we consider the stock price response to management forecasts.

2.2 Management incentives and market price response

In a model where the stock market has rational expectations about a manager's incentives to bias a report, Fischer and Verrecchia [2000] argue that when the manager's incentives are common knowledge, the market perfectly adjusts for bias, and consequently, bias does not affect the information content of the manager's report. Despite this market response, they note that in equilibrium the manager has a strict incentive to bias his report even though it may be costly for him to do so. On the other hand, they establish that when the market is uncertain about a manager's incentives and therefore incapable of perfectly adjusting for the bias in the report, it dampens its response to the report. Thus reporting bias reduces the information content of the manager's report.

The following hypotheses assume that the market can either explicitly or implicitly identify a manager's forecasting incentives and therefore adjust for the expected bias in the forecast. Since previous studies examining a firm's voluntary disclosure find that good and bad news are associated with differential market responses (e.g., Jennings [1987], Skinner [1994], and Kasznik and Lev [1995]), we separately hypothesize on the market response to good news and bad news forecasts.

Good News Forecasts Consistent with prior studies (e.g., Ajinkya and Gift [1984], Waymire [1984]), we expect a positive market reaction to good news forecasts.

If, however, the market believes that a forecast overstates expected earnings, or is optimistic, then we expect it to respond less positively to that forecast. Conversely, if the market believes that a forecast understates expected earnings, or is pessimistic, then we expect it to respond more positively to that forecast. In summary, we anticipate the market to respond in a fashion that unwinds, at least partially, the predicted bias contained in the forecast. These argument are formalized in the following directional hypothesis (stated in the alternative form):

H2a: For good news forecasts, the market will respond less positively to forecasts with higher predicted optimism and respond more positively to forecasts with higher predicted pessimism.

Bad News Forecasts We expect the market to respond negatively to the release of a bad news forecast, which, as already mentioned, is consistent with prior research. Further, we expect the market to predict when a management forecast understates the weakness in the firm's future earnings, or is optimistic, and accordingly, respond more negatively to the forecast. In contrast, if the market believes that the manager has overstated the weakness in the firm's earnings and offered a pessimistic forecast, then it will respond less negatively to the forecast.

In short, the market's response to predicted forecast errors in bad news forecasts is expected to be symmetric with its response to predicted errors in good news forecasts. Hence, we posit the following hypothesis (in the alternative form):

H2b: For bad news forecasts, the market will respond more negatively to forecasts with higher predicted optimism and respond less negatively to forecasts with higher predicted pessimism.

3 Sample and Descriptive Statistics

Our sample includes firms with management forecasts in the First Call Historical Database for the years 1996 to 2000. It has been established that the legal environment is associated with management forecasting behavior (Baginski, Hassell and Kimbrough, 2002). hence, we restrict our sample to forecasts released after the enactment of the Private Securities Litigation Reform Act, which became effective on December 22, 1995. We expect that forecast credibility will be more salient in this period because the Act reduces the expected litigation costs associated with unattained forecasts (Johnson, et al., 2001).

For each fiscal year-end, we include the first disclosed management forecast of annual earnings per share (EPS). We consider the first forecast of annual earnings rather than later annual forecasts and quarterly forecasts because this forecast is associated with a longer horizon between the forecast release and earnings announcement. A longer horizon is expected to enhance the benefits that managers obtain from issuing misleading forecasts and accordingly heighten the need for market participants to assess the veracity of forecasts.

To focus on management forecasts rather than earnings pre-announcements, we eliminate forecasts issued on or after the fiscal year-end. To mitigate the small denominator problem associated with using price as a deflator, we exclude firms with pre-release share prices under $2.00. Furthermore, to implement Ohlson's [1980] measure of financial distress, we exclude utilities, transportation companies, and financial services companies. We also exclude companies with insufficient data on Compustat and CRSP. The sample selection procedures, summarized in Table 1, result in a final sample of 600 firms with 955 firm-year observations (445 point estimates and 510 range estimates).

Table 2 describes the distribution of forecasts. The majority of the firms in the sample (62 percent) issue a forecast in only one of the five years (Panel A). The sample is skewed toward forecasts issued later in the sample period (Panel B). While the majority of forecasts are issued for firms that have December year-ends (Panel C), forecasts are released fairly evenly throughout the year (Panel D); thus forecasts do not appear to be clustered in time.

The sample represents a diverse cross-section of industries. No single two-digit SIC code accounts for more than 10 percent of our sample. The largest two-digit sectors are: business services (10 percent), chemical and allied products (10 percent), and industrial machinery and equipment (8 percent).

Table 3 reports descriptive statistics for the sample of management forecasts. The mean (median) market value of equity for firms in the sample is approximately $8.25 billion ($1.26 billion), which indicates that our sample firms tend to be large. Management forecasts, on average, are issued 191 days prior to the fiscal year-end. In addition, we note that the consensus analyst forecasts (prevailing when the management forecast is released) and the management forecasts are optimistic, on average. The latter finding contrasts Johnson, et al. [2001] who find that in the first year following the enactment of the Private Securities Litigation Reform Act, management forecast errors of computer hardware, computer software, and pharmaceutical firms were statistically indistinguishable from zero.

Table 4, Panel A, presents the correlation coefficients among forecast news, management forecast errors, and analyst forecast errors. Consistent with the expectation adjustment hypothesis, we observe a significantly negative correlation between consensus analyst forecast error and the forecast news. We find mixed evidence concerning the relation between forecast news and forecast errors. Specifically, the Pearson correlation is significantly negative whereas the Spearman correlation is significantly positive. Table 4, Panel B and C provide the correlation matrices for the independent variables used to test our hypotheses.

4 Hypothesis Testing

In this section, we formulate the research design to test the hypotheses examining, first, the relation between management incentives and forecast errors, and second, the association between predicted forecast errors and stock price response.

4.1 Research Design for Hypothesis 1

To examine the effect of a manager's incentives on forecast errors, we estimate the following model using cross-sectional ordinary least squares (OLS) regression for the pooled sample (firm and time subscripts have been suppressed):

$$\begin{aligned} FE = {} & \beta_0 + \beta_1 Difficulty + \beta_2 Distress + \beta_3 Distress \times Difficulty \\ & + \beta_4 Concen + \beta_5 Concen \times Difficulty + \beta_6 FE_{t-k} + \beta_7 Bad\_News \\ & + \beta_8 FN \times Good\_News + \beta_9 FN \times Bad\_News + \beta_{10} Horizon \\ & + \beta_{11} CAR_{-120,-2} + \beta_{12} Size + \beta_{13} M/B + \beta_{14} DAccruals + \varepsilon. \end{aligned} \tag{1}$$

The model's variables are defined and discussed below.

Forecast Error (FE): Forecast error, FE, is defined as:

$$FE = \frac{\text{Management forecast of EPS} - \text{Reported EPS}}{\text{Pre-release share price}}.$$

Management forecast of EPS is defined as either the point estimate or the mid-point of a range estimate of the firm's annual earnings.[15] We use the first disclosed point or range estimate of the annual earnings for each firm. Reported EPS is the actual EPS reported by First Call; when applicable we use revised EPS. Using EPS reported by First Call ensures consistency between the management forecasts and analyst forecasts.[16] Pre-release share price is the closing price on CRSP three days prior to the management forecast release date reported by First Call.

Forecast Difficulty (*Difficulty*): A key economic tension that this paper explores is whether or not market participants' (e.g., investors and competitors) ability to detect dissembling constrains managers from forecasting in a self-interested fashion. The market's ability to detect dissembling, in turn, is positively associated with managements' capacity to forecast accurately. Consequently, we require a measure of the difficulty of forecasting earnings accurately. No single variable, however, perfectly captures this underlying construct. Nevertheless, we believe several variables, which we discuss in a moment, measure the difficulty of forecasting, albeit with error. Accordingly, factor analysis is used to identify this underlying construct. We assume that the variance of each indicator variable is composed of two components: the variance associated with the latent construct and the variance specific to that indicator. Further, we assume that the indicator specific variances are uncorrelated across variables.

The following indicator variables generate a summary measure that proxies for forecast difficulty. First, when earnings are difficult to predict, we expect analysts to

[15]Prior research suggests that investors use the mid-point of a range forecast when forming their expectation of earnings (see Baginski, Conrad, and Hassell [1993], Hirst, et al. [1999], among others).
[16]First Call Corporation [1999, 9] adjusts actual EPS "to exclude any unusual items that a majority of the contributing analysts deem non-operating and/or non-recurring."

disagree about the forthcoming earnings. The standard deviation of analyst forecasts outstanding when the management forecast is released, STD_AF, measures lack of analyst consensus. Second, if the difficulty analysts experience forecasting earnings remains constant over time, the variability of previous analyst forecast errors is positively associated with the current difficulty of forecasting earnings. The standard deviation of previous consensus forecast errors for five years, STD_AFE, proxies for the difficulty analysts experience predicting earnings.[17] Third, a manager may have more difficulty forecasting a firm's earnings when its "true" earnings are more volatile. We regard "true" earnings as those that would be observed in the absence of the strategic manipulation or smoothing of earnings.[18] Volatility in the firm's "true" earnings is positively associated with volatility in a firm's stock price, which, in turn, is associated with the firm's bid-ask spread (see Coller and Yohn [1997]), denoted *Spread*. In addition, a portion of a firm's bid-ask spread is associated with a market specialist's perception of information asymmetry in the market, which is expected to increase with uncertainty about the firm's forthcoming earnings announcement. Fourth, a manager may experience more difficulty predicting "true" earnings of a growing firm. We use operating cash flow growth, OCF_Growth, to proxy for firm's true earnings growth. Fifth, Baginski, et al. [1993] argue that managers reveal their underlying uncertainty about a firm's earnings by issuing forecasts with wider ranges. We use the width of range estimates, denoted MF_Width, to proxy for manager revealed uncertainty; for point estimates, we set MF_Width equal to zero.

[17] Relatedly, Waymire (1985) uses the absolute value of analyst forecast errors as an ex post proxy for earnings volatility.

[18] We do not consider reported earnings because, to the extent managers have incentives to smooth reported earnings, reported earnings will be less volatile than "true" earnings. Barth, Elloitt, and Finn [1999] find evidence suggesting that earnings of firms with continual growth are valued more highly that those of firms with the same level but that have more volatile growth. See Ronen and Sadan [1981] for a nice discussion of income smoothing behavior.

Table 5 reports the results of factor analysis. The Pearson and Spearman correlations among the five indicator variables of forecast difficulty are presented in Panel A. All of the significant correlations among the indicators have the expected sign. The parameter estimates, derived using maximum likelihood estimation (MLE), are presented in panel B. Each of the factor loadings (λs) for the latent variable, $Difficulty$, has the predicted sign. A Chi-Square test rejects no common factors in favor of the hypothesis that there is at least one common factor (p-value < 0.001); moreover, we are unable to reject the hypothesis that one factor is sufficient (p-value 0.570). Since we reject normality (not tabulated) for each of the indicator variables, we re-estimate the factor using the asymptotic distribution-free estimation method (ADF) developed by Browne [1984].[19] Panel C reports the factor loadings derived using ADF analysis. Again, each indicator loads with the expected sign and each of the factor loadings are significant with the exception of the loading on the MF_Width indicator. This factor is highly correlated with the factor based on MLE analysis (Pearson 0.92, Spearman 0.95). In light of the distributional properties of ADF estimation, we use the ADF factor in the remainder of the paper.[20] Our results are unaffected, however, if we use the factor obtained from MLE.[21]

To ensure the robustness of our results, we examine an alternative proxy for forecast difficulty. We regress absolute management forecast errors on the previously described variables and use the predicted value from this regression as another measure of forecast difficulty. We note that both of these measures are highly correlated

[19]Joreskog and Sorbom [1989] impose a minimum sample size of 200 for ADF analysis with fewer than 12 variables.

[20]To ensure robustness, we also estimate Difficulty using Principal Axis Factoring (PAF). Standard factor analysis heuristics (e.g., scree plots and eigenvalues) also suggest a single factor. The PAF factor is highly correlated with the factor based on ADF analysis (Pearson 0.95, Spearman 0.95). Our results are unaffected if we use the factor obtained from PAF.

[21]Alternatively, we use the indicator STD_AF as a sole proxy for forecast difficulty. Our hypothesized results remain qualitatively similar.

(Pearson 0.93, Spearman 0.96), which suggests that both proxies measure the same underlying construct – the difficulty of predicting earnings. The OLS derived proxy based on forecast errors would reflect forecast difficulty if management forecasts were unbiased and subsequent earnings reports were representationally faithful (i.e., unmanaged). Since we hypothesize that managers strategically misrepresent their information when forecasting, we only report results using the factor score. Our results, however, are not sensitive to whether we use the factor score or the predicted value from OLS.[22]

Distress (*Distress*): We proxy for financial distress using Ohlson's [1980] bankruptcy prediction model 1, which has been used in recent studies (e.g., Barton, 2001). Since Ohlson's model uses industrial firms, we exclude utilities, transportation companies and financial services companies. Hypothesis 1a predicts that managers of financially distressed firms will issue optimistic forecast when it is more difficult for the market to detect the manager's misrepresentation. Accordingly, we expect the coefficient on $Distress \times Difficulty$ to be positive.[23]

Concentration (*Concen*): Industry concentration is commonly measured using the m-firm product-market concentration ratio in studies of firm disclosure. We define industry concentration, *Concen*, as the sales of the largest five firms in an industry divided by total sales in that industry during that year. An industry is defined as all firms reported on Compustat that share the same four-digit SIC code. Although

[22] To further validate the factor, we compare the factor score to the time-series standard deviation of management forecast errors, which are computed for all firms with at least two management forecasts (230 firms). We compare this statistic to the factor score for the last forecast released and find that the correlations between these measures (Pearson .363, and Spearman .395) are highly significant.

[23] Because we focus on interaction effects, we do not predict main effects for financial distress, industry concentration, or forecast difficulty.

prior studies (e.g., Bamber and Cheon [1998] and Harris [1998]) define firms with the same two digit and three digit SIC codes, respectively, as being in the same industry, we regard firms sharing the same four-digit SIC code as being in the same industry.[24] Firms in the same four-digit SIC code are more likely to view their competitors' product markets as being contestable.[25] Hypothesis 1b posits that managers of firms in concentrated industries will issue pessimistic forecasts when it is more difficult for the market to detect the manager's misrepresentation. Consequently, we anticipate that the coefficient on $Concen \times Difficulty$ will be negative.

Industry concentration also is measured using the Herfindahl index, which equals the sum of the squares of the market shares of the firms within an industry. Our results are unchanged if we use this measure of concentration.

Lagged Forecast Error (FE_{t-k}): The forecast error from the preceding forecast is used to implicitly reveal a manager's incentives. Forecasts are not required to be in consecutive years because, like Williams [1986], we observe an irregular pattern of voluntary forecasts. For our sample, 420 firm-year observations have lagged annual forecasts. When a lagged annual forecast error is not available, FE_{t-k} is set equal to the preceding quarterly forecast error (186 observations); if a quarterly forecast does not exist, then FE_{t-k} is set equal to zero (349 observations). Hypothesis 1c predicts a positive association between the current forecast error and the previous one. We therefore expect the coefficient on FE_{t-k} to be positive.

[24] SIC codes are structured in the following fashion: the first digit designates a Major Economic Division; the second digit designates an Economic Major Group; the third digit designates an Industry Group; the fourth digit designates a specific Industry.

[25] A market is perfectly contestable if entry and exit are free; see Tirole [1993] for further details.

Forecast News (FN): Forecast news, FN, is defined as:

$$FN = \frac{\text{Management forecast of EPS} - \text{Mean analyst forecast of EPS}}{\text{Pre-release share price}}.$$

The mean analyst forecast immediately preceding the manager's forecast is used to proxy for the market's current expectation of future EPS.[26] Management forecasts above the current consensus forecast (i.e., $FN \geq 0$) are said to convey good news, while those below the current consensus forecast (i.e., $FN < 0$) are said to convey bad news. The indicator variable, $Good\_News$, takes on a value of one when the forecast conveys good news and zero otherwise; and conversely for Bad_News.

Hypothesis 1d predicts that the forecast error is positively associated with forecast news and that the association is greater for good news forecasts than for bad news forecasts. Therefore, we expect the coefficient on forecast news to be positive, regardless of whether the forecast conveys good or bad news (i.e., β_8 and β_9 will be positive), and that $\beta_8 > \beta_9$.

Control Variables: We use several variables to control for factors that have been previously documented to affect forecast behavior. First, forecast horizon is introduced as a control variable. Choi and Ziebart [2000], Johnson et al. [2001], among others, find that forecast errors decline as forecasts are issued closer to fiscal year-end. $Horizon$ is defined as the firm's fiscal year-end date less the forecast release date. Second, McNichols (1989) finds that future forecast errors are correlated with previous cumulative abnormal returns. We control for this effect by calculating daily compounded returns less the size-decile matched CRSP Value-Weighted Index over the period 120 days before to 2 days before the forecast release date, denoted $CAR_{-120,-2}$. Third, several studies find that forecast behavior is associated with firm

[26]Using either the mean or median of the analyst forecasts does not affect our results.

size (e.g., Baginski and Hassell [1997] and Bamber and Cheon [1998]). The natural log of the firm's market capitalization three days prior to the forecast, denoted $Size$, is used to proxy for firm size. Fourth, Bamber and Cheon [1998] document that growth opportunities affect a firm's forecasting behavior. The firm's market value to book value of equity ratio, M/B, is a measure of a firm's growth opportunities. M/B is calculated as the ratio of the firm's market capitalization three days prior to the forecast divided by the previous year's book value of equity. Last, managers may enhance their forecast accuracy by managing earnings (McNichols [1989] and Kasznik [1999]). Kasznik [1999] finds evidence consistent with managers issuing an earnings forecast and then manipulating earnings to fall in line with the forecast. Hence, the firm's ability to manipulate earnings as reflected by its discretionary accruals is included as a control. We use a version of the cross-sectional modified Jones model (see Dechow, Sloan and Sweeney, 1995) to estimate discretionary accruals, $DAccruals.$ Like Kasznik (1999), we include change in operating cash flows as an additional explanatory variable and estimate the model for all firms within a particular year and two-digit SIC code.

4.2 Results for Hypothesis 1

Table 6 reports the results for the regression analysis of the management forecast errors. Using pooled OLS, we find strong evidence of the predictability of management forecast errors; the model is highly significant with an adjusted R^2 of 27.36%. We make several observations. First, in support of H1a, the coefficient on $Distress \times Difficulty$ is positive and highly significant (t-statistic of 8.98). Therefore, managers of financially distressed firms are more inclined to issue optimistic forecasts when it is more difficult for the market to detect dissembling. Second, the coefficient on $Concen \times Difficulty$ is negative and significant (t-statistic of -3.30), which is consistent with H1b. This relation indicates that firms in more concentrated industries are more likely to offer pessimistic forecasts in an environment where it is more difficult to assess the truthfulness of the forecast. Third, we find a positive but insignificant association between current forecast errors and previous forecast errors (t-statistic of 1.49), FE_{t-k}. The lack of a significant association might be attributable, in part, to measurement error in the variable. Recall that when a lagged forecast error is not available, which is the case for 349 firm-year observations, FE_{t-k} is set equal to zero. To partially mitigate measurement error, we reestimate the regression for the sub-sample of firms that have lagged forecast errors. For the reduced sample (untabulated), the coefficient remains positive but insignificant. Consequently, we do not find significant support for H1c. Fourth, for good news forecasts, there is a significant positive association between forecast news and forecast errors (t-statistic of 4.26), which is consistent with H1d. When a bad news forecast is released, however, we find a significant negative association between the forecast news and forecast errors (t-statistic of -3.15). Hence, contrary to the prediction in H1d, we find that forecasts containing bad news tend to be optimistic. This result suggests that although managers have incentives to bias investors' beliefs about earnings upward, they feel compelled to release bad news, perhaps because of concerns about shareholder litigation.

Regarding the control variables, we observe that the association between forecast errors and forecast horizon, $Horizon$, is positive and significant. Consistent with prior work, this relation implies that long-horizon forecasts are more optimistic. Consistent with McNichols [1989], we also find that forecast errors are negatively and significantly associated with cumulative abnormal returns prior to the forecast release,

$CAR_{-120,-2}$. This relation suggests that the market has information that managers do not impound in their earnings forecasts. The remaining control variables, namely, lagged firm size, $Size$, lagged market to book ratio, M/B, and lagged discretionary accruals, $DAccruals$, are insignificant.

4.3 Research Design for Hypothesis 2

To examine the stock price response to management forecasts, we estimate the following model using cross-sectional OLS regression on a pooled sample (firm and time subscripts have been suppressed):

$$\begin{aligned} CAR_{-1,+2} = \; & \gamma_0 + \gamma_1 FN + \gamma_2 FN \times FE_{fitted} \times Good\_News \\ & + \gamma_3 FN \times FE_{fitted} \times Bad\_News + \gamma_4 FN \times |FN| \\ & + \gamma_5 FN \times Dum\_Neg + \gamma_6 FN \times Type \\ & + \gamma_7 FN \times DAccruals + \gamma_8 FN \times M/B + \varepsilon. \end{aligned} \tag{2}$$

The model's variables are defined as follows.

Event Return ($CAR_{-1,+2}$): The market response to the forecast release, or event return, is the daily compounded return less the size-decile matched CRSP Value-Weighted Index over the window one day before the forecast release to two days after the release.

Predicted Forecast Error (FE_{fitted}): We hypothesize that the market response to a management forecast is a function of the predicted bias in the forecast. Consistent with a rational expectations equilibrium where a manager biases his forecasts and the market anticipates this behavior given its conjecture of the manager's forecasting strategy, we use the fitted, or predicted, forecast error, FE_{fitted}, from the model in expression (1) to proxy for forecast bias. The mean of the fitted forecast errors is 0.164, the median is 0.110, and the standard deviation is 0.030. The standard deviation of the predicted forecast errors is lower than that of the actual forecast error (see Table 3), as would be expected for fitted values. In operationalizing our hypotheses, we allow the response coefficient to vary with the fitted predicted error in the forecast and with whether the forecast contains good or bad news. Based on Hypotheses 2a and 2b, we predict γ_2 to be negative and γ_3 to be positive.

Control Variables: We use several variables identified in previous studies to control for cross-sectional differences in response coefficients. First, a number of studies document a non-linear relation between stock returns and earnings (e.g., Freeman and Tse [1992] and Subramanyam [1996]). Consistent with Lipe, Bryant and Widener [1998], $FN \times |FN|$ is used to control for potential non-linearities in the market's response. Second, prior research finds that the market is less responsive to reports of negative earnings (see Hayn [1995] and Basu [1997]). To control for this effect, we allow the response coefficient to vary depending on whether the manager forecasts positive or negative earnings by introducing $FN \times Dum\_Neg$, where, Dum_Neg equals one if forecasted earnings are negative and zero otherwise. Third, prior research notes that the stock price response varies according to forecast specificity (Baginski, et al., 1993). We introduce $FN \times Type$, where $Type$ equals one if the manager offers a range estimate and zero otherwise, to control for this effect. Fourth, a manager can issue a biased forecast and then hide his bias by manipulating reported earnings (Kasznik, 1999). To partially control for the effect of earnings management on forecast credibility, the response coefficient is allowed to vary with the lagged value of discretionary accruals, $DAccruals$. Last, the response coefficient is allowed to vary with the firm's market-to-book ratio, M/B. Collins and Kothari [1989] document an increasing relation between a firm's earnings response coefficient and its market-to-book ratio.

4.4 Results for Hypothesis 2

Table 7 reports the results from the pooled OLS analysis of the market response to management earnings forecasts and predicted forecast errors. The adjusted R^2 of 11.77 % indicates that our model explains a substantial portion of the variation in returns. While the market response is positively associated with the forecast news, FN, which is consistent with prior studies; i.e., $\gamma_1 > 0$, the response varies according to whether the forecast contains good or bad news. For good news forecasts, the market responds less positively to forecasts with higher predicted optimism and more positively to forecasts with higher predicted pessimism; i.e., $\gamma_2 < 0$ (t-statistic of -2.54). This result, which is consistent with Hypothesis 2a, suggests that for good news forecasts, the market uses publicly available information to predict forecast bias and modify its response. For bad news forecasts, in contrast, the market does not vary its response with the predicted error in the forecast; specifically, we find that γ_3 is not significantly different from zero (t-statistic of -0.87). Contrary to Hypothesis 2b, this result suggests that the market treats bad news forecasts as being credible and hence takes them at face value, regardless of the predicted forecast error.

Regarding the control variables, we find that only the control for non-linearities in the market response to forecast news, $FN \times |FN|$, is significant. The significantly negative coefficient is consistent with Lipe, et al. [1998].

Consistent with our results, Jennings [1987] and Williams [1996] also report differential stock price response and analyst forecast revisions to forecast news. Jennings uses analyst forecast revisions subsequent to the forecast release to proxy for the veracity or "believability" of the forecast. He finds a significant difference in the market response to good news forecasts that are confirmed relative to those that are not confirmed by analyst forecast revisions; in contrast, he finds no difference in the market response to bad news forecasts that are confirmed versus those that not confirmed. He therefore argues that bad news is more credible than good news. In a similar spirit, Williams uses prior forecast usefulness to capture the "believability" of forecasts. She finds that analysts consider prior forecast usefulness when responding to good news but not to bad news forecasts. Hence, she also contends that good news forecasts are less credible than bad news forecasts. Hutton, Miller and Skinner [2000] also argue that bad news forecasts are inherently more believable than good news forecasts.

While we show that the market behaves in a manner consistent with it viewing good news forecasts as being less credible than bad news forecasts, bad news forecasts are not less biased than good news forecasts. Specifically, the mean predicted forecast errors for good news forecasts (0.015) and bad news forecasts (0.018) are not significantly different.[27] Consequently, the asymmetric response to good and bad news suggests that the market does not efficiently impound all information conveyed in forecasts into the stock price.

To assess how efficiently the market impounds into price the predictable forecast error contained in the good and bad news forecasts, we estimate the following model using cross-sectional OLS regression for the pooled sample (firm and time subscripts have been suppressed):

[27] Actual mean forecast error for good news forecasts equals 0.015 and actual mean forecast error for bad news forecasts equals 0.018. These mean errors are not significantly different.

$$CAR_{+3,+32} = \delta_0 + \delta_1 FE_{\text{fitted}} \times Good\_News + \delta_2 FE_{\text{fitted}} \times Bad\_News$$
$$+\delta_3 Size + \delta_4 M/B + \delta_5 P/E + \delta_6 Beta + \varepsilon. \quad (3)$$

The post-event excess return, $CAR_{+3,+32}$, is the daily compounded return less the size-decile matched CRSP Value-Weighted Index for a 30 trading day window starting three trading days after the forecast release date. We introduce firm size, market-to-book ratio, price-earnings ratio, and historical beta as control variables to ensure that the predicted forecast error in good and bad news is incremental to the effects that have been shown to predict future stock returns (see Fama and French, 1992). The price-to-earnings ratio, P/E, is measured as the market price per share three days after the forecast announcement divided by the lagged EPS reported by First Call. Due to measurement error and the presence of outliers, we use the decile ranked values of P/E in our analysis.[28] Historical beta, $Beta$, is measured as the slope coefficient from regressing firm specific daily returns on the size-decile matched CRSP Value-Weighted Index for 120 trading days prior to the forecast release. The other variables in expression (3) were previously defined.

Table 8 reports the results of the regression specified in expression (3). For good news forecasts, we do not observe a significant association between post-event excess returns and predicted forecast errors; i.e., δ_1 is not significantly different from zero (t-statistic of -0.84). This finding is consistent with investors viewing good new forecasts skeptically, immediately adjusting for the predicted bias when responding to the forecast, and efficiently impounding good news into the firm's stock price. On the other hand, for bad news forecasts, we find a significant negative association between post-event excess returns and predicted forecast errors. Thus, while the market initially takes bad news forecasts at face value and responds negatively to

[28]Our results are unchanged if we use the actual P/E values.

them, it appears to subsequently recognize the bias embedded in these forecasts and impounds this information in stock price. Since δ_2 is negative (t-statistic of -2.93), the market moves in the predicted direction: on average, the market value falls for firms with predictably optimistic forecasts and rises for firms with predictably pessimistic forecasts. We conclude that although the ultimate market response to a bad news forecast is consistent with that hypothesized in H2b, the market is less efficient at impounding the information embedded in bad news forecasts into a firm's stock price.[29] Last, the control variables are all insignificant with the exception of the price-to-earnings ratio, P/E.

5 Summary and Conclusions

This paper examines the credibility of management forecasts. It recognizes that managers often have incentives to forecast in a self-interested fashion but are constrained by the possibility that the market will detect such behavior. The market's ability to detect dissembling and punish the manager, in turn, is a function of how difficult it is for the manager to forecast the firm's earnings. Therefore forecast bias is a function of both the manager's incentives and the difficulty of forecasting earnings.

[29]The current tests of H2a and H2b are joint tests for a market response to optimistic and pessimistic forecasts. In an attempt to identify whether our results are driven by forecasts predicted to be optimistic or pessimistic, we repeat our analysis allowing the coefficients to vary with both the news in the forecast (i.e., good or bad) and the predicted error (i.e., optimistic or pessimistic). This partition of the data suggests that the results we report above are mainly attributable to forecasts that are predicted to be optimistic and not those predicted to be pessimistic. In particular, when we partition our sample into four groups we find that our results for good news forecasts are driven primarily by the market appropriately dampening its response to forecasts predicted to be optimistic. We still fail to find evidence that the market appropriately responds to the predicted bias in bad news forecasts. In tests of post-event excess returns, we only find a significant (negative) association between post-event returns and predicted errors for the bad news forecasts that are predicted to be optimistic. Since 711 firms issue forecasts predicted to be optimistic whereas only 244 firms issue forecasts predicted to be pessimistic and the predicted error is an imperfect proxy for the forecast bias that the market infers, we question the robustness of the tests when we partition the firms into four groups. Hence, we report the results for the good and bad news partition only.

With this relation in mind, we first examine the association between forecast errors and manager incentives. We find that when it is more difficult for managers to forecast earnings, financially distressed firms are more optimistic than healthy firms and firms in more concentrated industries are more pessimistic than those in less concentrated industries.

Second, we investigate the stock market's response to management forecasts. We find that for good news forecasts, the market responds less positively to forecasts with greater predicted optimism and more positively to forecasts with greater predicted pessimism. In contrast, for bad news forecasts, the market does not immediately vary its response with the predicted bias. Subsequently, however, the risk-adjusted returns are consistent with the market identifying the predicted bias in the bad news forecasts and then modifying its valuation of the firm in the appropriate direction.

References

[1] Ajinkya, B.B. and M.J. Gift. "Corporate Managers' Earnings Forecasts and Symmetrical Adjustments of Market Expectations." *Journal of Accounting Research*, Vol. 22, No. 2 (1984): 425-44.

[2] Baginski, S.P., E.J. Conrad, and J.M. Hassell. "The Effects of Management Forecast Precision on Equity Pricing and on the Assessment of Earnings Uncertainty." *The Accounting Review*, Vol. 68, No. 4 (1993): 913-27.

[3] Baginski, S.P. and J.M. Hassell. "Determinants of Management Forecast Precision." *The Accounting Review*, Vol. 72, No. 2 (1997): 303-12.

[4] Baginski, S.P., J.M. Hassell, and M.D. Kimbrough. "The Effect of Legal Environment on Voluntary Disclosure: Evidence from Management Earnings Forecasts Issued in U.S. and Canadian Markets." *The Accounting Review*, Vol. 77, No. 1 (2002): 25-50.

[5] Bamber, L.S. and Y.S. Cheon. "Discretionary Management Earnings Forecast Disclosures: Antecedents and Outcomes Associated with Forecast Venue and Specificity Choices." *Journal of Accounting Research*, Vol. 36, No. 2 (1998): 167-90.

[6] Barth, M.E., J.A. Elloitt, and M.W. Finn. "Market Rewards Associated with Patterns of Increasing Earnings." *Journal of Accounting Research*, Vol. 37, No. 2 (1999): 387-413.

[7] Barton, J. "Does the Use of Financial Derivatives Affect Earnings Management Decisions." *The Accounting Review*, Vol. 76, No. 1 (2001): 1-26.

[8] Basu, S. "The conservatism principle and the asymmetric timeliness of earnings." *Journal of Accounting and Economics*, Vol. 24 (1997): 3-37.

[9] Besanko, D., D. Dranove, and M. Shanley. *Economics of Strategy*, Second Edition. New York, NY: John Wiley & Sons, 2000.

[10] Bresnahan, T.F. and P.C. Reiss. "Entry and Competition in Concentrated Markets." *Journal of Political Economy*, Vol. 99, No. 5 (1991): 977-1009.

[11] Brown, L.D. "Earnings forecasting research: its implications for capital markets research." *International Journal of Forecasting*, Vol. 9 (1993): 295-320.

[12] Browne, M. "Asymptotically Distribution-Free Methods for the Analysis of Covariance Structures." *British Journal of Mathematical and Statistical Psychology*, Vol. 37 (1984): 62-83.

[13] Choi, J-H and D.A. Ziebart. "A Reexamination of Bias in Management Earnings Forecasts." Mimeo: Hong Kong University of Science and Technology and University of Illinois at Urbana-Champaign (September 2000).

[14] Coller, M. and T.L. Yohn. "Management Forecasts and Information Asymmetry: An Examination of Bid-Ask Spreads." *Journal of Accounting Research*, Vol. 35, No. 2 (1997): 181-91.

[15] Collins, D.W. and S.P. Kothari. "An analysis of intertemporal and cross-sectional determinants of earnings response coefficients." *Journal of Accounting and Economics*, Vol. 11 (1989): 143-81.

[16] Darrough, M. and N. Stoughton. "Financial disclosure in an entry game." *Journal of Accounting and Economics*, Vol. 12 (1990): 219-43.

[17] Dechow, P.M., R.G. Sloan, and A.P. Sweeney. "Detecting Earnings Management." *The Accounting Review*, Vol. 70, No. 2 (1995): 193-225.

[18] Fama, E. and K. French. "The Cross-Section of Expected Stock Returns." *Journal of Finance*, Vol. 47 (1992): 427-64.

[19] First Call Corporation. *First Call Historical Database (FCHD) User Guide.* Boston, MA: First Call Corporation, 1999.

[20] Fischer, P.E., and R.E. Verrecchia. "Reporting Bias." *The Accounting Review*, Vol. 75, No. 2 (2000): 229-45.

[21] Frankel, R., M. McNichols, and G.P. Wilson. "Discretionary Disclosure and External Financing." *The Accounting Review*, Vol. 70, No. 1 (1995): 135-50.

[22] Freeman, R.B. and S.Y. Tse, "A nonlinear model of security price responses to unexpected earnings." *Journal of Accounting Research*, Vol. 30, (1992): 185-209.

[23] Frost, C.A. "Disclosure Policy choices of UK firms receiving modified audit reports." *Journal of Accounting and Economics*, Vol. 23 (1997): 163-87.

[24] Gigler, F. "Self-enforcing voluntary disclosures." *Journal of Accounting Research*, Vol. 32 (1994): 224-40.

[25] Grundfest, J.A. and M.A. Perino. "Securities Litigation Reform: The First Year's Experience." Working paper No. 140, Stanford Law School, 1997.

[26] Harris, M.S. "The Association between Competition and Managers' Business Segment Reporting Decisions." *Journal of Accounting Research*, Vol. 36, No. 1 (1998): 111–28.

[27] Hassell, J.M. and R.H. Jennings. "Relative Forecast Accuracy and the Timing of Earnings Forecast Announcements." *The Accounting Review*, Vol. LXI, No. 1 (1986): 58-75.

[28] Hayn, C. "The information content of losses." *Journal of Accounting and Economics*, Vol. 20 (1995): 125-53.

[29] Hirst, D.E., L. Koonce, and J. Miller. "The Joint Effect of Management's Prior Forecast Accuracy and the Form of its Financial Forecasts on Investor Judgement." *Journal of Accounting Research*, Vol. 37, Supplement (1999): 101-24.

[30] Hutton, A.P., G.S. Miller, and D.J. Skinner."Effective Voluntary Disclosure." Mimeo: Harvard Business School and University of Michigan Business School (July 2000).

[31] Jennings, R. "Unsystematic Security Price Movements, Management Earnings Forecasts, and Revisions in Consensus Analyst Earnings Forecasts." *Journal of Accounting Research*, Vol. 25, No. 1 (1987): 90-110.

[32] Johnson, M., and R. Kasznik, K. Nelson. "The Impact of Securities Litigation Reform on the Disclosure of Forward-Looking Information By High Technology Firms." *Journal of Accounting Research*, Vol. 39, No. 2 (2001): 297–327.

[33] Joreskog, K., and D. Sorbom. *LISREL 7: User's Reference Guide.* Mooresvill, Inc.: Scientific Software, 1989.

[34] Kasznik, R. "On the Association between Voluntary Disclosure and Earnings Management." *Journal of Accounting Research*, Vol. 37, No. 1 (1999): 57-81.

[35] Kasznik, R. and B. Lev. "To warn or Not to Warn: Management Disclosure in the Face of an Earnings Surprise." *The Accounting Review*, Vol. 70, No. 1 (1995): 113-34.

[36] Keane, M.P. and D.E. Runkle. "Are Financial Analysts' Forecasts of Corporate Profits Rational?" *Journal of Political Economy*, Vol. 106, No. 4 (1998): 768-805.

[37] King, R. "The 'liar's discount'." *Forbes* (May 30, 1988): 80-2.

[38] King, R., G. Pownall, and G. Waymire. "Expectations Adjustment Via Timely Management Forecasts: Review, Synthesis, and Suggestions for Future Research." *Journal of Accounting Literature*, Vol. 9 (1990): 113-44.

[39] Lev. B. and S.H. Penman. "Voluntary Forecast Disclosure, Nondisclosure, and Stock Prices." *Journal of Accounting Research*, Vol. 28, No. 1 (1990): 49-76.

[40] Lipe, R.C., L. Bryant, and S. Widener. "Do nonlinearity, firm-specific coefficients, and losses represent distinct factors in the relation between stock returns and accounting earnings?" *Journal of Accounting and Economics*, Vol. 25 (1998): 195-214.

[41] McNichols, M. "Evidence of Information Asymmetries from Management Earnings Forecasts and Stock Returns." *The Accounting Review*, Vol. LXIV, No. 1 (1989): 1-27.

[42] Newman, P. and R. Sansing. "Disclosure policies with multiple users." *Journal of Accounting Research*, Vol. 31 (1993): 92-112.

[43] Ohlson, J.A. "Financial ratios and the probabilistic prediction of bankruptcy." Journal of Accounting Research, Vol. 18, No. 1 (1980): 109-31.

[44] Penman, S.H. "An Empirical Investigation of the Voluntary Disclosure of Corporate Earnings Forecast." Journal of Accounting Research, Vol. 18, No. 1 (1980): 132-60.

[45] Pownall, G., C. Wasley, and G. Waymire. "The Stock Price Effects of Alternative Types of Management Earnings Forecast." The Accounting Review, Vol. 68, No. 4 (1993): 896-912.

[46] Pownall, G. and G. Waymire. "Voluntary Disclosure Credibility and Securities Prices: Evidence from Management Earnings Forecasts, 1969-73." Journal of Accounting Research, Vol. 27, No. 2 (1989): 227-45.

[47] Ronen, J. and S. Sadan. Smoothing Income Numbers: Objectives, Means, and Implications. Reading, MA: Addison-Wesley Publishing Co., 1981.

[48] Sansing, R.C. "Accounting and the credibility of management forecasts." Contemporary Accounting Research, Vol. 9, No. 1 (1992): 33-45.

[49] Skinner, D.J. "Why firms voluntarily disclose bad news." Journal of Accounting Research, Vol. 32, No. 1 (1994): 38-60.

[50] Stocken, P.C. "Credibility of voluntary disclosure." The RAND Journal of Economics, Vol. 31, No. 2 (2000): 359-74.

[51] Subramanyam, K.R. "Uncertain precision and price reactions to information." The Accounting Review, Vol. 71, No. 2 (1996): 207-20.

[52] Tirole, J. The Theory of Industrial Organization. Cambridge, MA: MIT Press, 1993.

[53] Trueman, B. "Why do Manager's Voluntarily Release Earnings Forecasts?" Journal of Accounting and Economics, Vol. 8 (1986): 53-71.

[54] Verrecchia, R.E. "Essays on Disclosure." Journal of Accounting and Economics Vol. 32, No. 1-3 (2001): 97-180.

[55] Wagenhofer, A. "Voluntary disclosure with a strategic opponent." Journal of Accounting and Economics, Vol. 12 (1990): 341-63.

[56] Waymire, G. "Additional evidence on the information content of management earnings forecasts." Journal of Accounting Research, Vol. 22, No. 2 (1984): 703-18.

[57] Waymire, G. "Earnings Volatility and Voluntary Management Forecast Disclosure." Journal of Accounting Research, Vol. 23, No. 1 (1985): 268-95.

[58] White, H. "A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity." Econometrica, Vol. 48, (1980): 817-38.

[59] Williams, P.A. "The Relation Between a Prior Earnings Forecast by Management and Analyst Response to a Current Management Forecast." *The Accounting Review*, Vol. 71, No. 1 (1996): 103-13.

Table 1

Sample Selection and Data Requirements

Point or range estimates of annual EPS per First Call		3,788
Less: Number of duplicate forecast for same fiscal year-end	(1,091)	
Forecasts issued later than one day prior to period-end	(586)	
Observations for which preannouncement share price was less than $2.00	(119)	
Firms with insufficient data on *CRSP* or *COMPUSTAT*	(713)	
Utilities, transportation companies or financial services companies	(324)	
Sample for testing Hypotheses (firm-year observations)		955

Table 2

Forecast Disclosure Per Firm and Over Time

Panel A. Number of Forecasts per Firm:

Number of Management Forecasts Per Firm	Number of Firms
1	370
2	146
3	54
4	19
5	11
	600

Panel B. Distribution of Forecasts Over Years:

Number of Year	Forecasts per Year
1996	75
1997	144
1998	222
1999	235
2000	279
	955

Panel C. Distribution of Fiscal Year-End (months):

Month of Fiscal Year	Number of Forecasts
1	64
2	23
3	35
4	20
5	21
6	59
7	20
8	21
9	58
10	21
11	9
12	604
	955

Panel D. Distribution of Forecasts Release Month:

Month of Forecast Release	Number of Forecasts
1	106
2	74
3	55
4	71
5	47
6	59
7	59
8	34
9	119
10	163
11	73
12	95
	955

Table 3

Descriptive Statistics

Variable	Mean		Median		Std. Dev
AFE	0.0181	**	0.0024	**	0.0632
FE	0.0164	**	0.0031	**	0.0559
FN	-0.0017	*	0.0002	*	0.0246
$CAR_{-1,+2}$ (Event Return)	-0.0342	**	-0.0123	**	0.1330
Market Value of Equity ($MM)	8247.41		1255.62		24231.32
Market-to-Book Ratio	5.67		3.03		14.55
Beta	0.87		0.77		0.57
Calendar days between management forecast and fiscal year-end	190.96		162.00		136.03

** Significant at .01 level; * significant at .05 level.

AFE is defined as the consensus analyst forecast (issued prior to the corresponding management forecast) minus actual earnings per share deflated by price preceding the management forecast. **FE** is defined as the management forecast less actual earnings (as reported by *First Call*) deflated by pre-forecast price. **FN** is defined as the management forecast minus the most recent consensus analyst forecast deflated by price. **$CAR_{-1,+2}$** is defined as the daily compounded return less the size-decile matched *CRSP* Value-Weighted Index over the window one day before to two days after the forecast release. **Market Value of Equity** is defined as pre-forecast share price times shares outstanding (as reported by *CRSP*). **Market-to-Book Ratio** is defined as market value of equity (pre-announcement) divided by book value of equity (at previous year-end). **Beta** is measured as the slope coefficient from regressing firm specific daily returns on the size-decile matched *CRSP* Value-Weighed Index for 120 trading days prior to the forecast release.

Table 4

Correlations (Pearson - Upper Triangle, Spearman - Lower Triangle)

Panel A. Correlations for FN, FE and AFE:

	FN	FE	AFE
FN	1	-0.098 **	-0.475 **
FE	0.168 **	1	0.922 **
AFE	-0.623 **	0.525 **	1

** Significant at .01 level; * significant at .05 level.

AFE is defined as the consensus analyst forecast (issued prior to the corresponding management forecast) minus actual earnings per share deflated by price preceding the management forecast. **FE** is defined as the management forecast less actual earnings (as reported by *First Call*) deflated by pre-forecast price. **FN** is defined as the management forecast minus the most recent consensus analyst forecast deflated by price.

Panel B. Correlations for Independent Variables Used to Test Hypothesis 1:

	Difficulty	Distress	Concen	FE_{t-k}	FN	Horizon	$CAR_{-120,-2}$	Size	M/B	DAccruals
Difficulty	1	0.044	-0.054	-0.099 **	-0.314 **	0.067 *	-0.279 **	-0.327 **	-0.036	0.013
Distress	0.021	1	0.195 **	-0.130 **	-0.154 **	-0.072 *	-0.021	-0.197 **	-0.035	-0.012
Concen	-0.060	0.185 **	1	0.012	-0.059	0.010	-0.054	-0.052	-0.037	-0.040
FE_{t-k}	-0.105 **	-0.154 **	0.026	1	0.219 **	0.007	0.120 **	0.217 **	0.118 **	-0.015
FN	-0.345 **	-0.192 **	-0.050	0.210 **	1	0.084 **	0.287 **	0.247 **	0.139 **	-0.034
Horizon	0.048	-0.079 *	0.019	0.007	0 **	1	-0.052	0.093 **	0.045	0.049
$CAR_{-120,-2}$	-0.323 **	-0.025	-0.037	0.131 **	0.384 **	-0.058	1	0.135 **	0.238 **	-0.045
Size	-0.332 **	-0.202 **	0.002	0.247 **	0.286 **	0.099 **	0 **	1	0.163 **	0.044
M/B	-0.184 **	-0.205 **	-0.119 **	0.196 **	0.377 **	0.133 **	0 **	0.515 **	1	-0.007
DAccruals	-0.015	-0.035	-0.091 **	-0.040	-0.050	0.025	-0.058	0.049	0.033	1

** Significant at .01 level; * significant at .05 level.

Difficulty is defined as the factor score from latent variable analysis on STD_AF, STD_AFE, Spread, OCF_Growth and MF_Width (defined in table 5). **Distress** is the fitted value from Ohlson's [1980] bankruptcy prediction model (model 1). **Concen** is defined as the sales (as reported by *Compustat*) of the largest five firms in an industry (four-digit *SIC* code) divided by total sales in that industry during that year. **FE_{t-k}** is defined as the forecast error (i.e., management forecast – actual earnings) deflated by price for the previous annual forecast; when a previous annual forecast is not available, previous quarterly forecasts are used; when previous annual and quarterly forecast are unavailable, FE_{t-k} is set to zero. **FN** is defined as the management forecast minus the most recent consensus analyst forecast deflated by price. **Horizon** is defined as the firm's fiscal year-end date less the forecast release date. **$CAR_{-120,-2}$** is defined as daily compounded returns less the size-decile matched CRSP Value-Weighted Index over the period 120 trading days before to 2 days before the forecast release date. **Size** is defined as the natural log of the firm's market capitalization three days prior to the forecast.
M/B is calculated as the ratio of the firm's market capitalization three days prior to the forecast divided by the previous year's book value of equity. **DAccruals** is defined as discretionary accruals (per share) based on the cross-sectional modified Jones model estimated by two-digit *SIC* code; change in operating cash flows is included as an additional explanatory variable.

Table 4 (cont.)

Correlations (Pearson - Upper Triangle, Spearman - Lower Triangle)

Panel C. Correlations for Independent Variables Used to Test Hypothesis 2:

	FN	FE_{fitted}	Bad_News	Dum_Neg	Type	DAccruals	M/B
FN	1	-0.219 **	-0.497 **	-0.338 **	-0.170 **	-0.034	0.139 **
FE_{fitted}	-0.001	1	0.058	0.301 **	0.041	0.005	-0.033
Bad_News	-0.866 **	-0.014	1	0.095 **	0.308 **	0.042	-0.119 **
Dum_Neg	-0.159 **	0.177 **	0.095 **	1	0.028	0.000	-0.015
Type	-0.253 **	0.047	0.308 **	0.028	1	-0.066 *	-0.044
DAccruals	-0.050	-0.059	0.023	0.003 **	-0.036	1	-0.007
M/B	0.377 **	-0.137 **	-0.284 **	-0.042	-0.176 **	0.033	1

** Significant at .01 level; * significant at .05 level.

FN is defined as the management forecast minus the most recent consensus analyst forecast deflated by price. **FE_{fitted}** is the predicted value from a pooled regression of forecast errors (FE) on variables (and interactions of variables) defined in Panel B. **Bad_News** is a dummy variable set equal to one if FN<0 and zero otherwise. **Dum_Neg** is a dummy variable set equal to one if the management forecast is less than zero and zero otherwise. **Type** is a dummy variable set equal to one if the manager issues a range forecast and zero otherwise. **DAccruals** is defined as discretionary accruals (per share) based on the cross-sectional modified Jones model estimated by two-digit *SIC* codes; change in operating cash flows is included as an additional explanatory variable. **M/B** is calculated as the ratio of the firm's market capitalization three days prior to the forecast divided by the previous year's book value of equity.

Table 5

Correlations and Factor Loadings for Forecast Difficulty Proxies

Panel A: Correlation Matrix for Forcast Difficulty Indicators
Pearson (Upper Triangle), Spearman (Lower Triangle)

	STD_AF	STD_AFE	Spread	OCF_Growth	MF_Width
STD_AF	1	0.046	0.240 **	0.029	0.120 **
STD_AFE	0.393 **	1	0.064 *	0.006	0.064 *
Spread	0.206 **	0.054	1	0.024	0.050
OCF_Growth	0.037	0.006	0.258 **	1	0.006
MF_Width	0.192 **	0.070 *	-0.011	-0.040	1

** Significant at .01 level; * significant at .05 level.

Panel B: Forecast Difficulty Factor Loadings - Maximum Likelihood Estimation

	l_1	l_2	l_3	l_4	l_5
Indicator	**STD_AF**	**STD_AFE**	**Spread**	**OCF_Growth**	**MF_Width**
Factor Loading	0.606**	0.108*	0.391**	0.051	0.188**

** Significant at .01 level; * significant at .05 level.

	DF	Chi-Square	p-value
Null Hypothesis: No common factors	10	79.80	<.0001
Null Hypothesis: One factor is sufficient	5	3.86	0.5698

Panel C: Forecast Difficulty Factor Loadings - Asymptotic Distribution-Free Estimation

	l_1	l_2	l_3	l_4	l_5
Indicator	**STD_AF**	**STD_AFE**	**Spread**	**OCF_Growth**	**MF_Width**
Factor Loading	0.406**	0.097**	0.588**	0.050**	0.090

** Significant at .01 level; * significant at .05 level.

STD_AF is defined as the standard deviation of analyst forecasts issued prior to the corresponding management forecast. **STD_AFE** is defined as the standard deviation of previous analysts forecast errors (over the five years prior to the management forecast). **Spread** is defined as the average closing spread over 23 trading days before to 2 days before the forecast release date. **OCF_Growth** is defined as the slope coefficient from a regression of operating cash flows (OCF) on time divided by the average OCF for the five years prior to the management forecast. **MF_Width** is defined as the width of a range forecast (i.e., top of range minus bottom of range) deflated by pre-forecast price; for point forecast, MF_Width is set equal to zero.

Table 6

Regression Results for Management Forecast Bias Hypotheses

$$\begin{aligned} \mathbf{FE} = \ & \mathbf{b_0 + b_1\ Difficulty + b_2\ Distress + b_3\ Distress \times Difficulty} \\ & \mathbf{+\ b_4\ Concen + b_5\ Concen \times Difficulty + b_6\ FE_{t\text{-}k} + b_7\ Bad\_News} \\ & \mathbf{+\ b_8\ FN \times Good\_News + b_9\ FN \times Bad\_News + b_{10}\ Horizon} \\ & \mathbf{+\ b_{11}\ CAR_{-120,-2} + b_{12}\ Size + b_{13}\ M/B + b_{14}\ DAccruals + e.} \end{aligned}$$

Variable	Predicted Sign	Coefficient	t-stat
Intercept	none	0.016	0.99
Difficulty	none	0.003	0.35
Distress	none	0.012	2.00 *
Distress × Difficulty	+	0.062	8.98 **
Concen	none	0.001	0.16
Concen × Difficulty	-	-0.034	-3.30 **
$FE_{t\text{-}k}$	+	0.183	1.49
Bad_News	none	-0.004	-0.99
FN × Good_News	+	0.704	4.26 **
FN × Bad_News	+	-0.271	-3.15 **
Horizon	+	0.000	4.62 **
$CAR_{-120,-2}$	-	-0.023	-3.90 **
Size	none	-0.002	-1.83
M/B	none	0.000	0.26
DAccruals	none	0.000	-0.42
Adjusted R^2		27.36%	
F		26.67 **	
N		955	

The White [1980] test for heteroskedasticity does not reject homoskedasticity (p-value of 0.54) therefore conventional t-statistics are reported.

** Significant at .01 level; * significant at .05 level based on two-tailed tests.

FE is defined as the management forecast less the most recent analyst forecast (consensus) deflate by pre-announcement price. **Difficulty** is defined as the factor score from latent variable analysis on STD_AF, STD_AFE, Spread, OCF_Growth and MF_Width (defined in table 5). **Distress** is the fitted value from Ohlson's [1980] bankruptcy prediction model (model 1). **Concen** is defined as the sales (as reported by *Compustat*) of the largest five firms in an industry (four-digit *SIC* code) divided by total sales in that industry during that year. **$FE_{t\text{-}k}$** is defined as the forecast error (i.e., management forecast – actual earnings) deflated by price for the previous annual forecast; when a previous annual forecast is not available, previous quarterly forecasts are used; when previous annual and quarterly forecast are unavailable, $FE_{t\text{-}k}$ is set to zero. **FN** is defined as the management forecast minus the most recent consensus analyst forecast deflated by price.

Good_News is a dummy variable set equal to one if FN≥0 and zero otherwise. **Bad_News** is a dummy variable set equal to one if FN<0 and zero otherwise. **Horizon** is defined as the firm's fiscal year-end date less the forecast release date. **$CAR_{-120,-2}$** is defined as daily compounded returns less the size-decile matched *CRSP* Value-Weighted Index over the period 120 trading days before to 2 days before the forecast release date. **Size** is defined as the natural log of the firm's market capitalization three days prior to the forecast. **M/B** is calculated as the ratio of the firm's market capitalization three days prior to the forecast divided by the previous year's book value of equity. **DAccruals** is defined as discretionary accruals (per share) based on the cross-sectional modified Jones model estimated by two-digit *SIC* code; change in operating cash flows is included as an additional explanatory variable.

Table 7

Regression Results for Market Response Hypotheses

$$\begin{aligned} CAR_{-1,+2} = \; & \gamma_0 + \gamma_1 FN + \gamma_2 FN \times FE_{fitted} \times Good\_News \\ & + \gamma_3 FN \times FE_{fitted} \times Bad\_News + \gamma_4 FN \times |FN| \\ & + \gamma_5 FN \times Dum\_Neg + \gamma_6 FN \times Type \\ & + \gamma_7 FN \times DAccruals + \gamma_8 FN \times M/B + \varepsilon. \end{aligned}$$

Variable	**Predicted Sign**	**Coefficient**	**t-stat**
Intercept	none	-0.027	-6.70 **
FN	+	3.372	7.32 **
FN × FE_{fitted} × Good_News	-	-20.650	-2.54 *
FN × FE_{fitted} × Bad_News	+	-5.553	-0.87
FN × |FN|	-	-0.718	-3.90 **
FN × Dum_Neg	-	-1.216	-1.43
FN × Type	-	0.129	0.28
FN × DAccruals	-	0.050	0.40
FN × M/B	+	0.004	1.91
Adjusted R^2		11.77%	
F		16.91 **	
N		955	

The White [1980] test for heteroskedasticity rejects homoskedasticity (p-value of 0.00), therefore heteroskedastic robust t-statistics are reported.
** Significant at .01 level; * significant at .05 level based on two-tailed tests.

$CAR_{-1,+2}$ is defined as daily compounded returns less the size-decile matched *CRSP* Value-Weighted Index over the period 1 trading days before to 2 days after the forecast release date. **FN** is defined as the management forecast minus the most recent consensus analyst forecast deflated by price. **FE_{fitted}** is the predicted value from a pooled regression of forecast errors (FE) on variables (and interactions of variables) detailed in Table 6. **Good_News** is a dummy variable set equal to one if FN≥0 and zero otherwise. **Bad_News** is a dummy variable set equal to one if FN<0 and zero otherwise. **Dum_Neg** is a dummy variable set equal to one if the management forecast is less than zero and zero otherwise. **Type** is a dummy variable set equal to one if the manager issues a range forecast and zero otherwise.
DAccruals is defined as discretionary accruals (per share) based on the cross-sectional modified Jones model estimated by two-digit *SIC* codes; change in operating cash flows is included as an additional explanatory variable. **M/B** is calculated as the ratio of the firm's market capitalization three days prior to the forecast divided by the previous year's book value of equity.

Table 8

Regression Results for Market Response Hypotheses

$CAR_{+3,+32}$ = d_0 + d_1 FE_{fitted} ´ Good_News + d_2 FE_{fitted} ´ Bad_News + d_3 Size + d_4 M/B+ d_5 P/E + d_6 Beta + e.

Variable	Predicted Sign	Coefficient	t-stat
Intercept	none	0.019	0.42
$FE_{fitted} \times$ Good_News	none	-0.259	-0.84
$FE_{fitted} \times$ Bad_News	-	-0.667	-2.93 **
Size	none	-0.002	-0.49
M/B	none	0.000	-1.14
P/E	none	0.004	2.15 *
Beta	none	-0.007	-0.52
Adjusted R^2		1.19%	
F		2.91 **	
N		955	

The White [1980] test for heteroskedasticity rejects homoskedasticity (p-value of 0.00) therefore heteroskedastic robust t-statistics are reported.

** Significant at .01 level; * significant at .05 level based on two-tailed tests.

$CAR_{+3,+32}$ is defined as daily compounded returns less the size-decile matched *CRSP* Value-Weighted Index over the period 3 trading days after to 32 days after the forecast release date. **FE_{fitted}** is the predicted value from a pooled regression of forecast errors (FE) on variables (and interactions of variables) detailed in Table 6. **Good_News** is a dummy variable set equal to one if FN≥0 and zero otherwise. **Bad_News** is a dummy variable set equal to one if FN<0 and zero otherwise. **Size** is defined as the natural log of the firm's market capitalization three days prior to the forecast.
M/B is calculated as the ratio of the firm's market capitalization three days prior to the forecast divided by the previous year's book value of equity. **P/E** is the decile ranking of the firm's stock price to earnings ratio, measured as the market price per share three days after the forecast announcement divided by lagged EPS reported by *First Call* . **Beta** is measured as the slope coefficient from regressing firm specific daily returns on the size-decile matched *CRSP* Value-Weighed Index for 120 trading days prior to the forecast release.