Biased Forecasts or Biased Earnings?
The Role of Reported Earnings in Explaining Apparent Bias and Over/Underreaction in Analysts' Earnings Forecasts

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Abstract

We demonstrate that distributions of analysts' forecasts errors are characterized by two relatively small but statistically influential asymmetries. The first asymmetry is characterized as optimistic tails that are longer and fatter than pessimistic tails and the second asymmetry is characterized as a higher frequency of small pessimistic than small optimistic errors. These asymmetries are shown to disproportionally impact traditional statistics on which inferences concerning the existence and nature of unconditional and conditional (on prior news) analyst forecast errors are based. Observations that comprise these asymmetries are also shown to be associated with reported earnings components of the forecast error calculation that reflect, transparently, the nature of conservative accounting rules and managerial discretion in the application of these rules. A simple firm reporting bias-related explanation is offered to explain the existence of the two documented asymmetries in distributions of analysts' forecast errors. This explanation may be consistent with *refined* versions of extant incentive and cognitive-based theories for why analysts deliberately or inadvertently bias their forecasts. However, it is also consistent with the possibility that practical obstacles prevent analysts from completely unraveling biases in reported earnings at the time they issue a forecast or the possibility that analysts are not motivated by investors to forecast components of earnings that result from strategic manipulations by firms.

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Four decades of research on analysts' earnings forecasts has produced a wide array of empirical evidence and a set of behavioral and incentive-based theories intended to account for apparent bias and inefficiency in earnings estimates. An unsatisfying feature of extant theories is that, while they can account for one property of cross-sectional forecast error distributions, e.g., mean optimism, they are often inconsistent with another observed property, e.g., zero or occasionally pessimistic median forecast errors. A similar inconsistency is found in the seemingly unrelated literature on analyst over and underreaction to prior realizations of economic variables, such as stock returns and earnings changes. Here, a number of hypotheses have been offered to explain empirical evidence that suggests analysts sometimes overreact to prior information and at other times they underreact.[1]

In this paper we demonstrate that inferences consistent with analyst optimism/pessimism (in unconditional forecasts) and analyst overreaction/underreaction (in forecasts conditioned on the realization of prior information) are not attributable to prevalent tendencies for analysts to commit systematic errors and are not robust to different statistical methodologies. This phenomenon occurs because traditional statistical tests of systematic analyst errors are disproportionally impacted by the presence of two relatively small but influential asymmetries in cross-sectional distributions of analysts' forecast errors. The first asymmetry can be characterized as longer and fatter optimistic than pessimistic tails (the tail asymmetry). The second asymmetry can be characterized as a higher frequency of small pessimistic errors than optimistic forecast errors of a similar magnitude in forecast error distributions (the middle asymmetry).

We show that the tail asymmetry is responsible for inferences in prior studies that analysts systematically issue forecasts that are above realized earnings (i.e., that they are *ex post* optimistic) while the middle asymmetry is responsible for inferences in prior studies that analysts systematically issue forecasts that are below realized earnings (i.e., the are *ex post* pessimistic). We

[1] A representative selection of evidence and theory relevant to the literatures concerned with the properties of distributions of analysts' forecast errors is discussed in the body of the paper.

also demonstrate how both asymmetries contribute to varied and often inconsistent inferences concerning analyst over or underreaction to prior information, depending on the test design adopted by the researcher.

Next, we offer an explanation of how these asymmetries in forecast error distributions arise. We begin by showing that forecast error observations that comprise these asymmetries are characterized by "atypical" reported earnings numbers that reflect, transparently, the nature of conservative accounting rules and managerial discretion in the application of these rules. Specifically, observations in extreme optimistic tails are associated with the recognition of extreme income-decreasing accruals (i.e., extreme non-cash charges to income), whereas observations associated with the middle asymmetry are linked to both positive and negative accruals that lead to reported earnings that fall slightly above analysts' outstanding forecasts.[2]

The relation between analyst forecast errors and unusual reported earnings observations is a reflection of firms' strategic application of conservative accounting rules that characterize Generally Accepted Accounting Principles (GAAP). Conservative accounting rules limit the ability of firms to revalue assets for financial reporting purposes when their market values rise above historical cost and preclude revenue recognition, for the most part, until goods and services have been shipped or received. GAAP rules are not even-handed, however, in that they permit immediate write-downs of assets when their market values fall below historical cost and give broad latitude to managers in determining when an asset has expired, giving rise to the recognition of an expense or loss. We emphasize that conservative accounting rules do not apply to cash and cash-equivalents, so their impact on reported earnings is reflected through the recognition of accruals, i.e., non-cash gains (or revenues) and losses (or expenses).

[2] Degeorge, Patel, and Zeckhauser [1999] also proposes the possibility that firm earnings management is associated with an unusually high frequencies of zero and slightly pessimistic forecast error observations, consistent with asymmetry in the middle of forecast error distributions. In this paper we present *direct* evidence of a link between firm reporting discretion and *two* separate asymmetries in cross-sectional distributions of forecast errors that would be predicted under firms' discretionary application of conservative accounting rules. In addition, we formally demonstrate how earnings management can generate evidence consistent with inferences of forecast optimism/pessimism and over/underreaction in analysts' forecast errors drawn in prior research. Finally, our analysis makes explicit the notion that earnings management is not completely forecasted by analysts, discusses possible explanations for this phenomenon, and identifies several implications for interpreting prior findings and conducting future empirical and analytical research.

Conservative accounting rules have a predictable impact on the exercise of managerial discretion in reporting earnings, in that they facilitate firms' ability to manipulate accruals downward in any given period to create accounting "slack" (alternatively, to pay back earnings "borrowed" from earlier periods) but constrain firms' ability to use accruals to inflate current earnings. The importance of strategic manipulation of reported earnings in interpreting evidence of systematic forecast errors is highlighted by two salient empirical findings. First, the tail asymmetry associated with extreme income-decreasing accruals is significantly attenuated in successive analyst earnings revisions over the forecast horizon. This suggest that analysts are aware of conservative biases in accounting rules that allow for the immediate recognition of economic losses and adjust their forecasts publicly available information about firm recognition of such losses. Nevertheless, at the time analysts issue their last forecast for a quarter they do not account for all cases in which firms recognize extreme income-decreasing accruals (e.g., firms that choose to take an "earnings bath"). Second, the middle asymmetry is not present when errors are calculated using forecasts issued at the beginning and the middle of the quarter and only appears when forecast errors are based on the last forecast prior to a firm earnings announcement. This suggest that even with the benefit of publicly available information generated over the quarter that can be used to predict firm accruals, analysts' forecasts do not fully account for cases in which firms accruals lead to a reported earnings number that meets or slightly beats analysts' outstanding forecast. Thus, the presence of the two relatively small but statistically influential asymmetries in forecast error distributions is linked to the fact that firms make the last move in determining the "forecast error", as they choose the reported earnings component subsequent to analysts issuing their last earnings forecast for the quarter.

The fact that analysts do not appear to anticipate firms strategic manipulation of reported earnings in their forecasts may be a reflection of cognitive biases that lead analysts to commit inadvertent errors or market incentives that induce analysts to deliberately bias their forecasts that are relevant only in circumstances in which firms also have incentives to manipulate earnings. However, it may also be a reflection of practical obstacles faced by analysts that prevent them from completely unraveling earnings management or the absence of market incentives for analysts to predict the component of earnings that is managed. The literature is replete with (apparently incomplete) arguments consistent with the view of that the sole source of systematic analyst forecast errors is inherent bias in their forecasts. We offer anecdotal, empirical and theoretical arguments consistent with the alternative view that identifies a role for firms' strategic behavior in choosing reported earnings to explain evidence of systematic analyst errors.[3] The ultimate resolution of this issue is an empirical matter. However, our findings suggest that progress in validating cognitive and incentive-based theories for systematic forecast errors will require more research attention to the role of the reported earnings number in generating forecast errors and drawing inferences concerning analyst rationality from statistical properties of forecast error distributions.

In the next section we present evidence of the sensitivity of statistical inferences concerning analyst optimism and pessimism to relatively small numbers of observations that comprise asymmetries in unconditional forecast error distributions. We also evaluate the descriptiveness of extant hypotheses intended to explain systematic forecast errors in light of this evidence. Section 2 extends the analysis to demonstrate the impact of the two asymmetries on inferences concerning analyst over and underreaction to prior information in conditional (on the sign and magnitude of prior stock returns) forecast error distributions. Section 3 introduces evidence of an association between the strategic application of conservative accounting rules in reporting earnings and asymmetries in analyst forecast error distributions. In section 4 we provide a simple firm reporting bias-related explanation for several important empirical findings, specifically, persistent optimistic cross-section mean forecast errors, occasional pessimistic cross-sectional median forecast errors, and differential apparent analyst underreaction to prior stock returns as a function of the sign of the prior return realization. The analysis in this section also provides a new and remarkably mundane interpretation of the empirical phenomenon of declining mean optimism in consecutive revisions of a given periods earnings, a result that has previously been attributed in prior research to analysts'

[3] We stress that these arguments are not intended to repudiate existing incentive and cognitive-based theories for systematic errors in analysts' forecasts. Our intent is to highlight the viability of an alternative interpretation of prior evidence and make researchers concerned with the question of expectational biases in markets aware of the confounding effects on inferences concerning such expectational biases of strategic manipulation of conservative accounting rules by firms in determining reported earnings.

incentives to deliberately issue biased forecasts or unwittingly commit cognitive errors. A summary of our findings and conclusions is provided in section 5.

1. Properties of typical distributions of analysts' forecast errors and inferences concerning optimism and pessimism in analysts' earnings forecasts

1.1 Asymmetry in tails of forecast errors distributions and analyst optimism

The empirical evidence in this paper is drawn from a large database of consensus quarterly earnings forecasts provided by *Zacks Investment Research*. The *Zacks* earnings forecast database contains approximately 180,000 consensus quarterly forecasts for the period 1985-1998. For each covered firm, we calculate forecast errors as the actual earnings per share (as reported in the *Zacks* database) minus the consensus earnings forecast outstanding prior to announcement of quarterly earnings. Forecast errors are scaled by stock price at the beginning of the quarter.[4] Lack of availability of price data reduces sample size to 123,822 quarterly forecast errors. Finally, data requirements for quarterly accruals reduce the sample to 33,548 observations. Our forecast error results and conclusions are qualitatively unaltered by the imposition of this last data requirement.

Asymmetry in the tails of the distribution of forecast errors is evident in figure 1. The figure depicts the 1st through the 100th percentile of the pooled cross-sectional distributions of forecast errors over the sample period where, moving from left to right, forecast errors range from the most optimistic to the most pessimistic.[5] An elongated and fatter left tail of the distribution is apparent. There are far more extreme forecast errors of greater absolute magnitude in the *ex post* "optimistic" tail of the distribution than in the "pessimistic" tail.[6] Table 1 presents simple descriptive statistics for the forecast error sample. To get a sense of proportion, the magnitude of the forecast error at the 5th percentile (extreme optimism) reported in table 1 is nearly 2 times the size observed for the 95th percentile (extreme pessimism). Alternatively, 13% of the observations fall below an optimistic

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[4] In a subsequent section we expand our sample to investigate the characteristics of error distributions pertaining to revisions of forecasts of a given reporting period earnings as the earnings announcement date is approached.

[5] To ensure comparability of our results to those of other studies, we follow the common practice of winsorizing the distributions of quarterly forecast errors at the 1st and 99th percentiles to mitigate the possible effect of possible data errors. All tests are performed on the winsorized data.

[6] Keane and Runkle [1998] provide pooled sample evidence consistent with our findings.

forecast error of .5 while only 7% fall above a pessimistic error of an equal magnitude. We stress that while the evidence in figure 1 summarizes the distribution of observations over the entire sample period, unreported results indicate the tail asymmetry is present in each quarter represented in the sample.

Returning to the evidence in table 1, we find the mean forecast error over the sample period is -0.126, consistent with prior evidence of optimism in analysts' forecasts. While the distribution is negatively skewed and leptokurtic, the median error is approximately zero for the entire time period, and the percentage of positive (pessimistic), negative (optimistic), and zero forecast errors is 48%, 40%, and 13%, respectively. Prior empirical studies have, almost universally, found cross-sectional mean errors to be optimistic, however, the sign of observed median forecast errors has varied, having been reported in different years as positive, negative, and zero. Similarly, the percentage of optimistic forecast errors has been reported to be above and below 50% in studies examining different sample periods. We note that the median errors and frequencies of optimistic errors observed over the relatively long sample period examined in this study are inconsistent with the prevailing wisdom in the business press and academic literature that analysts are hard-wired or motivated to produce optimistic forecasts (see also Brown [1999]).

To develop a sense of the degree of the tail asymmetry we employ standard data trimming techniques to evaluate the robustness of statistics (see, e.g., Andrews, Bickel, and Huber [1972]). Table 2 reports the mean, skewness, kurtosis, and number of forecast error observations remaining after successively larger, *two-sided* symmetric truncations of the tails of the quarterly forecast error distributions. For example, the second row presents forecast error distribution statistics after truncation of the data in each quarter at the 1st and 99th percentile while the sixth row presents the same statistics after truncation at the 5th and 95th percentile. In the absence of asymmetries in the distribution of forecast errors, there is no reason to believe that symmetric truncation would affect measures of average tendencies in the data. Nevertheless, truncation of only 4% of each tail of quarterly distributions causes the mean forecast error to drop to a third of the full distribution mean, and truncation of slightly more than 10% of each tail eliminates evidence of bias. In untabulated results, we find that a one-sided truncation of 5% of the extreme pessimistic forecast error tail causes the measure of kurtosis to increase only slightly from a value of 102 to a value of 126 for the remaining observations in the distribution and the measure of skewness to increase only from -7.0 to -8.0. In stark contrast, one-sided truncation of only 3% of the extreme optimistic tail of the forecast error distribution leads to a decline the measure of kurtosis from a value of 102 to 9.4 and the measure of skewness to a value of zero.

The evidence in tables 1 and 2 suggests that the frequency of pessimistic errors exceeds that of optimistic errors in the sample, and that a small symmetric truncation of tails of forecast error distributions eliminates evidence of mean optimism. This evidence raises questions about the descriptive validity of a number of hypotheses that attribute mean optimism to the presence of induced or unwitting bias included in the vast majority of analysts' forecasts. Included among these hypotheses are those that rely on assumed asymmetric analysts' loss functions that cause them to deliberately bias their forecasts upward, e.g., Kim and Lustgarten [1998] and Lim [2001], assumed flaws in screening procedures employed by analysts, e.g., McNichols and O'Brien [1997], and assumed errors in analysts' judgments, see e.g., Affleck-Graves, Davis and Mendenhall [1991]. In their current form, these arguments suggest a generic tendency for analysts to inflate forecasts for all firms or a subset of firms that share a particular characteristic. For example, if analysts have an incentive to deliberately inflate forecasts to increase brokerage fees or gain access to management, as suggested by the hypotheses offered by Kim and Lustgarten [1998] and Lim [2001], then there should be a high incidence of optimism throughout the cross-section of forecasts. Similarly, if analysts are hard-wired to make systematic mistakes when using heuristics, as suggested by Affleck-Graves *et al*., such behavior should translate into a high frequency of optimistic forecasts in the subset of firms where flawed heuristics are employed. The empirical evidence in tables 1 and 2, however, does not support these tendencies in distribution of forecast errors.

1.2 Asymmetry near the middle of forecast error distributions and analyst pessimism

Note in table 2 that symmetric, two-sided truncation of slightly more than 20% of the tails of quarterly forecast error distributions leads to a flip in the sign of the mean forecast error and that the magnitude of the mean pessimistic forecast error that applies to observations that remain after symmetric truncation of successively larger portions of each tail holds at a relatively small value of .029. This evidence indicates the presence of a second asymmetry in the distribution of forecast errors in the form of an increasingly higher incidence of pessimistic errors than optimistic errors as the absolute magnitude of errors declines.

Visual evidence consistent with a higher frequency of small pessimistic versus small optimistic forecast errors is provided in figure 2 (see also Degeorge *et al*, Matsumoto [1999], Brown [1999], Burgstahler and Eames [1999] and Dechow, Richardson, and Tuna [2000]). The figure presents the frequencies of forecast errors that fall in fixed sub-intervals of .025 for forecast errors that fall in the range of –1 to +1. It is clear from the figure that the incidence of small pessimistic relative to small optimistic errors increases as forecast errors become smaller in absolute magnitude. A graph of expected frequencies in ranges around zero assuming the distribution of errors was normally distributed is provided as an informal benchmark.

Panel A of table 3 provides additional information about the tendency for pessimism among small forecast errors. Columns 2 and 3 report the mean forecast errors and the ratio of pessimistic (good news) to optimistic (bad news) errors for observations that fall into increasingly smaller symmetric intervals centered on the value of zero. For example, forecast errors in the interval between -.1 and .1 that comprise 29% of sample observations are characterized by a pessimistic mean of 0.012 and a ratio of pessimistic to optimistic forecast errors of 1.63 (statistically different from 1). For progressively smaller, symmetric intervals of forecast errors (i.e., moving down the rows), mean forecast errors become more pessimistic and the ratio of pessimistic errors to optimistic increases, reaching a factor of 1.81 in the smallest interval examined. Note that the absolute values of forecast error by sign in each symmetric region are comparable (columns 3 of panels B and C), suggesting that the tendency toward mean pessimism in forecast errors in these regions is attributable to the frequency of pessimistic errors rather than their magnitude. The incremental impact of increasing the symmetric region around zero by relatively small amounts beyond [-.1, 1] on the ratio of pessimistic to optimistic forecast errors is minimal.

To get a sense of the degree of the middle asymmetry we provide some simple calculations. If one were to assume, for example, that some firms take steps to ensure analysts' forecast errors (scaled by price) are equal to a pessimistic value of .1, then approximately 1,160 pessimistic observations out of 33,548, or approximately 3.5% of all observations, account for the observed asymmetry in the middle of the distribution.[7] Of course these percentages will differ if the amount by which firms intended to beat forecasts was lower than .1% of price.

One explanation for the existence of higher incidence of small pessimistic versus optimistic errors is suggested by the analyses in Degeorge *et al* and Abarbanell and Lehavy [2000a]. These studies argue that some firms will have incentives to manage earnings to slightly beat market earnings expectations but to conserve or create accounting reserves while doing so. If there are good reasons to believe that analysts either cannot or are not motivated to anticipate earnings management in their forecasts as argued by Abarbanell [1999], then when firms engage in this earnings management behavior analysts' expectations will be exceeded by small amounts. Matsumoto [1999] and Burgstahler and Eames [2000] offer a second potential explanation for a higher incidence of small pessimistic errors than small optimistic errors. They argue that firms manage analysts' expectations to an earnings number below that the ultimately reported by the firm to generate good news earnings surprises. This explanation appears to be a variation of an incentive and/or cognitive bias theory as it implies analysts' expectations can be "successfully" managed so that they persistently underestimate earnings.

To summarize, we identify in this section the existence of two asymmetries in cross-sectional distributions of forecast errors and find that, although the number of observations that create asymmetry in the tails of the distribution of forecast errors is relatively small, the magnitude of these extreme optimistic forecast errors has a disproportional impact on the cross-sectional mean

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[7] There are 9,652 non-zero forecast error observations the interval [-.1, .1]. Thus, if forecast errors were random we would expect 4,826 to be pessimistic when, in fact, a total of 5,986 is observed. This calculation ignores the possibility that some zero forecast error realizations may not be random and more of these zero errors would have been, in the absence of some unspecified process, optimistic than pessimistic. Even assuming all of the nearly 4,200 zero forecast error observations in our sample were generated by an unspecified process by which non-zero forecast errors were transformed to zero values, this would require that zero observations fall in a ratio of nearly 2/3 optimistic to 1/3 pessimistic in the absence of this process to account for our results. Moreover, the ratio must increase for every "legitimate" zero forecast error observation in the sample. In unreported results we find that efforts by firms to manage earnings to *exactly* meet outstanding analysts' forecasts cannot explain the significantly higher incidence of small pessimistic forecast errors (see Degeorge *et al*.) An analysis of unscaled forecast errors indicates the result is also not systematically induced by rounding down more small optimistic than pessimistic forecast errors to a value of zero when errors are scaled by price (see Degeorge *et al*).

forecast error. Similarly, the increasingly higher incidence of pessimism as the absolute magnitude of forecast errors declines tends to influence cross-sectional means and medians towards small pessimistic values. A practical implication of our findings is that test designs that isolate forecast errors of a small magnitude will be disproportionally affected by a greater incidence of pessimistic versus optimistic forecast errors, whereas test designs that focus on forecast errors of a large magnitude will be disproportionately affected by a greater frequency of apparent (extreme) analyst optimism.[8] Moreover, even if these observed asymmetries result from an unknown selection bias or other methodological flaw, the fact that observations that comprise them have a disproportional influence on statistics that describe distributions of forecast errors requires an explication of how existing theories that are based on cognitive biases and analysts' incentives are related to this selection bias or methodological flaw.

2. Revisiting apparent analyst inefficiency: the case of underreaction to prior stock returns

In the previous section we showed how two distinct asymmetries in unconditional forecast error distributions play an important role in producing evidence consistent with analyst forecast optimism and pessimism. Before presenting new evidence relevant to understanding the source of these two asymmetries, we demonstrate their influential role in producing seemingly unrelated evidence of systematic errors in conditional distributions of forecast errors, i.e., those used to assess whether analysts over or underreact to prior realizations of economic variables. We note that the key to linking evidence of analyst optimism/pessimism and analyst overreaction/underreaction is recognition that an optimistic (pessimistic) forecast following a bad-news event indicates, by definition, analyst underreaction (overreaction), while an optimistic (pessimistic) forecast following a good news event indicates overreaction (underreaction), see Abarbanell and Bernard [1992].[9]

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[8] For example, contrary to our findings, Brown [1999] concludes the mean forecast error in 1996 and 1997 is pessimistic. However, Brown winsorizes forecast error observations greater than an arbitrarily selected value. Unreported results indicate that forecast error distributions for these years are less skewed and leptokurtotic than earlier years, hence truncation of errors of an arbitrary absolute magnitude will generate a mean error that is more likely to reflect the effect of asymmetry in the middle of the forecast error distribution than the effect of asymmetry in the tails of the distribution in these years.

[9] Over/underreaction is a special case of the more general phenomenon of forecast inefficiency. The distinction between over/underreaction and the broader notion of inefficiency hinges on the implicit assumption that the researcher has

From this perspective, any variable whose prior realization has the ability to sort firms, even coarsely, by the likelihood they will fall into one or the other documented asymmetries in forecast error distributions can generate statistical evidence consistent with apparent over/underreaction.

In this section, we demonstrate how the same observations that comprise documented asymmetries in tails and near the middle of forecast error distributions combine to generate evidence of apparent analyst underreaction and overreaction to information in prior stock returns. As in the case of inferences about analyst bias discussed in the previous section, existing explanations offered to account for evidence of analyst inefficiency with respect to prior returns are based on either analysts' incentives to bias forecasts or the commission of judgment errors. Moreover, analogous to the case of assessing analyst optimism/pessimism in unconditional distributions of forecast errors, we show that observations that comprise the asymmetries can generate contradictory conclusions about the nature of analyst inefficiency, depending on which statistic/statistical estimation method is chosen by the researcher.

2.1 The contribution of the tail asymmetry to evidence of analyst underreaction/overreaction to prior returns

We begin our analysis in this section by partitioning the sample based on the sign of prior abnormal returns. Consistent with previous literature, we define prior abnormal returns as equal to the return between 10 days after the last quarterly earnings announcement to 10 days prior to the current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period.

Panel A of table 4 reports that the mean forecast error is optimistic for both prior return groups. In each case the mean is statistically different from zero, although its magnitude is considerably smaller for the positive prior return group (-.041) than for the negative prior return

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identified the exact nature of analyst inefficiency. In the literature, over/under reaction is typically defined in terms of the sign of the most recent change in a prior information variable (e.g., prior period earnings changes or prior period returns). However, other definitions are possible. For example, analysts' errors could be assessed for over/underreaction to the momentum of an economic variable defined, say, by whether most recent realized change in the variable represented an increase or decrease relative to the change two periods ago. Thus, the conclusion of underreaction or overreaction depends entirely on the sign of the information variable analysts are hypothesized to underutilize and the sign of the forecast error that follows, whereas the conclusion of analyst inefficiency only requires a statistical association between forecast errors and prior realizations of an economic variable (see also footnote 12).

group (-.195). Thus, the mean optimistic forecast error of -.126 reported in table 1 is largely attributable to observations in the cross-sections associated with prior negative abnormal returns. Recall that an optimistic mean forecast for firms experiencing negative returns in the period before the forecast is issued is consistent with apparent analyst underreaction, whereas an optimistic mean forecast following a period of positive returns is consistent with apparent analyst overreaction.

Figure 3 sheds further light on the evidence of optimistic mean forecast errors conditional on the sign of returns. It depicts the percentiles of forecast errors after partitioning the sample by the sign of prior abnormal returns. The figure suggests that the optimistic mean forecast in both groups is attributable to a relatively small number of extremely optimistic forecast errors in each prior return partition. This is confirmed in panel B of table 4 which reports the same statistics found in panel A after symmetrically truncating forecast errors of the entire distribution at the 10^{th} and 90^{th} percentiles. Again, in the absence of asymmetries in the distribution of forecast errors, there is no reason to believe that symmetric truncation would affect measures of average tendencies in the data. Nonetheless, symmetric truncation yields a mean forecast error for the remaining positive prior return observations that is slightly pessimistic (i.e., apparent analysts' underreaction) while it reduces the mean forecast error in the negative prior return group from a relatively large optimistic value of -.19 to a substantially smaller optimistic value of -.03. Overall, the results in table 4 indicate that the decline in optimism in the negative prior return group after the symmetric truncation accounts for the near elimination of optimism in the overall sample documented earlier in table 2. That is, the degree of tail asymmetry is greater in the negative prior abnormal return group than in the positive prior abnormal return distribution.[10]

Additional insight into the nature of apparent analyst underreaction can be gleaned from figure 4, which depicts mean and median forecast errors in portfolios formed by ranking prior return

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[10] This result may overlap with the findings of Brown [1999], who reports that firms experiencing losses account for a disproportional amount of extreme optimism in cross-sectional distributions of forecast errors. The incidence of firms with losses is higher for firms with negative prior returns than for firms with positive returns. However, similar to the findings here, Abarbanell and Lehavy [2000a] demonstrate that elongated optimistic tails are a characteristic of forecast error distributions even for firms with apparent good news, as indicated by a Buy stock recommendation. They show that while loss firms are over-represented among the most extreme optimistic forecast errors partitioned by stock recommendation, the median earnings of firms rated a *buy* and *hold* in this extreme optimistic region are positive well over half the time. This suggests that the distinction between “loss and profit” firms is not perfectly aligned with the observed asymmetries in forecast error distributions.

observations, partitioning them into deciles, and then averaging the mean forecast errors by decile over all sample years. A number of interesting insights can be gleaned from the figure. First, there is a clear connection between the extremeness of prior returns and the tail asymmetry; specifically, the most extreme optimistic forecast errors are associated with the most extreme negative returns. Second, mean forecast optimism in the return deciles depicted in figure 4 does not increase smoothly as prior returns become more negative. Rather, the increase in the magnitude of mean optimism is precipitous for observations comprising the most negative decile of returns. In contrast, while mean optimism still prevails for intermediate and small values of negative prior returns (deciles 3-6), it is more similar in magnitude to mean optimism observed for deciles of firms experiencing positive prior returns (deciles 6-10) than in the most extreme negative return decile. In fact, figure 4 reveals that the median forecast errors is actually zero in 5 out of 6 of the deciles that contain negative prior return values, with only the most extreme negative prior returns associated with an optimistic median forecast error. Thus, while the evidence in table 4 suggests firms that experience extreme negative prior returns are characterized by a higher incidence of extremely optimistic forecast errors than firms with intermediate or small negative prior abnormal returns, the incidence of systematic underreaction is not high for the vast majority of firms experiencing negative prior returns.

It can also be seen in figure 4 that portfolios of firms with positive prior returns are associated with median forecast errors that are either zero or relatively small pessimistic values, indicating that the presence of a relatively small number of extremely optimistic forecast error observations accounts for mean optimism in each decile formed by ranking prior returns. Notably, for firms in the highest prior positive abnormal return decile, which is characterized by a pessimistic median error, a very small number of extremely optimistic observations account for mean optimism and the appearance of overreaction to good news. Note that the sign of the median forecast error in the most extreme negative and positive prior return decile is consistent with analysts' underreaction to prior returns.

The pattern of extreme optimistic forecast errors and negative returns indicated in figure 4 will tend to produce exactly the configuration of underreaction results reported in previous literature. For example, the common practice of regressing forecast errors on prior abnormal returns (regressions that clearly violate normality assumptions) will tend to produce positive slope coefficients because the most extreme optimistic forecast errors will be associated with the most extreme negative prior returns. In contrast, regressions of forecast errors on positive returns will tend to produce small slope coefficients because extreme optimistic forecast errors will be interspersed throughout the distribution of positive returns in no particular pattern.[11] Consistent with this argument, in unreported results we find that regressions of forecast errors on returns produce a significant slope coefficient of 1.6 for firms with negative prior returns and an insignificant slope coefficient of .09 for firms with prior positive returns (unreported in tables).[12] However, when we re-estimated these regressions after truncating observations outside of the 10^{th} and the 90^{th} percentile of forecast error distributions, the coefficient on negative returns drops from 1.6 to a statistically significant but considerably smaller value of .16 while the coefficient on positive prior returns increases to a statistically significant .11. Intercepts are now sufficiently small to draw the conclusion that both prior return groups display evidence consistent with small apparent

[11] An under appreciated feature of prior evidence of apparent analyst over/under reaction is the persistent finding that the significance of statistical associations between forecast errors and prior stock returns is driven primarily by cases of firms experiencing poor prior stock performance. A review of the literature suggest that, regardless of the conditioning variable, following realizations that are classified as bad news events, analysts always appear to be extremely optimistic, while following realizations classified as good news events analysts appear to be either efficient or slightly inefficient (where the finding of slight overreaction or underreaction to good news varies depending on the chosen conditioning variable, the sample period or the statistical technique employed). This conclusion can be drawn from studies investigating over/underreaction to prior returns, (see e.g., Brown, Foster and Noreen [1985], Klein [1990], Lys and Sohn [1990], Abarbanell [1991], Elgers and Murray [1992], Abarbanell and Bernard [1992], and Chan, Jagadeesh, and Lakonishok [1996]) and studies investigating over/underreaction to prior earnings changes (see e.g., Debondt and Thaler [1988], Abarbanell and Bernard [1992], Easterwood and Nutt [1999], and Abarbanell and Lehavy [2001]). Abarbanell and Lehavy [2000a and 2001] present evidence of apparent over/underreaction of a similar character when the favorableness of prior stock recommendation and the sign of prior analysts' forecast errors are used to delineate good and bad news, respectively.

[12] A positive (albeit insignificant) slope coefficient for firms with positive returns gives the appearance of analyst underreaction. This fact can be reconciled with the overall mean optimistic forecast error (i.e., apparent overreaction) reported for firms with positive returns in table 4, panel A by the presence of a large negative intercept for this regression. In view of the non-normal shape of forecast error distributions and the fact that evidence of bias and inefficiency is linked by the same observations, it is likely that intercepts will take on significant non-zero values. It is common for researchers to focus only on slope coefficients when assessing the question of analyst underreaction/overreaction and to ignore non-zero intercepts or dismiss them as a manifestation of some factor unrelated to the hypotheses they are testing. While a non-zero slope coefficient is sufficient for inferring statistical inefficiency, it is not sufficient for drawing the conclusion that analyst under or overreact to prior news when the sign of the prior change variable determines whether there was good news or bad news. To draw such an inference the combined effects captured in intercepts and slopes must be taken into account.

underreaction (similar to the mean results after symmetric truncation reported in panel B of table 4). Thus, in the same way truncation of observations associated with the extreme optimistic tail asymmetry nearly eliminates evidence of optimism, it simultaneously attenuates evidence of underreaction to negative prior returns and produces evidence consistent with apparent underreaction to positive prior returns news.

2.2 Non-parametric statistics and inferences concerning analysts over and underreaction

As indicated earlier, most inferences of analyst over or underreaction are based on parametric methods. However, our findings thus far of the impact of a relatively small number of observations on parametric tests for systematic analyst forecast errors suggest that had inferences concerning analyst bias and inefficiency been based instead on non-parametric tests of association, conclusions would have differed.[13] It could be further argued that non-parametric tests are more appropriate for the purpose of testing the descriptiveness of incentive and judgment-based explanations for systematic errors because these explanations appeal to generic tendencies or motivations that cause the typical analyst to bias forecasts and have little to say about the magnitudes of their errors. The results presented in table 5 demonstrate the impact of alternative statistical approaches have on inferences.

Columns 1 to 3 of table 5, panel A report statistics for partitions of the sample into optimistic, pessimistic, and zero forecast errors by the sign of prior abnormal returns. We provide evidence on means, medians, and frequency of signed forecast errors to allow simple comparisons between inferences that would be drawn from parametric and non-parametric methods. Consistent with evidence presented earlier, the optimistic sample mean forecast error is driven by long, fat optimistic tails in the conditional forecast error distributions and the preponderance of this effect is concentrated in firms with extreme negative returns. The magnitude of optimistic errors reliably

[13] For example, Klein [1990] reports results similar to the findings in figure 4 in reaching her conclusions but does not identify the role of a small number of extremely optimistic forecast errors in each positive prior return deciles in mitigating evidence of apparent underreaction to good news. In fact, a small number extremely optimistic observations among firms with largest positive prior abnormal returns in Klein's sample is likely to be driving evidence of a small apparent overreaction to good news among these firms.

exceeds the magnitude of pessimistic errors for both prior return groups, and the mean optimistic error for firms with negative returns (-.703) is reliably larger than the mean error for firms with prior positive returns (-.586). By comparison, the magnitudes of mean pessimistic errors in the two prior return groups are statistically indistinguishable from each other (both approximately .29).

Panel A of table 5 also presents evidence on the frequency of optimistic and pessimistic errors conditional on the sign of prior returns. Optimistic (pessimistic) forecast errors occur 45% (42%) of the time for observations in the negative prior return group. This reinforces the conclusion that firms with negative prior returns generally display only a slightly higher incidence of optimism (i.e., underreaction) than pessimism (i.e., overreaction). In contrast, forecast errors are optimistic 34% and pessimistic 54% of the time when prior returns are positive. Based on these percentages, a test of association between the sign of prior abnormal returns and the sign of forecast errors yields a reliably significant positive association of .129 as measured by the phi coefficient. Again, this positive association is consistent with analyst underreaction to the information in prior returns. However, in stark contrast to the case of parametric tests of association, the conclusion of underreaction is driven almost entirely by the high incidence of pessimistic forecast errors among firms with prior positive returns (see also, Abarbanell [1991]). This point is reinforced by the results in panel B which reveal that, after symmetric truncation of observations in the tails of forecast error distribution, optimistic and pessimistic forecast errors occur with equal frequency (42%) for firms with negative prior returns. Meanwhile, systematic truncation has virtually no qualitative effect on evidence of a high frequency of apparent underreaction to positive prior returns.

The preceding findings highlight concerns with interpreting evidence as consistent with existing theories for analyst over/underreaction. Non-parametric tests generate evidence of apparent analyst underreaction to good news, driven in large part by a high frequency of pessimistic errors among firms with prior good news, whereas parametric tests can generate evidence of overreaction to good news owing to a few large optimistic errors among firm with prior good news.[14] Next, we

[14] For example, the conclusion reached by Easterwood and Nutt [1999] that analysts overreact to good prior earnings news is based solely on the significance of slope coefficients that are disproportionally impacted by a small number of extremely optimistic forecast errors associated with firms with positive prior earnings changes. Abarbanell and Lehavy [2001] note that regressions relied on by Easterwood and Nutt violate assumptions of normality and demonstrate that,

analyze another feature of the data that contributes these seemingly inconsistent interpretations. In sections 3 and 4 we develop an explanation for the somewhat slippery character of evidence of systematic forecast errors documented in the literature.

2.3 The contribution of the middle asymmetry to evidence of analyst underreaction

Thus far, we have described how asymmetry in tails of forecast error distributions has contributed to the conclusion in prior studies that analysts apparently underreact to information in prior negative returns and not to information in prior positive returns. The non-parametric evidence in table 5 leads to the reversal of these conclusions and begs the question of why the incidence of pessimism is so high among firms with positive prior returns. A possible explanation for this result is that forecast error observations associated with positive prior returns are more likely to fall into the asymmetry noted in the middle of the distribution than those associated with negative prior returns. If so, a positive association between the sign of forecast errors and the sign of prior returns would be expected. The evidence presented earlier in table 4 is consistent with this argument. Firms with positive prior returns are characterized by a relatively small pessimistic median forecast error (panel A and B) as well as a small mean forecast error after the symmetric truncations of extreme observations in the tails (panel B). Furthermore, it was seen in figure 4 that zero or small median forecast errors characterize three of the five portfolios comprised of firms with positive prior returns.

Table 6 provides further evidence on firms' proclivity to report earnings that beat analysts' forecasts. The table reports evidence similar to that in table 3 on the ratio of pessimistic to optimistic forecast errors in small symmetric intervals around a forecast error of zero by sign of prior returns. The evidence indicates that firms with positive prior returns are more likely to report earnings that lead to small pessimistic forecast errors than firms with negative returns. For example, the ratio of pessimistic to optimistic forecast errors in the interval between -.1 and .1 is 1.86 for firms with prior positive returns compared to 1.39 for those with prior negative returns.

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even under these conditions, the conclusion that analysts overreact to prior positive earnings changes is not supported when both intercepts and slopes of regressions are taken into account.

Taken together, the evidence reported in this section demonstrates 1) the same asymmetries that account for apparent bias in analysts' forecasts are also responsible for the evidence of analyst inefficiency with respect to prior abnormal returns and, 2) that failure to account for such asymmetries can lead to different inferences about the existence and character of inefficiency, depending on the choice of statistical estimation procedures and statistics on which inferences are based.

The remainder of the paper is devoted to understanding the how asymmetries in conditional and unconditional forecast error distributions arise. In the next section we examine a property common to observations that comprise the two documented asymmetries in forecast error distributions. Specifically, we document an association between these observations and systematic biases in their reported earnings component that are linked to firms' strategic application of conservative accounting rules. Section 4 identifies potential reasons for why analysts' forecasts do not appear to fully account for biases in reported earnings.

3. Bias in reported earnings and apparent bias and inefficiency in analysts' forecasts

3.1 Conservative bias in accounting rules and managerial discretion in applying these rules

It is well known that prices lead earnings, that is, new information about future cash flows is impounded in price before it is reflected in firms' reported earnings (see, e.g., Ball and Brown [1968]). The primary reason for this phenomenon is that generally accepted accounting principles (GAAP) require certain conditions to be met before expected cash flows can be recognized as part of earnings. For example, even if a company signs a long-term contract to deliver goods or services, revenues arising from this contract can only be recognized for accounting purposes when the goods or services are actually delivered. In contrast, stock prices will, in principle, anticipate all contracted revenues and, perhaps, revenues expected from the renewal of the contract in the future. An important characteristic of GAAP accounting is that it is not even-handed with regard to the limitations it places on the recognition of non-cash items. Accounting principles are conservative in nature in that they are less restrictive in the case of immediate and full recognition of economic expenses and losses than in the case of recognition of economic revenues and gains.

Assuming necessary conditions have been met, recognition of non-cash revenues and expenses generate accounting accruals. For example, accruals create assets such as accounts receivables when credit sales are generated and reduce assets when non-cash expenses are recognized (e.g., depreciation). Thus, by definition, earnings in the period are equal to cash flows plus net accruals, where net accruals are equal to non-cash revenues less non-cash expenses. Analysts' earnings forecasts, therefore, can be thought of as a combination of forecasts of cash flows and accruals for the period.

There are two important distinctions between accruals and cash flows that are relevant to the discussion that follows. First, although monitored by auditors, the SEC and securities exchanges, the timing and magnitude of accruals recognized in a given period are subject to managerial discretion and the final balances of these items can be determined as late as the date of an earnings announcement.[15] In the absence of information to the contrary, analysts' forecasts of the accrual portion of earnings will be based on their sales forecasts for the quarter and assumed relations between sales and book values of assets updated, in principle, for new information received over the quarter. Therefore, analysts' earnings forecast errors will depend on any exercise of managerial discretion in recognizing accruals in a manner that is inconsistent with these assumed relations. Empirical tests described below employ an *ex post* measure of the portion of accruals that cannot be explained by the firm's *actual* sales realization for the accounting period and historical relations between book values and sales. We refer to these amounts as unexpected accruals.[16]

[15] This is not to say that actual cash flows for a given period are not subject to managerial discretion. However, once cash flows are realized there is no discretion in the amount of cash reported and there is no bias in accounting rules related to how cash assets are reported. It should also be kept in mind that double entry bookkeeping, which requires that total earnings must sum to total cash flows over time, implies that recognition of accruals in a the current period that is not justified by real firm performance, must eventually reverse, thereby constraining the set of possible reported earnings in any period.

[16] Unexpected accruals are the measure produced by the modified Jones model (Jones [1991]) applied to quarterly data (see the appendix for calculations). To facilitate comparison with our forecast error measure, we express unexpected accruals on a per-share basis scaled by price. The qualitative results we report in this paper are unaffected by whether unexpected accruals are measured using cross-sectional, time series or instrumental variable techniques.

The second important factor that affects the recognition of accounting accruals is the conservative bent to GAAP. Because conservative accounting principles facilitate the immediate recognition of economic losses but restrict the recognition of economic gains, it can be expected that the maximum amount of possible income-decreasing accruals that a typical firm can recognize in a given accounting period will be of greater magnitude than the maximum amount of income-increasing accruals. Table 7 provides evidence that supports this intuition. The table presents selected average percentile values of distributions of firms' unexpected accruals over the sample period. It is evident from the table 7 that, while the unexpected accrual distribution is relatively symmetric in the middle, it is characterized by a longer negative than positive tail. For example, the magnitude of the average values at the 25th and 75th percentile is nearly identical. However, counterpart percentiles outside of these values begin to diverge by relatively large amounts beginning with a comparison of the values at the 10th and the 90th percentiles. The differences become progressively larger with comparisons of counterpart percentiles farther out in the tails. For example, the average 5th and 3rd percentile values are approximately 1.17 times larger than the average 95th and 97th percentiles, and the average value of the 1st percentile is 1.30 times larger than the average value of the 99th percentile. We stress that, although the percentile values of unexpected accruals vary from quarter to quarter, the basic shape of the distribution is similar in every quarter.

3.2 Linking unexpected accruals and the asymmetry in tails of forecast error distributions

Assume, for the moment, that when analysts issue forecasts of earnings, they do not account completely for the fact that *some* firms will recognize accruals that place them in the extreme negative tails of the *ex post* cross-sectional distribution of unexpected accruals. If this were the case, then we would expect to observe a correspondence between the negative tail of this distribution and the extreme optimistic tail of the cross-sectional forecast error distribution. The conjectured correspondence is observed in figure 5. The figure depicts median unexpected accruals in intervals of (+/–) .5% centered on the percentiles of forecast errors. For example, the median unexpected accrual corresponding to the Xth percentile of forecast errors is computed using observations that fall in the interval of X–.5 to X+.5 percentiles of the forecast error distribution.

It is clear from figure 5 that extreme negative unexpected accruals go hand-in-hand with extreme forecast optimism in the last forecast issued before an earnings announcement. In contrast, there is no clear pattern in unexpected accruals around moderate forecast error values. The evidence indicates there is a direct link between asymmetry in tails of forecast error distributions documented earlier and asymmetry in tails of unexpected accrual measures that arises directly or indirectly from conservative accounting rules.

3.3 Linking unexpected accruals and the asymmetry in the middle of forecast error distributions

Table 8 provides evidence that suggests that unexpected accruals are also associated with the middle asymmetry in forecast error distributions. This table presents a comparison of the ratio of pessimistic to optimistic errors in narrow intervals centered on a zero forecast error (as reported in column 3 of table 3) to the analogous ratio when forecast errors are based on reported earnings after "backing out" the realization of unexpected accruals for the quarter. In sharp contrast to the results reported in column 2 of table 8, the results in column 3 indicate that after controlling for unexpected accruals, the number of small pessimistic forecast errors *never* exceeds the number of small optimistic forecast errors in any interval. For example, the ratio of good to bad earnings surprises in the interval between [-.05, .05] is 1.68 (a value reliably different from 1) when errors are computed using earnings as reported by the firm compared to 0.96 (statistically indistinguishable from 1) when errors are based on reported earnings adjusted for unexpected accruals.[17] Thus, as in the case of the tail asymmetry, there is a direct link between the realization of unexpected accruals and asymmetry in forecast error distributions in the form of a higher incidence of small pessimistic than small optimistic forecast errors.

[17] One concern with this test is that the level of error in measuring accruals exceeds the level of randomness in analysts' forecasts. Under certain circumstances an adjustment to forecast errors for very noisy estimates of unexpected accruals could drive the ratio of pessimistic to optimistic errors on a pre-managed basis to a value of 1. To test the sensitivity of our results to this concern we restricted the sample to those observations in which the absolute value of unexpected accruals falls within the absolute range of the size restriction on the forecast error. The restricted samples represent approximately 20% of the observations in each to forecast error intervals described in the table. Results are qualitatively similar, suggesting the reduction in the ratio of pessimistic to optimistic forecast errors on an adjusted earnings basis is not simply the result of systematically adjusting forecast errors with large misestimates of unexpected accruals.

Taken together, the evidence presented in this section indicates a potential causal link between unexpected accruals and the two statistically influential asymmetries in distributions of analysts' forecast errors. It is possible that incomplete estimates of firm accruals are a consequence of analysts' incentives and/or cognitive biases that cause them to deliberately or unwittingly bias their forecasts. If so, the evidence presented in this paper can help pinpoint the conditions in which apparent analyst forecast bias arises, as those same conditions systematically affect firm reporting decisions. However, it is also possible that incomplete estimates of accruals result from practical forecasting impediments faced by analysts and/or is encouraged by investors as part of a broader, rational communication channel between firms and investors. We discuss this possibility in the next section.

4. Analysts' forecasting objectives and reporting bias-related explanations for asymmetries in forecast error distributions

The evidence in sections 1 and 2 demonstrates that there are two asymmetries in cross-sectional distributions of analysts' forecast errors that have the potential, depending on differing test designs, to produce conflicting conclusions about the nature and existence of optimism/pessimism and over/underreaction embedded in analysts' forecasts. The evidence in section 3 demonstrates that if analysts do not include a complete estimate of unexpected accruals in their forecasts, then conservative accounting rules that impact the reported earnings component of the forecast error will play a role in producing these two statistically influential asymmetries. In this section we provide further evidence relevant to sorting out why analysts appear to provide incomplete estimates of firms' unexpected accruals which reflect managerial discretion in the application of conservative accounting rules.

Below we show that analysts *do* appear to make adjustments for new information about which firms will recognize the most extreme income-decreasing unexpected accruals in the cross-section in successive forecast revisions of a given quarter's earnings. This suggests that analysts are aware of the effects of conservative accounting rules and attempt to anticipate them in their forecasts. Nevertheless, as demonstrated in section 3, cases remain in which analysts either do not attempt to anticipate or do not make complete adjustments for unexpected accruals in the last forecast issued before an earnings announcement. We also show that when forecast errors are based on forecasts issued early in the period, there is no evidence of a higher incidence of small pessimistic than small optimistic errors. That is, the asymmetry near the middle of the distribution only arises after the analyst has issued a final forecast for the period. These two results are consistent with the view that, subsequent to the issuance of analysts' last forecast, firms exercise discretion in recognizing accruals (or, alternatively, withhold information from analysts about changes in the relation between sales and book values) in manner that is systematically related to analysts' forecast errors.

We end the section with a discussion of intuitive reasons and anecdotal and theoretical arguments that could account for incomplete analyst anticipation of strategic manipulation of accruals by firms. Some of these arguments are consistent with a market in which all participants are rational and prefer analysts to omit an estimate of unexpected accruals from their earnings estimates. An important implication of these arguments is that some evaluations of the descriptiveness of extant incentive and cognitive-based theories for analyst optimism/pessimism in past research has been based on the wrong forecast error benchmark. Furthermore, these arguments suggest that evidence of associations between realizations of prior economic variables and forecast errors may not be the result of analyst over or underreaction as explained below.

4.1 Do analysts adjust their forecasts for new information about accruals?

Rational analysts would be aware of the persistent tendency for *ex post* cross-sectional distributions of unexpected accruals to have longer and fatter negative than positive tails that results from the applications of conservative accounting rules. Nevertheless, it is unlikely that they will be able to predict at the beginning of a quarter where every firms' unexpected accruals will be located in the distribution eventually realized. One obvious reason for this is that at the time analysts issue a forecast, neither they nor the covered firm are aware of future economic events that will imply a change in historical relations between sales and accruals. It is reasonable, however, that as the quarter progresses, analysts will have the opportunity to revise their forecasts for new firm-specific information about the unexpected accruals a firm will recognize.

Figure 6 sheds light on the question of whether analysts adjust their forecasts for new information about individual firms' unexpected accruals over the period. This figure presents the percentiles of forecasts errors pertaining to analysts' forecast of earnings outstanding at the *beginning, middle,* and *end* of the quarter. One feature common to all three distributions depicted in this figure is the presence of the tail asymmetry. It is clear, however, that when compared to the distribution of forecast errors based on the last forecast before an announcement, the degree of tail asymmetry is much larger for the distributions of errors based on forecasts issued early in the quarter.

Additional evidence on analyst adjustment for unexpected accruals over the forecast horizon is presented in figure 7. This figure provides a comparison of mean forecast errors associated with forecasts issued at the beginning, middle and end of the quarter within deciles formed by the rank of prior abnormal stock returns. The reduction in the tail asymmetry over the horizon is quite large for the set of firms that experience the most extreme negative abnormal returns over the period. That is, analysts appear to revise forecasts issued early in the period downward by extreme amounts for firms that experience large negative stock returns during the quarter. This indicates that analysts understand the implications of conservative accounting rules that allow firms to immediately recognize any current period implications of bad news in their reported earnings. However, extremely optimistic errors associated with extreme negative accruals still remain when forecast errors are calculated with earnings estimates made at the end of the quarter, suggesting analyst adjustment for bad news is not complete.[18]

Next, we turn to another interesting feature of the data that is relevant to the question of analysts' ability to adjust forecasts for information revealed over the period about firms' unexpected accruals. Figure 8 depicts the distribution of forecast errors that fall within the interval of [–1, 1]

[18] Note that the evidence in figure 7 supports a simple conservative reporting bias-based explanation for the well-documented phenomenon of declining mean optimism in cross sectional distributions of analysts' forecast revisions as the earnings announcement date approaches. Greater mean optimism in the cross-section of forecasts issued earlier in the quarter is consistent with analysts' inability to guess, at the beginning of the period, which firms will experience extremely poor performance that can be fully recognized in current earnings under conservative accounting rules. The subsequent decline in mean optimism over the forecast horizon is consistent with analysts revising forecast for new information about firms whose unexpected accruals will be located in the extreme negative tail of the *ex post* distribution of unexpected accruals.

when forecast errors are based on forecasts issued at the beginning, middle and end of the quarter. In contrast to the case of declining tail asymmetry over the horizon, the results indicate that the size of the middle asymmetry actually increases as the earnings announcement date approaches. In fact, this asymmetry is statistically insignificant when forecast errors are based on forecasts outstanding at the beginning of the quarter. For example, the ratio of pessimistic to optimistic forecasts in the interval [-.1, .1] is 1.06 (1.07) (statistically indistinguishable from 1) for forecasts outstanding at the beginning (middle) of the period, but is 1.59 (reliably different from 1) for forecasts outstanding at the end of the period. While it is intuitive that forecast errors issued closer to earnings announcements will be more accurate than forecasts issued earlier in the quarter, this does not imply that the *incidence of slight pessimism* should increase as the announcement date approaches.

The fact that tail asymmetry, albeit attenuated, still remains when errors are based on forecasts issued late in a quarter and the fact that the middle asymmetry only emerges in forecasts issued late in the quarter is consistent with analysts' inability or their lack of motivation to forecast the impact of managerial discretion in the recognition of accruals. The former result is consistent with the notion that some firms in the cross-section (especially those with negative prior abnormal returns) will choose to take extreme income-decreasing accruals in excess of amounts justified by the firm's actual performance.[19] The later result suggests that some firms in the cross-section (especially those with positive prior abnormal returns) will strategically inflate (deflate) earnings in a manner that conserves (creates) accounting reserves while still reporting earnings that beat analysts' forecasts outstanding just prior to earnings announcement.[20] In the first case, firms apparently employ their discretion with little regard to the forecast error that will result from their actions. Such actions may be difficult for analysts to anticipate. In the latter case, the exercise of firm discretion is undertaken specifically with reference to the forecast outstanding at the announcement date. It can be inferred from these results that firm incentives to report earnings that

[19] Levitt [1998] describes two such accounting reserve creating behaviors by firms; "earnings baths" by firms whose recent performance has been poor and "cookie jar reserving" by firms whose recent performance has been strong.
[20] Intuitively, it would be expected that firms manage earnings with respect to the outstanding forecast at the announcement date, consistent with the finding that asymmetry in the form of a higher incidence of small pessimistic than small optimistic errors is not evident in forecast errors based on forecasts issued early in the quarter.

meet market expectations differ in the cross-section and that these differences are associated with the realization of prior returns.

4.2 Why would analysts omit forecast adjustments for strategic manipulation of accruals?

The evidence just presented suggests that analysts do make some adjustments for information revealed over the period about which firms will eventually recognize extreme-income decreasing accruals. Nevertheless, some of these cases go unforecasted even in forecasts issued at the end of the period. Moreover, such cases are more likely to occur when prior abnormal returns are extremely negative. Similarly, it was seen that a higher incidence of small pessimistic and small optimistic forecast errors is only evident in distributions of forecasts issued late in the period, and that the greatest disparity is among firms that experience positive abnormal returns during the quarter (see table 6).

Our results suggest that conditions exist at the time that analysts issue their final forecasts for the quarter that would allow them to make a conditional (on prior returns) adjustment for the likelihood that a firm will take extreme negative accruals in excess of what is justified by firm performance and positive or negative accruals that will yield a reported earnings number slightly in excess of the outstanding analyst forecast. However, the question of how to adjust poses a dilemma for the analyst. For example, it is possible for the analyst to adjust every individual forecast for an estimate of the average negative bias in *ex post* distributions of unexpected accruals. This strategy would be optimal if it were the analyst's objective to minimize the mean error of all of the forecasts he or she issues. But what are the consequences of such an adjustment? Figure 9 sheds some light on this question.

Figure 9 presents mean and median and percentage positive unexpected accruals for firms in deciles formed on the ranks of abnormal returns leading up to the last forecast before an earnings announcement. Note that although firms with extreme negative returns are associated with more frequent and larger extreme negative unexpected accruals, the correspondence is not strong. The percentage of positive and negative unexpected accruals is approximately 50% for all deciles in which negative returns are realized. Similarly, even though firms in the positive return deciles are more likely to take a positive unexpected accrual, judging from the mean unexpected accruals for these deciles, a number of these firms eventually recognize large negative unexpected accruals. Clearly, in the absence of information in addition to realized prior abnormal returns, any constant (or conditional constant) adjustment to individual forecasts for strategic manipulations of accruals in each decile has the potential to induce systematic errors in a large number of forecasts of firms that do not behave according to their expected "type".[21] Such a scenario is potentially at odds with the typical analyst's objectives. If so, any prior news partition that is informative about firm incentives to manipulate earnings in a manner not anticipated in analysts forecasts will also predict systematic *ex post* forecast errors.

Before moving to additional arguments for why analysts may be unable or unmotivated to adjust forecasts for anticipated earnings management, we wish to highlight an important implication of the preceding discussion. While the realization of prior abnormal returns is informative about the direction and magnitude in which firms will manage earnings, it is not likely to be a perfect partition. Even assuming analyst could use additional information to make a more refined (but still imperfect) estimate of earnings management, if the researcher testing for over or underreaction to prior news does not condition on this same set of information, an association between prior returns and forecast errors will be observed that is consistent with apparent forecast inefficiency. In the context of prior abnormal returns examined in this paper, firms that have previously experienced extreme negative returns would be more likely to take extreme income-decreasing accruals in excess of what is justified by current firm performance than other firms, while firms with positive prior returns are more likely to engage in earnings management that leaves reported earnings slightly above analysts' forecasts.[22] That is, empirical evidence will be generated of the exact character that has led to the inferences that analysts underreact to information in prior stock returns.

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[21] Note the potential for inducing systematic errors in individual forecasts through *ex ante* adjustment for *ex post* biases in reported earnings is also relevant to the question of why individual forecasts issued early in the period do not appear to be account for the fact that conservative accounting will produce more *ex post* extreme negative than extreme positive unexpected accruals in the cross-section. The problem will be more acute in this case because less information about the ultimate realization of accruals for the quarter is available at the beginning of the period than at the end (e.g., the analyst will not be able to learn from observing returns prior to issuing a forecast).

[22] Abarbanell and Lehavy [2000a] argue that the sign and magnitude of realized changes in many economic variables is a predictor of a firm's stock price sensitivity to earnings news and tendency to engage in a systematic form of earnings management. For example, firms with positive earnings changes, prior abnormal returns and favorable stock

Clearly, the argument that analysts are unable or unmotivated by investors to adjust individual forecasts *ex ante* for *ex post* bias in the cross-section of unexpected accruals falls into the category of an incentive-based explanation for apparent systematic errors. However, the flavor of this explanation is quite different from other incentive and cognitive-based explanations, which explicitly or implicitly assume someone in the market is being fooled (or is fooling themselves). In such a case the term underreaction would be a misnomer.

Thus far, we have suggested a possible incentive-based reason for analysts to deliberately omit adjustments for earnings management that highlights the importance of understanding whether it is in the best interest to minimize average errors or minimize errors for the largest number of forecasts. This begs the question of why analysts cannot eliminate uncertainty about individual firm earnings manipulations using more conditioning variables than just prior returns. This would also eliminate evidence of analyst underreaction to prior returns even if prior returns served as informative variable about firms' earnings management. We end this section with a discussion of theoretical reasons that suggest that no set of publicly observable conditioning variables will allow analysts to completely unravel earnings manipulations and other theoretical reasons for why analysts would not choose to incorporate an estimate of manipulation in their forecast even if they could unravel it.

A variety of motivations for managers to manipulate earnings have been explored in the accounting literature, including managers behaving opportunistically and managers signaling their private information. Abarbanell and Lehavy [2000a] analyzes the direction and magnitude of unexpected accruals in a setting in which firms' earnings management can be undertaken to meet contracting targets fixed at the beginning of the period or equity market earnings expectations that

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recommendations all have responses to small earnings surprises that are larger in magnitude than firms with negative realizations of these variables. In fact, the most negative realizations of these variables are characterized by subsequent responses to earnings surprise that are very small on average. The analyses of Hirshleifer et al [1998] and Veronesi [1999] are consistent with the notion that small bad news earnings surprises will lead to large downward price revisions for some firms. The former analysis relies on investor sentiment as the mechanism that drives price revisions, the latter analysis is based on large Bayesian adjustments by investors to current bad news which is informative about future earnings streams. Firm earnings management behavior to avoid such small negative earnings surprises predicted by Abarbanell and Lehavy [2000a] is consistent with either scenario.

may have been updated for new information over the period.[23] One reason that analysts' may not anticipate strategic earnings management in their forecasts suggested by Abarbanell and Lehavy is that managers' with private information have multiple objectives for managing earnings, the priority of which is not completely transparent to outsiders. This argument is consistent with the analysis in Fischer and Verrecchia [2000] which demonstrates that even though investors can, on average, properly price the cost of earnings manipulations, unobservability of the managers' objective function will prevent them from unraveling the actual manipulation in individual cases. But this is exactly the task that is required of analysts if they are to avoid forecast errors that result from firms' strategic manipulation of accruals.

It need not be assumed that earnings manipulation is a costly action for investors who must settle for second best contracts with managers that possess private information and accept the fact that analysts are also unable to perfectly anticipate the sign and magnitude of earnings management. It is possible that earnings manipulation is actually a viable method of avoiding costs to the investor. For example, managers may have private information that is proprietary in nature and whose value will be destroyed by truthful public disclosure (see e.g., Verrecchia [1983]). In such cases, earnings manipulation can serve as method to convey the value of the information to investors without revealing the details to competitors who could then exploit it. More important in the context of this study, the analyst's forecast error that results from earnings manipulation becomes the proxy for the value of the proprietary information.[24]

Finally, while it is implicitly assumed in the empirical literature that analysts are both able and motivated to incorporate the effects of strategic bias in their earnings forecasts, Abarbanell [1999] offers three related arguments that raise questions about the validity of such an assumption. First, while analysts can specialize in specific firms and industries, enabling them to produce superior estimates of the core earnings of these firms, their skill at estimating the amount of bias

[23] Abarbanell and Lehavy also find empirical support for the hypothesis that firms' some firms in the cross-section take extreme-income decreasing unexpected accruals in excess of what is justified by current firm performance (i.e., earnings baths and "cookie jar" reserves) while others take accruals of either sign that leave reported earnings slightly above analysts' forecasts outstanding at the date of the announcement.

[24] Note that the equilibrium in this case may include truthful revelation of the manager's information to private parties such as boards of directors or creditors. We are not suggesting that earnings manipulation is the only means of conveying private information without incurring proprietary cost, only the viability of this method.

included in reported earnings may not be sufficiently refined to warrant additional compensation. Second, if there is an element of randomness in unraveling bias at the individual firm level, investors may not be able to completely disentangle noise applicable to forecasting core earnings from noise associated with forecasting reporting biases when both elements are combined in a single earnings estimate. This would be problematic for investors who wish to make investment decisions based only on forecasts of unmanipulated earnings and learn from observing the difference between earnings that firms report and outstanding forecasts of these unmanipulated earnings (i.e., the realization of reporting bias is informative about managers' private information). Third, a more general question arises if capital markets are efficient *and* investors can costlessly unravel reporting biases. In this case there is no value added by incorporating common information (i.e., expected reporting bias) in forecasts. That is, a fundamental question remains as to whether an economic justification exists for investors to motivate analysts to incorporate reporting bias in their forecasts. Consistent with these arguments, we are unaware of any academic or anecdotal evidence that would suggest that analysts are inclined or, for that matter, trained to adjust their forecasts for reporting biases that result from managerial discretion in the application of conservative accounting rules when recognizing accruals.

5. Summary and discussion

In this paper we assess the impact of two relatively small asymmetries in cross-sectional distributions of forecast error observations that disproportionally impact statistics commonly relied upon to draw inferences about analysts' rationality and incentives. We find that observations associated with extreme unexpected negative accruals are associated with a relatively small number of extreme optimistic errors that are responsible for generating optimistic mean forecast errors. Unexpected accruals are also associated with a higher frequency of small pessimistic errors than small optimistic errors that tends to push cross-sectional median forecast errors toward pessimistic values. We offer an explanation for these findings that suggests the possibility that analysts do not adjust individual forecasts for predictable biases in cross-sectional distributions of firms' unexpected accruals. Such biases in reported earnings arise from conservative accounting rules and managerial discretion in the application of these rules. We demonstrate how this explanation reconciles a number of apparently anomalous and, heretofore, separately analyzed findings in the literature on systematic bias in analysts' forecasts.

The same observations comprising asymmetries in forecast error distributions that drive evidence of optimism/pessimism are also shown to have an important impact on inferences concerning analyst over and underreaction to the information in prior abnormal returns. We suggest that, to the extent prior realizations of economic variables can partition firms by their relative proclivity to report earnings that lead to small pessimistic analyst forecast errors or large optimistic forecast errors, statistical associations between these variables and forecast errors like those observed in prior literature will result if analysts do not completely anticipate earnings management in their forecasts.

While the evidence presented in this paper is consistent with the possibility that analysts commit judgment errors when forecasting or shade their individual forecasts in response to asymmetric (in the sign of forecast errors) loss functions, it is also consistent with the argument that analysts are not able or not motivated to adjust individual forecasts for predictable biases in cross-sectional distributions of reported earnings. In their current state of development, extant incentive and cognitive-based theories for systematic errors in analysts' forecasts do not account for the tail or middle asymmetry in cross-sectional distributions of forecast errors or the important impact of bias in unexpected accruals in generating these asymmetries. A possible avenue for refinement of such theories, therefore, would be to focus on how cognitive biases are exacerbated and/or asymmetric analyst incentives become binding in exactly the circumstances in which firms have incentives to manage reported earnings.

A second avenue of analytical and empirical exploration suggested by our results would be a focus on analysts' ability and/or motivation to incorporate adjustments for cross-sectional reporting biases in unexpected accruals and earnings management to their individual forecasts. That is, an exploration of equilibria in which evidence of apparent bias and inefficiency in forecasts may be observed even if individual forecasts are produced by fully rational analysts that face symmetric incentives in forecast errors based on earnings free from the effects of reporting biases. Such analyses would be consistent with anecdotal evidence that indicates analysts do not include certain (arguably discretionary) line items in their earnings forecasts, and the practice of commercial forecast databases of deliberately excluding certain line items from firms' reported earnings that analysts claim not to forecasts (see Abarbanell and Lehavy [2000b]).

The evidence presented in this paper does not address the question of whether investors can see through or are informed by earnings management carried out by firms or the question of whether investors' response to firms' earnings management and analysts' forecasts errors is completely rational. These issues are addressed in ongoing research. However, preliminary findings suggest a market that is well aware of and tempers its response to the most extreme cases of bias in reported earnings (see, Abarbanell and Lehavy [2000b]).

Appendix
Calculation of Unexpected Accruals

Our proxy for firms' earnings management, quarterly unexpected accruals (DA), is calculated using the modified Jones [1991] model (Dechow, Sloan, and Sweeney [1995]); see Weiss [1999] and Han and Wang [1998] for recent applications of the Jones model to estimate quarterly unexpected accruals). All required data (as well as earnings realizations) are taken from the 1999 Compustat Industrial, Full Coverage, and Research files.

According to this model, unexpected accruals (scaled by lagged total assets) equal the difference between the predicted value of the scaled non- unexpected accruals (*NDAP*) and scaled total accruals (*TA*). Total accruals are defined as:

$$TA_t = (\Delta CA_t - \Delta CL_t - \Delta Cash_t + \Delta STD_t - DEP_t) / A_{t-1}$$

where,

ΔCA_t = change in current assets between current and prior quarter,
ΔCL_t = change in current liabilities between current and prior quarter,
$\Delta Cash_t$ = change in cash and cash equivalents between current and prior quarter,
ΔSTD_t = change in debt included in current liabilities between current and prior quarter,
DEP_t = current quarter depreciation and amortization expense, and
A_t = Total Assets.

The predicted value of expected accruals is calculated as:

$$NDAP_t = a_1(1/A_{t-1}) + a_2(\Delta REV_t - \Delta REC_t) + a_3 PPE_t$$

where,

ΔREV_t = change in revenues between current and prior quarter scaled by prior quarter total assets,
ΔREC_t = change in net receivables between current and prior quarter scaled by prior quarter total assets,
PPE_t= Gross property plant and equipment scaled by prior quarter total assets,

We estimate the firm-specific parameters, α_1, α_2 and α_3 from the following regression using firms that have at least ten quarters of data:

$$TA_{t-1} = a_1(1/A_{t-2}) + a_2 \Delta REV_{t-1} + a_3 PPE_{t-1} + e_{t-1}$$

The modified Jones model resulted in 35,535 firm-quarter measures of quarterly unexpected accruals with available forecast errors on the *Zacks* database.

Figure 1

Percentiles of quarterly distributions of analysts' forecast errors. Forecast error equals reported earnings minus consensus forecast of quarterly earnings issued prior to earnings announcement scaled by beginning of period price. (N=33,548)

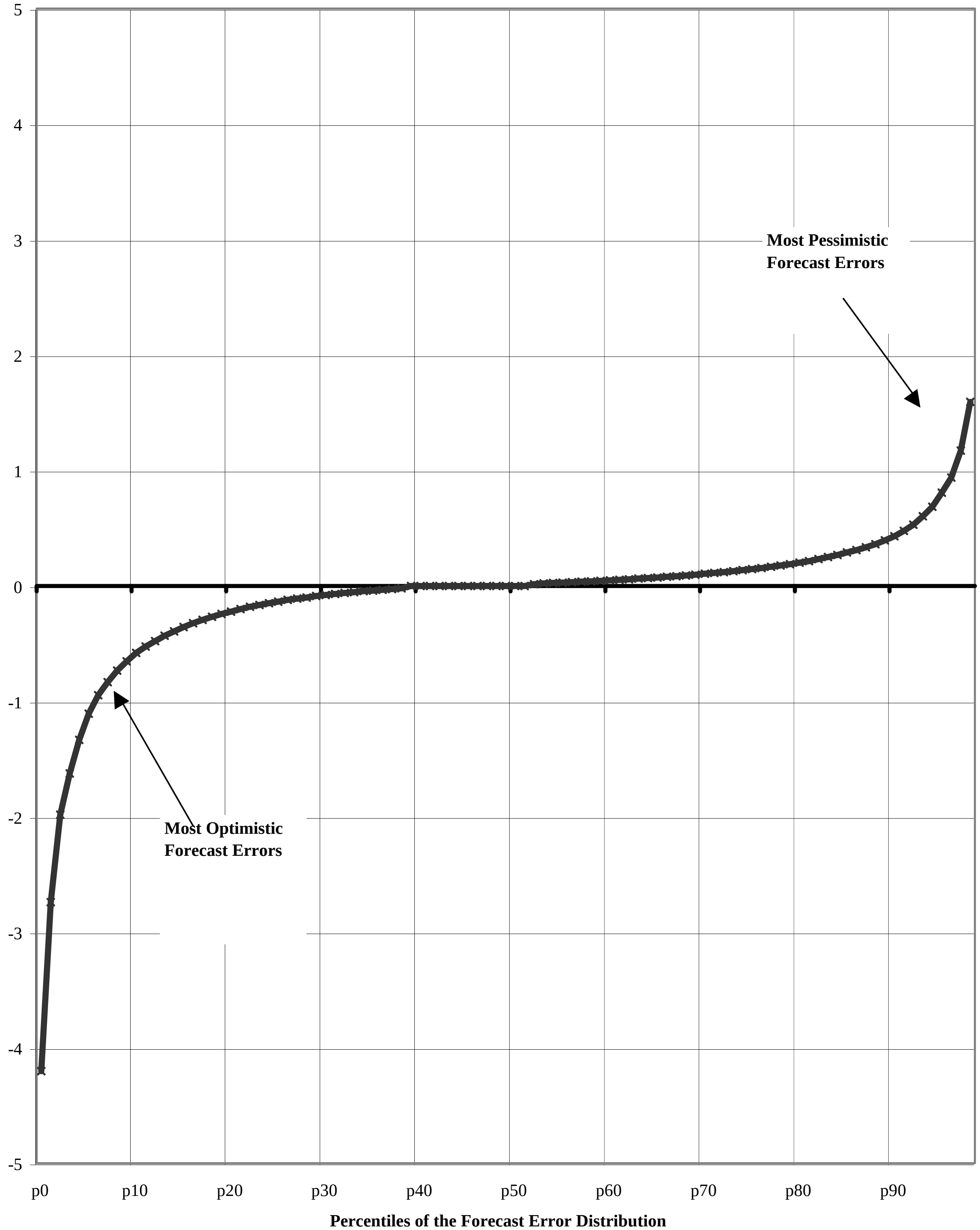

Figure 2
Histogram of Forecast Errors for Observation within Forecast Error of -1 to +1 (N=30,442)

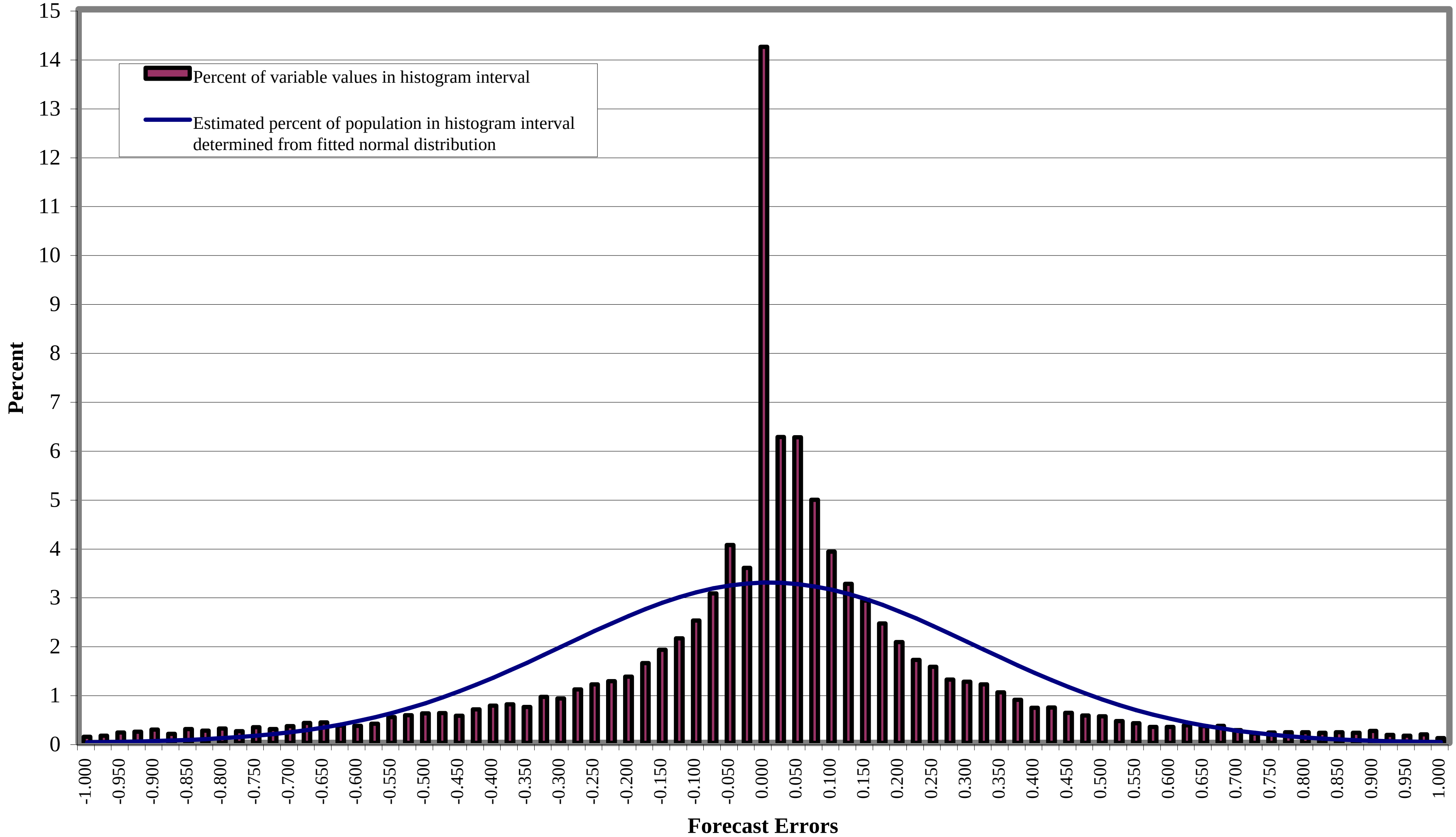

Figure 3

Percentiles of quarterly distributions of analysts' forecast errors by sign of prior market-adjusted return. Forecast error equals reported earnings minus consensus forecast of quarterly earnings issued prior to earnings announcement scaled by beginning of period price. Prior market adjusted return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period

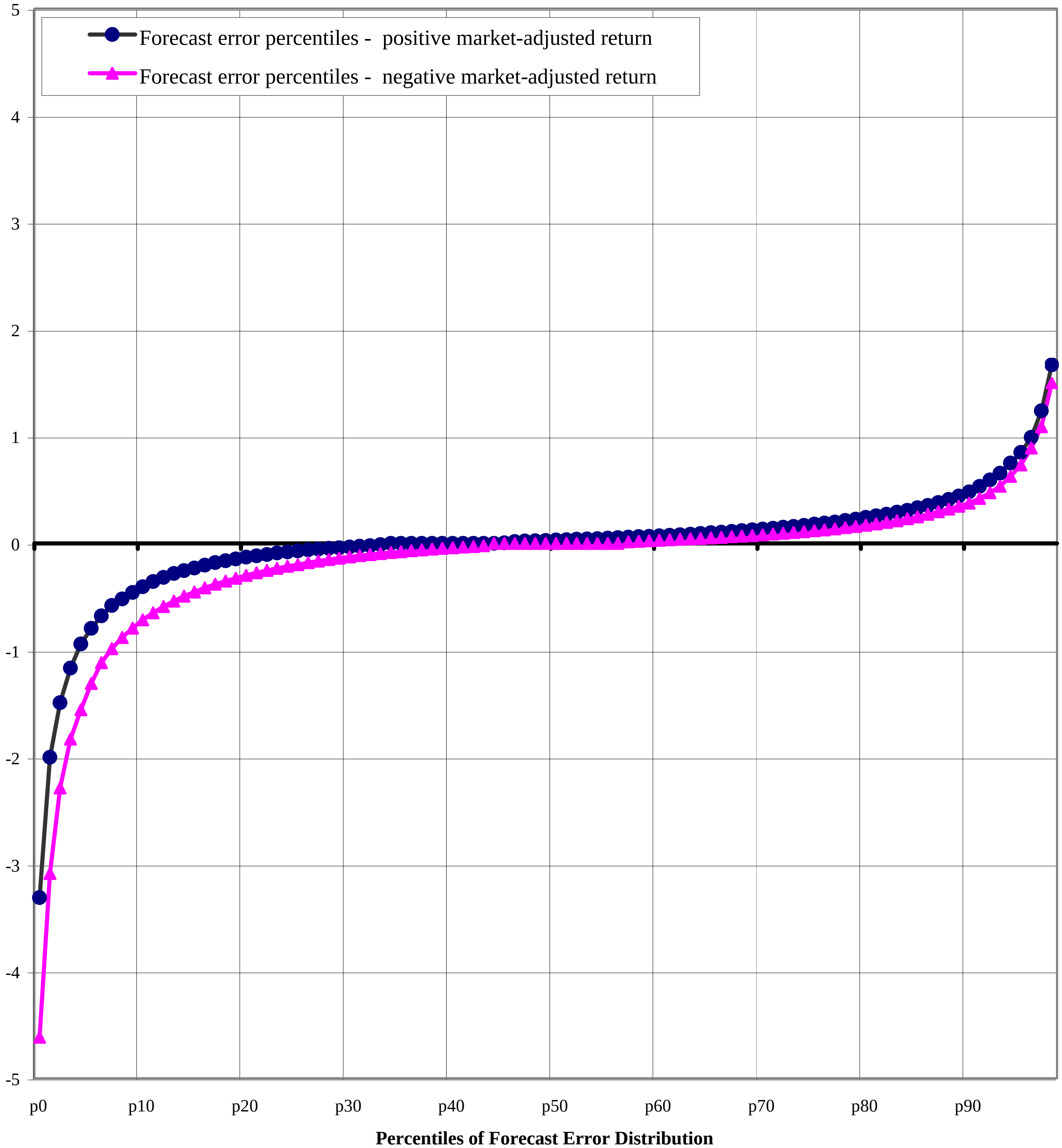

Figure 4

Mean and median forecast errors for portfolios ranked on the basis of prior market-adjusted return. Forecast error equals reported earnings minus consensus forecast of quarterly earnings issued prior to earnings announcement scaled by beginning of period price. Prior market adjusted return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period

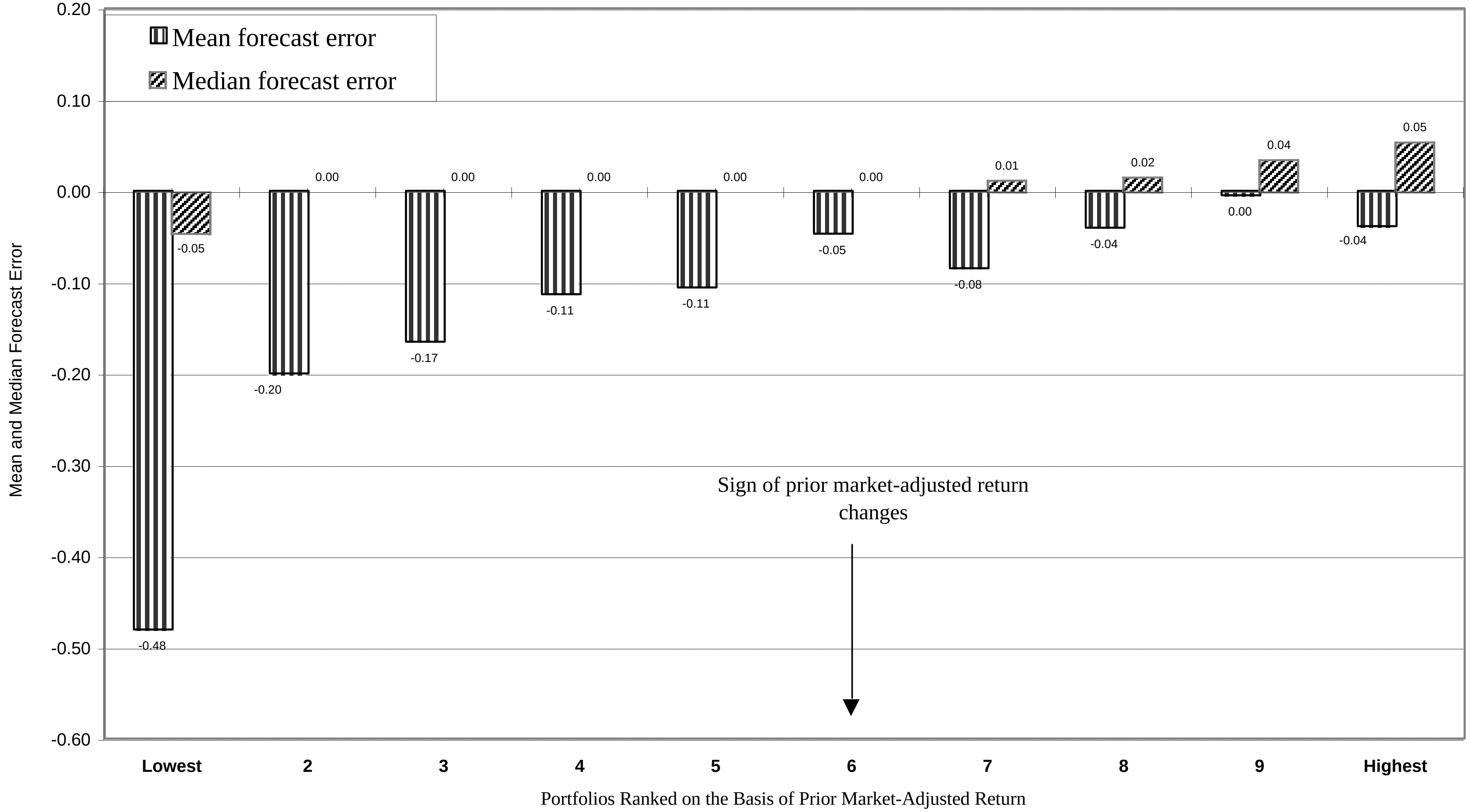

Figure 5

Percentiles Forecast Errors and Median Unexpected Accruals in intervals of plus/minus 0.5% around Forecast Error Percentiles

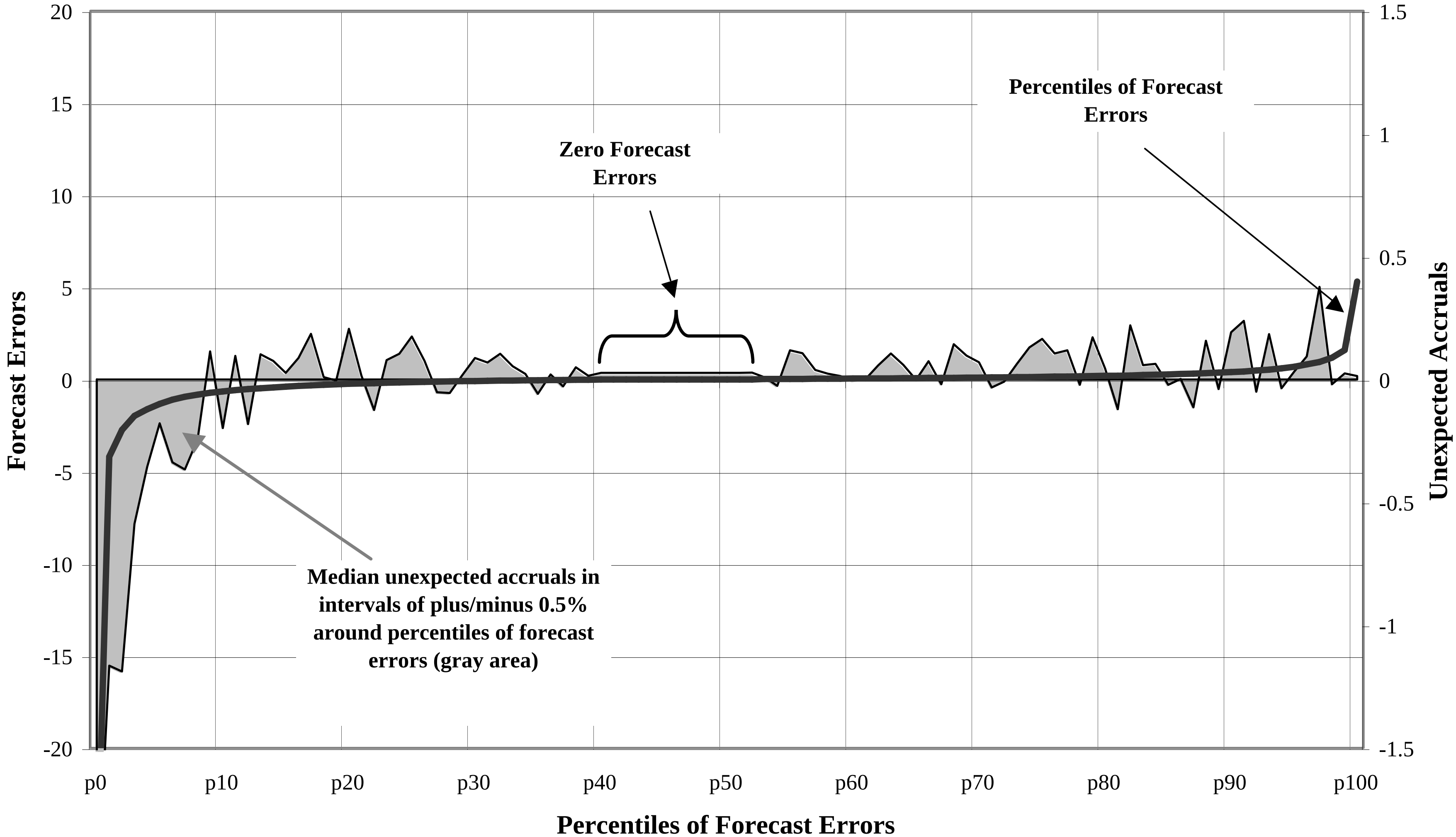

Figure 6

This figure presents percentiles of quarterly distributions of analysts' forecast errors at different horizons. Forecast errors equal reported earnings minus consensus forecast of quarterly earnings issued at the beginning of the quarter, the middle of the quarter, and prior to earnings announcement scaled by beginning of period price.

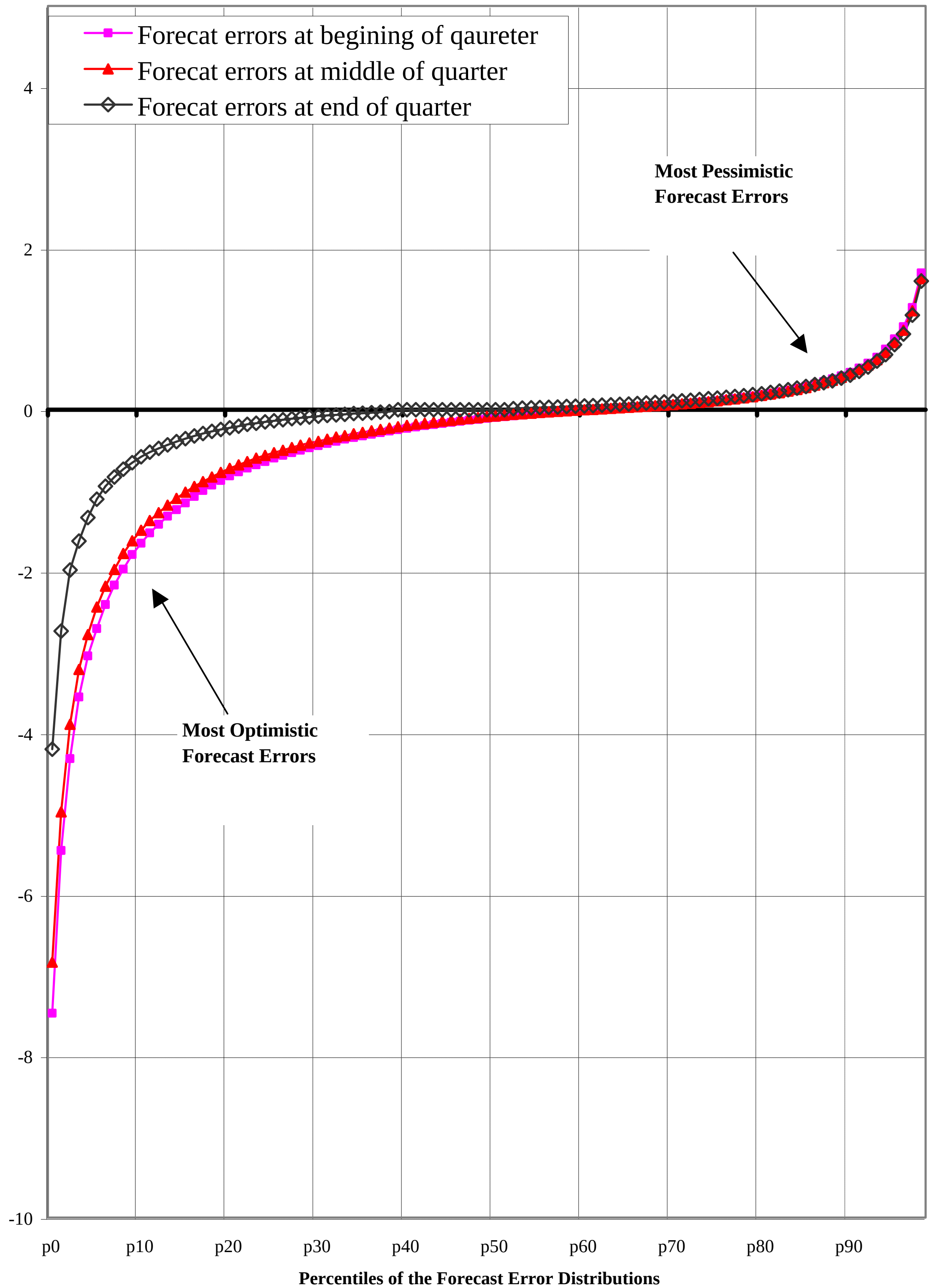

Figure 7

Mean forecast error for portfolios ranked on the basis of prior market-adjusted return. Forecast errors are calculated alternatively using the beginning, middle, end of quarter consensus forecast.

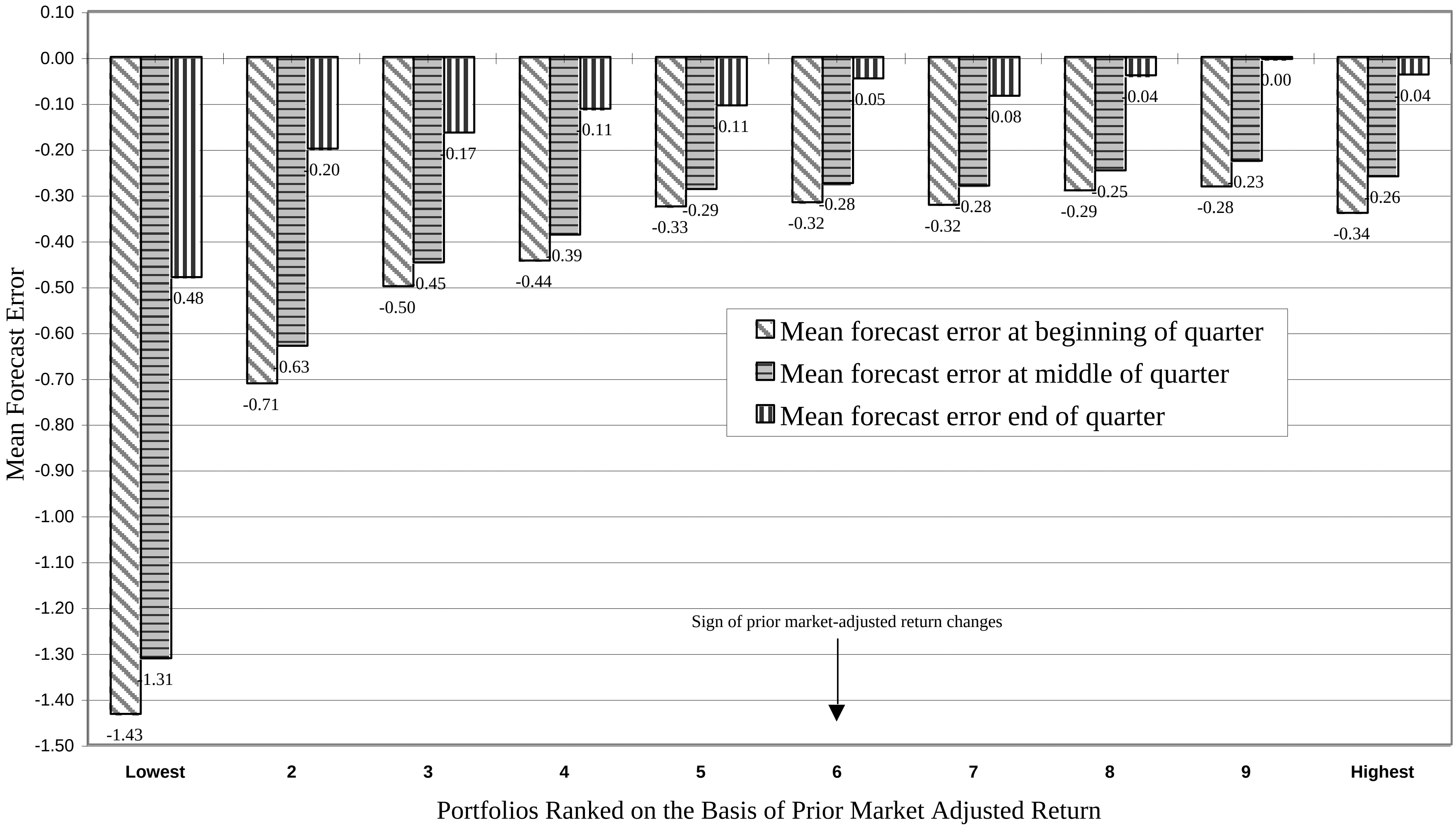

Figure 8

Histogram of forecast errors for observation within forecast error of -1 to +1. Forecast errors are calculated alternatively using the beginning, middle, and end of quarter consensus forecast. (N=30,442)

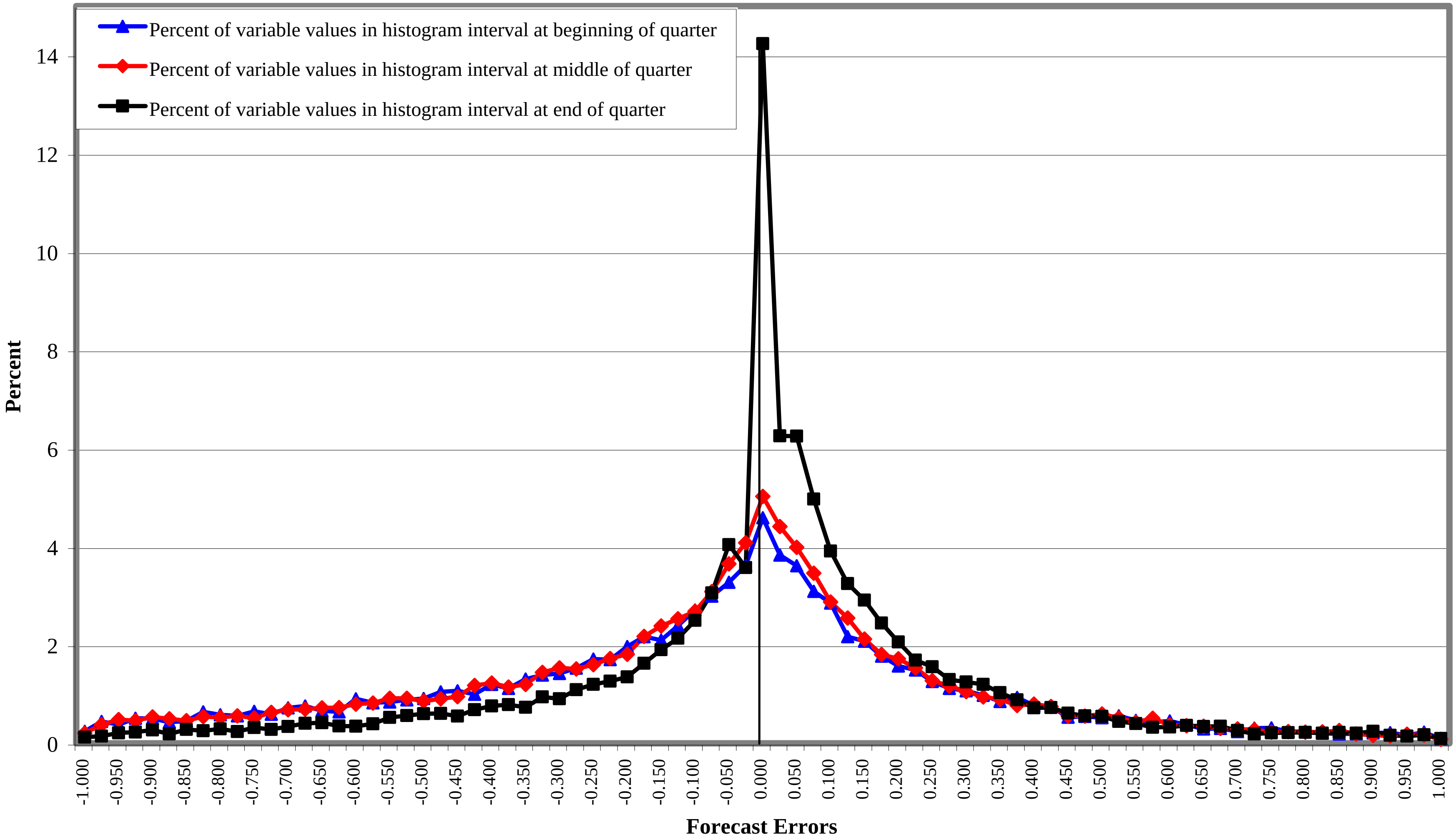

Figure 9

Mean, Median and Percent Positive Unexpcted Accruals for Portfolios ranked on the basis of Prior Market Adjusted Return

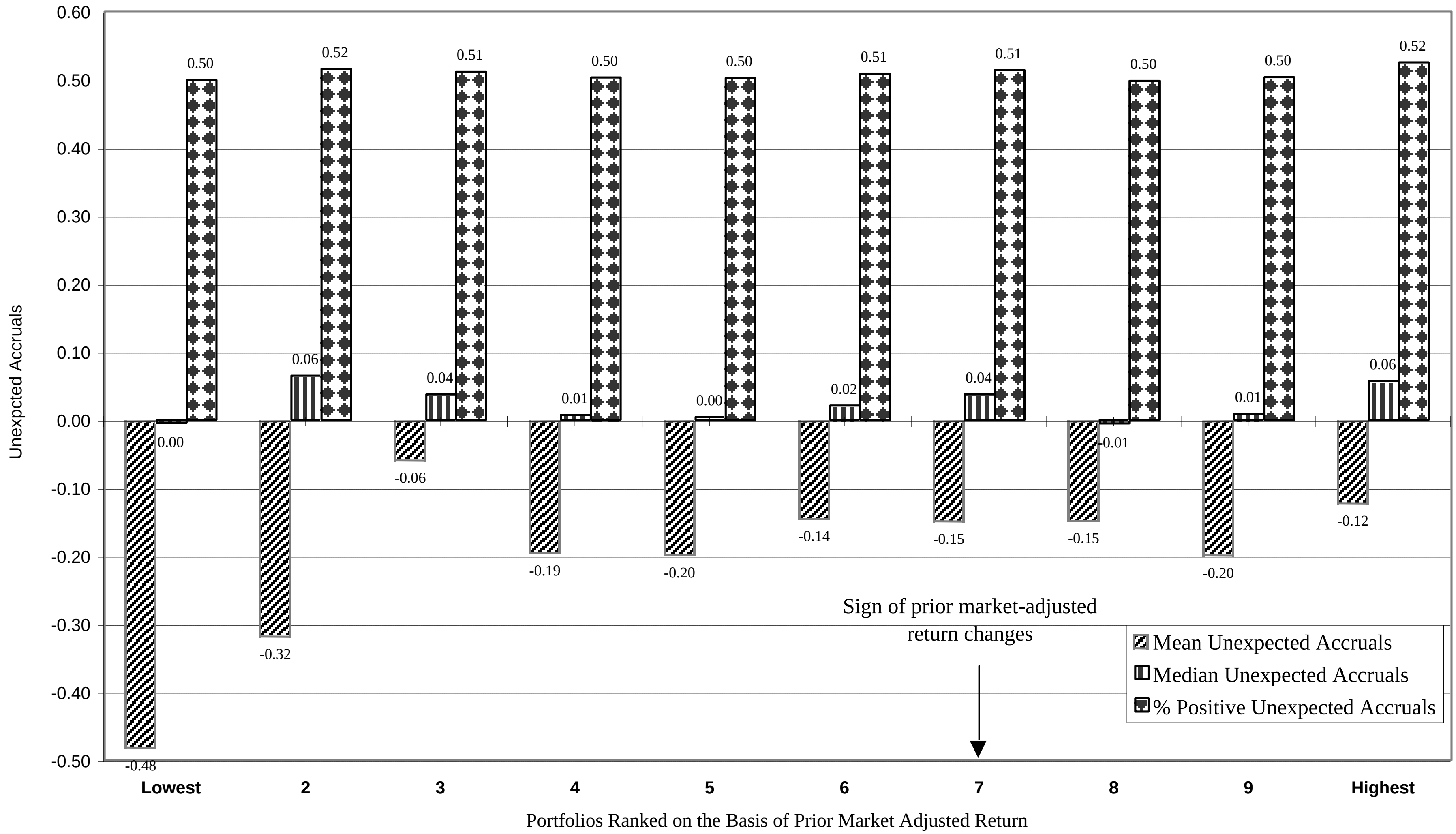

Table 1
Descriptive Statistics on Quarterly Distributions of Forecast Errors, 1985-1998.

This table provides descriptive statistics on quarterly forecast errors. Forecast error is reported earnings (per Zacks) minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price.

Forecast Errors Distributions	
Number of Observations	33,548
Mean	-0.126
Median	0.000
Standard Deviation	0.995
Skewness	-6.976
Kurtosis	102.307
% Positive	47.6
% Negative	39.9
% Zero	12.5
P1	-4.202
P3	-1.983
P5	-1.333
P10	-0.653
P25	-0.149
P75	0.137
P90	0.393
P95	0.684
P97	0.939
P99	1.594

Table 2

Statistics on Forecast Errors within Selected Percentiles of Forecast Error Distributions, 1985 to 1998

This table provides statistics on forecast errors within selected percentiles of quarterly forecast error distributions. For example, P1<FE<P99 reports mean/median forecast errors within the 1st and 99th percentiles of the forecast error distribution. Forecast error equals reported earnings (per Zacks) minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price.

Range of Forecast Error Distribution (1)	N (2)	Mean FE (3)	Skewness (4)	Kurtosis (5)
All Observations	33,548	-0.126	-6.976	102.307
P1<FE<P99	32,876	-0.082	-2.526	11.408
P2<FE<P98	32,205	-0.063	-1.909	6.739
P3<FE<P97	31,534	-0.050	-1.582	4.685
P4<FE<P96	30,864	-0.042	-1.386	3.605
P5<FE<P95	30,192	-0.035	-1.219	2.718
P10<FE<P90	26,835	-0.014	-0.816	0.950
P20<FE<P80	20,128	0.004	-0.427	-0.118
P30<FE<P70	13,411	0.010	-0.120	-0.575
P40<FE<P60	2,539	0.029	-0.199	-0.976

Table 3

Forecast Errors in Small Regions Centered on Zero Forecast Error, 1985 to 1998

This table provides statistics on forecast errors (FE) in small regions centered on zero forecast errors. Forecast error is reported earnings (per Zacks) minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price.

Panel A: Statistics on forecast errors around zero

Range (1)	Mean FE (2)	Ratio of pessimistic to optimistic forecast errors (3)	% of Total (4)
-0.2 ≤FE≤ 0.2	0.019	1.60 *	46.4
-0.1 ≤FE≤ 0.1	0.012	1.63 *	28.8
-0.05 ≤FE≤ 0.05	0.008	1.68 *	14.2
-0.025 ≤FE≤ 0.025	0.005	1.81 *	4.1
FE=0	0.000	0.00	12.5
		Total N= 33,548	

*A test of the difference in the frequency of pessimistic to optimistic forecast errors is statistically significant at or below a 1% level.

Panel B: Statistics on pessimistic (good news) forecast errors near zero

Range (1)	N (2)	Mean FE (3)	% of Total (4)
0 <FE≤ 0.2	9,569	0.087	28.5
0 <FE≤ 0.1	5,986	0.052	17.8
0 <FE≤ 0.05	2,994	0.032	8.9
0 <FE≤ 0.025	887	0.019	2.6

Panel C: Statistics on optimistic (bad news) forecast errors near zero

Range (1)	N (2)	Mean FE (3)	% of Total (4)
-0.2 ≤FE< 0	5,997	-0.088	17.9
-0.1 ≤FE< 0	3,666	-0.053	10.9
-0.05 ≤FE< 0	1,786	-0.032	5.3
-0.025 ≤FE< 0	490	-0.019	1.5

Table 4

Forecast Errors by Sign of Prior Market-Adjusted Return, 1985 to 1998

Panel A provides statistics on forecast errors by sign of prior market-adjusted return. Panel B provides similar statistics for observations that falls within 10th and 90th percentiles of the forecast error distribution . Prior market-adjusted return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Forecast error is reported earnings (per Zacks) minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price.

Panel A: Forecast Errors by Sign of Prior Market-Adjusted Return

	Positive Market-Adjusted Return (1)	Negative Market-Adjusted Return (2)
Forecast Errors:[1]		
Mean	-0.041	-0.195
Median	0.028	0.000
N	13,833	16,940

[1] A test for differences in the mean forecast error by sign of prior abnormal return is significant at below .01.

Panel B: Forecast Errors within the 10th and the 90th percentiles of the Forecast Error Distribution

	Positive Market-Adjusted Return (1)	Negative Market-Adjusted Return (2)
Forecast Errors:[1]		
Mean	0.007	-0.031
Median	0.020	0.000
N	11,194	13,433

[1] A test for differences in the mean forecast error by sign of prior abnormal return is significant at below .01.

Table 5

Sign and Frequency of Forecast Errors by Sign of Prior Market-Adjusted Return

Panel A provides statistics on forecast errors by sign of prior market adjusted return. Panel B provides similar statistics for observations that falls within 10th and 90th percentiles of the forecast error distribution . Prior market adjusted return is the return between 10 days after the last quarterly earnings announcement to 10 days prior to current quarterly earnings announcement minus the return on the value-weighted market portfolio for the same period. Forecast error is reported earnings (per Zacks) minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price. The phi coefficient equals the square root of the 2x2 chi-square measure of association between the frequency of forecast errors by sign of return divided by total number of observations.

Panel A: Forecast Errors by Sign of Prior Market-Adjusted Return [1,2]

	Forecast Errors		
	Optimistic (1)	Pessimistic (2)	Zero (3)
Positive Prior Market-Adjusted Return:			
Forecast Errors:			
Frequency	34%	54%	12%
Mean FE	-0.586	0.295	0.000
Median FE	-0.204	0.150	0.000
N	4,724	7,475	1,634
Negative Prior Market-Adjusted Return:			
Forecast Errors:			
Frequency	45%	42%	13%
Mean FE	-0.703	0.289	0.000
Median FE	-0.267	0.145	0.000
N	7,635	7,152	2,153
A 2x2 association between forecast errors and sign of prior market-adjusted return (the phi coefficient):		0.129	

[1] A non parametric test (2x2) for a positive relation between the sign of forecast error and sign of prior abnormal return is significant at below .01.

[2] A test for a positive association between the sign of prior abnormal return and the sign and magnitude of forecast errors is significant at below .01. A test of a difference in the pessimistic means by sign of prior return is insignificant at a 36% level. A test of a difference in the optimistic means by the sign of prior abnormal return is significant at below 1% level.

Table 5 - Continued

Panel B: Forecast Errors within 10th and 90th percentile of *Forecast Error* Distribution [1,2]

	Forecast Errors		
	Optimistic (1)	Pessimistic (2)	Zero (3)
Positive Market-Adjusted Return:			
Forecast Errors:			
Frequency	33%	52%	15%
Mean FE	-0.191	0.134	0.000
Median FE	-0.135	0.107	0.000
N	3,701	5,859	1,634
Negative Market-Adjusted Return:			
Forecast Errors:			
Frequency	42%	42%	16%
Mean FE	-0.211	0.135	0.000
Median FE	-0.158	0.107	0.000
N	5,584	5,696	2,153
A 2x2 association between forecast errors and sign of prior market-adjusted return (the phi coefficient):		0.108	

[1] A non parametric test (2x2) for a positive relation between the sign of forecast error and sign of prior abnormal return is significant at below .01.

[2] A test for a positive association between the sign of prior abnormal return and the sign and magnitude of forecast errors is significant at below .01. A test of a difference in the pessimistic means by sign of prior return is insignificant at a 98% level. A test of a difference in the optimistic means by the sign of prior abnormal return is significant at below 1% level.

Table 6

Ratio of Pessimistic to Optimistic Forecast Errors in Small Regions Centered on Zero Forecast Errors by Sign of Prior Market-Adjusted Returns, 1985 to 1998

This table reports the ratio of pessimistic to optimistic forecast errors in small regions centered on zero reported forecast errors by sign of prior market-adjusted returns. Reported forecast errors equal reported earnings (per Zacks) minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by beginning of period price.

Range of *reported* forecast errors (FE)	Ratio of pessimistic to optimistic forecast errors		
	Overall	Negative prior return	Positive prior return
(1)	(2)	(3)	(4)
-0.2 ≤ FE ≤ 0.2	1.56	1.34	1.87
-0.1 ≤ FE ≤ 0.1	1.59	1.39	1.86
-0.05 ≤ FE ≤ 0.05	1.63	1.46	1.84
-0.025 ≤ FE ≤ 0.025	1.74	1.64	1.85

Table 7
Descriptive Statistics on Quarterly Distributions of Unexpected Accrual, 1985-1998.

This table provides descriptive statistics on quarterly distributions of unexpected accrual. Unexpected accruals are the measure produced by the modified Jones Model as described in the Appendix (expressed as unexpected Accrual per share scaled by price).

Unexpected Accrual Distributions	
Number of Observations	33,548
Mean	-0.217
Median	0.023
Standard Deviation	5.600
Skewness	-1.399
Kurtosis	16.454
% Positive	50.8
% Negative	49.2
% Zero	0.0
P1	-20.820
P3	-11.547
P5	-8.386
P10	-4.574
P25	-1.349
P75	1.350
P90	4.185
P95	7.148
P97	9.891
P99	15.945

Table 8

Forecast Errors in Small Regions Centered on Zero Forecast Error, 1985 to 1998

This table provides statistics on forecast errors (FE) in small regions centered on zero forecast errors. Forecast error is reported earnings (per Zacks) minus the last consensus forecast of quarterly earnings issued prior to earnings announcement scaled by price. Earnings before unexpected accruals (used to compute the forecast error ratios in column (3)) are calculated as the difference between reported earnings and the empirical measure of unexpected accruals.

Range (1)	Ratio of pessimistic to optimistic forecast errors based on reported earnings (2)	Ratio of pessimistic to optimistic forecast errors based on earnings adjusted for unexpected (3)
$-0.2 \leq FE \leq 0.2$	1.60 *	0.95
$-0.1 \leq FE \leq 0.1$	1.63 *	0.95
$-0.05 \leq FE \leq 0.05$	1.68 *	0.96
$-0.025 \leq FE \leq 0.025$	1.81 *	0.96
FE=0	0.00	0.94
	Total N= 33,548	

*A test of the difference in the frequency of pessimistic to optimistic forecast errors is statistically significant at or below a 1% level.

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