

Management Forecasts, Disclosure Quality, and Market Efficiency

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ABSTRACT

We examine the future stock returns following management forecasts and the effect of disclosure quality on the magnitude of these returns. We find that investors underreact to forecast surprises. A post-management-forecast trading strategy leveraging on this underreaction generates economically significant abnormal returns. These returns are robust to traditional asset pricing models and to the deduction of estimated transaction costs. We also find that the underreaction is greater for good news forecasts than for bad news forecasts, consistent with investors being more conservative in their reaction to good news forecasts due to their perception that good news is less credible. Finally, we provide some evidence that higher quality disclosures, as proxied by forecast precision and prior forecast accuracy are associated with a smaller underreaction.

JEL Classification: G12; G14; G30; M41

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1. Introduction

Management earnings forecasts are increasingly common voluntary public disclosures through which managers can influence price formation in the equity markets. Many papers have examined the short-term returns in response to management forecasts to draw inferences from investors' immediate reaction to the forecasts (e.g., Ajinkya and Gift, 1984; Waymire 1984; Jennings, 1987; Rogers and Stocken, 2005). Although these papers show that management forecasts are informative, they do not address whether the market underreacts or overreacts to management forecasts. We address this question by examining the future long-term abnormal returns following management forecasts. In addition, we study the influence of disclosure quality on the magnitude of these returns.

The post-earnings-announcement drift (PEAD) literature provides substantial evidence that investors underreact to earnings news in a mandatory disclosure setting (e.g., Bernard and Thomas, 1989, 1990; Doyle, Lundholm, and Soliman, 2006; Livnat and Mendenhall, 2006). Management forecasts is an interesting setting to investigate whether and the extent to which the market underreacts to earnings news when the disclosure is voluntary. The existing literature on management forecasts emphasizes that there are likely to be credibility concerns arising from the voluntary and non-audited nature of the forecasts. For example, prior research have concluded that bad forecast news are more credible than bad forecast news from evidence that the magnitude of the abnormal returns around management forecasts is larger for bad news forecasts than for good news forecasts (e.g., Jennings, 1987; Skinner, 1994; Hutton, Miller, and Skinner, 2003; Rogers and Stocken, 2005, among others). Rogers and Stocken (2005), however, do not find any significant difference in the forecast bias (i.e., the difference between

actual earnings and forecasted earnings) between bad news and good news forecasts. This suggests that an underreaction, if any, could be asymmetric between good news forecasts and bad news forecasts. Management forecasts also offer a unique setting to examine whether disclosure quality related to the forecasts affects any underreaction to news. This is because we can measure disclosure quality for management forecasts given that management forecasts vary in terms of precision, prior accuracy, and horizon.

In our paper, we first examine the price reaction to management forecasts using concurrent short-term (three days around the forecast) and future long-term (12 months after the month of the forecast) return windows. In the short-term, the abnormal returns per dollar of bad news are at least six times larger than the abnormal returns per dollar of good news, supporting the argument that investors perceive good news as being less credible than bad news. The future long-term abnormal returns, however, are muted for each dollar of bad news but positive and significant for each dollar of good news. This suggests that the market underreacts more to good news than to bad news around the forecasts and subsequent market correction occurs in the 12 months following the month of the forecasts.

We then investigate the magnitude of the market underreaction to management forecasts by examining the abnormal returns to hedge portfolio strategies. A hedge portfolio buying (selling) firms in the top (bottom) quintile of the distribution of management forecast surprises earns annual size-adjusted returns of 23.77%. Such economically significant returns are robust to alternative asset pricing models. In our profitability analyses, we find that the deduction of transaction costs, estimated using bid-ask spreads, does not reduce the net returns from the trading strategy significantly.

Further, the hedge returns are mainly driven by the buy-side of the trading strategy; firms reporting extreme good news (the top quintile) earn size-adjusted returns of 19%, whereas firms reporting extreme bad news (the bottom quintile) earn size-adjusted returns of -5% over the next year.

Finally, we investigate whether disclosure quality, measured as forecast precision, prior forecast accuracy, and forecast horizon, affects the efficiency with which investors respond to management forecasts. We find that the hedge portfolio returns are smaller for firms issuing more precise forecast and for firms with higher prior forecast accuracy. This result contributes to the literature on market efficiency by showing that higher disclosure quality is associated with a smaller underreaction to news. Our finding on the association between disclosure quality and the magnitude of the post-management-forecast drift is conceptually related to the post-earnings-announcement-drift being smaller among firms with high quality accruals (Francis, LaFond, Olsson, and Schipper, 2005) and among firms that host conference calls (Kimbrough, 2005). It is also related to the accrual anomaly being smaller for more reliable accruals (Richardson, Sloan, Soliman, and Tuna, 2005).

We also investigate whether the hedge portfolio returns covary with the determinants of PEAD such as firm size (Bernard and Thomas, 1989, 1990), investor sophistication (Bartov, Radhakrishnan, and Krinsky, 2000), arbitrage risk (Mendenhall, 2004), and arbitrage cost (Bhushan, 1994; Ng, Rusticus, and Verdi, 2006). In multivariate analyses using Fama-MacBeth regressions, we find that firm size, arbitrage risk, and prior forecast accuracy are the main determinants of the cross-sectional variation in the PMFD.

Our results are consistent with the behavioral finance theory of conservatism, which assumes that investors with complete information are irrational due to intrinsic psychological biases (Barberis, Shleifer, and Vishny, 1998). This theory is based on the earlier work in psychology by Edwards (1968) who documents that people, when faced with new information, are conservative in updating their beliefs. That is, they update their beliefs in the right direction but not in full magnitude compared to a rational Bayesian. To the extent that investors' conservatism is a function of the credibility of news, the underreaction to management forecasts can be attributed to the lack of credibility of voluntary disclosures. Alternatively, the results are also consistent with the rational structural uncertainty theory which predicts that rational investors with incomplete information place less weight on signals in which there is larger structural uncertainty (Brav and Heaton, 2002). Due to the similar mathematical properties and empirical implications of the conservatism theory and the rational structural uncertainty theory, these theories are hard to distinguish empirically (we discuss these theories in more detail in Section 2). We note, however, that the asymmetric underreaction to good versus bad news appears to be more consistent with the argument of exacerbated conservatism for less credible good news disclosures.

Though theories on asset pricing generally do not predict the magnitude of the abnormal returns or appropriate risk premia, the economically large abnormal returns, coupled with evidence of low transaction costs, make our results interesting yet puzzling. One plausible explanation based on the conservatism theory is that investors suffer from significant conservatism bias due to the credibility concerns related to voluntary nature of management forecasts. Alternatively, our results could be explained by omitted risk

factors that we have not controlled for. To address this concern, we show that our abnormal returns are robust to alternative empirical asset pricing models that are used in the literature. It is possible that this economically significant underreaction has not been arbitrated away in the past due to the lack of prior systematic evidence of an underreaction related to management forecasts. As emphasized in Merton (1987), Lee (2001), Brav and Heaton (2002), and many others, knowledge of market inefficiency drives arbitrage activities and even when market inefficiency is uncovered, it may take time for the information to diffuse and be acted upon.

The remainder of the paper proceeds as follows. Section 2 develops the hypotheses. Section 3 describes our data and variable measurement and Section 4 discusses the results. Section 5 concludes.

2. Hypothesis Development

2.1. Theoretical explanations on underreaction to news

Prior work provides evidence of underreaction to news in different settings (see Hirshleifer, 2001 for a survey).¹ Due to mounting empirical evidence of market inefficiencies, researchers have developed alternative asset pricing theories by relaxing key assumptions in traditional efficient markets asset pricing theory: (i) that investors have complete information and (ii) that investors are completely rational information processors who make optimal statistical decisions (Brav and Heaton, 2002).

¹ For instance, researchers have documented underreaction to news events such as earnings surprises (e.g., Ball and Brown, 1968; Bernard and Thomas, 1989, 1990; Doyle, Lundholm, and Soliman, 2006; Livnat and Mendenhall, 2006), stock repurchases (Ikenberry, Lakonishok, and Vermaelen, 1995), seasoned equity offerings (Loughran and Ritter, 1995), convertible bond issues (Lee and Loughran, 1998), stock splits (Ikenberry, Rankine, and Stice, 1996), debt rating downgrades (Dichev and Piotroski, 2001), and analyst forecast revisions (Givoly and Lakonishok, 1980; Gleason and Lee, 2003), among others.

Barberis et al. (1998), relaxing the assumption that investors are completely rational, propose that conservatism could offer a generic explanation for underreaction to disclosure of single news (as opposed to a series of news).² Conservatism, a phenomenon documented in psychology and attributed to Edwards (1968), is the deviation from Bayesian judgment where individuals tend to update their beliefs in the right direction but not in the full magnitude, compared to a rational Bayesian. In the asset pricing context, Barberis et al. note the following:

“Individuals subject to conservatism might disregard the full information content of an earnings (or some other public) announcement, perhaps because they believe that this number contains a large temporary component, and still cling at least partially to their prior estimates of earnings. As a consequence, they might adjust their valuation of shares only partially in response to the announcement.”³

Brav and Heaton (2002), relaxing the assumption that investors have complete information, propose rational structural uncertainty as another explanation for underreactions. In their model, rational investors with incomplete information about the structure of the economic environment react in a Bayesian manner. Any underreaction then occurs as a result of mistakes or risk premiums that arise from the incomplete information. As noted by Brav and Heaton, the similar mathematical properties and the

² Barberis et al. (1998) distinguish between two types of pervasive regularities in empirical research in finance: underreaction to single news and overreaction to a series of good or bad news. Using a representative investor with two cognitive biases, conservatism and representativeness, they model underreaction by conservatism and overreaction by representativeness. We focus on conservatism because we study a single news event, management forecasts.

³ Daniel, Hirshleifer, and Subrahmanyam (1998) offer an alternative psychology theory based on investor confidence in their own private information. Though the empirical predictions related to conservatism and investor confidence are largely similar, we focus on conservatism because it seems to be more consistent with the notion of credibility promulgated in the existing management forecast literature. The management forecast literature proposes the investors vary their reactions to management forecasts because investors vary in terms of their perceived credibility of the forecast news, and not because investors' have varying confidence in their own private estimates.

similar empirical predictions of rational structural uncertainty models and the behavioral models makes it difficult to empirically distinguish which of these models best explain underreactions to news.

2.2 Market underreaction to management forecasts

The “expectation adjustment hypothesis” posits that managers’ issue forecasts to align investors’ expectations with their own (Ajinkya and Gift, 1984). Using the short-window returns around management forecasts, Ajinkya and Gift provide evidence that investors react to management forecast surprises. Subsequent papers have examined factors that lead to cross-sectional variation in market participants’ response to management forecasts (e.g., Skinner, 1994; Soffer et al., 2000; Hutton et al., 2003; Rogers and Stocken, 2005; Cotter, Tuna, and Wysocki, 2006, and Hutton and Stocken, 2006). Although these papers provide evidence of varying reactions to management forecast news, they do not address the question of whether there is any overreaction or underreaction. Following the extant capital markets literature, we investigate this question looking at post-forecast abnormal returns.

Management forecasts provide a setting in which one could potentially expect significant underreaction. First, management forecasts are voluntary in that managers can choose the amount and the timing of the disclosed numbers that are not audited. Second, the interpretation of the extent to which the forecast news map into a new firm value is also likely to be confounded by potential managerial misrepresentation due to agency conflicts and the difficulties in detecting such behavior (Hutton et al., 2003; Rogers and Stocken, 2005). Accordingly, when provided with management forecasts,

investors may over-weight their prior beliefs (either because of conservatism or because uncertainty about the nature of the forecast) which would result in an underreaction to forecast news. If investors correct their underreaction after the forecast, say due to receiving more information in the future, then we expect a post-forecast drift in returns following management forecasts. Formally stated in alternative form, our first hypothesis is:

H1: Future stock returns are positively associated with management forecast news.

A corollary of our first hypothesis is that a post-management-forecast-drift (PMFD) trading strategy that buys a portfolio of shares of firms announcing extremely high forecast surprises and short-sells a portfolio of shares of firms with extremely low forecast surprises will result in positive abnormal hedge portfolio returns.

Our first hypothesis does not predict an asymmetric underreaction to good news versus bad news. As emphasized in Hutton et al. (2003), however, good news and bad news forecasts are made for different reasons, in different ways, and have different effects on stock prices. Prior research documents a larger stock price reaction to bad news forecasts than to good news forecasts. For example, Hutton et al. (2003) find that the average stock price reaction to bad news forecasts equals -9.96% whereas that to good and confirming news forecasts is 1.93% and -0.96% respectively. They conclude that bad news forecasts are more credible than good news forecasts. Interestingly, Rogers and Stocken (2005) do not find any difference in the forecast bias between bad news and good news forecasts.

An interesting question then is whether there is an asymmetric underreaction to good news and bad news. It is likely that investors underreact more in response to good news because of the credibility concerns associated with good news. Hence, our second hypothesis stated in alternative form is:

H2: The magnitude of the future returns following management forecasts is larger for firms with extreme good news than for firms with extreme bad news.

2.3. *Disclosure quality and market efficiency*

One important feature of using management forecasts to study the underreaction of investors' response to news is that we can test the effect of disclosure quality on the underreaction. We characterize disclosure quality in three different ways: forecast precision, prior forecast accuracy, and forecast horizon.

The precision of disclosure is a common theoretical construct used in disclosure theory to represent disclosure quality (Verrecchia, 2001). Baginski, Conrad, and Hassell (1993) and Pownall, Wasley, and Waymire (1993) are two studies that investigate how precision of management forecasts affects the magnitude of the short-term price reaction to forecasts. Consistent with the theoretical predictions of Kim and Verrecchia (1991), Baginski et al. (1993) find that the price reaction to a management forecast increases in the precision of the forecast. Pownall et al. (1993), however, do not find significantly different price reactions for point and other forecasts (i.e., range, maximums, and minimums).

The above studies, however, do not provide evidence that links disclosure precision to the extent of the underreaction to management forecasts. We investigate

whether the precision of management forecasts affect the magnitude of the post-forecast drift in returns. Finding a smaller drift for precise forecasts compared to imprecise forecasts is consistent with the notion that the investors more fully impound the news upon the announcement of more precise forecasts, and hence higher disclosure quality mitigates the underreaction. Therefore, our third hypothesis, stated in alternate form, is:

H3a: The magnitude of the hedge portfolio returns from the post-management forecast-drift trading strategy is lower for forecasts that are more precise.

An alternative characterization of disclosure quality is the accuracy of the prior forecasts made by the firm. Williams (1996) finds that analysts respond more to management forecasts by firms whose prior forecasts have been more accurate. She argues that management acquires forecasting reputation through higher prior accuracy and her results are consistent with analysts treating management forecasts subsequent to more accurate prior forecasts to be more credible. We investigate whether the prior forecast accuracy affects the magnitude of the PMFD. Finding a smaller drift for forecasts by firms with higher prior forecast accuracy is consistent with the notion that higher disclosure quality mitigates the market underreaction to news. Therefore, our fourth hypothesis, stated in alternate form, is:

H3b: The magnitude of the hedge portfolio returns from the post-management forecast-drift trading strategy is lower for firms that have previously issued more accurate forecasts.

Finally, we expect that the forecast horizon is associated with the market reaction to management forecasts. The closer to the end of the fiscal year the forecast is, the more information would the manager be able use in generating the forecast. Hence, forecasts

that are made closer to the end of the fiscal year are likely to be of higher quality. Our fifth and last hypothesis in alternate form is:

H3c: The magnitude of the hedge portfolio returns from the post-management forecast-drift trading strategy is lower for firms that have issued forecasts with shorter horizons.

3. Data and Variable Measurement

3.1. Sample selection and computation of management forecast variables

We obtain the management forecasts of annual earnings per share from the First Call Company Issued Guidelines (FCCIG) file from 1995 to 2004. Management forecasts of annual earnings per share are identified as forecasts with FCCIG data_type ‘EPS’ and FCCIG periodicity ‘A’. We restrict our sample to two forms of forecasts, point forecasts and range forecasts, because of the difficulty in computing forecast surprises for open-ended forecasts. Some firms in our sample provide forecasts of annual earnings for multiple fiscal years (e.g., current and future fiscal years). To reduce the heterogeneity of forecast horizons in our analyses and to avoid having multiple forecasts from the same firm on a single forecast date, we retain only the earnings forecasts of the current fiscal year. In addition, we restrict the sample to forecasts that are announced between 300 days before the fiscal year end date and the fiscal year end date (i.e., from $t-300$ to t , where t is the fiscal year end date) to reduce the likelihood of including previous year’s and current year’s earnings pre-announcements in our sample.⁴

⁴ Our results are robust to alternative sample selection criteria. For example, when we use all available management forecasts of EPS rather than restricting our sample to those announced between $t-300$ and t , where t is the fiscal year-end date, we obtain similar results. Likewise, our results are robust to using a sample of management forecasts issued anytime during the fiscal year.

We match each management forecast to the median consensus analyst forecast of annual earnings per share just before the management forecast date from the First Call Summary Statistics (FCSS) file. Consensus analyst forecasts of annual earnings are identified as forecasts with FCSS data_type ‘EPS’ and FCSS periodicity ‘A’. To avoid using stale analyst forecasts, we remove all management forecasts without an updated median consensus analyst forecast within 90 days before the management forecast date. We then match each management forecast to data from the Center for Research in Security Prices (CRSP) database. We retain the forecasts of firms that have ordinary shares (CRSP share code ‘10’ or ‘11’) listed on NYSE / AMEX / NASDAQ (CRSP exchange code ‘1’, ‘2’ or ‘3’) as at the management forecast date. We then obtain the share price two days before the management forecast date (*Price*) from the CRSP daily file.

We define forecast surprise (*Surprise*) as:

$$Surprise = (Management\ Forecast - Analyst\ Forecast) / Price \quad (1)$$

where *Management Forecast* is the management forecast of earnings per share (defined as the announced amount for a point forecast and the mid-point of the announced range for a range forecast) and *Analyst Forecast* is the median consensus analyst forecast of earnings per share just before the management forecast.

After computing forecast surprises, we sort the observations into quintiles based on the distribution of the forecast surprises in the previous calendar year. The use of the distribution of previous year’s forecast surprises avoids a look-ahead bias when

determining the relative magnitude of forecast surprises (Foster, Olsen, and Shevlin, 1984). We partition forecast surprises into quintiles instead of deciles due to the small number of forecasts in the earlier years of our sample.

In our third hypothesis, we hypothesize that the extent to which the market underreacts to management forecast surprises is a function of the disclosure quality, with quality characterized as the precision of the forecasts. To investigate this hypothesis, we create three categories of forecast precision, *Precision*. The three categories, in decreasing order of forecast precision are: point forecasts, narrow range forecasts, and wide range forecasts. To classify the range forecasts into narrow range and wide range forecasts, we first determine *Relative Range*, the relative range of the forecasts which we calculate as follows:

$$\text{Relative Range} = (\text{Upper Bound} - \text{Lower Bound}) / \text{Price} \quad (2)$$

where *Upper Bound* is the upper bound of the forecast, *Lower Bound* is the lower bound of the forecast, and *Price* is the share price two days before the forecast. We classify forecasts with relative ranges above (below) the median relative range within the calendar year as wide range (narrow range) forecasts.

In our fourth hypothesis, we use prior forecast accuracy as an alternative characterization of disclosure quality. To obtain the prior forecast accuracy, *Accuracy*, we compute the forecast bias and multiply it by negative one as follows:

$$\text{Accuracy} = -1 * |\text{Prior Earnings} - \text{Prior Management Forecast}| / \text{Price} \quad (3)$$

where *Prior Earnings* is the earnings per share for the previous fiscal year as provided by First Call, *Prior Management Forecast* is the management forecast made in previous fiscal year, and *Price* is the share price two days before the announcement of *Prior Management Forecast*. For firms with more than one forecast in the previous fiscal year, we use the average forecast accuracy.

In our fifth hypothesis, we use forecast horizon as an alternative characterization of disclosure quality. Forecast horizon (*Horizon*) is measured as the number of days between the forecast date and the fiscal-year-end date.

3.2. *Computation of stock returns*

One key objective of this paper is to examine the market reaction to management forecast surprises. To do so, we use daily and monthly returns from the CRSP database to analyze the short-term and long-term price reaction to the forecasts. Unless stated otherwise, all the abnormal returns in our analyses are size-adjusted returns. For each stock, we compute the size-adjusted returns by subtracting from its buy-hold return the buy-hold return of the same CRSP size-matched decile portfolio, with size measured as the market capitalization at the beginning of the calendar year.

Using our sample, we first investigate whether there is any asymmetric price reaction to good news and bad news management forecasts in the short window around the forecasts (Jennings, 1987; Skinner, 1994; Hutton et al., 2003; Rogers and Stocken, 2005). To examine the short-term reaction to the forecast surprises, we obtain the average size-adjusted return in the three-day window around the forecast date of each

forecast (*AbRet3d*). For our analyses of market's underreaction to management forecasts, we obtain the 12-month cumulative size-adjusted returns (*AbRet12m*) beginning in the month following the month of the forecast. When a security delists during the return cumulation period, we include the delisting return in the month of the delisting if the delisting return is available. If the delisting return is not available, we assume a delisting return of -100%. For delisted firms, we reinvest the remaining proceeds in the CRSP size-matched decile until the end of the return cumulation period. We remove all forecasts for which there are insufficient data to compute *AbRet3d* and *AbRet12m*.

The final sample consists of 11,450 management forecasts for the period from 1996 to 2004. We lose the observations in 1995 since we use the prior year's distribution to sort firms into management forecast surprise quintiles. Table 1 presents the distribution of the forecasts in the sample by year. We observe a significant increase in the forecasts during the sample period, which could be due to an increase in the number of firms issuing forecasts and/or more extensive coverage of the forecasts by First Call. There are 198 forecasts from 169 firms in 1996 and 2,900 forecasts from 1,054 firms in 2004. For the full sample, there are more range forecasts than point forecasts. Point (Range) forecasts, however, appear to be relatively more common in the earlier (later) years of the sample.

Table 2 presents the sample characteristics by forecast news type, i.e., bad news, no news, and good news. Panel A provides a preliminary analysis of how the different news types differ in terms of the forecast surprise, three-day forecast return, 12-month post-forecast return, beta, market capitalization, book-to-market of equity, and the forecast horizon. The mean three-day size-adjusted return (*AbRet3d*) for bad (good) news

forecasts is -4.60% (1.84%), which is consistent with the market reacting negatively (positively) to bad (good) news forecasts in the three-day window around the forecasts. Consistent with a drift in returns after the forecast, the mean post-forecast twelve-month size-adjusted return (*AbRet12m*) for bad (good) news forecasts is -3.49% (7.10%). Taken together, the preliminary results suggest that (i) there is underreaction to both good news and bad news and (ii) the underreaction is asymmetric in that there appears to be a larger drift in future returns following good news than bad news.

Firms issuing management forecasts are less risky and larger than typical firms in Compustat, as evidenced by their mean beta of 0.84 and the mean market value of equity \$7.20 billion. Firms announcing good and bad news forecasts appear to be riskier than firms announcing no news forecasts because they have higher *Beta*, smaller *Size*, and higher *Book-to-Market*. In contrast, there appears to be no significant difference in *Beta*, *Size*, and *Book-to-Market* between firms announcing good and bad news forecasts. Finally, firms tend to delay the disclosure of bad news, i.e., the mean forecast horizon (i.e., the difference in days between the forecast date and the fiscal-year-end date) for bad (good) news firms is 149 (162) days. This difference in forecast horizon for bad and good news firms is statistically significant and suggests that firms tend to disclose bad news relatively closer to the end of the fiscal year, consistent with the finding of Kothari, Shu, and Wysocki (2005) that firms postpone the disclosure of bad news.

Table 2 Panel B presents the distribution of the forecast forms for each forecast news type. There are more good news forecasts (56%) than bad news forecasts (34%). In addition, there appears to be some variation in forecast form for different news types. We observe that when bad (good) news forecasts are issued, they tend to be issued relatively

more frequently as wide range (narrow range) forecasts. When no news forecasts are issued, they tend to be issued as point forecasts.

4. Results

4.1. Management forecast response coefficients

We analyze the price reaction to management forecast surprises by examining the size-adjusted returns per dollar of forecast surprise in the three-day window around the forecasts ($AbRet3d$) and in the 12 months after the month of the forecasts ($AbRet12m$). In particular, we test the market reaction to forecast surprises using the following regression:

$$AbRet = \beta_0 + \beta_1 Bad\ News + \beta_2 Good\ News + \beta_3 Bad\ News \times Surprise + \beta_4 Good\ News \times Surprise + \sum \beta_j Control\ Variable_j + \varepsilon \quad (4)$$

where $AbRet$ is either $AbRet3d$ or $AbRet12m$, $Bad\ News$ is equal to one if the $Surprise$ is negative and zero otherwise, $Good\ News$ is equal to one if the $Surprise$ is positive and zero otherwise, and $Surprise$ is the forecast surprise. Thus β_3 and β_4 are the forecast response coefficients (i.e., returns per dollar of forecast surprise) of negative forecast surprise and positive forecast surprise respectively. We also test the hypothesis that β_3 equals β_4 , i.e., whether the market reacts similarly to bad versus good news. We estimate Equation 4 as a pooled cross-sectional time-series regression with standard errors clustered by calendar quarter to control for cross-sectional dependence in the data.

Results using Fama-MacBeth regressions lead to similar inferences and are not presented for brevity.⁵

Following the literature on cross-sectional variation on earnings response coefficients (e.g., Collins and Kothari, 1989; Easton and Zmijewski, 1989), we include *Beta x Surprise* to control for the cross-sectional variation in systematic risk. We control for size (*Log Size x Surprise*) to control for the differential level of pre-event disclosure and analyst coverage in small versus large firms. We control for growth using *Book-to-Market x Surprise* as a control variable. All the variables used in Equation 4, except for size-adjusted returns (*AbRet*), are winsorized by calendar year at the 1% and 99% to reduce the influence of outliers. Finally, we also include industry dummies to control for industry effects.

Table 3 Panel A reports the results of the regressions that study the forecast response coefficients in the three-day window around the management forecasts. The objective of these regressions is to replicate the results in prior studies that investors react more to bad news than to good news in the announcement window. Column I reports the results when we constrain the intercept of good news forecasts and bad news forecasts to be the same. Column II reports the results when we allow separate intercepts for good news forecasts and bad news forecast. The remaining columns report the results when we include various control variables.

The coefficients of primary interest are the forecast response coefficients, i.e., the coefficients of *Bad News x Surprise* and *Good News x Surprise*. In all the regression specifications, we observe that the forecast response coefficients are significantly larger

⁵ We also estimate Equation 4 after ranking the *Surprise* variable into positive and negative deciles to reduce the influence of outliers and we obtain similar inferences.

for bad news forecasts than for good news forecasts. For example, in Column IV, the forecast response coefficient for bad (good) news forecasts is 4.07 (1.28), and the F-test indicates that the difference in the coefficients is statistically significant. Overall, the results in Table 3 Panel A confirm prior findings that the market reacts more strongly to bad news forecasts than good news forecasts. The common interpretation of this result is the perceived lack of credibility of good news forecasts (e.g., Jennings, 1987; Rogers and Stocken, 2005, among others).

Table 3 Panel B reports the results of the regressions that study the forecast response coefficients in the twelve months after the month of the forecasts. The objective of these regressions is to study the future returns subsequent to management forecast surprises. The regression framework that we use is similar to that used in Panel A, with the exception that we use future twelve-month size-adjusted returns (*AbRet12m*) as the dependent variable instead of the three-day size-adjusted returns (*AbRet3d*). In this case, a positive coefficient for β_3 or β_4 is consistent with a market underreaction to bad and good news respectively.

The results in Panel B are generally consistent with our hypothesis that there is an asymmetry in the market's underreaction to management forecasts. The underreaction to each dollar of good news is larger than the underreaction to each dollar of bad news. In Column I to Column IV, the coefficients of *Good News x Surprise* provide evidence that the market continues responding positively to each dollar of good news in the 12 months after the forecasts. In contrast, the coefficients of *Bad News x Surprise* are statistically insignificant in the first two models and positive and significant after control variables are included in the model. The positive coefficients for *Bad News x Surprise* in Columns

III and IV suggest that there is also underreaction to bad news forecasts. In all the columns, the F-test comparing the difference in the magnitude of the coefficients indicates that the drift in future returns is significantly larger for good news than bad news forecasts.

Overall, the results in Table 3 suggest that there is an asymmetric market response to good news and bad news in the short term, with a stronger market reaction for bad news. In the long term, however, the asymmetric response reverses such that the post-management-forecast drift is stronger for good news. Taken together, the results suggest that market underreacts more to each dollar of good news in the short-term, only to make up for the underreaction in the long-term.⁶

4.2. Analyses of the post-management-forecast-drift trading strategy

This section investigates the future abnormal returns associated with the implementation of a trading strategy based on management forecast surprises. We term this trading strategy the post-management-forecast-drift (PMFD) trading strategy.

Figure 1 presents the average monthly size-adjusted returns up to 12 months after the month of the forecast for each forecast surprise quintile. The X-axis represents the end of the month with month ‘0’ being the forecast month (i.e., month ‘-1’ represents the beginning of the forecast month and month ‘0’ represents the end of the forecast month). For firms in the bottom quintile of management forecast surprise (i.e., firms announcing extreme bad news), we find a sharp negative market reaction on the month of the forecast

⁶ We also find evidence of a similar pattern of returns following announcements of management forecasts in an earlier time period. Using the management forecast data from Pownall, Wasley, and Waymire (1993) that covers 91 firms for 1979 to 1987, we find that drift in stock returns after good news management forecasts is larger than that after bad news forecasts. We thank the authors for granting us access to their data.

(month '0') and no further drift in the remaining months. On the other hand, for firms in the top two forecast surprise quintiles (Q4 and Q5), there is no clear market reaction in the month of the forecast but there is a clear drift in the returns for the next 12 months. These results are consistent with those documented in Table 3, which provides evidence of relatively larger abnormal returns around the forecast dates for bad news forecasts and relatively larger post-forecast abnormal returns for good news forecasts. Finally, we note that the total reaction to good news is larger than the reaction for bad news. One possible explanation is that the average good news surprise is larger than the bad news surprise (+4.20% for good news versus -1.73% for bad news as reported in Table 4).

Following past literature (e.g., Bernard and Thomas, 1989, 1990), we determine the magnitude of the market underreaction to management forecasts by computing the returns of a PMFD trading strategy. This strategy involves buying (selling) the shares of firms in the extreme high (low) forecast surprises quintiles. The approach is similar to the post-earnings-announcement drift (PEAD) trading strategy of buying (selling) the shares of firms in the extreme high (low) earnings surprise portfolio. We examine the risk-adjusted returns from implementing our PMFD trading strategy. We assume a holding period of 12 months and compute the size-adjusted returns (we discuss the use of other benchmark asset pricing models below).

Table 4 Panel A reports cumulative raw returns, size-adjusted returns, and firm characteristics across the forecast surprise quintiles. Firms in the bottom (top) quintile earn raw returns of 9.08% (31.00%) and size-adjusted returns of -4.63% (19.14%) in the

12-month subsequent to the forecast.⁷ Besides the evidence of smaller market reaction to good news (Table 3), analyst forecast revisions are also smaller for good news than for bad news. For instance, the mean analyst forecast revision for firms forecasting good news (bad news) is 0.03% (-1.15%) despite the larger forecast surprise for good news (4.20%) than bad news (-1.73%). This suggests that analysts, as information intermediaries, are relatively less inclined to update their own forecasts to the full extent of management forecasts, especially for positive forecast news.

The next two columns present the returns across the forecast surprise quintiles and for the hedge portfolio. A trading strategy of buying the shares of firms in the top quintile and selling the shares of firms in the bottom quintile results in a raw return of 21.91% and a size-adjusted return of 23.77%. Further, most of the returns come from the buy side of the portfolio, consistent with the larger market underreaction to good news than bad news.^{8,9}

Table 4 Panel A also presents firm characteristics across quintiles. Compared to firms in the bottom quintile, firms in the top quintile have smaller betas, larger market value of equity, and similar book-to-market. Thus risk is unlikely to explain the larger abnormal returns for firms with extreme positive forecast surprises.¹⁰ Firms in the top

⁷ If bad news is perfectly credible, one would expect no negative drift. One might even expect a positive drift due to increased risk related to the bad news. The negative drift for firms forecasting bad news suggests that investors underreact to bad news, although to a lesser extent than to good news.

⁸ Among the 108 months in our sample, there are 5 months in which the hedge portfolio is not implementable because one of the extreme portfolios (i.e., either the top bottom quintile) is not populated. We still present results including these months because one could be interested in investing in either the buy or the sell side of the strategy. Results are similar if these months are excluded from the analysis.

⁹ In untabulated analyses, we examine the PMFD for a sample of 17,263 quarterly earnings forecasts during 1996 to 2004. The trading strategy of buying (selling) firms in the top (bottom) forecast surprise quintile provides an abnormal return of 19.2%.

¹⁰ Ball (1992) notes that risk shifts due to the news could affect the post-announcement expected returns. Firms issuing good news (bad news) forecasts are likely to experience a *decrease (increase)* in risk (we confirm this assertion by measuring beta, size, and book-to-market one year after the forecast). Thus not controlling for the risk shift may result in a downward bias in our hedge portfolio returns.

quintile, however, have larger 12-month past returns (*Momentum*) suggesting that the PMFD trading strategy may be capturing some momentum effect.

Figure 2 presents mean size-adjusted returns of the PMFD trading strategy in the extreme forecast surprise portfolios for each year in the sample. The returns from the trading strategy are positive in each year of the sample. Figure 3 presents median size-adjusted returns for the firms in the extreme forecast surprise portfolios for each year in the sample. It shows that the median returns for the top forecast surprise quintile is higher than the median returns for the bottom forecast surprise quintile in each year in the sample. This result is important because it shows that the abnormal returns are not driven by outliers (Kraft, Leone, and Wasley, 2006).

The returns documented above indicate the potential profits of the PMFD trading strategy. The recent finance literature has highlighted the importance of considering transaction costs in the analysis of the profitability of proposed trading strategies (e.g., Schwert, 2003; Lesmond Schill, and Zhou, 2004). To examine the profitability of the trading strategy in more detail, we estimate trading costs using relative bid-ask spreads (the detailed computation is in Appendix 1) and deduct trading costs from the size-adjusted returns (Lesmond et al., 2004; Hanna and Ready, 2005; Ng et al., 2006).

Table 4 Panel B reports the results of our profitability analysis. Consistent with firms releasing management forecasts being mainly larger firms, we find that the trading costs are generally low and have little impact on the profitability of the trading strategy. For instance, the 12-month profit of the trading strategy after deducting effective spreads (quoted spreads) from size-adjusted returns is 22.19% (20.70%). In addition, we show that the returns and profitability of the PMFD strategy is robust to the use of value-

weighted instead of equal-weighted returns and spreads. In particular, value-weighted profits equal 14.25% (13.33%) after the deduction of the effective (quoted) spreads from the size-adjusted returns. We note that the value-weighted returns and profits are smaller than the equal-weighted returns and profits. This suggests that firms with relatively smaller market capitalization (within our sample of firms that have large market capitalization on the average) are the ones that are generating the larger abnormal returns. Finally, although not directly tested, we observe that the buy-side of the trading strategy generates most of abnormal returns, indicating that short-sale restrictions are unlikely to constrain the implementability of the strategy.

Table 5 presents the portfolio analysis using portfolio time-series regressions of excess returns on the Fama and French (1993) three-factor and the Carhart (1997) four-factor models. Panel A presents the results with the three-factor model. We form our portfolios using only firms that announced forecasts in the previous month. For each portfolio, we then obtain the monthly portfolio returns for the next 12 months and regress these portfolio returns on the corresponding monthly Fama and French (1993) and Carhart (1997) factors. The bottom three quintiles of forecast surprise earn negative alphas and the top two quintiles earn positive alphas. The hedge portfolio strategy earns monthly abnormal returns of 2.09%, statistically significant at 1%. Further, the strategy has a negative exposure to the market premium and to the SMB factor suggesting that the PFMD strategy is not exposed to the types of risk captured by these factors. Panel B repeats the analysis using the Carhart four-factor model. In this case, we find that the hedge portfolio returns are slightly reduced, mainly because of the exposure of the

strategy to the UMD factor. Even after controlling for momentum the PMFD strategy earns monthly abnormal returns of 1.59%, statistically significant at 1%.

Overall, the results in Tables 4 and 5 provide evidence of drift in returns subsequent to management forecast surprises. The magnitude of the returns are substantial and do not seem to be explained by trading costs nor are they captured by traditional asset pricing models. Our results are consistent with market's underreaction to management forecast news. Further, the underreaction is large in magnitude, consistent with a larger underreaction to voluntary disclosures. It is also asymmetric with a larger underreaction to good news, consistent with our hypothesis that greater perceived lack of credibility of good news exacerbates the underreaction.

Prior studies investigating anomalies have examined the abnormal returns around future earnings announcements to determine whether there is a concentration of abnormal returns around future value-relevant disclosures (e.g., Bernard and Thomas, 1990; Sloan, 1996). Evidence of a concentration of abnormal returns around earnings announcements is consistent with investor correcting their earlier underreaction as a result of learning from these disclosures.

Table 6 presents the abnormal returns around the earnings announcements that relate to the management forecasts. The left column presents the abnormal returns around the annual earnings announcements that relate to the management forecasts of annual earnings. We find that the three-day abnormal returns around the next annual earnings announcement for the forecasts in the highest forecast surprise quintile (Q5) equals 1.37% (t-statistic of 8.36). In contrast, the abnormal returns for the forecasts in the lowest forecast surprise quintile (Q1) are neither statistically nor economically significant. The

lack of any future market correction for these forecasts around future disclosures is consistent with our earlier results that there is little underreaction to bad forecast news. The right column presents the sum of the abnormal returns in the three-day windows around each of the quarterly earnings announcements until the annual earnings announcements. The results, consistent with the results in the left column, indicate significant market correction for firms in the higher forecast surprise quintiles (specifically, Q4 and Q5).

4.3. *Disclosure quality and the post-management-forecast drift*

Table 7 investigates whether the magnitude of future returns varies with management forecast characteristics, in particular with three proxies of disclosure quality: (i) management forecast precision, (ii) prior management forecast accuracy, and (iii) management forecast horizon. In Panel A, we partition the forecasts into point, narrow range, and wide range forecasts with point (wide range) forecasts being the most (least) precise forecasts. We find returns to the PMFD trading strategy of 21.81% for point forecasts, 19.12% for narrow range forecasts, and 29.70% for wide range forecasts. Although the magnitude of size-adjusted returns does not increase monotonically from point to wide range forecasts, the results are generally consistent with the hypothesis that more precise disclosures are associated with smaller return drifts.¹¹

Panel B presents the post-forecast size-adjusted returns after partitioning the sample based on prior forecast accuracy. To the extent that prior accuracy increases the

¹¹ A concern is whether management forecast precision could be proxying for risk. For example, if one assumes that less precise forecasts create uncertainty and investors demand a higher return for uncertainty, then the higher returns for implementing the PMFD trading strategy using wide range forecasts could be due to risk. A risk explanation, however, is not likely to explain why (risky) firms issuing wide range forecasts of bad news have smaller returns than (less risky) firms issuing point forecasts of bad news.

credibility of the forecast, our fourth hypothesis predicts a smaller drift for firms with higher prior forecast accuracy. Consistent with our hypothesis, the 12-month size-adjusted hedge portfolio return equals 21.69% for firms with low past accuracy and -5.12% for firms with high past forecast accuracy. The larger drift for firms with lower prior forecast accuracy suggests that the initial reaction upon the announcement of management forecast is more complete for firms with higher past forecast accuracy. Our results are consistent with the findings of Hutton and Stocken (2006), who find that management forecasts of firms with higher forecasting reputation, measured as a function of prior forecast accuracy and frequency, result in bigger stock price reactions upon the issuance of management forecast.

Finally, Panel C presents the post-forecast size-adjusted returns after partitioning the sample based on forecast horizon, with high/low horizon characterized if the firm is above/below the median in forecast horizon in a given year. We find that the 12-month size-adjusted hedge portfolio return is 20.58% for short horizon forecasts and 26.85% for long horizon forecasts, although the difference is not statistically significant.

Overall, the results provide evidence that the magnitude of the drift is dependent on the disclosure quality, i.e. that disclosure quality mitigates underreaction to forecast news.

4.4. Determinants of the magnitude of the post-management-forecast drift

In this section, we investigate whether the magnitude of the size-adjusted returns for the PMFD trading strategy is driven by firm size, investor sophistication, arbitrage risk, and arbitrage cost. Prior research suggests that the PEAD is stronger for small firms

(Bernard and Thomas, 1990), firms with lower investor sophistication (Bartov, Radhakrishnan, and Krinsky, 2000), high arbitrage risk (Mendenhall, 2004), and high arbitrage cost (Bhushan, 1994; Ng et al., 2006). Thus we repeat the portfolio analysis after dividing the sample into sub-samples based on each determinant. Following the above papers, we proxy for size using the market value of equity, investor sophistication using institutional ownership, arbitrage risk using return volatility, and arbitrage cost using relative effective spreads.

Table 8 Panel A presents the trading returns separately for small and large firms, and for firms with small and large institutional ownership. A firm is classified as “large” if the firm is above the median in the distribution of market value of equity (measured two days before the forecast) within each calendar year, and “small” otherwise. Similarly, a firm is considered “high” institutional ownership if the firm is above the median in the distribution of percentage of institutional ownership within each calendar year, and “low” otherwise. Institutional ownership data is collected from Thomson Financial. Consistent with the results in the PEAD literature, we find larger hedge portfolio returns for small firms (compared to large firms) and for firms with low institutional ownership (compared to high institutional ownership). For instance, the size-adjusted hedge portfolio returns for small firms is 33.09% and compared to 13.68% for large firms. Similarly, the size-adjusted hedge portfolio returns for firms with low institutional ownership is 31.56% compared to 15.97% for firms with high institutional ownership.

Panel B repeats the analysis for firms with high versus low return volatility and effective spreads. A firm is coded as “high” volatility (effective spread) if the firm is above the median in the distribution of return volatility (effective spread) within each

calendar year, and “low” otherwise. Return volatility is measured as the standard deviation of the residuals in regressions of monthly returns on the S&P500 returns during the 48-months period (with the requirement of at least 12 months of returns) ending before the month of the forecast. The computation of effective spread is provided in Appendix 1. Consistent with arbitrage risk and arbitrage cost increasing the magnitude of future return drift, we find that the trading strategy earns a size-adjusted return of 14.58% for firms with low return volatility compared to 30.74% for firms with high return volatility. Likewise, the trading strategy earns size-adjusted return of 18.11% for firms with low effective spreads compared to 32.68% for firms with high effective spreads.

Overall results in Table 8 are consistent with the literature on the PEAD that suggest that magnitude of the trading returns are larger for smaller firms, firms with lower investor sophistication, firms with higher arbitrage risk, and firms with high arbitrage costs.

The analyses in Tables 7 and 8 are done on a univariate basis but the variables used to partition the sample are often correlated and therefore it is hard to distinguish which effect is more important. In addition, these analyses do not control for differences in risk such as beta, book-to-market, and momentum. To determine the relative importance of the different factors that influence the magnitude of the PMFD, we follow the existing literature and run Fama-MacBeth (1973) regressions of size-adjusted returns on the management forecast surprises and different factors hypothesized to affect the magnitude of the drift (Bartov, Radhakrishnan, and Krinsky, 2000; Mendenhall, 2004; Ng et al., 2006). In particular, we run yearly regressions of size-adjusted returns on risk

controls, forecast surprise quintiles, and interactions terms for the variables hypothesized to explain the cross-sectional variation in the PMFD.¹²

We replace the raw variables with their ranks in order to reduce the effects of measurement error. The *Surprise* variable is replaced by its quintile rank which is recoded to range from -0.5 to +0.5. Under the linearity assumption, the coefficient on this variable measures the return difference between the extreme quintiles of management forecast surprise. Each of the interactive variables is replaced by its quintile rank (with the exception of accuracy which is coded as a dummy variable due to the smaller sample size) and recoded to range from 0 to 1 before the interaction is done. This allows interpretation of resulting coefficient on the interaction term as the increase in the magnitude of the drift attributable to a move from the lowest to the highest quintile of that variable (or from low to high if the variable is accuracy).

Table 9 Panel A presents the results for management forecast characteristics. The dependent variable is the size-adjusted return for the twelve-month period after the management forecast month. All models include controls for beta, size, book-to-market, and momentum. In Column I we find that the hedge portfolio earns size-adjusted returns of 26.32% for firms issuing wide range forecasts (coefficient on the *Surprise Quintile* variable). The interaction coefficient on the forecast precision suggest that, among firms in the top quintile of forecast precision, the hedge portfolio return is 0.72% percent smaller than among firms issuing less precise although the difference is not statistically significant. In Column II, we find that the hedge portfolio return increases with forecast

¹² Because some firms make more than one forecast per year, the assumption of time-series independence in the Fama-MacBeth tests may not hold. Thus we re-estimate the regression models in Table 9 using pooled time-series cross-sectional regressions with standard errors clustered by firm-year. The results and inferences are similar to those reported in the paper.

horizon; the hedge portfolio earns size-adjusted return of 21.31% for firms in the bottom quintile of forecast horizon compared to 29.16% ($= 21.31\% + 7.85\%$) for firms in the top quintile of forecast horizon, although the difference is not statistically significant. In Column III, we find that the hedge portfolio return decreases with prior forecast accuracy. In particular, the hedge portfolio earns size-adjusted return of 29.69% for firms with low forecast accuracy compared to 10.61% for firms with high forecast accuracy. Finally, we find that when all forecast characteristics are included the effect of forecast accuracy remains statistically significant.

Panel B repeats the analysis using proxies of firm characteristics. Consistent with the results in Table 8, we find that the hedge portfolio return decreases with firm size (Column I) and institutional ownership (Column II), and increases with return volatility (Column III), and effective spreads (Column IV), although the interaction between *Surprise Quintile* and *ESpread Quintile* is not statistically significant. Finally, we find that, when all firm characteristics are included in the model, firm size and return volatility remain statistically significant, and effective spread gains significance.

Overall, the results in Table 9 suggest that the magnitude of the PMFD strategy varies with forecast and firm characteristics on a univariate basis. Prior forecast accuracy (firm size and return volatility) is the primary driver of the cross-sectional variation in hedge portfolio returns in the multiple regressions that contain all of our forecast (firm) characteristics variables.¹³

¹³ We also estimate a cross-sectional regression that includes both forecast characteristics and firm characteristics. In this case, we find that the interaction coefficients on size and institutional ownership are significant in the predicted direction, whereas the interaction coefficient on precision is significant in the direction opposite to what we predict.

5. Conclusion

We investigate the market reaction to management earnings forecasts by studying the short-term returns around and long-term returns subsequent to management forecast surprises. In the short-term, the market reaction per dollar of bad news is at least six times larger than the reaction per dollar of good news, consistent with findings in prior research. The long-term market reaction, on the other hand, is muted for bad news but positive and significant for good news, suggesting that the market underreacts more to good news than bad news around the forecast date. In addition, we show that a hedge portfolio that buys (sells) firms in the top (bottom) quintile of the distribution of management forecast surprises earns annual abnormal returns above 20%, robust to different expected return benchmarks. The magnitude of the post-management forecast-drift is decreasing in the management forecast precision and prior forecast accuracy, consistent with the hypothesis that better disclosure quality mitigates underreaction. Finally, we find that the hedge portfolio returns are larger for smaller firms, firms with lower investor sophistication, higher arbitrage risk, and higher arbitrage costs.

As far as we are aware, our paper is the first to uncover a drift in returns following management forecasts. The lack of prior systematic evidence of an underreaction to management forecasts could potentially explain why we are able to document an economically significant drift in returns after forecasts. Consistent with the prior literature that finds good news forecasts to be less credible than bad news forecasts, we document a smaller reaction to good news forecasts than to bad news forecasts at the time of the forecast. In sharp contrast, we find a significantly larger post-forecast drift for good news forecasts compared to bad news forecasts. We argue that this is consistent with the

relative lack of credibility exacerbating the conservatism in the reaction to forecast news at the time of the forecast. Although our results are consistent with psychology theory of conservatism that predicts an underreaction to news, alternative explanations such as structural uncertainty theory cannot be disregarded. These explanations are not mutually exclusive because a combination of factors can lead to an underreaction. For instance, in the context of the post-earnings-announcement drift, researchers attribute the drift to investors' misrepresentation of the serial correlation in unexpected earnings (Bernard and Thomas, 1989), inflation illusion (Chordia and Shivakumar, 2005), and disposition effect (Frazzini, 2006), among others.

The large magnitude of the abnormal returns documented in this paper and the low limits to arbitrage inherent in our setting (e.g., large firms with low transaction costs) make our results puzzling. An interesting question is whether the abnormal returns are likely to persist in the future. As Merton (1987) states: "...an anomaly must be uncovered and learned before one can arbitrage...even when learned, there are limits to arbitrage..." Hence, it is possible that a drift could still be observed in future time periods, albeit of a smaller magnitude.

References

- Ajinkya, B. B., and M. J. Gift. 1984. Corporate managers' earnings forecasts and symmetrical adjustments of market expectations. *Journal of Accounting Research* 22 (2), 425-444.
- Baginski, S., E. Conrad, and J. Hassell. 1993. The effects of management forecast precision on equity pricing and on the assessment of earnings uncertainty. *The Accounting Review* 68(4), 913-927.
- Ball, R. 1992. The earnings-price anomaly. *Journal of Accounting and Economics* 15, 319-345.
- Bernard, V., and J. Thomas. 1989. Post-earnings announcement drift: delayed price response or risk premium. *Journal of Accounting Research* 27, 1-36.
- Bernard, V., and J. Thomas. 1990. Evidence that stock prices do not fully reflect implications of current earnings for future earnings. *Journal of Accounting and Economics* 13, 305-340.
- Barberis, N., A. Shleifer, and R. Vishny. 1998. A model of investor sentiment. *Journal of Financial Economics* 49, 307-343.
- Bartov, E., S. Radhakrishnan, and I. Krinsky. 2000. Investor sophistication and patterns in stock returns after earnings announcements. *The Accounting Review* 75, 43-63.
- Bhushan, R. 1994. An informational efficiency perspective on the post-earnings announcement drift. *Journal of Accounting and Economics* 18, 45-65.
- Brav, A., and J. B. Heaton. 2002. Competing theories of financial anomalies. *The Review of Financial Studies* 15 (2), 575-606.
- Carhart, M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52, 57-82.
- Chordia, T., and L. Shivakumar. 2005. Inflation Illusion and Post-Earnings Announcement Drift. *Journal of Accounting Research* 43, 521-556.
- Collins, D. W., and S. P. Kothari. 1989. An analysis of intertemporal and cross-sectional determinants of earnings response coefficients. *Journal of Accounting and Economics* 11 (2-3), 143-181.
- Cotter, J., Í. Tuna, and P. Wysocki. 2006. Expectations management and beatable targets: how do analysts react to explicit earnings guidance? *Contemporary Accounting Research*, forthcoming.

- Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 1998. Investor psychology and security market under- and overreactions. *The Journal of Finance* 53 (6), 1839-2273.
- Dichev, I., and J. Piotroski. 2001. The long-run stock returns following bond ratings changes. *The Journal of Finance* 56 (1), 173-203.
- Doyle, J., R. Lundholm, and M. Soliman. The extreme future stock returns following I/B/E/S earnings surprises. *Journal of Accounting Research* 44, 849-887
- Easton, P. D., and M. E. Zmijewski. 1989. Cross-sectional variation in the stock market response to accounting earnings announcements. *Journal of Accounting and Economics* 11 (2-3), 117-141.
- Edwards, W. 1968. Conservatism in human information processing. In: Kleinmütz, B. (Ed.), *Formal Representation of Human Judgment*. John Wiley and Sons, New York, 17-52.
- Fama, E., and K. French. 1993. Common risk factors in the returns on bonds and stocks. *Journal of Financial Economics* 33 (1), 3-56.
- Fama, E. and J. MacBeth. 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy* 81, 607–636.
- Foster, G., Olsen, C., and T. Shevlin. 1984. Earnings releases, anomalies and the behavior of security returns. *The Accounting Review* 59, 574–603.
- Francis, J., R. LaFond, P. Olsson, and K. Schipper. 2005. Information uncertainty and post-earnings-announcement-drift. Duke University working paper.
- Frazzini, A. 2006. The disposition effect and underreaction to news. *The Journal of Finance*, forthcoming.
- Givoly, D., and J. Lakonishok, 1980. Financial analysts' forecast of earnings: the value to investors. *Journal of Banking and Finance* 4, 221-233.
- Gleason, C., and C. Lee, 2003. Analyst forecast revisions and market price discovery. *The Accounting Review* 78, 193-225.
- Griffin, D., and A. Tversky. 1992. The weighing of evidence and determinants of confidence. *Cognitive Psychology* 24, 411-435.
- Hanna, J. D., and M. J. Ready. 2005. Profitable predictability in the cross section of stock returns. *Journal of Financial Economics* 78 (3), 463-505.

- Hirshleifer, D. 2001. Investor psychology and asset pricing. *Journal of Finance* 56(4), 1533-1598.
- Huang, R., and H. Stoll. 1997. The components of bid-ask spread: a general approach. *Review of Financial Studies* 10, 995-1034.
- Hutton, A. P., G. S. Miller, and D. J. Skinner. 2003. The role of supplementary statements with management earnings forecasts. *Journal of Accounting Research* 41 (5), 867-890.
- Hutton, A. and P. Stocken. 2006. Effect of reputation on the credibility of management forecasts. Dartmouth College working paper.
- Ikenberry, D., J. Lakonishok, and T. Vermaelen. 1995. Market underreaction to open market share repurchases. *Journal of Financial Economics* 39, 181-208.
- Ikenberry, D., G. Rankine, and E. K. Stice. 1996. What do stock splits really signal? *Journal of Financial and Quantitative Analysis* 31, 357-375.
- Jennings, R. 1987. Unsystematic security price movements, management earnings forecasts, and revisions in consensus analyst earnings forecasts. *Journal of Accounting Research* 25 (1), 90-110.
- Kim, O., and R. E. Verrecchia. 1991. Trading volume and price reactions to public announcements. *Journal of Accounting Research* 29, 302-321.
- Kimbrough, M. D. 2005. The effect of conference calls on analyst and market underreaction to earnings announcements. *The Accounting Review* 80 (1), 189-219.
- Kothari, S.P., S. Shu, and P. Wysocki. 2005. Do managers withhold bad news? MIT working paper.
- Kraft, A., A. Leone, and C. Wasley. 2006. An analysis of the theories and explanations offered for the mispricing of accruals and accrual components. *Journal of Accounting Research* 44(2), 297-339.
- Lee, I., and T. Loughran. 1998. Performance following convertible bond issuance. *Journal of Corporate Finance* 4, 185-207.
- Lesmond, D., Chill, M., and C. Zhou. 2004. The illusory nature of momentum profits. *Journal of Financial Economics* 71, 349-380.
- Livnat, J., and R. R. Mendenhall. 2006. Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of Accounting Research* 44, 177-205.

- Loughran, T., and J. Ritter. 1995. The new issues puzzle. *Journal of Finance* 50, 23-52.
- Mendenhall, R. 2004. Arbitrage risk and post-earnings-announcement drift. *Journal of Business* 77, 875-894.
- Merton, R., 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance* 42, 483-510.
- Ng, J., T. Rusticus, and R. Verdi. 2006. Implications of trading costs for post-earnings-announcement drift. University of Pennsylvania working paper.
- Pownall, G., C. Wasley, and G. Waymire. 1993. The stock price effects of alternative types of management earnings forecast. *The Accounting Review* 68 (4), 896-912.
- Richardson, S., R. Sloan, M. Soliman, and I. Tuna. 2005. Accrual reliability, earnings persistence and stock prices. *Journal of Accounting and Economics* 39 (3), 437-485.
- Rogers, J. L., and P. C. Stocken. 2005. Credibility of management forecasts. *The Accounting Review* 80 (4), 1233-1260.
- Schwert, G. 2003. Anomalies and market efficiency. Chapter 15, *Handbook of the Economics of Finance*, eds. George Constantinides, Milton Harris, and René Stulz, North-Holland, pp. 937-972.
- Skinner, D. 1994. Why firms voluntarily disclose bad news. *Journal of Accounting Research* 32, 38-60.
- Shleifer, A., and R. W. Vishny. 1997. The limits of arbitrage. *The Journal of Finance* 52 (1), 35-55.
- Sloan, R. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71, 289-316.
- Soffer, L., S. Thiagarajan, and B. Walther. 2000. Earnings preannouncement strategies. *Review of Accounting Studies* 5(1), 5-26.
- Verrecchia, R. 2001. Essays on disclosure. *Journal of Accounting and Economics* 32, 91-180.
- Waymire, G. 1984. Additional evidence on the information content of management earnings forecast. *Journal of Accounting Research* 22 (2), 703-718.

Williams, P. A. 1996. The relation between a prior earnings forecast by management and analyst response to a current management forecast. *The Accounting Review* 71 (1), 103-113.

Appendix 1

1.A – Computation of relative quoted and effective spreads

The computation of relative quoted spreads and effective spreads are done after the data cleaning procedures documented in Appendix 1.B. There are two relative spread measures commonly used in recent market microstructure literature to measure trading cost, relative quoted spread and relative effective spread.

The underlying assumptions of the quoted spread are that market makers set the prevailing quotes and stand on the other side of the customer trades, and that the investors cannot trade within the quoted spread. For each quote at time s for firm i , we compute the intraday relative quoted spread, $IntraQSpread_{i,s}$, as:

$$IntraQSpread_{i,s} = \frac{ask\ price_{i,s} - bid\ price_{i,s}}{(ask\ price_{i,s} + bid\ price_{i,s})/2}$$

where $ask\ price_{i,s}$ ($bid\ price_{i,s}$) is the ask price (bid price) at time s . We then equal-weight the $IntraQSpread_{i,s}$ to obtain the average quoted spread for each day. We equal-weight the quoted spread for each day in the month prior to the portfolio formation month to estimate the trading cost of a stock of firm i in terms of quoted spreads, $QSpread$.

The effective spread is based on the notion that trade is only costly to the investor to the extent that the trade price deviates from the true price, approximated by the bid/ask midpoint. To compute each effective spread, we match each intraday trade to an intraday quote using the standard Lee and Ready (1991) algorithm described in Appendix 1.C. This process attempts to remove quotes for which trades have not been executed and could potentially reduce the noise from the trading cost estimation. For each trade-matched quote at time s for firm i , we compute the intraday relative effective spread, $IntraESpread_{i,s}$, as:

$$IntraESpread_{i,s} = \frac{2|trade\ price_{i,s} - (bid\ price_{i,s} + ask\ price_{i,s})/2|}{trade\ price_{i,s}}$$

where $ask\ price_{i,s}$ ($bid\ price_{i,s}$) is the ask price (bid price) for the quote for firm i at time s and $trade\ price_{i,s}$ is the trade price at which the trade executed at time s for firm i . We then equal-weight the $IntraESpread_{i,s}$ to obtain the average effective spread for each day. We then equal-weight the effective spread for each day in the month prior to the portfolio formation month to estimate the trading cost of a stock of firm i in terms of effective spreads, $ESpread$.

1.B – Cleaning the NYSE Trades and Quotes (TAQ) database

We use the intra-day quotes and trades from the NYSE TAQ database, which consists of the trades file and the quotes file, to compute the market microstructure variables from

January 1993 to December 2003. To ensure data integrity, we remove the errors and outliers from the files.

For the trades file, we retain the following:

1. Trades inside regular trading hours (9:30-16:00)
2. Good trades ($\text{corr} = 0, 1$)
3. Regular sale conditions ($\text{cond} = \text{blank or } *$)
4. Trades with positive trade price ($\text{price} > 0$) and positive trade size ($\text{siz} > 0$)
5. Trades with absolute change in trade price from the previous trade price of less than or equal to 10%

For the quotes file, we retain the following:

1. Quotes inside regular trading hours (9:30-16:00)
2. Regular quotes ($\text{mode} = 12$)
3. Quotes with positive bid price ($\text{bid} > 0$), positive ask price ($\text{ofr} > 0$), ask price greater than bid price ($\text{ofr} > \text{bid}$), positive bid size ($\text{bidsiz} > 0$) or positive ask size ($\text{ofrsiz} > 0$)
4. Quotes with relative quoted spreads (*IntraQSpreads*) less than or equal to 20%
5. Quotes with absolute change in bid price from the previous bid price in each day of less than or equal to 10% and with absolute change in ask price from the previous ask price in each day of less than or equal to 10%.
6. For the computation of relative effective spreads (*IntraESpreads*) only, quotes with relative effective spreads less than or equal to 20%.

1.C Matching of trades and quotes

The matching of trades and quotes is required for the computation of effective spreads. In combining the trades and quotes, we take the following steps. Following Lee and Ready (1991), we match each trade with the latest available quote at least 5 seconds earlier. Then, as in Huang and Stoll (1997), we collapse all trades that took place at the same price and quotes (bid price and ask price) into a single trade. The reason is that according to Huang and Stoll (1997) “a large order may be executed at a single price but be reported in a series of smaller trades” and “a single large limit order may be executed at a single price against various incoming market orders”.

Table 1 – Distribution of Management Forecasts across Years

This table presents the frequency of forecasts by year, the number of firms by year, and the respective number of forecasts for point and range forecasts. . Point forecasts are all forecasts with FCCIG cigcodeq in ('A', 'F', 'O', 'Z'). Range forecasts are all forecasts with FCCIG cigcodeq in ('B', 'G', 'H').

Year	# Forecasts	# Firms	# Point Forecasts	# Firms	# Range Forecasts	# Firms
1996	198	169	112	95	86	74
1997	261	219	165	139	96	80
1998	447	349	283	220	164	129
1999	503	351	242	177	261	174
2000	618	447	275	208	343	239
2001	1,616	834	399	208	1,217	626
2002	2,371	960	451	190	1,920	770
2003	2,536	972	372	155	2,164	817
2004	2,900	1,054	335	141	2,565	913
Total	11,450	5,355	2,634	1,533	8,816	3,822

Table 2 –Sample Characteristics

This table presents mean and median statistics for the sample across several characteristics. *Abret3d* is the 3-day size-adjusted returns around the management forecast date. *Abret12m* is the twelve-month size-adjusted returns starting on the month following the management forecast. *Surprise* is the difference between the management forecast of EPS and the latest consensus analyst forecast of EPS divided by price two days before the management forecast. *Beta* is estimated from a market model regression for each firm of monthly returns over the past five years ending at the month before the management forecast (with the minimum of 18 months of available data). *Size* is the market value of equity at the month before the management forecast and *Book-to-Market* is the ratio between the book value of equity and the market value of equity at the end of the previous fiscal year. *Horizon* is the difference in days between the management forecast day and the end of the firm fiscal year.

Panel A – Descriptive statistics

		# OBS	Total	Bad News	No News	Good News	Bad – Good <i>t-stat</i>
<i>Abret3d (%)</i>	Mean	11,450	-0.54	-4.60	0.13	1.84	-32.86***
	Median		0.15	-2.10	0.03	1.36	-26.70***
<i>Abret12m (%)</i>	Mean	11,450	2.36	-3.49	-3.97	7.10	-10.96***
	Median		0.42	-4.99	-4.37	4.08	-10.81***
<i>Surprise (%)</i>	Mean	11,450	0.61	-0.70	0.00	1.53	-67.88***
	Median		0.04	-0.20	0.00	0.57	-79.70***
<i>Beta</i>	Mean	11,163	0.84	0.86	0.80	0.83	2.08**
	Median		0.72	0.73	0.70	0.72	0.87
<i>Size (\$B)</i>	Mean	11,450	7.20	6.72	13.39	6.39	0.93
	Median		1.29	1.13	1.69	1.30	-2.74***
<i>Book-to-Market</i>	Mean	11,220	0.48	0.50	0.44	0.48	2.18**
	Median		0.41	0.43	0.35	0.41	1.36
<i>Horizon</i>	Mean	11,450	156.72	149.02	154.74	161.81	-7.80***
	Median		160.00	155.00	160.00	162.00	-7.32***

Panel B – Frequency table by forecast news and forecast precision

	Bad News	No News	Good News	Total
<i>Point</i>	640	611	1,383	2,634
<i>% of total forecasts</i>	5.59	5.34	12.08	23.00
<i>Narrow Range</i>	1,479	271	2,656	4,406
<i>% of total forecasts</i>	12.92	2.37	23.20	38.48
<i>Wide Range</i>	1,812	258	2,340	4,410
<i>% of total forecasts</i>	15.83	2.25	20.44	38.52
Total	3,931	1,140	6,379	11,450
<i>% of total forecasts</i>	34.33	9.96	55.71	100.00

Table 3 – Regression Analysis

Panel A (B) presents estimated coefficients of a regression of the three-day abnormal return (twelve-month future abnormal return) on the forecast surprise and some controls. *Bad News* (*Good News*) is a dummy variable if the *Surprise* is smaller (bigger) than zero. *Surprise* is the difference between the management forecast of EPS and the latest consensus analyst forecast of EPS divided by price two days before the management forecast. *Beta* is estimated from a market model regression for each firm of monthly returns over the past five years ending at the month before the management forecast (with the minimum of 18 month of available data). *Log Size* is the natural logarithm of the market value of equity at the month before the management forecast. *Book-to-Market* is the ratio of the book value of equity to the market value of equity at the end of the previous fiscal year. T-statistics using the Huber-White robust standard errors clustered by calendar quarter are presented in parenthesis below coefficient estimates. *, **, and *** indicate two-tailed statistical significance at 10, 5, and 1 percent levels.

Panel A: Short-term management forecast response coefficients

	I	II	III	IV
<i>Intercept</i>	-0.07 (-0.41)	0.13 (0.56)	0.14 (0.57)	1.13 (1.20)
<i>Bad News</i>		-2.61*** (-5.53)	-2.62*** (-5.56)	-2.62*** (-5.72)
<i>Good News</i>		1.59*** (6.08)	1.59*** (6.14)	1.59*** (6.02)
<i>Bad News x Surprise</i> (I)	3.94*** (13.23)	3.04*** (10.65)	3.94*** (6.35)	4.07*** (6.36)
<i>Good News x Surprise</i> (II)	0.56*** (9.16)	0.08 (1.03)	1.15* (1.86)	1.28** (1.98)
<i>Beta x Surprise</i>			0.21 (1.51)	0.22 (1.49)
<i>Log Size x Surprise</i>			-0.09** (-2.03)	-0.10** (-2.12)
<i>Book-to-Market x Surprise</i>			-0.02 (-0.13)	-0.04 (-0.26)
<i>Industry Dummies</i>	No	No	No	Yes
<i>R-Square</i> (%)	10.89	13.47	13.38	13.81
<i>F-Test</i> I = II	22.64***	22.47***	20.52***	20.10***
<i># OBS</i>	11,450	11,450	11,020	11,020

Table 3 – Regression Analysis - Cont'd

Panel B: Long-term future management forecasts response coefficients

	I	II	III	IV
<i>Intercept</i>	-3.22** (-2.06)	-3.97* (-1.93)	-3.56* (-1.66)	1.19 (0.21)
<i>Bad News</i>		0.07 (0.05)	-0.42 (-0.28)	-0.40 (-0.26)
<i>Good News</i>		1.50 (1.18)	1.47 (1.12)	1.40 (0.99)
<i>Bad News x Surprise (I)</i>	-0.33 (-0.37)	-0.58 (-0.58)	10.26*** (2.66)	9.87** (2.56)
<i>Good News x Surprise (II)</i>	6.47*** (16.67)	6.27*** (17.22)	18.77*** (4.45)	18.92*** (4.42)
<i>Beta x Surprise</i>			-0.66 (-0.89)	-0.52 (-0.69)
<i>Log Size x Surprise</i>			-0.88*** (-2.95)	-0.91*** (-3.07)
<i>Book-to-Market x Surprise</i>			0.38 (0.31)	0.55 (0.43)
<i>Industry Dummies</i>	No	No	No	Yes
<i>R-Square (%)</i>	4.54	4.55	5.04	5.84
<i>F-Test I = II</i>	14.50***	13.75***	15.32***	16.09***
<i># OBS</i>	11,450	11,450	11,020	11,020

Table 4 – Portfolio Analysis

Panel A presents our portfolio analysis and mean characteristics across management forecast surprise quintiles. *Surprise* is the difference between the management forecast of EPS and the latest consensus analyst forecast of EPS divided by price two days before the management forecast. *Raw Ret (Abret12m)* is the twelve-month raw (size-adjusted) returns starting on the month following the management forecast. *Analyst Rev.* is the difference between the post-management forecast consensus analyst forecast of EPS and the pre-management-forecast consensus analyst forecast of EPS divided by price two days before the management forecast. *Beta* is estimated from a market model regression for each firm of monthly returns over the past five years ending at the month before the management forecast (with the minimum of 18 month of available data). *Size* is the market value of equity at the month before the management forecast and *Book-to-Market* is the ratio between the book value of equity and the market value of equity at the end of the previous fiscal year. *Momentum* is the twelve-month raw return ending on the month of the management forecast. Panel B presents our profitability analysis. *ESpread* is relative effective spread, whereas *QSpread* is relative quoted spread. Appendix 1 describes the computation of these variables. *EProfit (QProfit)* is effective profit (quoted profit) and is equal to *Abret12m* minus *ESpread (QSpread)*. This panel also presents value-weighted analysis based on the market value of equity at the end of the month of the management forecast.

Panel A – Characteristics of forecast surprise quintiles

Quintile	<i>Surprise (%)</i>	<i>Analyst Rev.(%)</i>	<i>Raw Ret (%)</i>	<i>Abret12m (%)</i>	<i>Beta</i>	<i>Size (\$Bi)</i>	<i>Book-to-Market</i>	<i>Momentum (%)</i>
1	-1.73	-1.15	9.08	-4.63	1.02	3.36	0.53	4.89
2	-0.05	-0.06	2.94	-7.33	0.93	10.95	0.40	26.81
3	0.26	0.02	4.44	-5.38	0.92	14.08	0.40	29.91
4	1.18	0.11	20.50	8.14	1.00	10.43	0.45	38.25
5	4.20	0.03	31.00	19.14	0.83	5.40	0.49	31.17
5 - 1		1.18***	21.91***	23.77***	-0.19***	2.04**	-0.04	26.28***
t-stat		8.02	6.51	7.67	-4.79	2.30	-0.93	4.66

Panel B – Profitability analysis (all the numbers are in %)

Quintile	Equal-Weighted					Value- Weighted				
	<i>Abret12m</i>	<i>ESpread</i>	<i>QSpread</i>	<i>EProfit</i>	<i>QProfit</i>	<i>Abret12m</i>	<i>ESpread</i>	<i>QSpread</i>	<i>EProfit</i>	<i>QProfit</i>
1	-4.63	1.01	1.91	-3.63	-2.71	-4.85	0.32	0.85	-4.53	-4.00
2	-7.33	0.58	1.27			-8.75	0.25	0.66		
3	-5.38	0.65	1.30			-7.32	0.23	0.60		
4	8.14	0.62	1.26			3.86	0.21	0.54		
5	19.14	0.58	1.16	18.56	17.99	9.94	0.22	0.61	9.72	9.33
5 - 1	23.77***			22.19***	20.70***	14.79***			14.25***	13.33***
t-stat	14.79			14.25	13.33	4.59			4.44	4.18

Table 5 – Time-series Asset Pricing Regressions

This table presents time-series portfolio regressions of portfolio excess returns on factor mimicking portfolios based on the Fama and French three-factor model (Panel A) and the Carhart (1997) four-factor model (Panel B). Firms are sorted into quintiles based on the management forecast surprise. Management forecast surprise is the difference between the management forecast of EPS and the latest consensus analyst forecast of EPS divided by price two days before the management forecast. *MKTRF* is the market risk premium. *SMB* is a portfolio long in small firms and short in large firms. *HML* is a portfolio long in firms with high book-to-market equity and short in low book-to-market firms. *UMD* is a portfolio long in recent winners and short in recent losers based on the past six month of returns including month *t*.

Panel A – Fama and French three-factor model

Quintile		<i>Intercept</i>	<i>MKTRF</i>	<i>SMB</i>	<i>HML</i>	R ² (%)
1	Coeff.	-0.73*	1.21***	0.62***	0.81***	65.88
	t-stat	-1.85	12.80	6.30	6.41	
2	Coeff.	-0.76***	1.14***	0.34***	0.56***	77.74
	t-stat	-2.83	17.74	5.02	6.44	
3	Coeff.	-0.45*	1.06***	0.33***	0.51***	75.40
	t-stat	-1.69	16.51	4.94	5.94	
4	Coeff.	0.57***	1.10***	0.19***	0.43***	83.68
	t-stat	2.65	21.53	3.61	6.32	
5	Coeff.	1.37***	1.02***	0.37***	0.61***	66.56
	t-stat	4.36	13.51	4.70	6.00	
5-1	Coeff.	2.09***	-0.19*	-0.25**	-0.20	7.21
	t-stat	4.82	-1.81	-2.30	-1.46	

Panel B – Carhart four-factor model

Quintile		<i>Intercept</i>	<i>MKTRF</i>	<i>SMB</i>	<i>HML</i>	<i>UMD</i>	R ² (%)
1	Coeff.	-0.15	0.98***	0.72***	0.67***	-0.51***	85.06
	t-stat	-0.57	14.85	10.95	7.94	-11.44	
2	Coeff.	-0.55**	1.06***	0.37***	0.51***	-0.19***	81.33
	t-stat	-2.18	17.01	6.01	6.31	-4.43	
3	Coeff.	-0.24	0.97***	0.37***	0.46***	-0.19***	79.59
	t-stat	-0.95	15.78	5.97	5.78	-4.58	
4	Coeff.	0.70***	1.05***	0.21***	0.40***	-0.12***	85.31
	t-stat	3.37	20.48	4.21	6.09	-3.36	
5	Coeff.	1.44***	0.99***	0.38***	0.59***	-0.06	67.01
	t-stat	4.52	12.54	4.82	5.78	-1.18	
5-1	Coeff.	1.59***	0.01	-0.34***	-0.09	0.44***	39.93
	t-stat	4.45	0.13	-3.84	-0.74	7.45	

Table 6 – Future Earnings Announcement Returns

This table presents three-day cumulative abnormal returns around the next annual earning announcement and the sum of quarterly earnings announcements up to the annual earnings. The results are presented by management forecast surprise quintiles. Management forecast surprise is the difference between the management forecast of EPS and the latest consensus analyst forecast of EPS divided by price two days before the management forecast.

Quintile	Annual Earnings Announcement		Quarterly Earnings Announcements until Annual Earnings Announcement	
	Return (%)	t-stat	Return (%)	t-stat
1	0.07	0.36	0.29	0.94
2	0.26*	1.68	0.38*	1.72
3	-0.01	-0.08	0.04	0.16
4	0.34**	1.98	1.38**	5.17
5	1.37***	8.36	3.11***	12.35

Table 7 – Partition by Forecast Characteristics

This table presents the twelve-month size-adjusted returns starting on the month following the management forecast across several sub-groups for each quintile of management forecast surprise. Management forecast surprise is the difference between the management forecast of EPS and the latest consensus analyst forecast of EPS divided by price two days before the management forecast. Precision is divided into point, narrow range, and wide range forecasts. We classify range forecasts with relative ranges below (above) the median relative range within the calendar year as wide range (narrow range) forecasts where relative range is the difference between the forecast upper and lower bound divided by the share price two days before the forecast. *Accuracy* is the mean of the absolute value of management forecast errors in the previous year, scaled by price on two days before the current management forecast multiplied by negative one. *Horizon* is the difference in days between the management forecast day and the end of the firm fiscal year.

Panel A – Forecast precision

Quintile	<i>Precision</i>		
	Point	Narrow Range	Wide Range
1	-1.48	-2.39	-7.26
2	-6.63	-12.76	-6.19
3	-6.89	-6.31	-5.09
4	9.05	4.88	13.37
5	20.34	16.73	22.44
5 - 1	21.81***	19.12***	29.70***
t-stat	3.82	5.26	7.47
Point vs. Narrow Range	0.40		
Narrow vs. Wide Range		-1.96**	
Point vs. Wide Range			-1.13

Panel B – Forecast accuracy

Quintile	<i>Accuracy</i>	
	Low	High
1	1.60	0.17
2	-1.74	-1.90
3	-0.88	-0.62
4	8.60	4.76
5	23.28	-4.96
5 - 1	21.69***	-5.12
t-stat	4.05	-0.38
Low vs. High		1.84*

Panel C – Forecast horizon

Quintile	<i>Horizon</i>	
	Short	Long
1	-3.16	-6.43
2	-8.46	-6.91
3	-5.22	-5.30
4	8.72	7.20
5	17.42	20.42
5 - 1	20.58***	26.85***
t-stat	7.83	4.61
Short vs. Long		-1.15

Table 8 – Partition by Firm Characteristics

This table presents the twelve-month size-adjusted returns starting on the month following the management forecast across several sub-groups for each quintile of management forecast surprise. Management forecast surprise is the difference between the management forecast of EPS and the latest consensus analyst forecast of EPS divided by price two days before the management forecast. *Size* is the market value of equity at the month before the management forecast. *Institution* is the percentage of shares held by institutional investors at the end of the calendar quarter before the management forecast. *Volatility* is the standard deviation of the residuals in regressions of monthly returns on the S&P500 returns during the 48-months period (with the requirement of at least 12 months of returns) ending before the month of the forecast. *ESpread* is the average daily relative effective spread during the month before the management forecast.

Panel A – Firm characteristics

Quintile	<i>Size</i>		<i>Institutions</i>	
	Small	Large	Low	High
1	-5.68	-1.76	-8.45	0.62
2	-7.34	-6.97	-5.09	-10.22
3	-5.14	-6.31	-4.17	-6.68
4	14.05	5.98	9.48	6.06
5	27.42	11.92	23.11	16.59
5 - 1	33.09***	13.68***	31.56***	15.97***
t-stat	9.38	3.81	5.46	3.77
Small vs. Large	3.85***			
Low vs. High			2.17**	

Panel B – Limits to arbitrage

Quintile	<i>Volatility</i>		<i>ESpread</i>	
	Low	High	Low	High
1	-0.86	-6.76	-5.32	-3.95
2	-5.08	-8.46	-8.23	-5.84
3	-2.04	-9.80	-5.99	-4.59
4	7.80	10.65	6.18	11.80
5	13.72	23.98	12.79	28.73
5 - 1	14.58***	30.74***	18.11***	32.68***
t-stat	5.16	6.87	5.79	8.03
Low vs. High	-3.05***			
Low vs. High			-2.84***	

Table 9 – Two-Way Partitions – Regression Method

This table presents estimated coefficients and t-statistics using the Fama-MacBeth procedure. The dependent variable is the twelve-month size-adjusted returns starting on the month following the management forecast (*Abret12m*). *Beta* is estimated from a market model regression for each firm of monthly returns over the past five years ending at the month before the management forecast (with the minimum of 18 month of available data). *Log Size* is the natural logarithm of the market value of equity at the month before the management forecast *Book-to-Market* is the ratio between the book value of equity and the market value of equity at the end of the previous fiscal year. *Momentum* is the twelve-month raw return ending on the month of the management forecast. *Surprise Quintile* is the quintile rank of management forecast surprise. *Precision Quintile* is coded as ‘0’ for the widest quartile of forecast range (Q4), ‘0.25’ for Q3, ‘0.5’ for Q2, ‘0.75’ for the narrowest quartile (Q1) , and ‘1’ for point forecasts. *Accuracy* is the mean of the absolute value of management forecast errors in the previous year, scaled by price on two days before the current management forecast multiplied by negative one. *Horizon* is the difference in days between the management forecast day and the end of the firm fiscal year. *Size* is the market value of equity at the month before the management forecast. *Institution* is the percentage of shares held by institutional investors at the end of the calendar quarter before the management forecast. *Volatility* is the standard deviation of the residuals in regressions of monthly returns on the S&P500 returns during the 48-months period (with the requirement of at least 12 months of returns) ending before the month of the forecast. *ESpread* is the average daily relative effective spread during the month before the management forecast. *Surprise Quintile* ranges from ‘-0.50’ to ‘0.50’ and all other quintiles range from ‘0’ to ‘1’. T-statistics are presented in parenthesis below the estimated coefficients.

Panel A – Forecast characteristics

	I	II	III	IV
Intercept	5.25 (0.61)	4.71 (0.52)	6.35 (0.42)	3.46 (0.21)
<i>Beta</i>	1.67 (0.43)	1.80 (0.46)	-2.61 (-1.04)	-2.71 (-1.06)
<i>Log Size</i>	-0.59 (-1.40)	-0.59 (-1.35)	-0.29 (-0.45)	-0.12 (-0.17)
<i>Book-to-Market</i>	9.29** (2.22)	9.73** (2.22)	11.97** (2.05)	12.85** (2.05)
<i>Momentum</i>	-2.95 (-1.30)	-3.00 (-1.36)	-4.67 (-0.96)	-4.81 (-1.00)
<i>Surprise Quintile</i>	26.32*** (5.71)	21.31*** (6.41)	29.69*** (26.49)	24.70*** (5.20)
<i>Precision Quintile</i> <i>x Surprise Quintile</i>	-0.72 (-0.19)			12.30 (1.62)
<i>Horizon Quintile</i> <i>x Surprise Quintile</i>		7.85 (1.15)		-2.82 (-0.59)
<i>Accuracy Quintile</i> <i>x Surprise Quintile</i>			-19.08** (-2.33)	-17.49* (-1.92)
R-square	7.87	8.07	9.69	10.22
# OBS	11,450	11,450	6,780	6,780

Table 9 – Two-Way Partitions – Regression Method – (Cont'd)

Panel B – Firm characteristics

	I	II	III	IV	V
Intercept	6.71 (0.82)	5.24 (0.58)	6.29 (0.73)	6.35 (0.77)	6.20 (0.73)
<i>Beta</i>	1.94 (0.49)	1.92 (0.48)	2.00 (0.51)	1.91 (0.48)	2.06 (0.50)
<i>Log Size</i>	-0.71* (-1.71)	-0.61 (-1.35)	-0.69 (-1.62)	-0.69* (-1.68)	-0.69* (-1.70)
<i>Book-to-Market</i>	9.59** (2.20)	9.28** (2.20)	9.45** (2.29)	9.60** (2.21)	9.71** (2.35)
<i>Momentum</i>	-2.97 (-1.32)	-2.75 (-1.24)	-3.01 (-1.37)	-2.88 (-1.30)	-2.82 (-1.34)
<i>Surprise Quintile</i>	32.25*** (6.92)	30.53*** (6.40)	18.66*** (6.35)	21.51*** (8.07)	36.90*** (5.46)
<i>Size Quintile</i> <i>x Surprise Quintile</i>	-14.73*** (-4.54)				-15.59*** (-2.74)
<i>Institutions Quintile</i> <i>x Surprise Quintile</i>		-11.06* (-1.70)			-8.33 (-1.07)
<i>Volatility Quintile</i> <i>x Surprise Quintile</i>			12.55** (2.39)		10.68** (2.08)
<i>ESpread Quintile</i> <i>x Surprise Quintile</i>				7.01 (1.44)	-10.36* (-1.68)
R-square	8.08	8.14	8.05	7.98	8.93
# OBS	11,450	11,450	11,294	11,450	11,294

Figure 1 – Cumulative Abnormal Return up to 12 months

This figure presents cumulative side-adjusted monthly returns for five portfolios sorted based on management forecast surprise quintiles. Month “0” is the month in which the management forecast is released, i.e., month -1 represents the beginning of the forecast month and month ‘0’ represents the end of the forecast month. Management forecast surprise is calculated as the difference between the management forecast of EPS and the latest consensus analyst forecast of EPS divided by price two days before the management forecast.

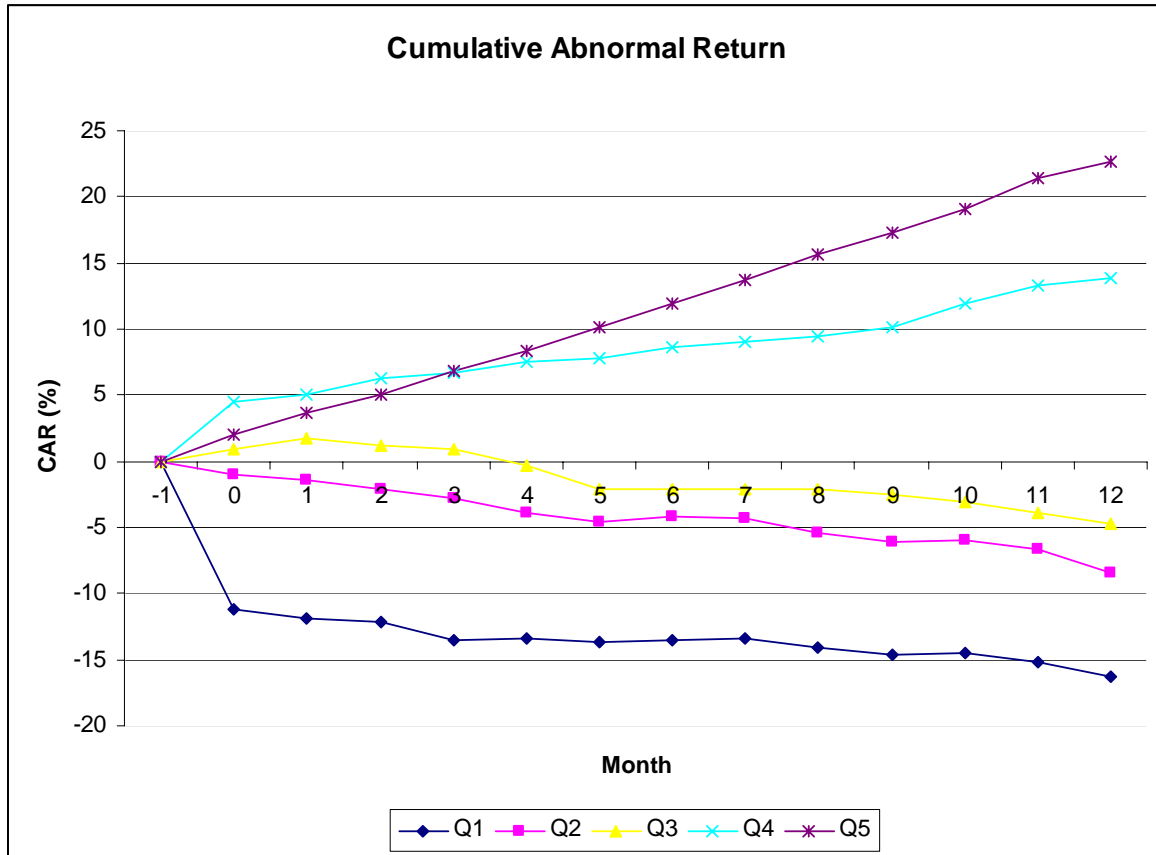


Figure 2 – Mean Abnormal Return by Year

This figure presents mean 12-month side-adjusted monthly returns for portfolios of firms in the bottom (Q1), the top (Q5) quintile, and the hedge portfolio that buys (sells) firms in the top (bottom) quintile based on the management forecast surprise. Management forecast surprise is calculated as the difference between the management forecast of EPS and the latest consensus analyst forecast of EPS divided by price two days before the management forecast.

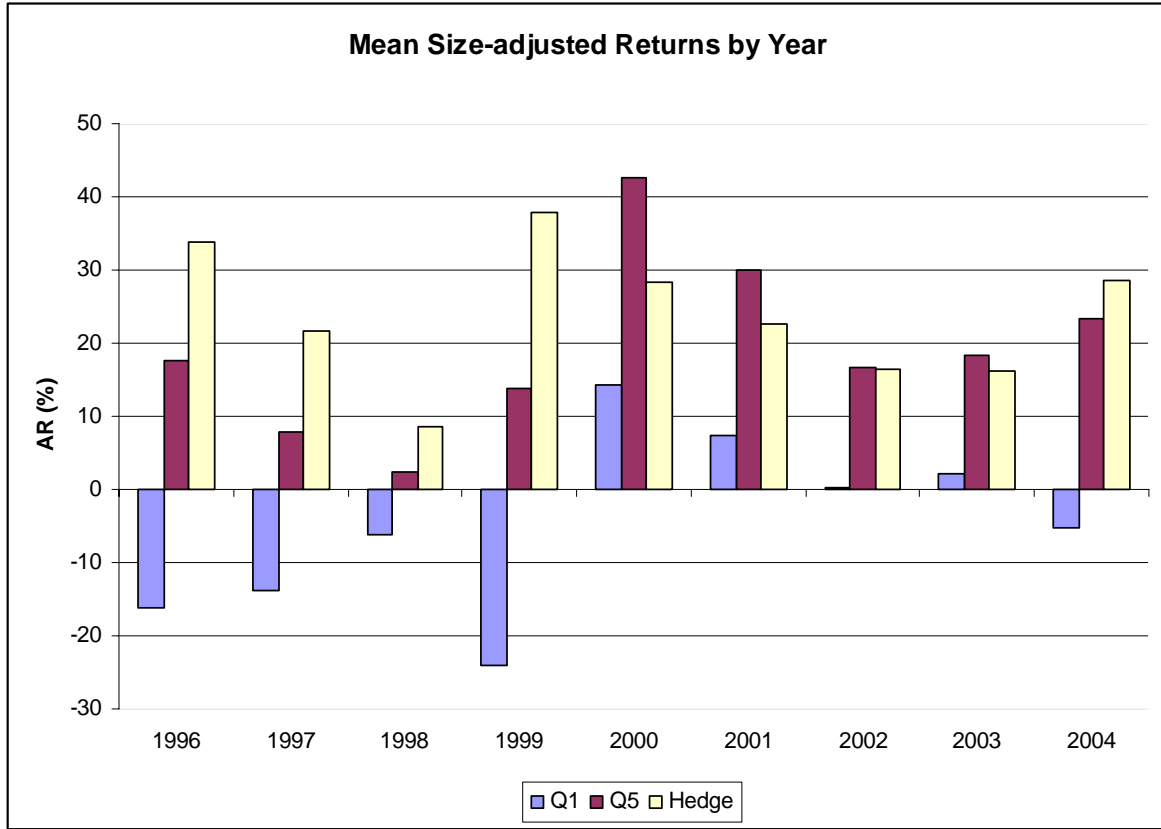


Figure 3 – Median Abnormal Return by Year

This figure presents median 12-month side-adjusted monthly returns for portfolios of firms in the bottom (Q1), the top (Q5) quintile, and the hedge portfolio that buys (sells) firms in the top (bottom) quintile based on the management forecast surprise. Management forecast surprise is calculated as the difference between the management forecast of EPS and the latest consensus analyst forecast of EPS divided by price two days before the management forecast.

