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ABSTRACT

Analysts' Response to Earnings Management

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Previous literature studies analysts' earnings forecasts without considering firms' response to analysts' forecasts. This study improves upon previous research by considering firms' earnings management with respect to analysts' forecasts. I hypothesize that analysts understand these earnings management practices, and incorporate firms' expected behavior into their forecasts. I demonstrate that for firms with high tendencies and flexibilities to manage earnings downwards, and / or firms with negatively skewed earnings, analysts account for earnings management practices by lowering the otherwise optimal forecasts. Comparing analysts' consensus forecasts with proxy for *non-strategic* forecasts (otherwise optimal forecasts), I find that analysts' forecasts are systematically below the *non-strategic* forecasts for firm-quarters that have: high accounting reserves available to manage earnings downwards, high unmanaged earnings, low debt to equity ratios, negative forecasted earnings, and negatively skewed unmanaged earnings. These results suggest that analysts forecast below the *non-strategic* level in order to avoid the large optimistic forecast errors that occur when firms who cannot meet forecasts manage

earnings downward. The test results also suggest that analysts forecast above the *non-strategic* forecasts when earnings are positively skewed, and / or when firms have high tendencies and flexibilities to manage earnings upwards.

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1. INTRODUCTION

The earnings management literature that analyzes the properties and effects of earnings surprises, defined as the difference between analysts' earnings forecasts and realized earnings, suggests that firms manage earnings to meet or beat analysts' forecasts (Burgstahler and Eames, 1998; Abarbanell and Lehavy, 2000; Lopez and Rees, 2002). However, these studies treat analysts' forecasts as exogenous, and assume that analysts ignore the possibilities of such manipulations. Most of the analyst's forecast literature focuses on the same variable, earnings surprises (also called analysts' forecasts error). In addition to suffering from other defects common to earnings management research, the analysts' forecasts literature tends to ignore the fact that firms' earnings management practices respond to analysts' forecasts.

This paper investigates the properties of analysts' forecasts by accounting for the interaction between firms' earnings management practices and analysts' response to those practices. I hypothesize that analysts are aware of firms' intentions to manage earnings so that they slightly beat forecasts or maximize positive earnings surprises, and that analysts make strategic forecasts in view of firms' anticipated behavior. Suppose that, without considering firms' strategic responses to analysts' forecasts, a *non-strategic* forecast seeks to minimize analysts' expected loss due to forecast errors. Considering both how firms' earnings management practices respond to analysts' forecasts and how analysts in turn anticipate these practices, I demonstrate that *strategic* forecasts deviating from the *non-strategic* forecast can lower analysts' expected losses under certain circumstances. If firms are likely manage earnings downward after observing analysts' high forecasts, or their unmanaged earnings are negatively skewed, analysts are predicted to forecast below the *non-strategic* forecast. Conversely, analysts are predicted to forecast above the *non-strategic* forecast when firms are likely manage earnings upward in response to analysts' forecasts, or their unmanaged earnings are positively skewed. The intuition of this prediction is as follows: by forecasting below the *non-strategic* forecast, analysts seek to increase the likelihood that firms can meet or beat their forecasts, then reducing the likelihood that firms manage earnings downward. In other words, such forecasting practices protect the analyst's accuracy from the effects of earnings management practices like the "big bath," a scenario in which firms manage earnings dramatically downward when they cannot meet the benchmark analysts have set (see Healy, 1985; Brown, 1997). Similarly, forecasting above the *non-strategic* forecast will dissuade firms from managing earnings in response to analysts' forecasts that are too low, as when firms manage earnings upward to beat analysts' forecasts by as great a margin as possible. When analysts perceive that firms may attempt to maximize their earnings surprise, raising the forecast benchmark reduces firms' incentive to manage earnings in this way and results in a lower expected loss for the analyst.

Using a sample of 31,695 firm-quarter observations over the period 1987-2003, I compare three different analysts' consensus forecasts with a proxy for the *non-strategic* forecasts. Consistent with my hypotheses, after controlling for firm size, uncertainty in the forecasting environment, and firms' previous performance, I find that analysts are more likely to forecast below the *non-strategic* forecasts for firm-quarters that have a greater ability/tendency to manage earnings downwards, negatively skewed unmanaged earnings, or both. The empirical proxies for firms' ability/tendency to manage earnings downwards include: (1) accumulated discretionary accruals for the eight past consecutive quarters: when the accumulated discretionary are positive, the likelihood that firms will manage earnings downward in the current period is high;[1] (2) unmanaged earnings: the higher the unmanaged earnings are, the more likely it is for the firms will manage earnings downwards; (3) debt to equity ratios: debt covenants are not likely to be binding when debt to equity ratios are low; (4) the sign of analysts' forecasts: analysts will only forecast a loss when they believe firms cannot manage earnings upwards to report a profit. Failure to lower their forecasts, analysts fear, might induce firms to manage earnings downward, which would lead to large optimistic forecast errors. The test results also provide evidence that analysts forecast above *non-strategic* forecasts when such a precaution is appropriate, for example, when forecasts may induce firm-quarters to manage earnings upward, or when the earnings distribution is positively skewed.

This study contributes to existing research on analysts' earnings forecasts by demonstrating that a consideration of firms' strategic announcement behavior changes the optimal forecast, and by providing evidence that, in order to avoid large optimistic

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[1] Accruals must revert in the long run (see Dechow, 1994; Sloan, 1996).

forecast errors, analysts forecast below the *non-strategic* forecast level for certain firm-quarters. Investigating earnings management from the analysts' perspective, this study also contributes to earnings management research. It shows that the observed asymmetric distribution of earnings surprises results not only from firms' earnings management behavior, but also from analysts' anticipation of such behavior.

The remainder of this dissertation is organized as follows: section 2 presents a discussion of previous research. Section 3 develops the hypotheses. Section 4 describes the research design, section 5 describes both the sample selection procedure and the descriptive statistics, section 6 reports the empirical results, and section 7 presents robustness tests. Finally, section 8 concludes and discusses directions for future research.

2. PRIOR WORK

2.1. Earnings management with respect to analysts' forecasts

There is a growing body of research that examines firms' reported earnings in relation to analysts' forecasts. These studies commonly assume that analysts' earnings forecasts are one of the benchmarks by which the market evaluates the earnings performance of a firm.

Many researchers contend that firms manage earnings to meet or narrowly exceed analysts' earnings forecasts (Burgstahler and Eames, 1998; Brown, 1997; Degeorge et al., 1999; Dechow et al., 2000). However, no consensus exists regarding the amount by which firms want to exceed this benchmark.

Burgstahler and Eames (1998) are among the first to document that there exists a disproportionately large number of small positive earnings surprises (or forecast errors) and a disproportionately small number of negative earnings surprises. Their conclusion that firms manage earnings and / or guide analysts' forecasts so that earnings meet or slightly beat analysts' forecasts rests on the assumption that, in the absence of earnings management and / or forecasts guidance, the distribution of earnings surprises would be symmetrical around zero. Burgstahler and Eames argue that firms whose earnings are likely to fall short of analysts' forecasts manage earnings and / or guide analysts' forecasts so that earnings equal or slightly exceed forecasts, resulting in zero or small positive earnings surprises. This behavior results in a disproportionately large number of quarterly observations in the small positive earnings surprises region.

In the same vein of research, Degeorge et al. (1999) suggest that if firms find that earnings sufficiently exceed forecasts, they will manage earnings downwards, and again report small, positive earnings surprises rather than large ones (this behavior is also known as "reigning in"). They use the same techniques as Burgstahler and Eames (1998), plotting the empirical distribution of the earnings surprises in small value (1-penny) bins in a range around zero. The figure approximates a normal distribution except that there is a discontinuity around zero, in which there is a smaller mass to the left of zero compared to the right. In addition to documenting the presence of reigning in, Degeorge et al. (1999) also sketch a model suggesting that corporate executives may be using reigning in to increase their compensation in the future. The authors conclude that this practice reinforces the natural tendency corporate executives to manage earnings upwards to meet analysts' forecasts, which results in a disproportionately large number of zero or small positive earnings surprises.

However, Degeorge et al (1999) conclude that avoiding negative earnings surprises is less important to managers than avoiding loss as or avoiding earnings decreases. Brown and Caylor (2004) revisit this research question and show that there has been a shift in managers' target earnings thresholds. Since the mid-1990s, avoiding negative earnings surprises has become the primary goal for managers.

Skinner and Sloan (1999) document evidence that failing to meet analysts' forecast has resulted in dramatically lower stock prices, that is, small earnings disappointments lead to large stock price declines. In addition, the negative stock price response is a concave function of the earnings surprises. Large negative earnings surprises will lead to large stock price decline at a declining rate. Firms' tendency to take a large loss rather than come up just short of analysts' forecasts results in a disproportionately small number of small, negative earnings surprises, and also large number of large, negative earnings surprises. Brown (1997) and Barua et al. (2003) argue that when analysts' forecasts are unattainable, after having exhausted all of their accounting flexibility, firms will manage earnings downwards. That is, firms will manage earnings down even further in order to build up accounting reserves.

More importantly, it has also been documented that firms who meet or beat analysts' forecasts have different patterns of discretionary (unexpected) accruals than firms who do not. Barua et al. (2003) find that for profit-reporting firms, those who just meet or narrowly exceed analysts' forecasts are more likely to have income-increasing discretionary accruals. This is after controlling for both earnings performance and opportunity to use discretionary accruals.

Since earnings per share (EPS) is the earnings number that is frequently evaluated against analysts' forecasts, Das and Zhang (2003) suggest that in order to meet analysts' forecasts, firms manage earnings by rounding up the earnings number such that the reported EPS is one cent higher. For each firm, the authors recalculate EPS by dividing earnings (and earnings before extraordinary items) by the number of common shares used to calculate quarterly basic EPS. They find that for more than 54% of the recalculated EPS, the digit immediately right of the decimal of the reported EPS expressed in cents is greater than or equal to five, thus rejecting the null hypothesis that there is no earnings management. This phenomenon is more pronounced when managers ex-ante expect that rounding-up the earnings numbers will enable them to meet analysts' forecasts.

Moehrle (2001) provides evidence that firms use restructuring charge reversals to meet analysts' forecasts. Specifically, the author posits that firms inflate charges when restructure activities occurred and then reverse it in the future. Focusing on the restructuring charges reversals, he finds that for Managers are more likely to record reversals when pre-reversal earnings are below analysts' forecasts and that the amount of reversals increases with the amount by which pre-reversal earnings fall short of analysts' forecasts.

Overall, these results provide evidence to support the notion that the anomaly of earnings surprises distribution is caused by earnings management, rather than by chance or by the nature of reported earnings.

At the same time, other researchers are only interested in whether or not firms beat analysts' forecasts, and make no explicit distinction between narrowly beating forecasts and maximizing earnings surprises (Bartov et al., 2002; Lopez and Rees 2002; Chevis et al., 2001).

Bartov et al. (2002) study the rewards of meeting or beating analysts' forecasts. They compare the market return for firms that have met or exceeded analysts' forecasts with those who have failed to do so. They find that there is a positive linear relationship between earnings surprises and market premium, defined as risk and market adjusted cumulative abnormal return over the announcement day.[1] Their paper also shows that meeting or beating analysts' forecasts is a leading indicator for firms' future performance even when firms do so by managing earnings. Implicitly, the authors suggest that positive earnings surprises are optimally beneficial for firms, irrespective of whether those earnings result from real performance or from accrual management

Lopez and Rees (2002) document another benefit of exceeding analysts' forecasts. They examine the relation between stock price sensitivity and earnings surprises. They expand the original earnings response coefficient regression model, by adding a dummy variable to indicate whether earnings have exceeded the analysts' forecasts. The results indicate that the earnings response coefficient to positive earnings surprises is significantly greater than the earnings response coefficient for negative earnings surprises, especially for firms that have constantly beaten analysts' forecasts.

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[1] Although Bartov et al. (2002) finds that investors discount the effect of earnings management, the extent of the discount is economically minor (page 198).

They also find that the negative response to not meeting forecasts is significantly greater in absolute terms than the response to beating forecasts. This is after controlling for the level of earnings surprises, which suggests that stock market penalize firms who miss this important benchmark.

Chevis et al. (2001) focus only on firms that consistently meet or beat analysts' forecast over a long time period spanning multiple quarters.[2] The main test discussed in their paper is a logit model, which compares the characteristics of the firms who have consistently met or beaten analysts' forecasts with those firms who have repeatedly failed to do so. The results suggest that firms that consistently beat analysts' have higher growth, larger analyst following, lower forecast dispersion among analysts, and greater earnings stability. Consistent with Lopez and Rees (2002), Chevis et al. (2001) also document higher earnings response coefficient for these firms.

Overall, these studies provide a wide range of evidence that either investors or other stakeholders reward firms who meet or exceed analysts' forecasts. Other studies focus on top managers' incentive to report earnings that meet or exceed analysts' forecasts. Richardson et al (2003) suggest that managers are more concerned about meeting or beating analysts' expectation either before firms' equity issuance or before insider trading activities of top managers. Specifically, they investigate analysts' annual

[2] The paper defines "consistently meeting or beating analysts' forecasts" as meeting or exceeding the forecasts 10 out of 12 consecutive quarters.

forecasts made between 1992 and 1998, and find that in comparison to analysts' forecasts prior to this period forecasts made between 1992 and 1998 are more likely to be revised downwards. The authors argue this is a result of managers' "earnings-guidance" game, i.e., managers manipulate analysts' expectation rather than reported earnings. The explanation provided by the authors for the above result is that the period through 1998 witnessed an increase in the use of stock-based compensation. By guiding analysts' expectations such that their forecasts were beatable, firms were able to enjoy a higher stock price around earnings announcement. This in turn enabled managers to maximize their compensation. Richardson et al (2003) further find that this "earnings-guidance" phenomenon is especially pronounced for firms that issue equity and / or firms with top managers sell stock from their personal accounts after the earnings announcement.

In the same vein of research, Cheng and Warfield (2004) find evidence that managers with more stock-based compensation and stock ownership are more likely to report earnings that meet or narrowly exceed analysts' forecasts. Matsumoto (2002) also investigates management's incentives to avoid negative earnings surprises. She claims that firms use two mechanisms to avoid negative earnings surprises: they either manage earnings upwards or they guide analysts' forecasts downward. The empirical evidence suggests that both mechanisms are used more by firms with higher institutional ownership, greater reliance on implicit claims with their stakeholders, and higher value relevance of earnings. As in Richardson et al (2003), both Cheng and Warfield (2004) and Matsumoto (2002) argues that managers are likely to be more concerned about meeting or exceeding analysts' forecasts when negative earnings surprise will lead to significantly lower stock prices which will adversely affect their wealth.

Matsunaga and Park (2001) provide more direct evidence on CEO's incentive to manage earnings in order to exceed analysts' forecasts. They investigate the relation between a change in the annual cash bonus of a CEO and four dummy variables indicating whether the firm's quarterly earnings are below the consensus analysts' forecasts for the quarter. After controlling for firms' accounting and stock market performance (return on asset, and monthly return, respectively), the authors find that the failure of earnings to meet analysts' forecasts for at least two quarters during the year adversely affected CEO's annual cash bonuses.

In a related study, Farrell and Whidbee (2003) provide evidence that boards focus on deviation from expected performance, rather than performance alone in evaluating CEO. They use a probit analysis and find that the likelihood of CEO turnover is adversely related to industry-adjusted analysts' forecast errors, especially for companies with less dispersions in analysts' forecasts.

Common to most of the earnings management literature is that it treats analysts' earnings forecasts as exogenous, thus assuming either that analysts are unaware of firms' earnings management, or that their awareness is not reflected in their forecasts. However, if forecast accuracy is important, analysts will anticipate firms' earnings management behavior and issue forecasts that reflect this anticipation.

However, ignoring analysts' anticipation of earnings management may lead to erroneous inferences. Specifically, an earnings surprise is defined as reported earnings minus analysts' forecasts. As such, it is affected by strategies of both the firms and analysts. By investigating only the net effect of these two party's behavior, one cannot attribute the result to either party. As a result, earnings surprises cannot provide unambiguous inferences with respect to earnings management.

In contrast, I hypothesize that analysts incorporate earnings management in their forecasts, resulting in smaller earnings surprises (forecasts errors). Specifically, analysts' forecasts are likely to differ from forecasts that do not take earnings management into account. To provide evidence on this issue, I investigate the difference between analysts' forecasts and the forecast generated by a modified Foster model (Foster, 1977), rather than the difference between analysts' forecasts and reported earnings, which can set aside the earnings management effect.

In a concurrent theory paper, Guttman et al (2004) make similar assumptions as in this paper, although their focus is not on firms meeting or beating analysts' forecasts. Rather Guttman et al (2004) try to explain the discontinuity in the earnings distribution using a game theory approach. Specifically, in their model, managers manipulate earnings to maximize their compensation, and investors *form expectations* of such a manipulative behavior by managers. The effort of managers to fulfill investor's expectation causes a discontinuity in the distribution of reported earnings. The same theoretical argument may be applied in the case of strategic interaction between analysts and firm studied in this paper.

2.2. Analysts' forecast bias

A number of studies have investigated the properties of analysts' forecast bias and have offered different accounts of why these biases exist (often defined in the same manner as earnings surprises, namely reported earnings minus analysts' forecasts). This section reviews this literature (see also Kothari (2001) for a thorough summary of this research). Overall there are three different explanations of why analysts' forecasts bias exists: the economic incentives based explanation, behavioral cognitive-based explanation, and research design based explanation.

Some studies argue that the bias results from analysts' incentives. For example, one school of thought holds that compensation consideration motivates sell-side analysts to make optimistic forecast to please their clients firms. Dugar and Nathan (1995) show that financial analysts employed by brokerage firms (also known as sell-side analysts) are more optimistic on average than those employed by money management firms, pension funds, mutual funds, and the investment department of insurance companies (also known as buy-side analysts). The reason is that brokerage commissions are a major source of revenue for brokerage firms. Therefore, even though the research reports sell-side analysts provide are free of charge, an optimistic earnings forecast and a buy recommendation will attract more investors to trade in the company's stock.

A pessimistic earnings forecast or a sell recommendations can cause the brokerage firm to fall out of favor with the management of the company and thus leading to loss of access to management information. Therefore, others argue that analysts intentionally issue more optimistic forecasts to gain access to management information, even after controlling for underwriting activities. Relying on a quadratic-loss utility function of financial analysts, Lim (1998) shows that analysts trade off bias to improve management access and future forecast accuracy. This is especially true for firms with an information environment that has a higher degree of uncertainty. The empirical evidence is consistent with this model. There is a negative relation between the forecast bias and proxies for the richness of a company's information environment, after controlling for underwriting relationships. Similar evidence has been provided by Das et al (1998). They regress analysts' forecast bias on an earnings predictability measure, and find a negative association between earnings predictability and forecast optimism. They posit that when earnings are less predictable, analysts issue increasingly optimistic forecasts to curry favor with management in order to gain access to management information.

However, as pointed out by Eames and Glover (2003, page 708), "issuing intentionally optimistic earnings forecasts is not an effective means for pleasing managers and improving access to their private information", especially when there is ample evidence on managers' incentives to avoid negative earnings surprises. Eames and Glover (2003) show that after controlling for the level of earnings, there is no significant association between forecast bias and earnings predictability.

Bradshaw et al. (2004) provide incentive-related explanation beyond analyst affiliations from a different perspective. They investigate the association between corporate financing activities and analysts' forecast bias, and find that analysts are over-optimistic about the future performance of firms that raise new financing, regardless of the existence of explicit investment banking affiliations of the analysts with these firms. The authors argue that some combination of indirect investment banking pressures, incentives to generate brokerage business and analyst naiveté drives the on-average optimistic forecasts.

DeBondt and Thaler(1990) are among the first to propose a cognitive-bias explanation for analysts' forecast optimism. Specifically, they investigate analysts' tendencies to make forecasts that are too extreme. They test the relation between actual earnings changes and forecasted earnings changes, and find that analysts' forecasts not only are too extreme, but also are over-optimistic.

At the same time, Lys and Sohn (1990) documents that analysts' under-react to information. They test the association between stock market price changes and analysts' forecast revisions. The evidence fails to support the null hypothesis that analysts' forecasts fully incorporate prior price changes. The authors suggest that analysts omit some price change information from their earnings forecasts, which is a form of under-reaction.

However, as pointed out by Kothari (2001, page 158), "in order for an optimistic bias in analysts' forecasts to arise, there must be some asymmetry in over-reaction such that analysts' over-reaction to good news is not fully offset by their over-reaction to bad news". By the same reasoning, without asymmetry, under-reaction cannot explain analysts' forecast bias, either. Easterwood and Nutt (1999) document such an asymmetry. They suggest that analysts over-react to good earnings news and under-react to bad earnings news, which lead to optimistic analysts' forecasts on average.

In an altogether different vein, Gu and Wu (2003) argue that forecast bias results from earnings skewness rather than analysts' economic incentives or cognitive bias. They claim that forecast bias may appear to present even when analysts are issuing unbiased forecasts. Specifically, analysts will forecast the median, rather than the mean of the earnings distribution when their objective function is linear in forecast errors. This behavior may give the appearance of forecast bias when the distribution of earnings is not symmetric. Therefore, the analysts' forecast bias documented in the literature may be simply result from a skewed earnings distribution. Gu and Wu's evidence is consistent with this conjecture.

Basu and Markov (2003) also provide evidence that the observed analysts' forecast bias is likely to be a result of researchers' assumption that analysts face a quadratic rather than linear loss function. Specifically, the paper conducts rational expectations tests using different information variables that have been shown to predict analysts' forecast bias. For each variable, the rational expectation test is estimated using Ordinary Least Squares (OLS) and Least Absolute Deviation (LAD) regressions. Their assertion is that prior tests are based on OLS, relying on the implicit assumption that analysts try to minimize their mean squared forecast errors. On the other hand, the LAD method is based on a linear function of forecast errors. By comparing the results of these two methods, the authors find that they can reproduce most prior findings of inefficiency when they use OLS regression, whereas they find no evidence of forecast inefficiency when they use LAD regressions.

Abarbanell and Lehavy (2003) suggest that analysts' forecast bias is caused by firms' earnings management practice, rather than analysts' incentive. They show the association between discretionary accruals and analysts' forecast bias. Firms with extremely negative forecast errors typically have large and negative discretionary accruals. If one removes the discretionary accruals from the reported earnings, the pattern of disproportionately large amount of small positive forecast errors disappears. They conclude that these two pieces of evidence suggest that the documented forecast bias is due to earnings management rather than analysts' behavior.

As in the earnings management literature, these analysts' forecast studies make earnings surprises their key variable. Once again, researchers assume that analysts issue forecasts independently of their knowledge of firms' earnings management practice. My study provides a better understanding of the properties of analysts' forecasts by modeling firms' earnings management practices and analysts' response to them. Methodologically, my paper expands prior research by analyzing forecasts' deviation from statistically generated earnings rather than from actual earnings. This allows me to isolate the effects of earnings management and to investigate the nature of analysts' forecasts more precisely.

This paper most closely resembles Gu and Wu (2003), which hypothesizes that forecast error is positively related to earnings skewness. Specifically, Gu and Wu argue that the median earnings generate the lowest mean absolute forecast error. Negatively skewed earnings distributions would therefore lead to an optimistic forecast bias because of the mean-median difference in the earnings distribution.

My results suggest a more refined view, however, I argue that negatively skewed earnings induce analysts to forecast below median earnings when analysts' loss function is the absolute value of forecast error. Despite this apparent discrepancy between my results and those obtained by Gu and Wu (2003), the results are reconcilable. For a negatively skewed distribution, the median is higher than the mean. Thus, even if analysts' intend to forecast below median earnings, such a forecast may also be higher than the mean of the earnings distribution. In fact, I re-estimate Gu and Wu's major tests using my sample and get similar results to their findings. That is, I find that analysts' forecasts are on average lower than the median earnings but still higher than the mean earnings for negatively skewed earnings distribution.

To the best of my knowledge, Kim and Schroeder (1990) is the only paper that incorporates the strategic interaction between analysts' forecasts and firms' earnings management. They suggest that analysts' forecasts anticipate management's discretionary accrual choices in response to compensation incentives. That paper tests whether there is a systematic difference in analysts' forecasts errors when reported and forecasted earnings lie in different bonus ranges. They predict that if analysts account for earnings management in their forecasts, their forecasts will be more accurate when forecasted and reported earnings are separated by the upper bonus bound than when they are separated by the lower bonus bound. The rational is that when the forecast is lower than the upper bonus bound, the analyst is expecting managers to manage earnings upwards to maximize their compensation. However, since the earnings are actually above the upper bonus bound, the manager manages earnings downwards to save some accounting reserves for the future. Therefore, if the forecast and the reported earnings are separated by the upper bonus bound, the analysts' forecasts and the earnings are closer to each other than they otherwise should be, causing a small forecast error. The empirical tests are consistent with that prediction. Therefore, the study provides some evidence that managers manage earnings to maximize their compensation and analysts account for these practices in their forecasts. Kim and Schroeder (1990), however, only focus on earnings management that is caused by managers' attempts to maximize their compensation. In that scenario the benchmark against which firms manage earnings is fixed, which is not the case when earnings are managed with respect to analysts' forecasts. Therefore, this study both extends and complements prior work.

3. HYPOTHESES DEVELOPEMENT

3.1. Endogeneous earnings and forecasts

Suppose an analyst's objective is to forecast accurately. I compare what the analyst's strategy would be given two different sets of assumptions. The first set of assumptions, the *non-strategic* setting, posits that a firm's earnings announcement strategy exists independently of the analyst's forecast. The second set of assumptions, the *strategic* setting, posits that the firm manages earnings in response to the analyst's forecast, and that the analyst expects the firm to do so. The only difference between these two settings is whether or not the analyst's forecasting strategy anticipates that firms manage earnings in response to analysts' forecasts. Therefore, the *strategic* forecast can be seen as the *non-strategic* forecast adjusted upward or downward in anticipation of how the forecast would have affected a firm's earnings management behavior.

In the *strategic* setting, after observing the analyst's forecast, the firm manages the unmanaged earnings to meet or beat the forecast. Assuming that the analyst can anticipate the firm's response, I propose that the *strategic* forecast deviates from the *non-strategic* forecast, and that the direction and the amount of the deviation depend on the distribution of the firm's unmanaged earnings and the flexibilities the firm has to manage earnings.

I recognize, however, that the firms have multiple earnings announcement objectives, which are known to analysts. The "unmanaged earnings" considered here, then, are in reality earnings that have been managed to meet other earnings management objectives, but that have not been managed to meet or beat analysts' forecasts. The *non-strategic* forecast is the forecast for these unmanaged earnings. Also notice that when adjusting the *non-strategic* forecast to anticipate firms' earnings management practices, other earnings management objectives must still be considered. In addition, a firm's flexibility to manage earnings to meet or beat analysts' forecasts may be diminished if a firm draws on its accounting reserve to meet other earnings objectives.

3.1.1. Case 1 – Exactly meet or slightly beat analysts' forecasts

Suppose a firm's objective is to exactly meet or slightly beat an analyst's forecasts. The simplest forecasting scenario, in which the analyst does not revise the forecast,[1] has three possible outcomes:

i. Managing earnings will allow the firm to slightly beat the forecast;

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[1] Section 4.4 discusses analysts' forecasts revision.

The firm will announce earnings that slightly exceed the forecasted benchmark. The firm therefore succeeds in beating the forecast by a small amount and the analyst's forecast error is small. This possibility represents an optimal outcome for both the firm and the analyst.

ii. The forecast is too high and the firm cannot manage earnings so as to beat the forecast (the big bath scenario);

Since the firm cannot beat the forecast for this period, it will manage earnings downward and save an accounting reserve for the future. The announced earnings will fall below the forecast, and the forecast error is therefore a large negative number.

iii. The forecast is so low that earnings will inevitably exceed the forecast (the reign in scenario).

This situation resembles the previous one. The firm will manage its earnings downward, ideally bringing them to a level that just exceeds the forecast. If attaining this ideal level proves impossible even after exhausting the firm's accounting flexibility, and earnings will still significantly exceed the forecast, the firm will manage earnings downward as low as it is able in order to create the largest possible accounting reserve for future use. This scenario results in a strictly positive forecast error.

To make an accurate forecast, the analyst must consider the three situations listed above. In big bath scenarios, negatively skewed earnings or the accounting flexibility to manage earnings significantly downward will yield large forecast errors. To avoid such errors, analysts are likely to forecast below the *non-strategic* forecast, thereby ensuring that the firm can meet the analyst's forecast.

Suppose, for example, that the analyst intends to minimize the mean absolute forecast error. Further suppose that the firm being analyzed has a negatively skewed unmanaged earnings distribution: \$4 with probability 0.2, \$6 with probability 0.2, \$8 with probability 0.5, and \$10 with probability 0.1. The *non-strategic* forecast is the median, \$8. Now suppose that the analyst will issue a *strategic* forecast, and that he or she knows that the firm can either increase or decrease its unmanaged earnings by \$2. In this case, \$8 results in a mean absolute forecast error of 0.2 x |\$4 - \$8| + 0.2 x |\$8 - \$8| +0.2 x |\$8 - \$8| + 0.1 x |\$8 - \$8|, which is \$0.8. However, if the analyst adjusts the *non-strategic* forecast downward and issues a *strategic* forecast of \$6, the mean absolute forecast error will be 0.2 x |\$6 - \$6| + 0.2 x |\$6 - \$6| +0.2 x |\$6 - \$6| + 0.1 x |\$8 - \$6|, which is \$0.2. Thus, the lower *strategic* forecast reduces the likelihood of the firm's deciding to take a big bath.

Another analyst loss function commonly considered in the literature is the mean squared forecast error. In the scenario just discussed, the non-*strategic* forecast is the mean of the earnings distribution, \$6.1, and the *strategic* forecast remains \$6. Again, analysts are better off forecasting below the *non-strategic* forecast to ensure that this firm can meet the forecast.

Notice that when unmanaged earnings are positively skewed, the *strategic* forecast will be higher than the *non-strategic* one. Positively skewed unmanaged earnings have the potential for creating the reign in scenario if analysts do not adjust the non-strategic forecast upward. A strategic, upward adjustment to the *non-strategic* forecast makes certain that there will not be a large pessimistic forecast error.

Since earnings tend to be negatively skewed with a long tail (Basu, 1997; Givoly and Hayn, 2000), this paper focuses primarily on forecasting below the *non-strategic* forecast, though test results provide evidence that forecasting both above and below this mark does occur.

3.1.2. Case 2 – Maximizing the earnings surprises

Suppose a firm's earnings announcement objective is to maximize the positive earnings surprise. Two situations are likely:

i. The forecast can be beaten by managing the earnings;

   Since the firm aims to maximize the earnings surprise, it will manage earnings upward to achieve the maximum possible value, thereby producing a positive forecast error.

ii. The forecast cannot be reached even by exhausting all of the firm's accounting flexibility (the big bath scenario);

Previous studies indicate that failing to meet the analysts' forecast has resulted in dramatically lower stock prices, that is, small earnings disappointments lead to large stock price declines (see Skinner and Sloan, 1999). Moreover, the negative stock price response is a concave function of the earnings surprises. A firm that cannot meet the forecasted benchmark is better off taking a big bath to save an accounting reserve for future use. The firm will therefore manage earnings to the lowest level possible. Consequently, the forecast error is a large negative number.

As in the previous section, it is clear that when earnings are negatively skewed, a firm's decision to take a big bath will result in a large optimistic forecast error. Analysts are better off forecasting below the *non-strategic* forecast to ensure that the firm can beat the forecasted benchmark.

3.2 Hypotheses

Based on the discussions in 3.1.1 and 3.1.2, my main hypotheses are:

H1: For firm-quarters when firms have more flexibility to manage earnings downward, analysts' forecasts are more likely to be lower than the non-strategic forecasts.

Alternatively, analysts are more likely to forecast above the *non-strategic* forecasts when firms have more flexibility to manage earnings upward. This suggests that the reign-in scenario is a major concern for analysts. On the other hand, the deviation of analysts' forecasts from the *non-strategic* forecasts may be unrelated to firms' flexibility to manage earnings. If this is the case, analysts do not take earnings management into consideration when making their forecasts.

H2: For firm-quarters with a negatively skewed earnings distribution, analysts' forecasts are more likely to be lower than the non-strategic forecasts.

Alternatively, the deviation of analysts' forecasts from the *non-strategic* forecasts may be unrelated to firms' earnings distribution, which would suggest that analysts do not anticipate firms' earnings management behavior.

4. RESEARCH DESIGN

4.1 Earnings prediction (*non-strategic* forecasts)

Creating a proxy for the *non-strategic* forecast requires a careful consideration of the time-series properties of quarterly earnings. Most studies investigating this issue (for a review, see Brown, 1993 and Kothari, 2001) employ the Box-Jenkins autoregressive integrated moving average (ARIMA) models (Foster, 1977; Griffin, 1977; Watts, 1975; Brown and Rozeff, 1979). Among these various ARIMA models, evidence suggests that the Brown and Rozeff model has a slightly higher degree of accuracy over short horizons (see Brown et al., 1987). These models are commonly used and have frequently been compared with each other, but the literature pays little attention to their differing estimation procedures. Typically, the Box-Jenkins model is estimated using the least squares estimation method, which minimizes the mean square errors. There are two problems, though, associated with this estimation methodology (see the concurrent work by Basu and Markov, 2003).

First, the least squares method depends strongly on the assumption of normality. When the population of errors and the dependent variables are not normal distributed, the least squares estimators are inefficient. The asymmetric distribution of most financial variables, including earnings, has been well documented (see Foster, 1986). Earnings tend to be negatively skewed with a long tail (see Basu, 1997; Givoly and Hayn, 2000). Therefore, using the least squares method to estimate ARIMA models inevitably generates poorly-fitted estimators. In addition, most studies exploring the time-series properties of quarterly earnings suffer from a small-sample problem, using only 30-60 observations to estimate ARIMA parameters. With a small sample, especially a small sample from a long-tailed distribution, outliers can dramatically bias the least squares estimators.

The least squares method is also problematic because its estimating and forecasting objective is to minimize the mean square errors. Although the exact forms of forecasting utility (loss) functions are unknown, recent research suggests that minimizing the mean absolute errors results in a better fit (see Gu and Wu, 2003). Indeed, some researchers evaluate the accuracy of earnings forecasts by comparing the mean absolute errors (see Brown et al., 1987) rather than the mean square errors. Clearly, the least squares method's estimation objective is not the same as researchers' evaluation objective. Hence conclusions drawn from the comparison of different ARIMA models are not necessarily valid.

To address these problems, I use the least absolute deviation (LAD) method (also known as L1-norm statistics or the least absolute value (LAV) method) to estimate the ARIMA model. The LAD method is particularly robust in my setting because, unlike the least squares method, it is especially well-suited for distributions of errors that have long tails or are asymmetric (see Birkes and Dodgem, 1993). Researchers' limited use of the LAD method is most likely due to the complexity of the computations it requires, since the LAD estimator does not have a close-formed formula. In fact, even today, there is no software available that uses the LAD method to estimate ARIMA models. For pragmatic reasons, I therefore use the LAD method to estimate the simpler Foster model, rather than the Brown and Rozeff model, despite the fact that the latter may be more accurate. The Foster model is given as follows:

$$EPS\_LAD_{jq} = EPS_{jq-4} + \theta_{j0} + \theta_{j1}\,(EPS_{jq-1} - EPS_{jq-5}) + error_{jq} \qquad (3).$$

Determinants of earnings management are discussed next.

4.2. Determinants of earnings management

4.2.1. Estimation of accounting reserve

H1 states that for firm-quarters with more flexibility to manage earnings downwards, analysts are more likely to forecast below the *non-strategic* forecast. The more flexibility firms have to manage earnings downwards, the easier it is for firms to take a big bath. Hence it benefits analysts more to make certain firms will not do so in this situation. Since accruals must revert in the long run (see Dechow, 1994; Sloan, 1996), if firms have been managing earnings upwards continuously in prior periods, there is a greater likelihood that firms will manage earnings downwards in the current period. Based on Sloan (1996)'s evidence that most of the mean reversion of accruals takes place in the first year and that mean reversion is completed by the third year (page 299), I use the accumulated discretionary accruals in the past two years[1] as indicators for the magnitude of firm's flexibility to manage earnings for the current quarter.

H1.1: Ceteris Paribus, for firm-quarters in which the accumulated discretionary accruals in the eight most recent prior quarters are positive, analysts' forecasts are more likely to be below the non-strategic forecast.

Discretionary accruals are estimated using the modified Jones' model (see Subramanyam, 1996; Chaney et al., 1999). Mathematically, I estimate the parameters α_j, β_{j1}, β_{j2}, and β_{j3} in

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[3] Using accumulated discretionary accruals of the most recent 4 quarters does not change the test results.

$$TA_{jq} / A_{jq-1} = \alpha_j + \beta_{j1} \, [(\Delta REV_{jq} - \Delta REC_{jq})/A_{jq-1}] + \beta_{j2} \, [PPE_{jq}/A_{jq-1}] + \beta_{j3} \, [CFO_{jq}/A_{jq-1}] + \varepsilon_{jq} \quad (4)$$

where:

TA_{jq} = total accruals, defined as earnings minus cash flow for firm j in quarter q;

A_{jq} = total assets for firm j in quarter q;

ΔREV_{jq} = change in revenues for firm j in quarter q;

ΔREC_{jq} = change in accounts receivables for firm j in quarter q;

PPE_{jq} = gross property, plant, and equipment for firm j in quarter q;

CFO_{jq} = cash flow for firm j in quarter q.

Then I use the estimated parameters $\hat{\alpha}_j, \hat{\beta}_{j1}, \hat{\beta}_{j2}, \text{and} \hat{\beta}_{j3}$ to calculate

$$DA_{jq} = TA_{jq}/A_{jq-1} - \{ \hat{\alpha}_j + \hat{\beta}_{j1} \, [(\Delta REV_{jq} - \Delta REC_{jq})/A_{jq-1}] + \hat{\beta}_{j2} \, [PPE_{jq}/A_{jq-1}] + \hat{\beta}_{j3} \, [CFO_{jq}/A_{jq-1}]\} \ (5)$$

I define $KMINUS_{jq}$ as 1 if $\sum_{t=1}^{8} DA_{jq-t}$ is positive, and as 0 if it is not. A positive association between analysts' tendencies to forecast below the *non-strategic* forecast and *KMINUS* is expected.

4.2.2. Multiple earnings management objectives

In the previous section, I estimate the total accounting reserve available for firms to manage earnings. However, since the difference between the *non-strategic* forecast and the *strategic* forecast is the consideration of earnings management with respect to analysts' forecasts, when comparing them, the accounting flexibility should be the residual accounting reserve after earnings have been managed to achieve other objectives. As the literature on earnings management demonstrates, these objectives may include any or all of the following: managing earnings to maximize managers' compensation (see Healy, 1985; Holthausen et al., 1995), managing earnings to avoid certain debt covenants violations (see Healy and Palepu, 1990; Sweeney, 1994; Holthausen, 1981), managing earnings to avoid loss (see Burgstahler and Dichev, 1997), managing earnings to avoid unfavorable ruling by government regulatory bodies and the costs associated with it (see Cahan, 1992; Healy and Palepu, 1999), or managing earnings to meet certain regulations (see Jones, 1991).

First, according to the compensation hypothesis, managers tend to manage earnings upwards when the bonus increases with earnings and to manage earnings downwards when unmanaged earnings are high enough that they have no financial incentive to manage them further upwards, i.e. the unmanaged earnings are at or above the upper bound of the manager's bonus plan (see Healy, 1985; Holthausen et al., 1995).[2] Therefore, when a firm's unmanaged earnings are below the upper bound of the bonus plan, even if the firm has enough flexibility to manage earnings downwards, the manager may be reluctant to do so because his or her compensation will diminish. Consequently, the relation between unmanaged earnings and managers' bonus plans imposes a constraint on the relation between the accounting reserve and analysts' tendencies to forecast below the *non-strategic* forecast. Only if the unmanaged earnings exceed the upper bound of firms' bonus plan does forecasting below the *non-strategic* forecast yield a smaller expected loss. Since the upper bound of firms' bonus contract is unobservable, I assume that the higher the unmanaged earnings are, the more likely it is for analysts to forecast below the *non-strategic* forecast.

The political cost hypothesis introduces another constraint on the relation between the accounting flexibility and analysts' tendencies to forecast below the *non-strategic* forecast. It predicts that firms will manage high earnings downwards to reduce political costs (Cahan, 1992; Healy and Palepu, 1999). This hypothesis has the same implications as the compensation hypothesis. Therefore, ceteris paribus, high unmanaged earnings will be associated with analysts' tendencies to forecast below the *non-strategic* forecast.

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[2] Healy (1985) argues that managers will also manage earnings downwards when unmanaged earnings are significantly below the lower bound of the compensation contract. However, the findings in both Gaver et al. (1995) and Holthausen et al. (1995) suggest that this result is driven by Healy's research design.

H1.2: Ceteris Paribus, the higher the firms' unmanaged earnings are, it is more likely for analysts' forecasts to be below the *non-strategic* forecast.

I use *UME*, the difference between earnings before extraordinary items and discretionary accruals as proxy for unmanaged earnings. I expect a positive correlation between *UME* and analysts' tendencies to forecast below the *non-strategic* forecast, where *UME* is defined as earnings minus discretionary accruals, deflated by lagged total assets.

Previous studies have also demonstrated that debt covenant violations are costly to firms (Healy and Palepu, 1990; Sweeney, 1994; Holthausen, 1981). I assume that violating bond covenants is expensive relative to the benefits obtained from meeting or beating analysts' forecasts. As a consequence, if a debt covenant is binding, even though firms may have otherwise the flexibilities to manage earnings downwards, they will choose not to do so. Therefore, ceteris paribus, firms are less likely to manage earnings downwards the close the debt-covenants are to specific limits.

H1.3: Ceteris Paribus, the lower the firms' debt to equity ratios are, it is more likely for analysts' forecasts to be below the non-strategic forecast.

To test this hypothesis, I calculate debt to equity ratio, DE_{jq}, as total debt divided by total equity. A negative relation between *DE* and analysts' tendencies to forecast below the *non-strategic* forecast is expected.

Finally, Burgstahler and Dichev (1997) provide evidence that firms have incentives to manage earnings upwards to avoid losses. They also demonstrate that when a firm does not have the accounting flexibility to report a profit, it will choose to manage the earnings downwards, reporting a large loss, so that it can save accounting reserve for future use. Therefore, firms are more likely to manage earnings downwards when reporting a loss is inevitable. Based on Burgstahler and Eames (1998)'s evidence that analysts anticipate firms' earnings management to avoid loss, I use the sign of analysts' forecasts as an indicator of whether or not the loss is unavoidable. Analysts only release negative forecasts when they believe that firms cannot avoid losses.

H1.4: Ceteris Paribus, for firm-quarters in which analysts' earnings forecasts are losses, analysts' forecasts are more likely to be below the non-strategic forecast.

I create a dummy variable $LOSS_{jq}$. $LOSS_{jq}$ equals to 1 when F_{jq} is negative, and 0 otherwise. I predict that there is a positive correlation between *LOSS* and analysts' tendencies to forecast below the *non-strategic* forecast.

4.3. Skewness of earnings distribution

As stated in H2, the expected loss will be lower if analysts forecast below the *non-strategic* forecast for firm-quarters whose distributions of unmanaged earnings are negatively skewed.

The skewness is estimated using the skewness metric,[3]

$$SKEW_{jq} = \frac{n_j}{(n_j - 1)(n_j - 2)} \sum ((UME_{jq} - \overline{UME_j}) / s_j)^3 , \qquad (6)$$

where UME_{jq} is unmanaged earnings for firm j at quarter q.[4] $\overline{UME_j}$ is the mean, s_j is the standard deviation, and n_j is the number of observations of firm j's *UME* within the relevant rolling window. Following Gu and Wu (2003), the rolling window includes observations from quarters q-8 to q-1 and quarters q+1 to q+8, and requires a minimum

[3] Another measurement of skewness, the mean and median difference of earnings, is also used, and generates similar results.

[4] Using realized *EPS* doesn't change the result.

of four observations in each segment.[5] I predict that the more negative $SKEW_{jq}$ is, the more likely it is for analysts to forecast below the *non-strategic* forecast.

4.4. Analysts' Forecasts

The previous sections assume that analysts do not revise their forecasts. However, at least one third of analysts' forecasts in my sample have been revised (see section 5) before the actual earnings announcement. There is also evidence (see Matsumoto, 2002) that on average, analysts revise their forecasts downwards. In the test I divide the forecast data into two sets, one comprising forecasts that were not revised and the other forecasts that were. From these two data sets, I am able to test three analysts' consensus forecasts: 1) the median of the forecasts that were not revised, *F_NOREVISE*; 2) the median of forecasts which that were later revised, *F_ORIGINAL*; and 3) the median of the revised forecasts after their final revision, *F_FINAL*. Testing these three consensus forecasts separately will enable me to demonstrate that analysts consider earnings management when generating their forecasts, regardless of further revision.

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[5] As a sensitive test, I try to calculate skewness metrics in 2 other different rolling windows. One includes observations from quarter q-8 to q-1 only, and the other includes all the observations from quarter q-8 to quarter q+8. The results remain unchanged.

In the test I assume that analysts always try to make accurate forecasts, and that analysts only revise their forecasts when they believe they have new or more accurate information that will allow them to make better forecasts. Hence, *ex ante*, when analysts release *F_ORIGINAL*, they do not foresee that they will revise their forecasts. Therefore, I predict that *F_ORIGINAL* will have characteristics similar to *F_NOREVISE*, and that these two groups will generate similar results in my hypotheses tests.

Since the forecasts in *F_FINAL* are based on updated information, I predict that *F_FINAL* will be more accurate than *F_NOREVISE* and *F_ORIGINAL*. And since the forecasting period following *F_FINAL*'s release is much shorter than that following the release of the other two forecasts, the opportunity for firms to manipulate discretionary accruals diminishes. In addition, as time passes, analysts may gain additionally information with respect to firms' tendencies and flexibilities to manage earnings other than previous accounting report. Because the proxies in my tests are mainly based on previous quarters' accounting information, and do not reflect the new information becomes available to analysts as the earnings announcement date approaches, the possibility of measurement error increases, and this will weaken test results.

Based on H1 and H2, I predict that the consensus forecasts will be systematically lower than the *non-strategic* forecast for firm-quarters with negatively skewed earnings and when firms' tendencies and flexibilities to manage earnings downwards are high. Each consensus forecasts, *F_NOREVISE, F_ORIGINAL*, and *F_FINAL*, will generate similar results. However, I predict that *F_FINAL* will generate the weakest result.

4.5. Control variables

Following prior research, I include several variables in my test to control for other factors that might contribute to analysts' tendencies to forecast below or above the *non-strategic* forecast. [6]

First, because Brown (1997) finds that analysts' forecasts exhibit less optimistic bias for larger firms, I control for size using the log of the equity's market value at the end of the previous quarter, $LOGMV_{jq-1}$. I predict that the correlation between *LOGMV* and analysts' tendencies to make lower forecasts will be positive.

Second, I consider analyst following as a variable related to forecast bias. The nature of this relation, however, remains an open question. Lim (2001) finds evidence that proxies for the richness of a company's information environment, including analyst following, are inversely related to optimistic bias in forecasts. The reason is that analysts temper their optimistic bias to gain access to management. Gu and Wu (2003), on the other hand, argue that the number of analysts following is positively correlated with optimistic bias. A greater degree of analyst following, according to Gu and Wu, indicates

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[6] Most of the control variables are similar to the ones used by Gu and Wu (2003). The relation between this research and Gu and Wu (2003) is discussed in detail in section 2.2.

intense competition, and will drive analysts to issue increasingly optimistic forecasts in order to compete for management's favors. Because the effects of analyst following are still unclear, I make no predictions here regarding this factor. I use the natural log of the number of analysts making quarterly forecasts ($LOGAF_{jq}$) as a proxy for analyst following.

Two additional variables are used to proxy for uncertainty in the forecasting environment. These two variables are forecast dispersion ($FDISP_{iq}$), and variation of *EPS* ($EVAR_{iq}$). $FDISP_{iq}$ is defined as the standard deviation of forecasts deflated by lagged price. The forecasts must be released between the previous earnings announcement date and the current earnings announcement date. $EVAR_{iq}$ is measured as the standard deviation of *EPS* divided by the absolute value of the mean *EPS*, within the same rolling window as which the $SKEW_{iq}$ is measured. Since *FDISP* and *EVAR* are correlated with firm size, no clear prediction can be made as to how these variables correlate with analysts' tendencies to forecast below or above the *non-strategic* forecast.

Finally, according to Abarbanell and Bernard (1992), analysts tend to underreact to recent earnings surprises. I control for this underreaction by adding the variables $RWSUR\_1_{jq}$ and $RWSUR\_2_{jq}$. These two variables are lagged-price-deflated lag-one and lag-two earnings surprises measured using a random walk model. I predict a positive relation between *RWSUR* and analysts' tendencies to forecast below the *non-strategic* forecast.

Because the magnitude of forecasting below the *non-strategic* forecast is not necessarily a linear function of the variables I have described, I use a logit model. I classify firm-quarters as forecasted below the *non-strategic* forecast ($LOWER_{jq}$=1) if the consensus forecast is lower than the earnings prediction generated by the LAD method, or as forecasted above the *non-strategic* forecast ($LOWER_{jq}$ =0) if not. The logit regression is as follows:

$$\begin{aligned}&\text{Prob}\ \{LOWER\_i_{jq} = 1\}\\ &= F\ (\gamma_0 + \gamma_1\ KMINUS_{jq} + \gamma_2\ UME_{jq} + \gamma_3\ DE_{jq} + \gamma_4 LOSS\_i_{jq} + \gamma_5 SKEW_{jq}\\ &\quad + \gamma_6\ LOGMV_{jq-1} + \gamma_7\ LOGAF_{jq} + \gamma_8\ FDISP_{jq} + \gamma_9\ EVAR_{jq}\\ &\quad + \gamma_{10} RWSUR\_1_{jq} + \gamma_{11}\ RWSUR\_2_{jq}) \qquad (7)\end{aligned}$$

where:

$$F(\gamma' X) = \frac{e^{\gamma' X}}{1+e^{\gamma' X}}$$

i = *NOREVISE, ORIGINAL* or *FINAL*

5. DATA AND DESCRIPTIVE STATISTICS

5.1. Data

Earnings per share, excluding extraordinary items and other accounting variables have been obtained from the 2004 COMPUSTAT quarterly industrial and research files. The sample period is from 1987 to 2003. I choose to start from 1987 because the data on cash flow from operations reported in the statement of cash flows, which are necessary for calculating discretionary accruals, are only available from 1987. Previous research (Jones, 1990; Dechow et al., 1995) use balance sheet data to calculate cash flow from operations, but as Collins and Hribar (2000a) point out, such an approach can introduce measurement errors. Therefore, I limit my data to the 1987 to 2003 period, using cash flows from operations excluding extraordinary items and discontinued operations (COMPUSTAT data item #108 minus data item #78) to calculate accruals and discretionary accruals.[1]

I also restrict my analysis to firms that do not have any missing data for the variables used in the empirical analysis. In order to estimate both the Foster model using

[1] See Collins and Hribar (2000b). If data78 is missing, I assume it is 0.

the LAD method and the modified Jones' model in a rolling window for each firm-quarter, I must first estimate the necessary parameters. To make these preliminary estimations, I require that for each firm-quarter, there must be at least 10 consecutive observations prior to that quarter. I further eliminate observations with SIC codes 4400-5000 and 6000-6999. These codes correspond to the utility and financial service industries whose earnings predictions are quite different from others.

Analysts' forecasts are obtained from 2004 Zacks Investment Research database. In order to ensure that analysts have all of the previous quarters' accounting information, I use only those forecasts that follow the previous quarters' earnings announcement.

As discussed in section 4.4, I divide the Zacks forecast data into two sets, one composed of forecasts that have not been revised, and the other containing forecasts that have, and then merge each set separately with the COMPUSTAT data. The criteria I have described generate a no-revising-forecasts sample with 19,340 firm-quarter observations, representing 1,794 firms, and a revising-forecasts sample with 12,355 firm-quarter observations, representing 1,514 firms.

5.2. Descriptive Statistics

Table 2 and Table 3 represent the descriptive statistics for several key variables. Consistent with prior studies (Kazsnik and McNichols, 1999; Lys and Sohn, 1991), earnings surprises have negative means (-0.25% of lagged stock price for earnings surprises with respect to *F_NOREVISE*, -0.35% with respect to *F_ORIGINAL*, and -0.17% with respect to *F_FINAL*), and positive medians (0.8% of lagged stock price for surprises with respect to *F_NOREVISE*, 0.09% with respect to *F_ORIGINAL*, and 0.10% with respect to *F_FINAL*). These statistics suggest that majority of the firms in the sample beat analysts' forecasts, and that the negative surprises have larger absolute values than positive surprises.

As predicted, *F_FINAL* is the most accurate forecasts, with an average forecasting horizon of 27 days, and mean absolute forecast error of 1.11% of lagged stock price. *F_ORIGINAL* is the least accurate forecasts among the three consensus forecasts, with a mean absolute forecast error of 1.23% of lagged stock price. Other descriptive statistics show that the firms whose forecasts are most frequently revised are larger firms with more analysts following and less variable earnings. Hence, even though *F_ORIGINAL* is made for firm-quarters with a better forecast environment, the longer forecasting horizon (78 days vs. 55 days of *F_NOREVISE*) causes it to be less accurate than *F_NOREVISE*, which has a mean absolute forecast error of 1.21%.

6. EMPIRICAL RESULTS

6.1. Is it possible for firms to take a big bath?

One of the premises for my hypotheses is that firms will manage earnings downwards when forecasts cannot be met or beaten, and the anticipation of this downward earnings management induces analysts to forecast below the *non-strategic* forecast. The frequency of downward earnings management provides some preliminary evidence for this claim. Of the 8,592 firm-quarters in which unmanaged earnings fail to meet *F_NOREVISE*, 1,182 firm-quarters, approximately 13.8%, realize negative discretionary accruals when earnings are announced, i.e., have managed earnings downwards. [1]On average, discretionary accruals of these 1,182 firm-quarters' are -2.5% of total assets, or approximately negative 75 million dollars per firm. These numbers show that there are firms who take a big bath when analysts' forecasts cannot be met without earnings management.

[1] Use *F_ORIGINAL*, the percentage is 13.7%. Use *F_FINAL*, the percentage is 16.9%.

6.2. Earnings prediction

Before formally testing my hypotheses, I will assess the validity of my claim that earnings predictions estimated by the LAD method are more accurate than those generated by the least squares method. For each firm-quarter, I calculate three different lagged-price-deflated absolute forecast errors ($ABSUR\_LAD_{jq}$, $ABSUR\_FOSTER_{jq}$, and $ABSUR\_BR_{jq}$) by calculating the absolute difference between realized EPS_{jq} and proxies of expected earnings generated by one of the following three method: Foster prediction using the LAD method, Foster prediction using the least squares method, and Brown and Rozeff prediction using the least squares method. For firm-quarters with forecasts that have not been revised, *ABSUR_LAD* has a mean of 1.67% of lagged stock price, which is significantly smaller than the 1.89% generated by *ABSUR_FOSTER*, and the 1.88% derived from *ABSUR_BR*.[2] For firm-quarters with revised forecasts, the results remain unchanged. Thus, as predicted, earnings predictions estimated by the LAD method have a smaller mean absolute forecast error than those estimated by the least squares method.

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[2] The t-statistics for the null hypothesis that mean (*ABSUR_LAD*) is bigger than mean (*ABSUR_FOSTER*) is -2.81. The null hypothesis is rejected at 1% confident level. The t-statistics for the null hypothesis that mean (*ABSUR_LAD*) is bigger than mean (*ABSUR_BR*) is -2.69. The null hypothesis is rejected at 1% confident level.

6.3. Test of Hypotheses--- Logit model

Tables 4 and 5 show the descriptive statistics and the regression results of the logit model (equation 7). Panel B reports the Pearson (above the diagonal) and the Spearman (below the diagonal) correlations among the variables used to estimate equation (7). As predicted, analysts' tendencies to forecast below the *non-strategic* forecast, as measured by *LOWER_i*, is significantly positively associated with *KMINUS*, *UME* and *LOSS_i*, and significantly negatively associated with DE and *SKEW*. The positive correlation between *LOWER_i* and *KMINUS* suggests that analysts are more likely to forecast below the *non-strategic* forecast during firm-quarters when firms have more flexibility to manage earnings downwards. The level of unmanaged earnings, *UME*, is positively correlated with *LOWER_i*, indicating that analysts are more likely to forecast below the *non-strategic* forecast for firm-quarters with higher unmanaged earnings, in anticipation of downward earnings management by firms. *LOSS_i* is also positively associated with *LOWER_i*, providing evidence that analysts anticipate firms' big bath behavior when losses are inevitable. The fact that *LOWER_i* is negatively correlated with *DE* suggests that, for firm-quarters with binding debt covenants, it is less likely earnings will be managed downwards. As a result, analysts do not need to forecast below the *non-strategic* forecast. Finally, the negative association between *LOWER_i* and *SKEW* provides evidence that supports H2, i.e., for firm-quarters with earnings belonging to a negatively skewed distribution, analysts tend to forecast below the *non-strategic* forecast because doing so generates a lower expected loss. Taken together, the univariate analysis indicates that analysts consider firms' earnings management when shaping their forecasts, and that it is not necessarily optimal for them to forecast the *non-strategic* forecast.

The analysis also suggests several significant correlations among independent variables. For example, *SIZE* is correlated with most of the variables. Larger firms tend to have lower debt to equity ratio, more analyst following, and less variable earnings. Though several of these correlations are statistically significant, the magnitudes of most correlations have absolute values less than 0.2, suggesting that multi-colinearity is not an issue.[3] Since omitting any of the independent variables will lead to an omitted correlated variables problem, I incorporate all of them in the logit model.

As predicted by H1 and H2, whichever consensus forecasts are used, *F_NOREVISE, F_ORIGINAL, or F_FINAL, DOWN, UME, DE, LOSS_i,* and *SKEW* all have significant coefficients, and all of which are in the predicted direction. These results suggest that analysts are more likely to forecast below the *non-strategic* forecast for those firm-quarters with higher accounting reserves, with higher unmanaged earnings, with non-binding debt covenants, with negative forecasted earnings, and with negatively skewed unmanaged earnings. Also notice that among the three forecasts, *F_FINAL*

[3] When I conduct sensitive test using OLS model (section 6.5), I test the multicollinearity using the Variance Inflation Factor (VIF) method. The variance inflation values also indicate that multicollinearity is not a concern.

generates the weakest result, with the smallest log likelihood chi-square, and the smallest marginal effect on variable *DOWN*, *UME*, and *DE*. This weak result reflects the fact that as the earnings announcement date approaches, analysts have additional information about whether firms are likely to manage earnings downward. The additional information available to analysts weakens the relation between the deviation of forecasts and the variables based only on previous accounting information.

As for the control variables, the coefficient of *LOGAF* is insignificant at conventional levels, suggesting that analyst following is not a factor associated with analysts' bias. This is not surprising insofar as previous studies offer mixed results. *FDISP* has a significantly negative coefficient, indicating that analysts tend to forecast lower when the forecast dispersion is low. *EVAR* does not have a significant coefficient. The proxies for analysts' underreaction to firms' previous performance do not have significant coefficients either.

6.4. Asymmetric distribution of earnings surprises

In this section, I analyze the distribution of earnings surprises. According to previous studies, earnings management that responds to analysts' forecasts causes an asymmetric distribution of earnings surprises. That is, more firms beat analysts' forecasts than fail to do so. As a result, there are a disproportionately large number of positive earnings surprises and a disproportionately small number of negative earnings surprises. Since earnings surprises depend upon two variables, earnings and analysts' forecasts, one variable must be fixed in order to draw a valid conclusion about the other. My hypotheses indicate that analysts predict firms' earnings management behavior. Therefore, the studies that analyze earnings surprises mix the effect of analysts' prediction of earnings management and that of firms' realized earnings management behavior together. By comparing earnings surprises derived from analysts' forecasts and earnings surprises derived from the forecasts generated by a statistical model, it becomes clear that analysts' forecasts likely contribute to the asymmetric distribution of earnings surprises.

First, for the 19,340 firm-quarters with forecasts that have not been revised, 11,999 firm-quarters, approximately 61.99%, have earnings per share that meet or beat *F_NOREVISE*; while only 9,858, approximately 50.97%, have earnings per share that meet or beat *EPS_LAD*. Similar statistics are obtained when I use the revised-forecasts sample. The pessimistic bias, hence, is more pronounced for the analysts' forecasts, than for the statistical-model-generated forecasts. This might be caused by the fact that analysts sometime intentionally lower their forecasts to incorporate earnings management.

Figure 1 presents distributions of earnings surprises over a range of lagged-price-deflated earnings surprises, from – 2% of lagged stock price to 2% of lagged stock price.[4]

[4] See Burgstahler and Eames (1998).

Panel A shows that the distribution of earnings surprises defined with respect to the median forecast (*F_NOREVISE*[5]), and Panel B presents the distributions of earnings surprises defined with respect to the earnings prediction generated by the LAD method. Panel A shows a pattern of low frequency to the left of zero and high frequency immediately to the right of zero. This pattern closely resembles the results of previous studies. Such a pattern, however, does not exist in Panel B. The standardized difference for the first interval left of zero is used to assess the significance of the asymmetric distribution.[6] Using analysts' forecast to calculate earnings surprises, the standardized difference for the interval is -17.22, significant at the 0.0001 level. However, using statistical model generated forecast, the standardized difference for the interval immediately left of zero is only -0.21, insignificant at conventional levels.

These figures and statistics suggest that the pattern of asymmetric distribution, which is prominent when analysts' consensus forecasts are used, disappears when

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[5] Using *F_ORIGINAL*, *F_FINAL* generates similar figures, not reported here.

[6]Following Burgstahler and Dichev (1997), the standardized difference is defined as the difference between the actual and expected number of observations in an interval, divided by the estimated standard deviation of the difference. Denoting the probability that an observation will fall into interval i by p_i, the expected number of observations in interval I is $N*\frac{p_{i-1}+p_{i+1}}{2}$, and the variance of the difference between the observed and expected number of observations for interval I is approximately $N*p_i*(1-p_i)+N*\frac{(p_{i-1}+p_{i+1})*(1-(p_{i-1}+p_{i+1}))}{4}$.

predictions generated by the statistical models are used. Therefore, analysts' behavior likely contributes to the asymmetric distribution of earnings surprises.

7. ROBUSTNESS TEST

7.1. Firms' earnings management objectives

Firms are likely to have multiple earnings management objectives, which do not necessarily always include managing earnings to meet or beat analysts' forecasts. This section uses the *ex post* observed firms' earnings surprises to control for different firms' different tendencies to manage earnings with respect to analysts' forecasts. I assume that for the firms with a high frequency of meeting or beating analysts' forecasts, i.e., firms with a high frequency of non-negative earnings surprises, analysts' forecasts are more important when evaluating firms' performance. Therefore, I expect for such firms, analysts take more precaution against earnings management behavior such as a big bath. Similarly, for firms who fail to meet or beat analysts' forecasts most of the time, analysts do not need to concern about earnings management with respect to their forecasts.

In order to test this hypothesis, I investigate three sub-samples. First, I calculate the frequency of meeting or beating analysts' forecasts for each firm. The first sub-sample contains the firms whose frequencies of meeting or beating analysts' forecasts fall into the top ten percent. The second sub-sample is composed of the firms whose frequencies of meeting or beating analysts' forecasts fall into the bottom ten percent.

Finally, I randomly select firms from the overall sample to construct the last sub-sample. I ran the logit model from section 4 (page 30) using the three sub-samples respectively. I predict that for the first sub-sample, the relation between analysts' tendency to forecast lower than the *non-strategic* forecast and the proxies for firm-quarter's properties is the most significant, and that for the second sub-sample, there is no significant result.

The test results for the three sub-samples are shown in Table 10. As predicted, the sub-sample with firms who beat analysts' forecasts more frequently, the result is the strongest among the three sub-samples. The analysts' forecast used is *F_FINAL*. Using the other two proxies does not change the results.

7.2. Communication between analysts and firms

One of the assumptions in this study is that there is no private communication or collusion between analysts and firms. It would be interesting to investigate the effect of communication on analysts' forecasting strategy. For example, firms might tip off analysts about their earnings level in order to make sure that they can meet or beat the forecast. Consequently, analysts might release dramatically high forecast at the very beginning to initiate such a talk. The impact of Regulation Fair Disclosure (Reg FD) offers such an opportunity. In October 2000, Securities and Exchange Commission passed a rule, Reg FD, in an effort to prevent selective disclosure by public companies to market professionals and certain shareholders. This changes the private communication channels between analysts and firms. Even though the effect of Reg FD is still being debated, there is no doubt in the post Reg FD period, analysts have less private communication channels with the firms. I divide the sample into the pre Reg FD period and the post Reg FD period and run the logit tests (see page 30) in the two sub-samples respectively. There is no significant difference between the two periods. However, this lack of difference can also be explained as the ineffectiveness of Reg FD. Therefore, no conclusion with respect to private communication can be drawn from this test.

7.3. Model specifications

I conducted additional sensitivity analyses. First, the logit model (equation 7) only indicates the probability of analysts forecasting below the Foster prediction generated by the LAD method, but it does not generate any information about the magnitude of analysts' forecasts' deviation from the *non-strategic* forecast. Therefore, I ran an OLS regression using the logit model's independent variables as independent variables, and the difference between the proxy of the *non-strategic* forecast and the consensus forecasts as dependent variables. This test illustrates by how much analysts are willing to deviate from the *non-strategic* forecasts in response to firms' future earnings management.

$$
\begin{aligned}
&DELTA\_i_{jq} \\
&\quad = \lambda_0 + \lambda_1\, KMINUS_{jq} + \lambda_2\, UME_{jq} + \lambda_3\, DE_{jq} + \lambda_4 LOSS\_i_{jq} + \lambda_5 SKEW_{jq} \\
&\quad + \lambda_6\, LOGMV_{jq-1} + \lambda_7\, LOGAF_{jq} + \lambda_8\, FDISP_{jq} + \lambda_9\, EVAR_{jq} \\
&\quad + \lambda_{10}\, RWSUR\_1_{jq} + \lambda_{11} RWSUR\_2_{jq} \qquad (8)
\end{aligned}
$$

where $DELTA\_i_{jq} = EPS\_LAD_{jq} - F\_i_{jq}$

i = *NOREVISE, ORIGINAL* and *FINAL*

As before, the estimated coefficients of *KMINUS*, *UME*, and *LOSS_i* are predicted to be positive, and those of *SKEW* and *DE* are predicted to be negative. Generally, the bigger the *KMINUS* are, and / or the higher the unmanaged earnings are, and/or the more likely losses are inevitable, the more likely analysts are to forecast below the *non-strategic* forecast. Analysts also have stronger reasons to forecast below the *non-strategic* forecast when firm-quarters have negatively skewed unmanaged earnings, and/or firm-quarters' debt covenants are not binding. The results are reported in Table 6. All the estimated coefficients have the predicted sign, though several of them, including *SKEW* and *UME*, are not significant, suggesting that the relation between the dependent variable and these independent variables is not necessarily linear.

Gleason and Lee (2003) point out that multiple observations from the same firm could result in correlation among errors in one equation, leading to inaccurate statistics. In order to correct for this, I run the logit model (equation 7) using a sub-sample. In the sub-sample, for each firm, only the data from the most current quarter are included. The results are consistent with those in the earlier test.

I conduct several other sensitivity checks. The results are unchanged when I use the traditional Foster predictions and Brown and Rozeff predictions as proxies for the *non-strategic* forecast. I also try different discretionary accruals models (see Thomas and Zhang, 2000), and use the most recent forecasts instead of the consensus forecasts, and use total assets as deflators in the analysis. Similar results are obtained for each case.

8. CONCLUSION

Previous earnings management studies suggest that firms manage earnings to meet or to beat analysts' earnings forecasts. The evidence shows that earnings surprises are asymmetrically distributed; that is, more firms beat analysts' forecasts than fail to do so. There are a disproportionately large number of small positive earnings surprises. However, analysts' forecasts literature tends to ignore that firms' earnings management practices respond to analysts' forecasts.

This study investigates the properties of analysts' earnings forecasts by hypothesizing that analysts are aware of the earnings management practices of firms, and incorporate such behavior into their forecasts. Under these assumptions, forecasting either below or above the optimal forecast in a *non-strategic* setting can lower analysts' expected loss. For firms that have greater abilities / tendencies to manage earnings downwards, negatively skewed unmanaged earnings, or both, forecasting lower than the *non-strategic* optimal forecast can produce a lower expected loss. Similarly, forecasting higher than the *non-strategic* optimal forecast can generate a lower expected loss for firms that have the capacities to manage earnings upwards, positively skewed unmanaged earnings, or both.

Using the quarterly consensus forecasts data and accounting data from 1987 to 2003, I provide evidence that the higher the flexibility firms have to manage earnings downwards, the higher the unmanaged earnings are, the less likely debt covenants are to be violated, the more likely losses are inevitable, and/or the more negatively skewed the unmanaged earnings are, the more likely the analysts will forecast lower than the *non-strategic* forecasts. I also provide evidence consistent with analysts' attempts to avoid big bath practices by firms contribute to the asymmetric distribution of earnings surprises.

This paper raises a couple of important issues for future research. First, this research shows the importance of endogeneity when analyzing earnings surprises. Before any conclusion about earnings management and analysts' forecasts bias is reached, the interaction between analysts and firms has to be considered. Second, in this research, I consider analysts' forecasts as analysts' *strategic* response to predicted firms' behavior. After observing analysts' forecasts, firms' actual behavior is also worth investigating. For example, it would be interesting to examine why some firms would like to issue their own forecasts in response to analysts' forecasts.

Table 1: Variable Definitions

Variables From COMPUSTAT	***EPS***	Earnings per share excluding extraordinary items (COMPUSTAT quarterly data item #19) deflated by lagged closing price at the end of the quarter (COMPUSTAT quarterly data item #14)
	CFO	Net cash flow from operating activities (COMPUSTAT quarterly data item #108) excluding extraordinary items and discontinued operations (COMPUSTAT quarterly data item #78)
	A	Total Assets (COMPUSTAT quarterly data item #44)
	TA	Total accruals, defined as earnings before extraordinary items (COMPUSTAT quarterly data item #76) minus *CFO*.
	ΔREV	Change in total sales (COMPUSTAT quarterly data item #2)

	ΔREC	Change in accounts receivable account (COMPUSTAT quarterly data item #37)
	PPE	Gross property, plant and equipment (COMPUSTAT quarterly data item #42)
	DA	Discretionary accruals (see section 4.2.1)
	UME	Unmanaged earnings, defined as earnings before extraordinary items (COMPUSTAT quarterly data item #76) deflated by *A* minus *DA*.
	EPS_LAD	Earnings per share prediction using the LAD method
	EPS_FOSTER	Earnings per share prediction by the Foster model
	EPS_BR	Earnings per share prediction by the Brown and Rozeff model

	ABSUR_k	$\|EPS - EPS\_k\|$, k=*LAD, FOSTER*, or *BR*
Variables From Zacks	***F_NOREVISE***	Median of analysts' forecasts[1] which have not been revised
	F_ORIGINAL	Median of analysts' forecasts which have been revised later
	F_FINAL	Median of analysts' forecasts which are the final results of the revising
	HORIZON_i	Number of days before earnings announcement data when analysts' forecast is released
	SUR_i	*EPS – F_i, i = NOREVISE, ORIGINAL, or FINAL*
Variables Used in Logit Model (Equation 7)[2]	***LOWER_i***	Equals to 1 if lagged-price-deflated *F_i* < *EPS_LAD*, and 0 otherwise
	DELTA_i	*EPS_LAD* – lagged-price-deflated *F_i*
	KMINUS	Equals to 1 if 1 if $\sum_{t=1}^{8} DA_{jq-t}$ >= 0, and 0 otherwise

[1] All the forecasts were released after the previous quarters' earnings announcement and before current quarters' earnings announcement.

[2] Descriptive statistics of these variables are shown in Tables 4 and 5.

	DE	Debt to equity ratio, ((COMPUSTAT quarterly data item #45 + #51) / (#61 x #14))
	LOSS_i	Equals to 1 if *F_i* <0, 0 otherwise
	SKEW	$SKEW_{jq} = \frac{n_j}{(n_j - 1)(n_j - 2)} \sum ((UME_{jq} - \overline{UME_j}) / s_j)^3$ (see section 4.3)
	LOGMV	Log of equity's market value, log(COMPUSTAT quarterly data item #61 x #14)
	LOGAF	Log of the number of analysts releasing the quarterly forecasts
	FDISP	The standard deviation of *F_i* deflated by lagged price
	EVAR	The standard deviation of *EPS* divided by the absolute value of the mean *EPS*, within the same rolling window as which the *SKEW* is measured
	RWSUR_q	Lagged-price-deflated lag-one and lag-two earnings surprises measured using a random walk model

Table 2: Descriptive Statistics for Non-revised Forecasts Sample

	Mean	Median	Std. Dev.
EPS (%)	0.73	1.26	8.06
SUR_NOREVISE (%)	-0.25	0.08	8.45
ABSFE_NOREVISE (%)	1.21	0.37	8.37
HORIZON_NOREVISE	54.78	53.5	18.19
LOWER_NOREVISE	0.57	1	0.50
KMINUS	0.18	0	0.38
UME	0.01	0.01	0.04
DE	0.38	0.18	0.71
LOSS	0.08	0	0.27
SKEW	-0.37	-0.45	0.10
LOGMV	6.86	6.77	1.70
LOGAF	1.59	1.61	0.64
FDISP (%)	0.24	0.07	0.02
EVAR	2.50	0.50	31.19
RWSUR_1(%)	0.07	0.00	6.65
RWSUR_2(%)	-0.02	0.00	7.54

This table reports descriptive statistics for firm-quarters with forecasts which have not been revised (Sample size = 19,340 firm-quarters). All the variables in this table are defined in Table 1.

Table 3: Descriptive Statistics for Revised Forecasts Sample

	Mean	Median	Std. Dev.
EPS (%)	0.77	1.23	6.42
SUR_ORIGINAL (%)	-0.35	0.09	8.19
SUR_FINAL (%)	-0.17	0.10	7.05
ABSFE_ORIGINAL (%)	1.23	0.46	7.93
ABSFE_FINAL (%)	1.11	0.37	6.97
HORIZON_ORIGINAL	78.31	17.5	79.62
HORIZON_FINAL	26.57	15.10	23.25
LOWER_ORIGINAL	0.56	1	0.50
LOWER_FINAL	0.60	1	0.49
KMINUS	0.17	0	0.25
UME	0.02	0.02	0.03
DE	0.36	0.18	0.60
LOSS_ORIGINAL	0.06	0	0.24
LOSS_FINAL	0.08	0	0.27
SKEW	-0.38	-0.45	1.02
LOGMV	7.29	7.23	1.68

LOGAF	1.84	1.79	0.60
FDISP (%)	0.22	0.07	1.48
EVAR	2.32	0.50	28.98
RWSUR_1(%)	0.01	0.01	6.82
RWSUR_2(%)	0.07	0.00	7.92

This table reports descriptive statistics for firm-quarters with forecasts which have been revised (Sample size = 12,355 firm-quarters). All the variables in this table are defined in Table 1.

Table 4: Earnings Prediction for Non-revised Forecasts Sample

	Mean	Median	Std. Dev.
EPS_LAD (%)	0.74	1.24	5.57
EPS_FOSTER (%)	0.75	1.21	5.70
EPS_BR (%)	0.73	1.23	5.89
ABSUR_LAD (%)	1.67	0.54	7.36
ABSUR_FOSTER (%)	1.89	0.55	7.72
ABSUR_BR (%)	1.88	0.56	7.32

The table reports the earnings predictions using three different statistical models for firm-quarters with forecasts which have *not* been revised (Sample size = 19,340 firm-quarters). The three models are Foster model estimated by LAD method, Foster model estimated by OLS method, and Brown and Rozeff model estimated by OLS method. The detail is discussed in section 4.1. All the variables in this table are defined in Table 1.

Table 5: Earnings Prediction for Revised Forecasts Sample

	Mean	Median	Std. Dev.
EPS_LAD (%)	0.74	1.22	5.86
EPS_FOSTER (%)	0.71	1.21	6.17
EPS_BR (%)	0.72	1.22	6.02
ABSUR_LAD (%)	1.62	0.54	8.08
ABSUR_FOSTER (%)	1.82	0.55	8.56
ABSUR_BR (%)	1.82	0.53	8.17

The table reports the earnings predictions using three different statistical models for firm-quarters with forecasts which have been revised (Sample size = 12,355 firm-quarters). The three models are Foster model estimated by LAD method, Foster model estimated by OLS method, and Brown and Rozeff model estimated by OLS method. The detail is discussed in section 4.1. All the variables in this table are defined in Table 1.

Table 6: Correlation Matrix of Variables in the Logit Model --- Non-revised Forecasts Sample

	LOWER_ NOREVISE	*KMINUS*	*UME*	*DE*	*LOSS_ NOREVISE*	*SKEW*	*LOGMV*	*LOGAF*	*FDISP*	*EVAR*	*RWSUR_ 1*	*RWSUR _2*
LOWER_ NOREVISE		0.02*	0.14**	-0.13**	0.03**	-0.02*	0.10**	0.07**	-0.23**	-0.14**	0.01	0.07**
KMINUS	0.02*		0.01	0.00	-0.02**	-0.02	-0.01	0.02**	0.01	0.01	0.01	0.01
UME	0.09**	0.01		-0.43**	-0.29**	0.05**	0.12**	0.10**	-0.34**	-0.53**	-0.05**	-0.00
DE	-0.10**	0.01*	-0.10**		0.20**	0.02*	-0.20**	-0.12**	0.20**	0.26**	0.03**	-0.01
LOSS_ NOREVISE	0.04**	-0.02**	-0.27**	0.22**		-0.01	-0.17**	-0.08**	0.17**	0.25**	-0.05**	-0.02**
SKEW	-0.02*	-0.02*	0.045**	0.03**	-0.00		0.00	-0.00	-0.01	-0.06**	0.01	0.01
LOGMV	0.132**	-0.01	0.12**	-0.20**	-0.17**	-0.00		0.66**	-0.34**	-0.24**	0.00	-0.00
LOGAF	0.08**	-0.01	0.10**	-0.12**	-0.08**	-0.01	0.66**		-0.09**	-0.11**	0.01	0.00
FDISP	-0.01	-0.00	-0.07**	0.20**	0.17**	0.00	-0.11**	-0.05**		0.38**	0.01	-0.02*
EVAR	-0.02*	-0.01	-0.02**	0.05**	0.02**	-0.00	-0.04**	-0.03**	0.01		0.01	0.00
RWSUR_1	0.00	-0.00	-0.00	0.02**	-0.04**	-0.00	0.00	-0.01	0.01*	0.01		-0.31**
RWSUR_2	0.01	0.01	-0.03**	-0.01	0.01	0.01	0.00	0.00	-0.01	-0.00	-0.48**	

The table reports the correlation among variables used in equation (7) for firm-quarters with forecasts which have been revised (Sample size = 19,340 firm-quarters). Pearson correlations appear below the diagonal, Spearman correlations above it. All the variables in this table are defined in Table 1.

*,** Significant at p-value<0.05 0.01respectivel

Table 7: Logit Analysis of the Analysts' Tendency to forecast lower than the *non-strategic* forecast --- Non-revised Forecasts Sample

$$\text{Prob}\{LOWER\_NOREVISE_{jq} = 1\} = F(\gamma_0 + \gamma_1 KMINUS_{jq} + \gamma_2 UME_{jq} + \gamma_3 DE_{jq} + \gamma_4 LOSS\_NOREVISE_{jq} + \gamma_5 SKEW_{jq} + \gamma_6 LOGMV_{jq-1} + \gamma_7 LOGAF_{jq} + \gamma_8 FDISP_{jq} + \gamma_9 EVAR_{jq} + \gamma_{10} RWSUR\_1_{jq} + \gamma_{11} RWSUR\_2_{jq})$$

Variables	*Predicted Signs*	*Estimated Coefficients*	*Standard Errors*	*Marginal Effects*	*P-Value*
Intercept		-0.620	0.07		<0.0001
H1					
KMINUS	+	0.199	0.065	0.048	0.0022
UME	+	5.717	0.613	0.434	<0.0001
DE	–	-0.199	0.025	-0.049	<0.0001
LOSS	+	0.202	0.061	0.049	0.0009
H2					
SKEW	–	-0.038	0.013	-0.009	0.0044
Control Variables					
LOGMV	+	0.101	0.012	0.026	<0.0001
LOGAF	?	-0.018	0.031	-0.005	0.5482
FDISP	?	-2.075	1.232	-0.348	0.0923
EVAR	?	-0.000	0.001	-0.000	0.5925
RWSUR_1	+	0.181	0.266	0.014	0.9458
RWSUR_2	+	0.359	0.250	0.102	0.1502
Log Likelihood		26077.066			
Chi-Square		525.03			
p-value		<0.0001			
No. of Observations:					
LOWER_NOVEVISE$_{iq}$ **=1**		10890			
LOWER_NOVEVISE$_{iq}$ **=0**		8450			
Total		19340			

This table provides the results from estimating equation (7) for the Non-revised Forecasts sample firms. For each variable in the table, the estimated coefficient, the standard errors, the marginal probability, and the p-value are provided. The marginal probability represents the change in the probability of providing high quality financial information for a one standard deviation change in the independent variable of interest.

The table reports a logit analysis of the analysts' tendency to deviate from the *non-strategic* forecasts. The binary dependent variable is equal to 1 if analysts' forecasts < *non-strategic* forecasts, where the *non-strategic* forecasts are the forecasts generated by LAD method.

All the variables in this table are defined in Table 1.

Table 8: Correlation Matrix of Variables in the Logit Model — Non-revised Forecasts Sample

	LOWER_ ORIGINAL	*LOWER_ FINAL*	*KMINUS*	*UME*	*DE*	*LOSS_ ORIGINAL*	*LOSS_ FINAL*	*SKEW*	*LOGMV*	*LOGAF*	*FDISP*	*EVAR*	*RWSUR_1*	*RWSUR_2*
LOWER_ ORIGINAL		0.88**	0.02*	0.12**	-0.12**	0.04**	0.03**	-0.02*	0.16****	0.10**	-0.04**	-0.16**	-0.01	0.08**
LOWER_ FINAL	0.88**		0.02*	0.16**	-0.13**	0.04**	0.04**	-0.02*	0.11**	0.08**	-0.26**	-0.14**	-0.01	0.08**
KMINUS	0.02*	0.02**		0.01	0.01	-0.02*	-0.02**	-0.01	-0.00	0.00	0.01	-0.01	0.01	-0.02
UME	0.13**	0.11**	0.01		-0.48**	-0.30**	-0.31**	0.06**	0.16**	0.13**	-0.37**	-0.44**	-0.03**	-0.01
DE	-0.13**	-0.11**	0.01	-0.17**		0.12**	0.14**	0.01	-0.11**	-0.11**	0.42**	0.28**	0.03**	0.01
LOSS_ ORIGINAL	0.04**	0.05**	-0.02**	-0.29**	0.25**		0.84**	-0.01	-0.15**	-0.06**	0.26**	0.25**	-0.06**	-0.02**
LOSS_ FINAL	0.04**	0.03**	-0.02**	-0.26**	0.24**	0.84**		-0.00	-0.16**	-0.06**	0.34**	0.25**	-0.07**	-0.03**
SKEW	-0.02*	-0.02**	-0.01	0.08**	0.03**	-0.01	-0.01		-0.02*	-0.02	0.00	-0.06**	0.02	0.00
LOGMV	0.16**	0.12**	-0.01	0.14**	-0.21**	-0.15**	-0.18**	-0.02*		0.65**	-0.41**	-0.23**	0.01	0.00
LOGAF	0.10**	0.08**	0.00	0.12**	-0.14**	-0.06**	-0.07**	-0.02*	0.65**		-0.19**	-0.09**	0.01	0.01
FDISP	-0.05**	-0.01	-0.00	-0.05**	0.16**	0.13**	0.14**	-0.01	-0.11**	-0.07**		0.42**	0.00	-0.00
EVAR	-0.01	-0.01	-0.01	-0.02	0.03**	0.02*	0.03**	-0.01	-0.03*	-0.03*	0.01		0.01	0.02*
RWSUR_1	0.01	0.01	0.01	0.00	-0.02	-0.04**	-0.05**	0.00	0.01	0.01	-0.03	0.00		-0.31**
RWSUR_2	0.03**	0.03**	-0.01	-0.02	0.03**	0.01	0.02	-0.00	-0.01	-0.01	0.02*	-0.00	-0.45**	

The table reports the correlation among variables used in equation (7) for firm-quarters with forecasts which have been revised (Sample size = 12,355 firm-quarters). Pearson correlations appear below the diagonal, Spearman correlations above it. All the variables in this table are defined in Table 1.

Table 9: Logit Analysis of the Analysts' Tendency to forecast lower than the *non-strategic* forecast --- Revised Forecasts Sample

$$\text{Prob}\{LOWER\_i_{jq} = 1\} = F(\gamma_0 + \gamma_1 KMINUS_{jq} + \gamma_2 UME_{jq} + \gamma_3 DE_{jq} + \gamma_4 LOSS\_i_{jq} + \gamma_5 SKEW_{jq} + \gamma_6 LOGMV_{jq-1} + \gamma_7 LOGAF_{jq} + \gamma_8 FDISP_{jq} + \gamma_9 EVAR_{jq} + \gamma_{10} RWSUR\_1_{jq} + \gamma_{11} RWSUR\_2_{jq})$$

		i= ORIGINAL				*i=FINAL*			
Variables	*Pred Signs*	*Est Coeffs*	*Stad. rrors*	*Marg. Effects*	*P-value*	*Est Coeffs*	*Stad. rrors*	*Marg. Effects*	*P-value*
Intercept		-0.965	0.096		<0.0001	-0.539	0.095		<0.0001
H1:									
KMINUS	+	0.132	0.078	0.032	0.0922	0.156	0.081	0.039	0.0265
UME	+	10.339	0.931	0.447	<0.0001	10.647	0.847	0.367	<0.0001
DE	–	-0.302	0.040	-0.075	<0.0001	-0.322	0.035	-0.053	<0.0001
LOSS_i	+	0.309	0.078	0.075	<0.0001	0.567	0.081	0.114	<0.0001
H2:									
SKEW	–	-0.042	0.017	-0.010	0.0124	-0.032	0.017	-0.011	0.0071
Control Variables									
LOGMV	+	0.151	0.015	0.037	<0.0001	0.117	0.014	0.030	<0.0001
LOGAF	?	-0.079	0.041	-0.020	0.0515	-0.029	0.047	-0.006	0.4634
FDISP	?	-2.893	2.485	-0.489	0.2444	-0.887	1.317	-0.192	0.5571
EVAR	?	-0.000	0.001	-0.000	0.6874	-0.000	0.001	-0.000	0.5867
RWSUR_1	+	0.096	0.356	0.024	0.7875	0.122	0.375	0.035	0.8231
RWSUR_2	+	0.790	0.424	0.193	0.0627	1.115	0.423	0.216	0.0160
Log Likelihood		16994.101				14862.978			
Chi-Square		517.555				431.222			
p-value		<0.0001				<0.0001			
No. of Observations:									
LOWER_i_{iq} = 1		6824				7251			
LOWER_i_{iq} = 0		5531				5104			
Total		12355				12355			

This table provides the results from estimating equation (7) for the Non-revised Forecasts sample firms. For each variable in the table, the estimated coefficient, the standard errors, the marginal probability, and the p-value are provided. The marginal probability represents the change in the probability of providing high quality financial information for a one standard deviation change in the independent variable of interest.

The table reports a logit analysis of the analysts' tendency to deviate from the *non-strategic* forecasts. The binary dependent variable is equal to 1 if analysts' forecasts < *non-strategic* forecasts, where the non-strategic forecasts are the forecasts generated by LAD method.

All the variables in this table are defined in Table 1.

Table 10: Logit Analysis of the Analysts' Tendency to forecast lower than the *non-strategic* forecast --- 3 Sub Samples

$$\text{Prob}\{ LOWER\_FINAL_{jq} = 1 \} = F(\gamma_0 + \gamma_1 KMINUS_{jq} + \gamma_2 UME_{jq} + \gamma_3 DE_{jq} + \gamma_4 LOSS\_FINAL_{jq} + \gamma_5 SKEW_{jq} + \gamma_6 LOGMV_{jq-1} + \gamma_7 LOGAF_{jq} + \gamma_8 FDISP_{jq} + \gamma_9 EVAR_{jq} + \gamma_{10} RWSUR\_1_{jq} + \gamma_{11} RWSUR\_2_{jq})$$

		Firms who frequently beat analysts' forecasts		*Random Sample*		*Firms who frequently fail to analysts' forecasts*	
Variables		*Coefficients (p-value)*	*Marginal Effects*	*Coefficients (p-value)*	*Marginal Effects*	*Coefficients (p-value)*	*Marginal Effects*
Intercept		1.8664		0.9245		-0.6158	
H1:							
KMINUS	+	0.5065 (0.0454)	0.0564	0.2310 (0.0500)	0.0277	-0.6677 (0.3010)	-0.1281
UME	+	12.3896 (0.0014)	0.1581	10.0012 (0.0200)	0.1326	8.4048 (0.2000)	0.6703
DE	-	-0.4303 (0.0554)	-0.0493	-0.2057 (0.0664)	-0.0364	0.0000 (0.9990)	0.0000
LOSS	+	0.3487 (0.0006)	0.0411	0.2841 (<0.0001)	0.0308	0.8142 (0.2143)	0.1963
H2:							
SKEW	-	-0.1150 (<0.0001)	-0.0159	-0.1199 (<0.0001)	-0.0122	-0.1228 (0.1560)	-0.0265
Control Variables:							
LOGMV	+	0.1537 (0.0009)	0.0215	0.2219 (<0.0001)	0.0336	-0.0782 (<0.0001)	-0.0170
LOGAF	?	0.4124 (0.1166)	0.0475	0.2329 (0.1466)	0.0391	0.1845 (0.1559)	0.0419
FDISP	?	-3.556 (<0.0001)	-0.0842	-3.5789 (0.2450)	-0.0763	-3.4896 (0.6951)	-0.3145
EVAR	?	-0.0016 (0.9361)	-0.000	-0.0009 (0.8912)	-0.0000	-0.0000 (0.9669)	0.0035
RWSUR_1	+	6.519 (0.2986)	0.1570	4.0003 (0.3018)	0.1330	1.0052 (0.4459)	0.2436
RWSUR_2	+	6.6367 (0.2780)	0.8350	4.2013 (0.3210)	0.6629	0.8254 (0.5477)	0.1523
Log Likelihood		1745.185		1678.134		1246.250	
Chi-Square		70.1931		59.6431		21.5757	
p-value		<0.0001		<0.0001		<0.0001	

No. of Obs.			
Lower= 1	1602	993	472
Lower= 0	324	661	932
Total	1926	1654	1404

This table provides the results from estimating equation (7) for the Revised Forecasts sample firms. I divide the sample into 3 sub-samples based on the firm's frequency of beating analysts' forecasts. The first sub-sample contains the firms whose frequencies of meeting or beating analysts' forecasts fall into the top percentile. The last sub-sample is composed of the firms whose frequencies of meeting or beating analysts' forecasts fall into the bottom percentile. I randomly select firms from the overall sample to construct the second sub-sample.

For each variable in the table, the estimated coefficient, the marginal probability, and the p-value are provided. The marginal probability represents the change in the probability of providing high quality financial information for a one standard deviation change in the independent variable of interest.

The table reports a logit analysis of the analysts' tendency to deviate from the *non-strategic* forecasts. The binary dependent variable is equal to 1 if analysts' forecasts < *non-strategic* forecasts, where the non-strategic forecasts are the forecasts generated by LAD method.

All the variables in this table are defined in Table 1.

Table 11: OLS Analysis of the Analysts' Tendency to forecast lower than the *non-strategic* forecast --- Non-revised Forecasts Sample

$$\begin{aligned}&DELTA\_NOREVISE_{jq}\\ &\quad = \lambda_0 + \lambda_1 KMINUS_{jq} + \lambda_2\, UME_{jq} + \lambda_3\, DE_{jq} + \lambda_4 LOSS\_NOREVISE_{jq}\\ &\qquad + \lambda_5 SKEW_{jq}\\ &\quad + \lambda_6\, LOGMV_{jq-1} + \lambda_7\, LOGAF_{jq} + \lambda_8\, FDISP_{jq} + \lambda_9\, EVAR_{jq}\\ &\quad + \lambda_{10}\, RWSUR\_1_{jq} + \lambda_{11} RWSUR\_2_{jq}\end{aligned}$$

Variables	*Predicted Signs*	*Estimated Coefficients*	*Standard Errors*	*t-Statistics*	*P-Value*
Intercept					0.0930
H1					
KMINUS	+	0.001	0.000	1.48	0.2108
UME	+	0.0079	0.013	6.23	<0.0001
DE	–	-0.003	0.000	-3.85	0.0001
LOSS _NOREVISE	+	0.016	0.002	8.02	<0.0001
H2					
SKEW	–	-0.001	0.000	-1.86	0.0626
Control Variables					
LOGMV	+	0.001	0.000	2.09	0.0362
LOGAF	?	-0.001	0.001	-0.69	0.4918
FDISP	?	-0.749	0.031	23.28	<0.0001
EVAR	?	-0.000	0.000	-0.95	0.3402
RWSURP_1	+	0.057	0.009	6.87	<0.0001
RWSURP_2	+	0.007	0.007	0.95	0.3430
R-square		0.336			
Adj. R-square		0.330			
F Value		611.02			

This table provides the results from estimating equation (8) for the Non-revised Forecasts sample firms. For each variable in the table, the estimated coefficient, the standard errors, the t-statistics, and the p-value are provided.

The table reports an OLS analysis of the analysts' tendency to deviate from the *non-strategic* forecasts. The dependent variable is the amount analysts' forecast lower than the *non-strategic* forecasts, where the *non-strategic* forecasts are the forecasts generated by LAD method.

All the variables in this table are defined in Table 1.

Table 12: OLS Analysis of the Analysts' Tendency to forecast lower than the *non-strategic* forecast --- Revised Forecasts Sample

$$\begin{aligned} DELTA\_i_{jq} &= \lambda_0 + \lambda_1 KMINUS_{jq} + \lambda_2 UME_{jq} + \lambda_3 DE_{jq} + \lambda_4 LOSS\_i_{jq} + \lambda_5 SKEW_{jq} \\ &+ \lambda_6 LOGMV_{jq-1} + \lambda_7 LOGAF_{jq} + \lambda_8 FDISP_{jq} + \lambda_9 EVAR_{jq} \\ &+ \lambda_{10} RWSUR\_1_{jq} + \lambda_{11} RWSUR\_2_{jq} \end{aligned}$$

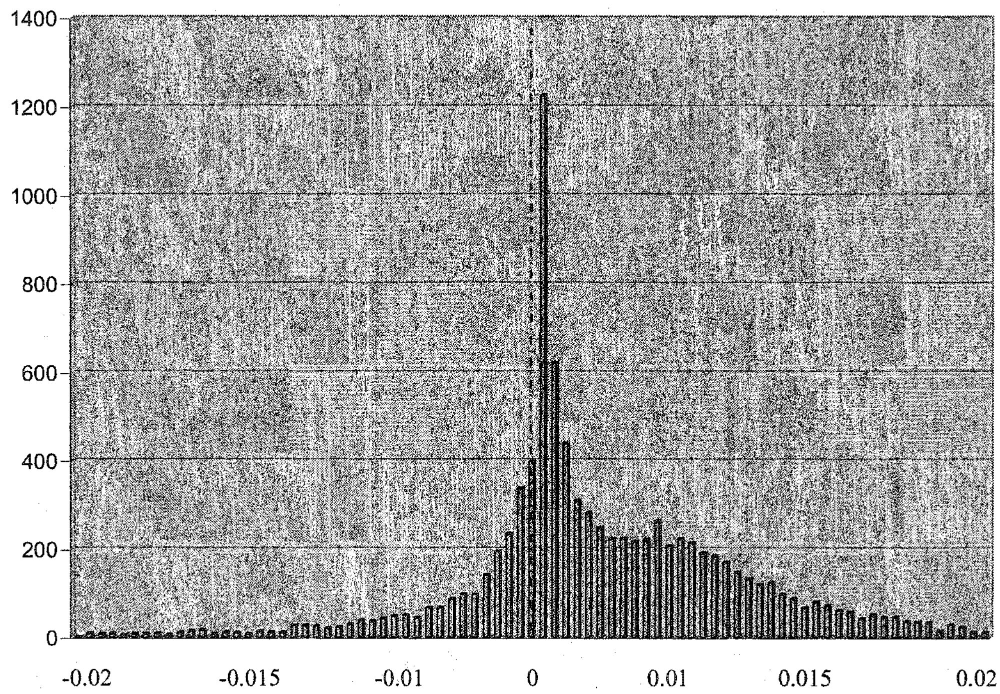
		i= ORIGINAL				*i=FINAL*			
Variables		*Est Coeffs*	*Std. Errors*	*T-Stat*	*P-value*	*Est Coeffs*	*Std. Errors*	*T-Stat*	*P-value*
Intercept		0.004	0.003	1.38	0.1691	0.000	0.003	0.02	0.9802
H1									
KMINUS	+	0.001	0.002	0.42	0.6392	0.001	0.002	0.46	0.6127
UME	+	0.146	0.020	7.40	<0.0001	0.138	0.016	7.21	<0.0001
DE	–	-0.001	0.000	-3.15	0.0251	-0.007	0.001	-4.08	<0.0001
LOSS_i	+	0.025	0.002	11.07	<0.0001	0.029	0.002	10.24	<0.0001
H2									
SKEW	–	-0.001	0.000	-0.15	0.8120	-0.001	0.000	-1.21	0.2182
Control Variables									
LOGMV	+	-0.000	0.000	-0.02	0.6475	0.000	0.000	0.75	0.4401
LOGAF	?	-0.002	0.001	-1.26	0.2206	-0.002	0.001	-1.63	0.0927
FDISP	?	-0.271	0.033	-69.53	<0.0001	-1.204	0.040	-30.21	<0.0001
EVAR	?	-0.000	0.000	-0.66	0.4829	-0.000	0.000	-0.69	0.4012
RWSUR_1	+	0.091	0.013	9.64	<0.0001	0.096	0.010	10.23	<0.0001
RWSUR_2	+	0.007	0.008	0.80	0.5605	0.009	0.009	1.05	0.2768
R-Square		0.295				0.089			
Adj. R-Square		0.295				0.088			
F-value		439.99				82.63			

This table provides the results from estimating equation (8) for the Revised Forecasts sample firms. For each variable in the table, the estimated coefficient, the standard errors, the t-statistics, and the p-value are provided.

The table reports an OLS analysis of the analysts' tendency to deviate from the *non-strategic* forecasts. The dependent variable is the amount analysts' forecast lower than the *non-strategic* forecasts, where the non-strategic forecasts are the forecasts generated by LAD method.

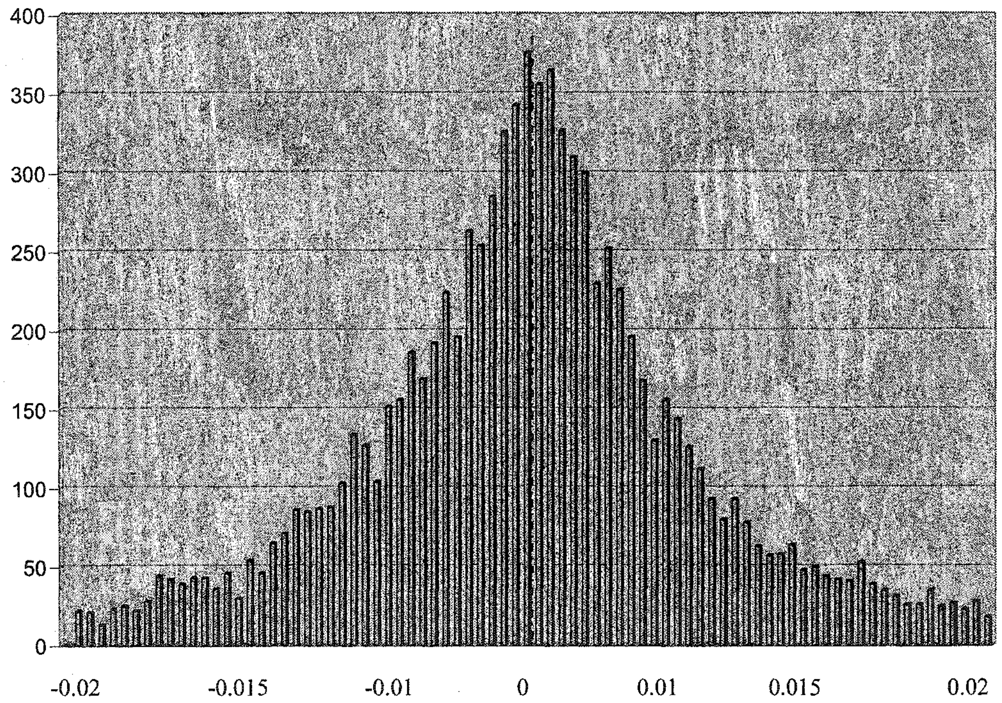
All the variables in this table are defined in Table 1.

Figure 1: Earnings Surprises (Realized Earnings – Analysts' Forecasts) Scaled by lagged stock price



This figure illustrates the distribution of earnings surprises, defined as realized earnings minus median analysts' forecasts after revision, and scaled by stock price.

Figure 2: Earnings Surprises (Realized Earnings – LAD Forecasts) Scaled by lagged stock price



This figure illustrates the distribution of earnings surprises, defined as realized earnings minus LAD earnings forecasts, and scaled by stock price.

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