6-2013

Examining the Informational Role of Analysts' Forecasts and its Impact on the Relation between Earnings Surprises and Investors' Responses

Joonho LEE
Singapore Management University, joonholee@smu.edu.sg

Kevin OW YONG
Singapore Management University, kevinowyong@smu.edu.sg

Clement Michael

Examining the Informational Role of Analysts' Forecasts and its Impact on the Post-Earnings-Announcement-Drift

Michael Clement
McCombs School of Business
University of Texas at Austin
1 University Station, B6400
Austin, TX, 78712
Phone: (512) 471-0332
Fax: (512) 471-3904
michael.clement@mccombs.utexas.edu

Joonho Lee
School of Accountancy
Singapore Management University
60 Stamford Road, Singapore, 178900
Phone: (65) 6828-0984
Fax: (65) 6828-0600
joonholee@smu.edu.sg

Kevin Ow Yong
School of Accountancy
Singapore Management University
60 Stamford Road, Singapore, 178900
Phone: (65) 6828-0575
Fax: (65) 6828-0600
kevinowyong@smu.edu.sg

May 2013

Examining the Informational Role of Analysts' Forecasts and its Impact on the Post-Earnings-Announcement-Drift

Abstract

Prior research documents the existence of two distinct post-earnings-announcement-drifts. Interestingly, investors seem to underreact more toward analyst-based earnings surprises than toward seasonal random walk earnings surprises. In this paper, we measure the extent of investors' delayed reaction relative to the total market response to the earnings surprises. Using this measure, we find that investors react proportionately faster and more thoroughly to analyst-based earnings surprises than to random walk earnings surprises, suggesting that analyst-based earnings surprises are *relatively* less related with a delayed investor reaction compared with random walk earnings surprises. We also find that as the informativeness of analyst earnings forecasts increases, investors' response to earnings surprises increases more in instant form than in delayed form. In contrast, as the informativeness of random walk earnings expectations increases, investors' delayed response increases more than their instant response. Finally, we find that investors' faster and more thorough response to analyst-based earnings surprises increases in the quality of the firms' information environment. Our results complement existing research findings by utilizing a relative PEAD measure and provide a greater understanding toward the interpretation of both drifts.

1. Introduction

We examine the extent of delayed investor reaction toward earnings announcements based on seasonal random walk earnings surprises (hereafter RW drift) and analyst-based earnings surprises (hereafter AF drift). The existence of two distinct post-earnings-announcement-drifts (hereafter PEAD) has been well documented in prior research (e.g., Doyle, Lundholm, and Soliman 2006; Livnat and Mendenhall 2006). Specifically, these studies show that the pattern of returns around subsequent earnings announcements is markedly different for analyst forecast errors than for time-series errors. Interestingly, they also find that AF drift (based on I/B/E/S analyst forecast) is consistently and significantly larger than RW drift.

To better understand the nature of both drifts, extant research has been focused on examining factors that will account for the differences driving the AF and RW drifts. For example, Livnat and Mendenhall (2006) find that differences between both drifts are not attributed to either Compustat's policy of restating quarterly earnings or I/B/E/S's policy of excluding special items from their definition of reported (street) earnings. Doyle, Lundholm, and Soliman (2006) find that industry differences, scaling effects or risk factors do not explain the differences in patterns of returns between both drifts. More recently, Ayers, Li and Yeung (2011) provide a partial explanation to the existence of both drifts. The authors find that the RW drift is partly attributed to delayed trading by small investors who fail to understand the time-series properties of earnings, whereas the AF drift is partially due to delayed trades associated with institutional and other large traders.

The conventional approach in PEAD-related studies is to compare hedge returns between the top and bottom surprises deciles ranked by a chosen measure of earnings surprises. Using this method, Livnat and Mendenhall (2006) find that there is a one percentage point per quarter difference in hedge returns between the two measures of earnings surprises. Thus, the authors conclude that the AF drift is about 30% larger in magnitude than the RW drift. What remains unclear is why and whether we should expect analysts' forecasts based earnings surprises to have a more delayed investor reaction than those based on random walk forecasts.

To examine this issue, we provide an alternative perspective and examine the magnitude of both drifts using a relative measure of investor underreaction. We construct a *relative* PEAD measure (i.e., drift ratio) that measures the extent of investor underreaction based on their total market response to the earnings announcements. Using the drift ratios, we are able to show that the extent of investor underreaction is proportionally lower when investors react to analyst-based earnings surprises than when they react to random walk earnings surprises. Specifically, we find that the mean (median) extent of investor underreaction is 44% (45%) relative to investors' total response to the earnings announcements for the analyst-based earnings surprises. In contrast, the mean (median) extent of investor underreaction is 51% (55%) relative to investors' total response to the earnings announcements for random walk earnings surprises.

Previous research has shown that both the RW drift and the AF drift have declined in recent years (e.g., Ayers, Li and Yeung 2011). We conduct further analyses to examine not only the drift but also the earnings announcement window response. Based on the trend of the drift ratios across the years, we find that there is evidence to indicate that the earnings response coefficients during the earnings announcement window have increased monotonically over the years whereas the delayed investor reaction to earnings announcements during the drift period have significantly declined in recent years. Furthermore, we find that these changes are more prominent for analyst-based earnings surprises than for the time-series earnings surprises. More specifically, the AF drift ratio has decreased to less than 25% (2005-2010) compared to greater than 50% in the earlier years (1984-1995), while the RW drift ratio has decreased to about 48% (2005-2010) compared to about 60% in the earlier years (1984-1995). Based on these findings, we conclude that analysts, on average, provide more relevant and useful earnings forecasts in recent years than in earlier years of our sample period. Our findings also suggest that the market is increasingly more efficient in interpreting the impact of current news information to future earnings, which is consistent with the efficient market hypothesis arguing that arbitrage opportunities are competed away.

To examine the construct validity of our measure (i.e., drift ratio), we also perform several analyses. We measure each earnings forecast's past accuracy, which is our operational proxy for the informativeness of earnings forecasts, and we examine its impact on the drift ratio. We find that the total market response increases in the accuracy of past earnings forecasts for both the time-series based and the analyst-based earnings forecasts. However, past accuracy of each earnings forecast measure affects two drift ratios in different ways. The AF drift ratio decreases in the accuracy of past analysts' earnings forecasts, whereas the RW drift ratio increases in the accuracy of past time-series based earnings expectations. This result suggests that the past accuracy of analyst earnings forecasts provides more relevant and useful information to investors than the past accuracy of time-series based earnings forecasts.

Finally, we find that there is a cross-sectional variation to the drift ratio with information environment of the firms. Specifically, firms with a higher quality information environment (e.g., bigger firms, firms with greater analyst following, firms with high share prices, and firms with larger trading volume) experience a lower drift ratio. In addition, we find that the AF drift ratio is much smaller than the RW drift ratio for the firms with a higher quality of information environment, suggesting that investors respond much faster and more thoroughly to the earnings news at the earnings announcement window toward analyst-based earnings surprises than toward time-series based earnings surprises when it is likely that there exist more concurrent information about the firm's fundamentals. In other words, this result suggests that analyst forecasts are even more useful and relevant to investors than time-series earnings forecasts when the quality of the firm's information environment is higher.

Our study has implications as to how one examines the PEAD. By augmenting traditional PEAD analysis with our measure, we are able to show more clearly the nature and underlying implications of the extent of investor underreaction to earnings surprises. This is important because Livnat and Mendenhall (2006) call upon researchers to better understand the true nature of the PEAD anomaly. Hence we provide a new perspective toward examining the PEAD anomaly that reconciles potentially conflicting findings in prior research. Our study also suggests that analyst-based earnings surprises are *relatively* less (not more) related with a delayed investor reaction compared with time-series based earnings surprises.

Our study also contributes to the literature that examines the role of analysts as information intermediaries (e.g., Schipper 1991). By exploiting a relative PEAD measure, we demonstrate the relative extent to which investors pay attention to analyst reports. That is, our tests enable researchers to better assess how promptly investors react to analyst-based earnings surprises across different firms in a comparable fashion, and how informative these analyst forecasts are to investors. Specifically, our results show that analyst earnings forecasts brings greater and more instant investor reactions than time-series based earnings expectations, suggesting that analyst earnings forecasts are better measure of earnings expectations than time-series based earnings expectations. Our results also show that analyst forecasts are even more useful and relevant to investors when the quality of the firm's information environment is good.

Hence, our study supports the importance of analysts as information intermediaries in mitigating the post-earnings-announcement-drift. In that regard, we extend research that examines the role of analyst intermediation toward facilitating stock market efficiency.

The remainder of the paper proceeds as follows. Section 2 develops the hypotheses. Section 3 describes our data and measurement of variables. Section 4 presents the main results and other additional analyses. Section 5 checks robustness of our results and Section 6 concludes.

2. Literature Review and Main Hypotheses

The PEAD is viewed as one of the best-documented and most-resilient capital markets anomalies (Fama 1998). The efficient market hypothesis implies that in a (semi-strong) efficient market, investors should instantaneously adjust their expectations upon receiving new information that have implications on firms' future earnings. This, in turn, should be reflected instantaneously in stock prices. However, researchers have documented evidence inconsistent with this implication. Various explanations have been put forward to suggest why there is investor underreaction. Specifically, there is a rich literature exploring how the PEAD varies with the cross-sectional variation in various firm-specific characteristics.[1]

Research into the PEAD typically requires a measure for estimating the earnings surprise (i.e., actual earnings minus forecasted earnings) scaled by a deflator. Livnat and Mendenhall (2006) document that most studies traditionally use a time-series expectation model to predict earnings, although more recent studies utilize some forms of analysts' forecasts. Hence, recent research that compares different forms of earnings surprises has found the existence of two

[1] See, for example, Bernard and Thomas (1989) for a comprehensive review of possible explanations of causes for the post-earnings announcement drift. More recently, Richardson, Tuna and Wysocki (2010) provide a review of research advances made toward understanding the post-earnings announcement drift anomaly in the last ten years.

distinct PEADs. Specifically, Livnat and Mendenhall (2006) and Doyle, Lundholm, and Soliman (2006) demonstrate the existence of two distinctly different PEADs. In their related study, Ayers, Li, and Yeung (2011) also conclude that both drifts are quite different even through both empirical regularities are being manifested as an investor underreaction to earnings surprises.

Interestingly, all three studies show that the magnitude of the AF drift is larger than that of the RW drift. For example, Livnat and Mendenhall (2006) document a 4.91% return based on a hedging trading strategy formed using the top and bottom analyst-based earnings surprise deciles. In contrast, the Compustat drift for their subsample of firms is only 3.77%, which is more than a percentage point difference in quarterly hedged returns. Likewise, Doyle, Lundholm, and Soliman (2006) find that returns subsequent to earnings announcements for earnings surprises relative to analyst forecasts are much larger, persist for much longer and are positive for every quarter between 1988 and 2000. Ayers, Li, and Yeung (2011) also reported results that are comparable to Livnat and Mendenhall (2006). Specifically, they find that the magnitude of AF drift in their sample is 4.8% whereas the magnitude of the RW drift for their sample firms is 4.3%.

To ascertain whether these are distinctly different forms of investor underreaction, these studies also implement additional analyses to examine the underlying source(s) that could potentially explain differences between both drifts. For example, Livnat and Mendenhall (2006) show that differences between both drifts are not attributed to either Compustat's policy of restating quarterly earnings or I/B/E/S's policy of excluding special items from their definition of reported earnings. Specifically, they find that 75-90% of their total sample is unaffected by restatements, special items or the total difference between Compustat and I/B/E/S measures of reported earnings. Hence, they conclude that differences between both drifts appear to be attributable to differences between analyst and time-series forecasts or factors associated with these differences, and not attributable to differences in reported earnings between the two data sources.

Likewise, Doyle, Lundholm, and Soliman (2006) find that industry differences, scaling effects or risk factors do not explain the differences in patterns of returns between both drifts. They also find that extreme stock returns following I/B/E/S earnings surprises tend to be concentrated among firms that are "neglected" (i.e., firms with relatively high book-to-market ratios), firms with low analyst coverage, and firms with high analyst forecast dispersion. Consistent with prior research, they also show that the returns to their trading hedge strategy are highest in the quartile of firms where transactions costs are highest (e.g., Bhushan 1994; Ng, Rusticus, and Verdi 2008) and institutional investor interest is lowest (e.g., Bartov, Radhakrishnan, and Krinshy 2000; Ke and Ramalingegowda 2005).

More recently, Ayers, Li, and Yeung (2011) examine whether both drifts are driven by different sets of investors. They hypothesize that the RW (AF) drift is attributable to the trading activities of small (large) traders who underreact to different forms of earnings innovations. Consistent with their hypotheses, they find that small (large) traders continue to trade in the direction of RW (AF) earnings surprises after earnings announcements. They also find that the RW (AF) drift attenuates when small (large) traders react more thoroughly to RW (AF) based earnings surprises during the announcement period. Hence they conclude that the RW drift is largely explained by small traders' failure to understand the time-series property of earnings whereas the AF drift is due to a longer price discovery process by large traders (with a more sophisticated earnings expectation model) who underreact due to information uncertainty toward the analyst-based earnings surprises. In sum, they conclude that the underlying natures of the two drifts are qualitatively different.

While it is clear from these studies that there are two distinctly different PEADs, what remains unaddressed in extant research is whether and why we should expect analyst-based earnings surprises to have a *more* delayed investor reaction than random walk based earnings surprises. This is especially so given that there is potentially more investor attentions toward the analyst-based earnings surprises than the random walk forecasts. More specifically, even though an earlier study by Walther (1997) shows that both random walk earnings surprise and analyst-based earnings surprise have incremental explanatory power of market responses, more recent studies discuss propensities and consequences of meeting or beating analysts' forecasts of earnings (e.g., Bartov, Givoly, and Hayn 2002; Brown and Caylor 2005; Koh, Matsumoto, and Rajgopal 2008). Brown and Caylor (2005) show that valuation consequence of avoiding negative earnings surprise, which is based on analysts' forecasts, is greater than that of avoiding earnings decrease compared to the same quarter last year, especially in recent years. To explain this phenomenon, Brown and Calyor (2005) also propose several potential reasons such as an increased media coverage given to analyst forecasts, more analyst following, more firms covered by analysts, and temporal increases in both the accuracy and precision of analyst forecasts. Another important reason that we may expect less delayed investor reaction toward analyst-based earnings surprises than toward random walk earnings surprises is that analysts play as information intermediaries in improving firms' information environment and reducing information uncertainty, which consequently enhances market efficiency and therefore reduces underreactions (Schipper 1991; Jiang, Lee, and Zhang 2005; Zhang 2006; Francis et al. 2007).[2]

Considering above mentioned studies, we expect analyst-based earnings surprises to have *less* (not more) delayed investor reaction than random walk based earnings surprises, which is however not clearly supported by previous studies. The conventional approach in PEAD-related studies is to compare hedge returns between the top and bottom surprises deciles ranked by a chosen measure of earnings surprises. Instead, we examine the magnitude of both drifts using a *relative* measure of investor underreaction. In other words, we examine the differences in the delayed portion of investors' response relative to their total market response (i.e., the drift ratio), and then we hypothesize that the magnitude of the AF drift based on our relative PEAD measure (i.e., AF drift ratio) is expected to be lower than the magnitude of RW drift (i.e., RW drift ratio). We formulate our first hypothesis as follows:

H1: The delayed portion of investors' response relative to investors' total response toward analyst-based earnings surprise is smaller than that toward random walk based earnings surprise (i.e., AF drift ratio is smaller than RW drift ratio).

The classical efficient market hypothesis suggests that arbitrage opportunities are competed away and the profitability of the strategy designed to exploit the arbitrage eventually eliminated. Letting aside the debate on whether the efficient market hypothesis itself is valid or not, we have seen several empirical findings to support some forms, if not all, of arbitrage opportunities are competed away over time. For example, Ke and Ramalingegowda (2005)

[2] Ayers, Li, and Yeung (2011) suggest that a potential reason to explain cross-sectional variation in the AF drift is because of a longer price discovery process when the analyst-based earnings surprises are more difficult to interpret (e.g., when analyst forecast dispersion is large). However, they do not explain why the AF drift is larger than the RW drift.

provide evidence that transient institutional investors exploit the PEAD and those investors generate abnormal returns of 5.1 percent (or 22 percent annualized) after transaction costs. In addition, their arbitrage trades accelerate the speed that stock prices reflect the implications of current earnings for future earnings. Green, Hand, and Soliman (2011) also find that hedge returns to Sloan's (1996) accruals anomaly have decayed in U.S. stock markets to the point that they are no longer positive, and they suggest that the anomaly's demise partly due to an increase in the capital invested by hedge funds into exploiting the signal. Consistent with these findings, Ayers, Li, and Yeung (2011) show that both the RW drift and the AF drift have declined over time. To extend these studies and provide a more complete perspective of the relation between earnings surprises (either based on analyst forecasts or time-series) and investors' responses (either in the immediate form or in a delayed form), we examine whether there are over-time changes to the extent of investor underreaction based on our relative PEAD measure.

Although both AF drift and RW drift have been good targets for arbitrage profits, we may infer from the literature that investors pay attention on AF drift and try to exploit AF drift more than RW drift because the magnitude of AF drift is larger than that of RW drift as shown by Doyle, Lundholm, and Soliman (2006) and Livnat and Mendenhall (2006). In addition to these studies, by examining short earnings announcement window returns, Brown and Calyor (2005) show that investors reward firms for reporting quarterly earnings that meet or beat analysts' estimates more than for meeting other thresholds such as avoiding loss or earnings decrease in later sample period (i.e., 1993-2002) but not in earlier sample period (i.e., 1985-1992) of their study. This finding suggests that investors' response toward analyst-based earnings surprises and time-series earnings surprise change over time. Another related study which examines cross-sectional variation in the AF drift is Zhang (2008). Zhang (2008) finds that the market reacts earlier when analysts are responsive and revise their forecasts promptly in response to earnings announcements. She further finds that analysts revise their forecasts promptly more in recent years than in previous years. Specifically, she finds that the percentage of responsive analysts, defined as analysts who issue a forecast revision within two trading days after the earnings announcements have doubled from 26% in 1996 to almost 53% in 2002. Given the increasing frequency of analysts who revise their earnings forecasts, we would expect that there should be less delayed reaction in recent years than in previous years.

Combining these findings, we expect to find a greater (less) investor response toward both analyst-based and time-series earnings surprises in the earnings announcement window (in the drift window) in recent years than in previous years. In addition, we expect that this change in investor response toward earnings surprises over time is more prominent for analyst-based earnings surprise than for time-series earnings surprise. We develop the hypotheses as follows:

H2a: *The market response to earnings announcements during the earnings announcement window (during the drift period) increases (decreases) over time (i.e., drift ratio decreases over time).*

H2b: *The increasing (decreasing) market response to earnings announcements during the earnings announcement window (during the drift period) over time is more prominent toward analyst-based earnings surprise than toward random walk earnings surprise (i.e., AF drift ratio decreases more than RW drift ratio over time).*

It goes without saying that investors' response increases in the informativeness of the earnings news, and we may assume that analysts who forecast accurately provide more useful information to the investors than the analysts who do not forecast very accurately. By using the accuracy of analysts' past forecasts, Park and Stice (2000) show that investors indeed recognize the differential forecasting ability of individual analysts, and this difference is reflected in the price reaction to forecast revisions. By using the accuracy of past earnings forecasts (not only analysts' past forecasts but also time-series earnings expectations), we extend Park and Stice (2000) and expect that when the current earnings news provides more useful information about the future earnings (i.e., when the accuracy of past earnings forecasts is high) investors react more in an immediate form than in delayed form.

With respect to the value relevance of each earnings news, Brown and Caylor (2005) suggest that the valuation consequence of meeting or beating analyst forecasts is getting greater than that of meeting or beating earnings of the same quarter last year. If the value relevance of analyst-based earnings surprise is greater than that of time-series earnings surprise, we can also expect that the past accuracy of analyst forecasts is more informative and useful than the past accuracy of time-series earnings forecasts. Therefore, we hypothesize that as the accuracy of the past earnings forecasts increases the delayed portion of investors' response to their total market response toward earnings surprise decreases. We also hypothesize that the accuracy of past analysts' earnings forecasts plays a bigger role than the accuracy of past time-series earnings expectation in decreasing the delayed portion of investors' response to their total market response toward earnings surprise.

H3a: The delayed portion of investors' response relative to their total market response toward earnings surprise decreases in the accuracy of past earnings forecasts (i.e., drift ratio decreases in the accuracy of past earnings forecasts).

H3b: The delayed portion of investors' response relative to their total market response toward analyst-based earnings surprise decreases in the accuracy of past analyst earnings forecasts more than the delayed portion of investors' response relative to their total market response toward random walk earnings surprise decreases in the accuracy of past random walk earnings surprise (i.e., AF drift ratio decreases in the accuracy of past analyst earnings forecasts more than RW drift ratio decreases in the accuracy of past random walk earnings forecasts).

Finally, we examine whether there is a cross-sectional variation in our relative PEAD measure to changes in firms' information environment characteristics. Prior research postulates that the magnitude of the PEAD is negatively associated with the richness of a firm's information environment proxied for by firm size, number of analyst following, share prices, and trading volumes, etc. (Jiang, Lee, and Zhang 2005; Zhang 2006; Francis et al. 2007). If what early studies mean by the magnitude of the PEAD is a less delayed investor reaction to the earnings announcements, this postulation should be also true to our alternative measure for the PEAD (i.e., drift ratio). In other words, the drift ratio should be negatively associated with the richness of a firm's information environment.

In addition, if the value relevance of analyst-based earnings surprise is greater than that of time-series earnings surprise as we discussed earlier, we can also expect that the richness of a firm's information environment makes analysts' forecasts more informative and useful than time-series earnings forecasts. For example, suppose two firms; one is very big and followed by many analysts and the other is relatively small and followed by only a few analysts. When the same magnitude of earnings surprises, which are based on analysts' forecasts, occur to these two companies, the value relevance of earnings surprise should be greater to the former than the latter, because the big company is less likely to have earnings surprise than the small company due to heavy monitoring by sophisticated expertise (i.e., analysts). Based on this reasoning, we develop our last two hypotheses as follows:

H4a: The delayed portion of investors' response relative to their total market response toward earnings surprise decreases as the firm specific information environment improves (i.e., drift ratio decreases as the firm specific information environment improves)

H4b: The delayed portion of investors' response relative to their total market response toward analyst earnings surprise decreases more than toward random walk earnings surprise as the firm specific information environment improves (i.e., AF drift ratio decreases more than RW drift ratio as the firm specific information environment improves).

3. Research Design and Data

3.1. Estimating Earnings Surprise

Consistent with many prior studies, we define the earnings surprise as actual earnings minus expected earnings, scaled by stock price. We use two different earnings surprise measures: time-series based earnings surprise and analyst forecast based earning surprise. We name the former *SUE* and the latter *SUEAF*. For *SUE*, we use a rolling seasonal random walk model following many prior drift studies. Specifically, our time-series measure of earnings surprise (*SUE*) is given by the following equation:

$$SUE_{it} = \frac{(X_{it} - X_{it-4})}{P_{it}} \qquad (1)$$

where X_{it} is primary Earnings Per Share (EPS) before extraordinary items for firm *i* in quarter *t* (Compustat item EPSPXQ), and P_{it} is the price per share for firm *i* at the end of quarter *t* from Compustat. X_{it} and P_{it} are unadjusted for stock splits, but X_{it-4} is adjusted for any stock splits and stock dividends during the period $\{t-4, t\}$. If most analyst forecasts of EPS are based on diluted EPS, we use Compustat's diluted EPS figures (Compustat item EPSFXQ) in equation (1).

As for *SUEAF*, we replace the seasonal random work forecast (X_{it-4}) with a measure of analysts' expectations, and replace Compustat actual EPS (X_{it}) with I/B/E/S actual. Considering only the most recent forecast for each analyst, our measure of analysts' expectations is the median of forecasts reported to I/B/E/S in the ninety days prior to the earnings announcement.[3]

To address the existence of outliers and nonlinearities in the earnings surprise–return relation, most drift studies classify firms into ten portfolios based on earnings surprises (e.g., Bernard and Thomas (1990), Bhushan (1994), and Bartov, Radhakrishnan, and Krinsky (2000)). The analysis is then performed on portfolio ranks scaled between 0 and 1. Following a methodology used in Livnat and Mendenhall (2006), we subtract 0.5 from the *SUE* (or *SUEAF*) decile rank in order to assign a score of 0 to a mythical median observation. Thus, the slope coefficient in the regression of abnormal returns on the earnings surprise decile rank (*DSUE* or

[3] This measure of earnings surprise is one of the earnings surprise measures used by Livnat and Mendenhall (2006). They also use Compustat actual instead of I/B/E/S actual for their analyses and obtain similar results. Other prior studies use similar earnings surprise measures. For example, Abarbanell and Bernard (1992) take forecasts from Value Line, and Mendenhall (2004) takes actual earnings from their forecast providers and deflates earnings surprise by the dispersion of analysts' forecasts.

DSUEAF) may be interpreted as the return to a hedge portfolio that takes long position on the most positive *SUE* or *SUEAF* decile and short position on the most negative *SUE* or *SUEAF* decile. Bernard and Thomas (1990) report that the drift is insensitive to whether one assigns firms into *SUE* deciles based on the current quarter's *SUE* values, or one uses implementable rule such as *SUE* cutoffs from quarter $t-1$, so we use the current quarter's *SUE* values for our analyses.

3.2. Cumulative abnormal returns

Daily abnormal returns are calculated as the raw daily return from the Center for Research in Security Prices (CRSP) minus the daily return on the portfolio of firms with approximately the same size (the market value of equity as of June) and book-to-market (B/M) ratio (as of the prior December). We use six classifications of the population (two size and three B/M portfolios), and we obtain the daily returns and cutoff points from Professor Kenneth French's library.

To estimate the drift, we sum daily abnormal returns over the period from two days after the current earnings announcement through one day after the following quarterly earnings announcement, and we name it *CAR(Drift)*.[4] To measure the immediate short-term earnings announcement return we sum three daily abnormal returns, including the day preceding the Compustat announcement date, the announcement date, and the following day, and we name it *CAR(Earnings Announcement Window)*. We also measure the total market response by summing *CAR(Drift)* and *CAR(Earnings Announcement Window),* and we name it *CAR(Total).*

[4] This drift period is the same as the one used in Livnat and Mendenhall (2006). Some other studies use (2, 60) or (5, 65) trading day window, where 0 is the earnings announcement date (e.g., Liang (2003), Ayers, Li, and Yeung(2011))

3.3. Relative drift measure

To examine the relation between earnings surprises and investors' responses, we regress each abnormal return on earnings surprise measures such as following.

$$CAR_{it} = \beta_0 + \beta_1 Earnings\_Surprise_{it} + \varepsilon_{it} \quad (2)$$

For these regression analyses, our two earning surprise measures (*SUE* and *SUEAF*) are adjusted and transformed into *DSUE* and *DSUEAF*, which have the values between -0.5 and 0.5, as discussed earlier. We also use three different cumulative abnormal returns in our analyses (i.e., *CAR(Total)*, *CAR(Earnings Announcement Window)*, and *CAR(Drift)*). Therefore, we obtain three different hedge returns which represent investors' total market response, investors' immediate market response, and their delayed market response to the earnings surprise, respectively.

Using the estimates from these regressions, we construct a *relative* PEAD measure (i.e., drift ratio) that measures the extent of investor underreaction based on their total market response to the earnings surprise. Specifically, the drift ratio of time-series based earnings surprise is calculated by the coefficient estimate on *DSUE* in the regression of *CAR(Drift)* divided by the coefficient estimate on *DSUE* in the regression of *CAR(Total).* Similarly, the drift ratio of analyst-based earnings surprise is calculated by the coefficient estimate on *DSUEAF* in the regression of *CAR(Drift)* divided by the coefficient estimate on *DSUEAF* in the regression of *CAR(Total).* Therefore, a high (low) level of drift ratio is interpreted to imply that a large (small) portion of response is delayed relative to its total market response.

3.4. Informativeness of earnings forecasts

In addition to typical variables used in drift studies, we construct new variables to measure the informativeness of earnings forecasts. *Mean Abs.* $SUE_{(t\text{-}12,\ t\text{-}1)}$ is the average absolute values of *SUE* of the past twelve quarters for a specific firm-quarter, while *Mean Abs.* $SUEAF_{(t\text{-}12,\ t\text{-}1)}$ is the average absolute values of *SUEAF* of the past twelve quarters. These variables capture how much the actual earnings have been deviated from earnings forecasts historically. Thus, a low value for these variables indicates that there have been less deviations or surprises from the earnings forecasts for a specific firm for the past twelve quarters. For example, a low *Mean Abs.* $SUEAF_{(t\text{-}12,\ t\text{-}1)}$ means that analyst forecasts for the past three years have been quite accurate, thus we can infer that for this firm analyst forecasts provide more relevant information compared with other firms for which analyst forecasts have not been very accurate. When we estimate these measures, *Mean Abs.* $SUE_{(t\text{-}12,\ t\text{-}1)}$ ($SUEAF_{(t\text{-}12,\ t\text{-}1)}$) is marked as missing if the firm-quarters have less than nine *SUE*s (*SUEAF*s) during the past twelve quarters.

3.5. Sample selection

An initial sample is obtained from Compustat for all firms with available data over the period 1981–2010. Since our analysis focuses on a comparison between time-series based earnings expectations and analyst forecasts, we require that observations have at least one analyst forecast from I/B/E/S. Other selection criteria for each observation for firm-quarter *t* are as follows:

1) The earnings announcement date is reported in Compustat for both quarter *t* and quarter *t*+1 (returns are cumulated through the next earnings announcement date). The difference of earnings report dates in Compustat and in I/B/E/S should not be more than one calendar day.

2) The price per share is available from Compustat as of the end of quarter *t*, and is greater than $1. This reduces noise caused by small *SUE* deflators, and it also reduces issues related with stocks with low liquidity.

3) The market (book) value of equity at the end of quarter $t-1$ is available from Compustat and is larger than $5 million (positive). This eliminates very small firms with low liquidity, as well as firms at their initial stages or close to liquidation.

4) The firm's stocks are traded on the New York Stock Exchange, American Stock Exchange, or NASDAQ.

5) Daily returns are available in CRSP from one day before quarter *t*'s earnings announcement through one day after the announcement of earnings for quarter t+1.

6) Data are available to assign the firm to one of the six Fama–French portfolios based on size and B/M.

7) *SUE* as defined in equation (1) can be calculated for the quarter.

8) Average absolute values of *SUE* or *SUEAF* of the past twelve (at least nine) quarters can be calculated.

After applying the above data requirements, our final sample comprises 224,412 observations for 9,470 firms from Q1/1984 to Q4/2010. Our sample size is bigger than the corresponding sample size (107,893) of Livnat and Mendenhall (2006) because their sample period (Q1/1987 to Q2/2003) is shorter than ours. Our sample expands from 109 firms in the first quarter of 1984 to 2,127 firms in the fourth quarter of 2010.

Table 1 provides summary statistics for all observations. Overall, the summary statistics of the variables are similar with those of previous studies. Specifically, the mean and median *SUE* and *SUEAF* are close to zero, while the time-series *SUE* exhibits a wide distribution with extreme values compared to *SUEAF*. Therefore, we need to transform both earnings surprise measures into their decile ranks for the analyses. The mean (median) of *CAR(Total)* is -0.91% (-0.51%), and the mean (median) of *CAR(Earnings Announcement Window)* is 0.16% (0.08%). The results also show that the mean (median) of *CAR(Drift)* is -1.07% (-0.68%).

The mean (median) *Mean Abs.* $SUE_{(t-12,\, t-1)}$ is 0.0870 (0.0089), while the mean (median) *Mean Abs.* $SUEAF_{(t-12,\, t-1)}$ is 0.0074 (0.0023), suggesting that analyst forecasts, on average, tend to reflect market earnings expectations more accurately than time-series earnings forecasts. Note that the sample has a wide distribution of firms in terms of size. The mean (median) of market value of equity at the end of the quarter is approximately $3.7 billion ($552 million). The mean (median) price per share is $45.03 ($20.50). The mean (median) number of analysts' forecasts for firm quarter is 4.7 (3.0). Finally, we calculate the trading volume (*VOLUME*) as the average daily turnover during forty-five days before the earnings announcement, where daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding. The mean and median of the *VOLUME* are 0.70% and 0.44%, respectively.

4. Results

4.1. Relation between earnings surprises and the market responses

Table 2 shows the regression results based on various combinations of independent and dependent variables of interest. Panel A (Panel B) of Table 2 shows the regression results using adjusted *SUE (SUEAF)* variable as an independent variable, and using *CAR(Total)*, *CAR(Earnings Announcement Window)*, and *CAR(Drift)* as dependent variables, respectively. The coefficient estimate on *DSUE (DSUEAF)* represents the hedge returns of taking a long position on the highest decile of *SUE (SUEAF)* and a short position on the lowest decile of *SUE (SUEAF)*, while the intercept is an estimate of return for the median observation.

As we can see in the column (3) of Table 2, the magnitude of drift hedge return of *DSUE* (3.33%) shown in Panel A is smaller than the magnitude of drift hedge return of *DSUEAF* (3.90%) shown in Panel B. This implies that there is more drift in analyst-based earnings surprises than in time-series based earnings surprises, consistent with the finding of previous studies (e.g., Livnat and Mendenhall 2006; Doyle, Lundholm, and Soliman 2006).[5]

Investors' immediate responses to earnings surprises, as examined in column (2), provide more prominent differences between the two earnings surprise measures. The coefficient estimate on *DSUE* in column (2) is 0.0407 (or 4.07% hedge returns) and it is much smaller than 0.0690 (or 6.90% hedge returns), which is the coefficient estimate on *DSUEAF* shown in Panel B. We interpret this result to suggest that investors respond a lot more to analyst-based earnings surprises than to the time-series based earnings surprises around earnings announcement dates. These results indicate that there are differences not only in the delayed market responses between the analyst forecast based and time-series based models, but also highlight that there are differences in instant investor response between the two earnings surprise measures.

Further, we note that the coefficient estimate on *DSUE* in column (2) is 0.0407 and it is 0.0077 greater than the coefficient estimate on *DSUE* (0.0330) in column (3) of Panel A. However, the coefficient estimate on *DSUEAF* (0.0690) in column (2) is much greater than the corresponding coefficient estimate in column (3) (0.0390). This result reflects that unlike time-series based earnings surprises, analyst forecast based earnings surprises are interpreted by investors as good or bad news instantaneously rather than in the form of a delayed market

[5] In fact, the difference of hedge returns between *DSUE* and *DSUEAF* in Livnat and Mendenhall (2006) is greater than the results reported in our study. The coefficient estimate on *DSUE* is 3.77(%) while the coefficient estimate on *DSUEAF* is 4.91(%) in Livnat and Mendenhall (2006). These differences are due to differences in the sample periods between the two studies.

reaction. Finally, when we consider the total market response to earnings surprises (i.e., *CAR(Total)*, which is the sum of *CAR(Earnings Announcement Window)* and *CAR(Drift)* in column (1)), we observe that there is a stronger investor response in *DSUEAF* (10.80%) than in *DSUE* (7.37%).

The second last row in Panel B of Table 2 provide results of a likelihood ratio test suggested by Vuong (1989) that allows the researcher to determine which model explains more of the dependent variable. The results show that for all dependent variables analyst-based earnings surprise measure (*DSUEAF* in Panel B) explains much better than time-series based earnings surprise measure (*DSUE* in Panel A). While all the comparisons are statistically significant at the 0.01 level, in particular the *DSUEAF* explains much better for the market responses around earnings announcement window with Vuong's Z-statistic of 42.78 (column (2)).

These findings provide an alternative interpretation in explaining why there is a larger drift in analyst-based earnings surprises compared with that in time-series based earnings surprises. Since the delayed portion of market response in *DSUEAF* (0.36 = 0.0390/0.1080 in Panel B) is smaller than the delayed portion of market response in *DSUE* (0.42 = 0.0330/0.0737 in Panel A), this result implies that there is *relatively* less underreaction toward analyst-based earnings surprises than for time-series based earnings surprises. That is, the greater magnitude of drift in the *SUEAF* model compared with that in the *SUE* model should be considered with respect to the size of the total market responses to both earnings surprises. To examine whether the difference in drift ratios between *DSUE* and *DSUEAF* models is statistically significant, we run the regressions at every quarter to calculate the drift ratio of each quarter, and then average them across time. The last two columns of Table 2 show that the mean (median) RW drift ratio is

0.51 (0.55). Compared to these drift ratios, the mean (median) AF drift ratio is 0.44 (0.45). Statistical tests show that the AF drift ratio is significantly smaller than the RW drift ratio at the 0.01 level. These results support the argument that there is relatively less underreaction in analyst-based earnings surprise than in time-series based earnings surprise, which is our *H1*.[6]

4.2. Relation between earnings surprises and the market responses: across time

In this sub-section, we further examine the changes of RW and AF drift ratios over time. Table 3 reports the results of the regression model based on equation (2) on different sample periods. Results in the last two columns show that there is no significant difference in the drift ratios between *SUE* and *SUEAF* model until 1998. However, the AF drift ratio has been consistently lower than the RW drift ratio since 1999. We also note that there is no drastic change in the magnitude of *CAR(Earnings Announcement Window*) and *CAR(Drift)* in *DSUE* model over time. On the contrary, there have been a significantly greater *CAR(Earnings Announcement Window*) and smaller *CAR(Drift)* since 1999 for the *DSUEAF* model than in earlier sample periods, which results in a smaller AF draft ratio in recent years compared with that in previous years.

Alternatively, to examine the changes of RW and AF drift ratios over time we include recency variable in the regression model and interact it with earnings surprise measures as follows:

$$CAR_{it} = \gamma_0 + \gamma_1 Earnings\_Surprise_{it} + \gamma_2 Earnings\_Surprise_{it} * Recency_{it} + \varepsilon_{it} \quad (3)$$

[6] If either the coefficient estimate on *Earnings_Surprise* for *CAR(Earnings Announcement Window)* or for *CAR(Drift)* is negative for a certain quarter, the quarter is dropped for the mean and median drift ratio calculations. Out of one hundred and eight sample quarters (Q1/1984-Q4/2010), seventeen quarters are dropped for the mean RW drift ratio calculation, while fourteen quarters are dropped for the mean AF drift ratio calculation.

where *Earnings_Surprise* is either *SUE* or *SUEAF*, and *Recency* indicates how current the sample firm-quarters are. *Recency* equals zero if a firm-quarter belongs to Q1/1984 and increases by one as the firm-quarters move on to the following quarters. Thus its maximum value is 107 when the firm-quarters belong to the most recent sample quarter (Q4/2010).

The results in Table 4 show that the market response toward earnings news changes over time both in time-series based and analyst-based earnings surprises. Specifically, the results in column (1) (i.e., *CAR(Total)* as a dependent variable) show that when recency is zero, which means at Q1/1984, the hedge portfolio strategy of taking a long position on highest decile *SUE* and a short position on the lowest decile *SUE* brings 9.58% return (in Panel A), while the corresponding strategy brings 9.23% return for *SUEAF* model (in Panel B). However, -0.0003 coefficient estimate on *DSUE***Recency* in Panel A indicates that as time passes by and samples get one-quarter recent the same hedge portfolio strategy for *SUE* model get 0.03% smaller returns, while the hedge portfolio strategy for *SUEAF* model gets 0.03% greater returns (note that the coefficient estimate on *DSUEAF***Recency* is 0.0003 in Panel B).

The results in column (2) and column (3) provide more detailed information. When *CAR(Earnings Announcement Window)* is used as a dependent variable the coefficient estimates on both *DSUE***Recency* (0.0001 in Panel A) and *DSUEAF***Recency* (0.0007 in Panel B) are positive and significant. On the contrary, when *CAR(Drift)* is used as a dependent variable the coefficient estimates on both *DSUE***Recency* (-0.0004 in Panel A) and *DSUEAF***Recency* (-0.0005 in Panel B) are negative and significant. These results suggest that investors' instant response toward analyst forecast based earnings surprise increase much more than toward time-series based earnings surprise over time. However, investors' delayed reactions decrease about the same magnitudes for the time-series based earnings surprise and the analyst-based earnings surprise over time. From these results, we can infer that the delayed portion of investors' response relative to its total market response (i.e., a drift ratio) becomes smaller in recent years than in previous years especially for analyst-based earnings surprises.

Figure 1 confirms the difference in drift ratios between *SUE* and *SUEAF* models graphically. In this figure, we plot the drift ratios of both the *SUE* and *SUEAF* model for each year from 1984 to 2010. The figure shows that the drift ratio of *SUEAF* has consistently been lower than the drift ratio of *SUE* since 1993 and that the gap has widened following years.

In sum, the findings in Table 3, Table 4, and Figure 1 support our *H2* and show that there is an increase in the magnitude of investor response to earnings surprises at the earnings announcement window, while there is a decreasing delayed investor reaction in the drift window over time. From the former, we infer that on average the informativeness of earnings news, especially when it is based on analyst forecasts, has increased over time. In other words, we infer that analysts are providing more relevant and meaningful earnings forecasts in recent years than in previous years. Additionally, from the finding of a decreasing delayed investor reaction in the drift window over time, we infer that the market is increasingly more efficient in interpreting the impact of current news information to future earnings.

4.3. Effect of informativeness of earnings forecasts on the relation between earnings surprises and the market responses

To examine the informational role of earnings forecasts and its impact on the relation between earnings surprises and the market responses, we use proxies for the informativeness of earnings forecasts (i.e., *Mean Abs.* $SUE_{(t-12,\ t-1)}$ and *Mean Abs.* $SUEAF_{(t-12,\ t-1)}$). As discussed earlier, lower values mean that earnings forecasts, which are either based on time-series or analyst forecasts, were closer to the actual earnings for the past twelve quarters for a specific firm. Therefore, we can infer that a low value is associated with a more informative earnings forecasting model for the firm.

We apply our operational proxies to the analysis as follows. First, we multiply by negative one to the measure to make a high value mean high informativeness. Next, similar to the adjustment process for *SUE*, we transform *(-)Mean Abs.* $SUE_{(t\text{-}12,\, t\text{-}1)}$ into decile ranks scaled between 0 and 1 by sorting firms according to every quarter. We then subtract 0.5 from the measure to create *D_Mean Abs.* $SUE_{(t\text{-}12,\, t\text{-}1)}$. Finally, we interact *DSUE* with *D_Mean Abs.* $SUE_{(t\text{-}12,\, t\text{-}1)}$ and include the interaction term in our original regression model. Similarly, we also adjust *Mean Abs.* $SUEAF_{(t\text{-}12,\, t\text{-}1)}$ and interact with *DSUEAF*. We run the regression model as follows:

$$CAR_{it} = \gamma_0 + \gamma_1 Earnings\_Surprise_{it} + \gamma_2 Earnings\_Surprise_{it} * Informativeness_{it} + \varepsilon_{it} \quad (4)$$

The results of the regression analyses are shown in Table 5. The results show that the informativeness of earnings forecasts has an incremental effect on the relation between earnings surprises and the market responses both in time-series based and analyst-based earnings surprises. Specifically, from the results shown in column (1) (i.e., *CAR(Total)* as a dependent variable), for median *Mean Abs.* $SUE_{(t\text{-}12,\, t\text{-}1)}$ observations, the hedge portfolio strategy of taking a long position on highest decile *SUE* and a short position on the lowest decile *SUE* brings 7.62% return (in Panel A), while the corresponding strategy brings 11.13% return for *SUEAF* model (in Panel B). However, the hedge portfolio strategy of taking a long position on both the highest decile *SUE* and the highest decile of *D_Mean Abs.* $SUE_{(t\text{-}12,\, t\text{-}1)}$ and taking a short position on both the lowest decile *SUE* and the lowest decile of *D_Mean Abs.* $SUE_{(t\text{-}12,\, t\text{-}1)}$ brings an additional 3.71% return. Similarly, the hedge portfolio strategy considering *D_Mean Abs.* $SUEAF_{(t\text{-}12,\, t\text{-}1)}$ brings additional (and coincidentally the same) 3.71% returns, which can be seen in Panel B. These results suggest that investors understand the historical performances of both earnings forecasts measures and respond more to the same size of earnings surprise when earnings forecasts have been historically accurate than when earnings forecasts have not been very accurate.

Moreover, we note that the results in Panel A show that the larger incremental effect occurs in the drift window (2.25% shown in column (3)) than at earnings announcement window (1.46% shown in column (2)) in time-series based earnings surprises. On the contrary, the results in Panel B show that the larger incremental effect occurs in the earnings announcement window (3.16% shown in column (2)) compared to the drift window (0.55% shown in column (3) and insignificant) in analyst-based earnings surprises. This finding suggests that investors respond faster to the earnings news with more accurate analyst forecasts than to the earnings news with more accurate time-series earnings expectations. Therefore, we can infer that the informativeness of analyst-based earnings forecasts, proxied by historical forecast accuracy, is superior to the informativeness of time-series based earnings forecasts in terms of inducing investors' timely responses.

The last two columns of Table 5 show how different the drift ratios are with and without consideration of the past earnings forecast accuracy. Without considering the incremental effect of informativeness of earnings forecasts, the drift ratio of *SUE* is 45%, while the drift ratio of *SUEAF* is 35%. However, after including the informativeness interaction term, the drift ratio of *SUE* model becomes 50%, which is five percentage point higher than the model without the interaction term. On the contrary, after including the informativeness interaction term, the drift ratio of *SUEAF* model becomes 26%, which is nine percentage point lower than the model without the interaction term. These results suggest that the informativeness of analyst earnings forecasts expedites investors' responses, while informativeness of time-series based earnings forecasts brings delayed investors' responses.[7]

We also run the regression model (4) separately in each quintile rank of our informative measures. The results are provided in Table 6. Rank 1 represents the firm-quarter observations with the least informative earnings forecasts (i.e., the worst accurate past forecasts), while rank 5 represents those with the most informative earnings forecasts (i.e., the most accurate past forecasts). Consistent with the results in Table 5, the total market responses to the earnings surprises (i.e., *CAR(Total)*) increase both in the *SUE* (shown in Panel A) and *SUEAF* models (shown in Panel B) as the level of earnings forecast informativeness improves.

The results also show that both *CAR(Earnings Announcement Window*) and *CAR(Drift)* increase almost monotonically in the level of informativeness in both the *SUE* and *SUEAF* models. However, the increasing patterns in *CAR(Earnings Announcement Window*) and *CAR(Drift)* are different between *SUE* and *SUEAF* models. In the *SUE* model (Panel A), the market response in the drift window (i.e., *CAR(Drift)*) increases more than the market response in the earnings announcement window (i.e., *CAR(Earnings Announcement Window*)) as the level of informativeness increases, consistent with the results in Table 5. For example, at *(-)Mean Abs.* $SUE_{(t-12,\, t-1)}$ *Rank 1 CAR(Drift)* is 0.0269, while at *(-)Mean Abs.* $SUE_{(t-12,\, t-1)}$ *Rank 5 CAR(Drift)* is 0.0418, suggesting that *CAR(Drift)* increases about 55%. In contrast, the *CAR(Earnings Announcement Window*) increases from 0.0380 to 0.0536, which represents a 41% increase. Therefore, as we can see in the last column of Table 5, the drift ratio increases in the level of informativeness of *SUE* model.

[7] Ex ante, we do not expect to find that delayed investor reaction increases more toward historically more accurate time-series based earnings news than toward historically less accurate time-series based earnings news.

We find in Table 5 that the drift ratios have decreased when the informativeness of earnings forecasts for the *SUEAF* model has increased. The results in Panel B of Table 6 confirm this finding. For example, the market response in the earnings announcement window (i.e., *CAR(Earnings Announcement Window)*) increases more than the market response in the drift window (i.e., *CAR(Drift)*) as the level of informativeness increases. For example, at *(-)Mean Abs.* $SUEAF_{(t\text{-}12,\ t\text{-}1)}$ *Rank 1 CAR(Earnings Announcement Window)* is 0.0605, while at *(-)Mean Abs.* $SUE_{(t\text{-}12,\ t\text{-}1)}$ *Rank 5 CAR(Earnings Announcement Window)* is 0.0916, suggesting that *CAR(Earnings Announcement Window)* increases about 51%. In contrast, the *CAR(Drift)* increases from 0.0359 to 0.0452, which represents only 26% increase. Thus, as we can see in the last column of Table 6, the drift ratio decreases in the level of informativeness of *SUEAF* model.

In sum, based on the findings in Table 5 and Table 6, we infer that investors do care about the accuracy of past earnings forecasts which are either analyst-based or time-series based. Moreover, the results suggest that investors put more weight on the accuracy of analyst forecasts than on the accuracy of time-series based earnings forecasts when they instantly interpret and respond to the earnings news, which consequently mitigate the post-earnings-announcement drift. On the contrary, the accuracy of time-series based earnings forecasts increases, not decreases, the post-earnings-announcement drift.[8]

[8] Previous studies show that drift is positively associated with information uncertainty (e.g., Jiang et al. 2005; Zhang 2006; Francis et al. 2007). The characteristics of their measures of information uncertainty are different from our infomativeness measure and they are mainly firm specific. For example, they use firm size, number of analyst following, return volatility, stock trading volume, cash flows-accruals matching, etc, while the informativeness of earnings forecasts in our analysis is regarding the performance of past earnings forecasts. However, we can infer that highly accurate past earnings forecasts certainly reduce overall information uncertainty. Therefore, we should expect to find a greater AF drift for firms with lower informativeness levels in our analysis. Instead, we find that the magnitude of the AF drift for the lowest informativeness level (i.e., *(-)Mean Abs.* $SUEAF_{(t\text{-}12,\ t\text{-}1)}$ *Rank 1*) is 3.59%, while the magnitude of the AF drift for the highest informativeness level (i.e., *(-)Mean Abs.* $SUEAF_{(t\text{-}12,\ t\text{-}1)}$ *Rank 5*) is 4.52%. This is inconsistent with the reasoning based on prior literature. However, when we consider the total market reaction to earnings announcements and use drift ratios as alternative measure of underreaction, we see that the drift ratio decreases across the quintiles of firms ranked by their historical forecast accuracy.

4.4. Effect of firm-quarter characteristics on the relation between earnings surprises and the market responses

Finally, we examine whether there is a cross-sectional variation in the drift ratios to firm specific information environment. Prior research postulates that the magnitude of the post-earnings announcement drift is negatively associated with the quality of a firm's information environment. Following prior studies, we use firm size, number of analyst following, share price of the firm, and trading volumes as proxies for information environment and split the sample into two subsamples based on the median value at each quarter. We then run our main regression model based on the equation (2) separately.

Consistent with our hypothesis, the results in Table 7 show that when the quality of information environment is better or when information uncertainty is low, we find smaller drifts both in terms of the magnitude of the drifts and drift ratios. For example, in the sub-sample for firms smaller than median firm size (Panel A), the *CAR(Drift)* and the RW drift ratio are 0.0419 and 0.46, respectively, while they are 0.0168 and 0.39 in the sub-sample for firms greater than the median firm. Similarly, in the sub-sample for firms smaller than median firm size, the *CAR(Drift)* and the AF drift ratio are 0.0462 and 0.40, respectively, while they are 0.0250 and 0.27 in the sub-sample for firms greater than the median firm. The tests using three other information environments (in Panel B through Panel D) provide similar results as in Panel A.

More importantly, we note that the effect of information environment on the drift ratio is more prominent in the *SUEAF* model than in the *SUE* model. This is due to the fact that for the *SUE* model, for large firms, both the magnitude of the drift (0.0168) and the magnitude of the earnings announcement window response (0.0262) are significantly smaller than the corresponding drift (0.0419) and the earnings announcement window response (0.0494) for small firms. On the contrary, for the *SUEAF* model, the magnitude of the drift of large size firm sub-sample (0.0250) is significantly smaller than the corresponding drift of small size firm sub-sample (0.0462), but the magnitude of the earnings announcement window response of large size firm sub-sample (0.0667) is not very small compared to the corresponding earnings announcement window response of small size firm sub-sample (0.0703).

Likewise, in the analysis of number of analyst following (Panel B) for the *SUEAF* model, we find that in the sub-sample where the firms are followed by greater than median number of analysts, earnings announcement window response (0.0734) is even greater than that in the sub-sample where firms are followed by less than median number of analysts (0.0660), while the drift (0.0250) is smaller than the drift in the sub-sample where the firms are followed by smaller than median number of analysts (0.0482). The results are similar in share price analysis (Panel C) and trading volume analysis (Panel D).

Due to differences in the impact of a firm's information environment on changes in the magnitude of *CAR(Earnings Announcement Window)* and *CAR(Drift)* between *SUE* and *SUEAF*, the difference in RW drift ratio and AF drift ratio is more pronounced when the quality of information environment is good. Specifically, for smaller firms the RW drift ratio is 46% and the AF drift ratio is 40%, whereas for large firms the RW drift ratio is 39% and the AF drift ratio is 27%.

In sum, the findings in Table 7 show that the AF drift ratios are more sensitive to the firm's information environment than the drift ratios for time-series based earnings surprises. In other words, investors respond even faster and more thoroughly at the earnings announcement window to analyst-based earnings surprises than to time-series based earnings surprises when the quality of information environment is high. Based on this result, we infer that analyst forecasts are especially more useful and informative to investors than time-series based earnings forecasts when the quality of the information environment is high.

5. Additional tests

To check the robustness of the results, we conduct several additional tests. First, although we follow the typical research design of the most PEAD studies (i.e., pooled ordinary least squared regression), current research reveals that in the panel dataset the residuals may be correlated across firms or across time and thus OLS standard errors can be biased (Peterson 2009). Therefore, we examine our results using both firm and year-quarter clustered standard errors, and we find that our results are not affected by this alternative approach.

Second, we examine whether our results change depending on how to measure an earnings announcement window and a drift window. Replacing the original three day event window (i.e., (-1, 1) where 0 is earnings announcement date), we use five trading days as an earnings announcement window (i.e., (-1, 3)), and we measure a drift window starting on day four and ending one day after the following quarterly earnings announcement. Alternatively, we also define a drift window as (2, 60), following previous research (e.g., Liang (2003)), while maintaining the same three day earnings announcement window (-1, 1). Neither of the approaches makes significant differences in our findings, even though the magnitudes of the coefficients on various *CAR(Earnings Ann. Window)* and *CAR(Drift)* change a bit.

Third, when we measure analyst forecast based earnings surprise we include firm-quarters which are followed by at least one analyst. In an alternative setting, we increase the minimum number of analyst following to two or three, and examine if this stringent requirement makes any difference. The results show that as the minimum number of analyst following increases the coefficient estimate on *CAR(Drift)* decreases. Specifically, the coefficient estimate on *CAR(Drift)* is 0.0308 (0.0229) when firm-quarters are followed by at least two (three) analysts, while the corresponding coefficient is 0.0390 when firm-quarters are followed by at least one analyst. Even though the magnitudes of the coefficient estimates get smaller, however, they are still significant at the 0.01 level. We also find that AF drift ratio decreases as the minimum number of analyst following increases. These findings are consistent with earlier results in Table 7, showing that when firms are large or followed by more analysts both the magnitude of the drift and the drift ratio are small compared to the firms which are small or followed by less analysts.

6. Summary and conclusion

In this study, we examine differences in market responses between two different earnings forecasts model: analyst-based earnings forecasts and time-series based earnings forecasts. Extending prior literature which focuses on differences in post-earnings-announcement-drifts between the two models, we examine the differences in the delayed portion of investors' response relative to its total market response (i.e., a drift ratio). We believe that this alternative approach improves our understanding of the relation between different earnings surprises and its corresponding market reaction.

We find that the total market responses toward analyst-based earnings surprises are much greater than those toward time-series based earnings surprises. On the other hand, we find that the AF drift ratio is significantly smaller than the RW drift ratio. This result suggests that analyst forecasts, on average, are more relevant and meaningful to investors than time-series based forecasts. Hence, investors respond faster and more thoroughly around earnings announcement dates toward analyst-based earnings surprises than toward time-series based earnings surprises.

Examining sub-samples over time, we find that the differences mentioned above are more prominent in recent years. Specifically, investors' immediate responses toward analyst-based earnings surprises become larger over time, while investors' delayed responses become smaller over time. Based on these findings, we conclude that analysts, on average, provide more relevant and meaningful earnings forecasts in recent years compared with the earlier years in our sample period.

We also measure the informativeness of different earnings forecasts by using their past accuracy, and we examine its impact on the relation between earnings surprises and the market responses. We find that the total market response increases in the informativeness of earnings forecasts for both time-series based and analyst-based earnings forecasts. However, as the informativeness of earnings increase, investors' responses to the analyst-based earnings surprises increase more in instant form than in delayed form. In contrast, investors' delayed responses increase more than investors' instant responses toward time-series based earnings surprises. Thus, the AF drift ratio decreases, while the RW drift ratio increases as the informativeness of earnings forecasts increases. This result means that the past accuracy of analyst earnings forecasts provides more relevant and useful information to investors than the past accuracy of time-series based earnings forecasts in terms of inducing investors' timely responses.

Finally, we find that the drift ratio of analyst-based earnings surprise is smaller when the quality of the firms' information environment improves. More importantly, we find that the AF drift ratio is much smaller than the RW drift ratio when the quality of the firm's information environment is high. This means that investors respond much faster and more thoroughly at the earnings announcement window to analyst-based earnings surprises than to time-series based earnings surprises when the quality of the firms' information environment is high. Overall, our results complement existing research findings by utilizing a relative PEAD measure and provide a greater understanding toward the interpretation of both drifts.

References

Abarbanell, J. and V. Bernard. 1992. Tests of analysts' overreaction / underreaction to earnings information as an explanation for anomalous stock price behavior. *Journal of Finance* 47: 1181-1207.

Ayers, B., O. Li, and E. Yeung. 2011. Investor trading and the post-earnings-announcement drift. *The Accounting Review* 86: 385-416.

Bartov, E., D. Givoly and C. Hayn. 2002. The rewards to meeting or beating earnings expectations. *Journal of Accounting and Economics* 33: 173-204.

Bartov, E., S. Radhakrishnan and I. Krinsky. 2000. Investor Sophistication and Patterns in Stock Returns after Earnings Announcements. *The Accounting Review* 75: 43-63.

Bernard, V. and J. Thomas. 1989. Post-earnings announcement drift: delayed price response or risk premium? *Journal of Accounting Research* (Supplement): 305-340.

Bernard, V. and J. Thomas. 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics* 13:305-340.

Bhushan, R. 1994. An informational efficiency perspective on the post-earnings announcement drift. *Journal of Accounting and Economics* 18:45-65.

Brown, L., and M. Caylor. 2005. A temporal analysis of quarterly earnings thresholds: Propensities and valuation consequences. *The Accounting Review* 80: 423–440.

Brown, L. D., and J. C. Y. Han. 2000. Do Stock Prices Fully Reflect the Implications of Current Earnings for Future Earnings for AR1 Firms? *Journal of Accounting Research* 38: 149-164.

Brown, L., P. Griffin, L. Hagerman, and M. Zmijewski. 1987. An Evaluation of Alternative Proxies for the Market's Assessment of Unexptected Earnings. *Journal of Accounting and Economics* 159-193.

Dontoh, A., J. Ronen and B. Sarath. 2003. On the Rationality of the Post-Announcement Drift, *Review of Accounting Studies* 8: 69-104.

Doyle, J., R. Lundholm, M. Soliman. 2006. The extreme future stock returns following I/B/E/S earnings surprises. *Journal of Accounting Research* 44: 849-887.

Fama, E. F. 1998. Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics* 49:283-306.

Francis, J., R. LaFond, P. Olsson, and K. Schipper. 2007. Information uncertainty and post-earnings-announcement-drift. *Journal of Business Finance and Accounting* 34: 403-433.

Garfinkel, J. A. and J. Sokobin. 2006. Volume, Opinion Divergence, and Returns: A Study of Post-Earnings Announcement Drift. *Journal of Accounting Research* 44: 85-112.

Green, J., J. R. M. Hand, and M. T. Soliman. 2011. Going, Going, Gone? The Apparent Demise of the Accurals Anomaly. *Mangement Science* 57 (5): 797-816.

Grossman, S. J., and J. E. Stiglitz. 1980. On the Impossibility of Informationally Efficient Markets. *The American Economic Review* 70(3): 393-408.

Jacob, J., T. Lys and J. Sabino. 2000. Autocorrelation structure of forecast errors from time-series models: Alternative assessments of the causes of post-earnings announcement drift. *Journal of Accounting and Economics* 28: 329-358.

Jiang, G., C. Lee, and Y. Zhang. 2005. Information uncertainty and expected returns. *Review of Accounting Studies* 10: 185–221.

Ke, B., and S. Ramalingegowda. 2005. Do institutional investors exploit the post-earnings announcement drift? *Journal of Accounting and Economics* 39: 25-53.

Koh, K., D. A. Matsumoto, and S. Rajgopal. 2008. Meeting or beating analysts expectations in the post-scandal world: Changes in stock market rewards and managerial actions. *Contemporary Accounting Research* 25 (4): 1067–1098.

Liang, L. 2003. Post-earnings announcement drift and market participants information processing biases. *Review of Accounting Studies* 8: 321-345.

Livnat, J., and 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.

Mendenhall, R. 2002. How naïve is the market's use of firm-specific earnings information? *Journal of Accounting Research* 40: 841-863.

Mendenhall, R. 2004. Arbitrage risk and post-earnings-announcement drift. *Journal of Business* 77: 875-894.

Ng, J., T. O. Rusticus, and R. S. Verdi. 2008. Implications of transaction costs for the post-earnings announcement drift. *Journal of Accounting Research* 46: 661-696.

Park, C. W., and E. K. Stice. 2000. Analyst forecasting ability and the stock price reaction to forecast revisions. *Review of Accounting Studies* 5:259-272.

Peterson, M. A. 2009. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches *Review of Financial Studies* 22(1): 435-480.

Richardson, S., I. Tuna, and P. Wysocki. 2010. Accounting anomalies and fundamental analysis: A review of recent research advances. *Journal of Accounting and Economics* 50: 410-454.

Schipper, K. 1991. Analysts' forecasts. *Accounting Horizons* 5: 105-131.

Soffer, L. C., and T. Lys. 1999. Post-Earnings Announcement Drift and the Dissemination of Predictable Information. *Contemporary Accounting Research* 16: 305–31.

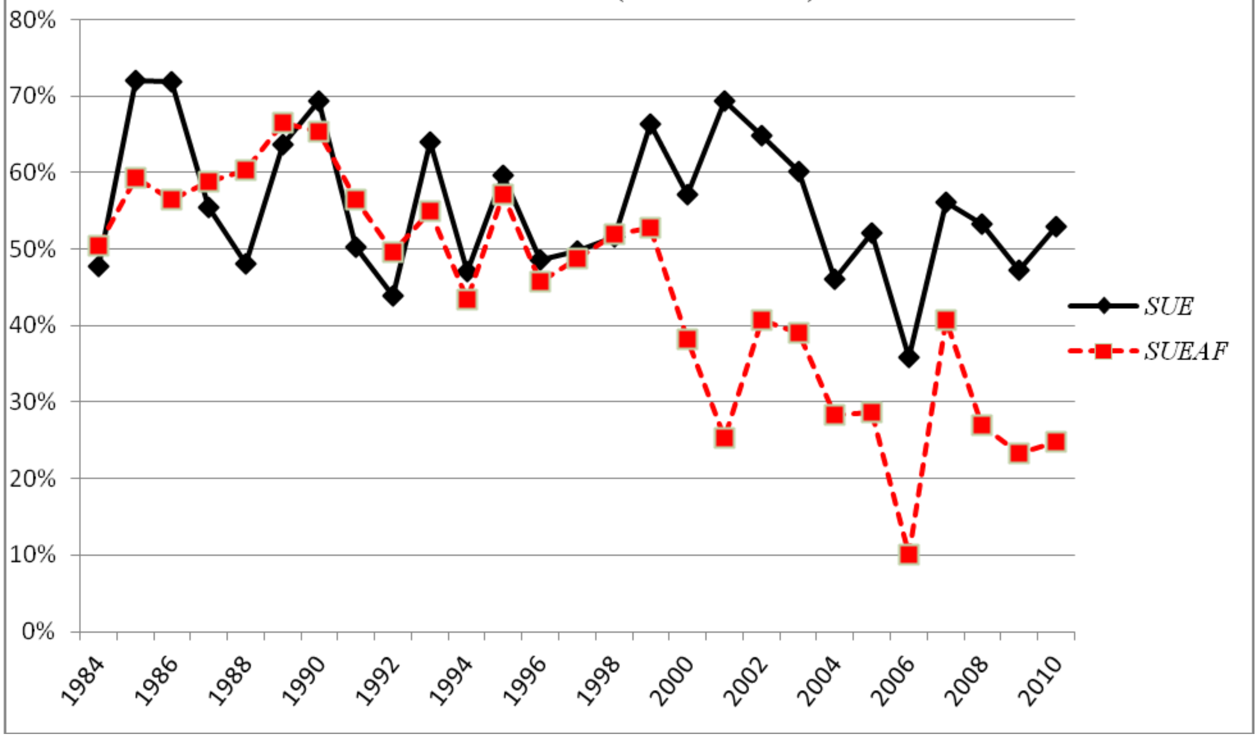
Vuong, Q.H.1989. Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica* 57, 307-333

Walther, B. R. 1997. Investor sophistication and market earnings expectations. Journal of Accounting Research 35 (2):157-179.

Zhang, F. 2006. Information uncertainty and stock returns. *Journal of Finance* 61:105-136.

Zhang, Y. 2008. Analyst responsiveness and the post-earnings announcement drift. *Journal of Accounting and Economics* 46: 201-215.

FIGURE 1
Drift Ratios over Time (*SUE* vs. *SUEAF*)



This figure reports drift ratio patterns across years when earnings surprises are measured using time-series model (*SUE*) and analysts' forecast based model (*SUEAF*). Drift ratio is calculated by the slope coefficient in the regression of *CAR(Drift)* on the earnings surprise decile rank (*DSUE* or *DSUEAF*) divided by the slope coefficient in the regression of *CAR(Total)* on the earnings surprise decile rank (*DSUE* or *DSUEAF*). *CAR(Drift)* is the abnormal return on a stock, cumulated from two days after an earnings announcement through one day after the next quarterly earnings announcement. *CAR(Total)* is the abnormal return on a stock, cumulated from one day before an earnings announcement through one day after the next quarterly earnings announcement. The abnormal return is the raw return minus the average return on a same size-B/M portfolio (six portfolios), as provided by Professor French.

TABLE 1
Summary Statistics

Variable	N	Mean	Std. Dev.	10^{th} Pctl.	25^{th} Pctl.	50^{th} Pctl.	75^{th} Pctl.	90^{th} Pctl.
SUE	224,412	-0.0004	0.4106	-0.0238	-0.0047	0.0015	0.0056	0.0180
SUEAF	224,412	-0.0028	0.1150	-0.0069	-0.0010	0.0003	0.0019	0.0055
CAR(Total)	224,412	-0.0091	0.2384	-0.2674	-0.1217	-0.0051	0.1083	0.2412
CAR(Earnings Ann. Window)	224,412	0.0016	0.0824	-0.0816	-0.0334	0.0008	0.0372	0.0871
CAR(Drift)	224,412	-0.0107	0.2209	-0.2469	-0.1132	-0.0068	0.0964	0.2177
Mean Abs. $SUE_{(t\text{-}12,\ t\text{-}1)}$	219,196	0.0870	3.1516	0.0025	0.0042	0.0089	0.0210	0.0513
Mean Abs. $SUEAF_{(t\text{-}12,\ t\text{-}1)}$	215,609	0.0074	0.0518	0.0005	0.0010	0.0023	0.0053	0.0126
MCAP(in $million)	224,412	3,692	15,597	68	171	552	1,922	6,430
Price	224,412	45.03	1393.00	5.50	10.90	20.50	33.88	49.81
NUMEST	224,412	4.7	4.6	1.0	1.0	3.0	6.0	11.0
VOLUME	224,325	0.0070	0.0087	0.0012	0.0022	0.0044	0.0087	0.0155

This table includes all firm-quarters with data to calculate *SUE*, *SUEAF*, and returns during the period Q1/1984 to Q4/2010.

SUE = earnings per share before extraordinary items (Compustat item EPSPXQ) minus (adjusted) earnings per share in the same quarter of the prior year, scaled by the price per share at the end of the quarter;

SUEAF = the I/B/E/S actual minus I/B/E/S median forecast in the 90-day period before the earnings announcement date, scaled by price per share at quarter end. We require firm-quarters to have at least one analyst forecast during the 90-day period before the disclosure of earnings;

CAR(Total) = *CAR(Drift)* + *CAR(Earnings Announcement Window)*;

CAR(Earnings Ann. Window) = cumulative abnormal return for the three-day window (−1,+1) centered on the earnings announcement date of the current quarter *t*. The abnormal return is the raw return minus the average return on a same size-B/M portfolio (six portfolios), as provided by Professor French;

CAR(Drift) = abnormal return on a stock, cumulated from two days after an earnings announcement through one day after the next quarterly earnings announcement;

Mean Abs. $SUE_{(t\text{-}12,\ t\text{-}1)}$ = average absolute values of *SUE* of the past twelve quarters. If the firm-quarters have less than nine *SUE*s during the past 12 quarters, it is regarded as missing;

Mean Abs. $SUEAF_{(t\text{-}12,\ t\text{-}1)}$ = average absolute values of *SUEAF* of the past twelve quarters. If the firm-quarters have less than nine *SUEAF*s during the past 12 quarters, it is regarded as missing;

MCAP (in $million) = number of shares outstanding * price per share at the end of the quarter;

Price = share price at the end of the quarter;

NUMEST = number of analyst forecasts used in *SUEAF*;

VOLUME = average daily turnover during forty-five days before the earnings announcement, where daily turnover is the ratio of the number of share traded each day to the number of shares outstanding.

TABLE 2
Regression of Abnormal Returns on Earnings Surprises

Panel A. *Regression of CARs on DSUE*

	Dependent Variable			Drift ratio	
	CAR(Total) (1)	*CAR(Earnings Ann. Window)* (2)	*CAR(Drift)* (3)	Mean	Median
Intercept	-0.0088	0.0018	-0.0106		
	(-17.49)	(10.49)	(-22.68)		
DSUE	0.0737	0.0407	0.0330	0.51	0.55
	(42.35)	(68.02)	(20.41)		
n	224,412	224,412	224,412		
Adj. R^2 (%)	0.79	2.02	0.19		

Panel B. *Regression of CARs on DSUEAF*

	Dependent Variable			Drift ratio	
	CAR(Total) (1)	*CAR(Earnings Ann. Window)* (2)	*CAR(Drift)* (3)	Mean	Median
Intercept	-0.0092	0.0016	-0.0107		
	(-18.40)	(9.44)	(-23.09)		
DSUEAF	0.1080	0.0690	0.0390	0.44	0.45
	(68.16)	(129.25)	(26.31)		
n	224,412	224,412	224,412		
Adj. R^2 (%)	2.03	6.93	0.31		
Incremental R^2 (%) over results in Panel A	1.24	4.91	0.12		
(Vuong's *Z*-statistic)	(18.02)	(42.78)	(4.31)		
Test of difference in drift ratios between Panel A and Panel B (p-value)				0.0041	0.0009

This table reports the results of regressing three different *CAR*s (i.e., *CAR(Total), CAR(Earnings Announcement Window),* and *CAR(Drift)*) on *DSUE (DSUEAF)*, respectively.

DSUE (or *DSUEAF*) is an adjusted decile rank of *SUE* (or *SUEAF*). It is calculated by sorting firms according to *SUE* (or *SUEAF*) every quarter, assigning the firms to ten groups, and assigning the decile rank to each firm within a decile. The measure is then divided by 9 minus 0.5.

Figures in parentheses denote *t*-statistics unless noted otherwise. A *t*-statistic of 2.58 implies a significance level of 0.01 using a two-tailed test. Vuong's *Z*-statistic refers to the *Z*-statistic from the likelihood ratio test proposed by Vuong (1989) for non-nested model selection. A *Z*-statistic of 2.58 implies a significance level of 0.01 using a two-tailed test.

TABLE 3
Instant vs. Delayed Earnings Response Coefficients and Drift Ratios over Time (Comparison between *DSUE* and *DSUEAF* measures)

Sample period (n)		*CAR(Total)*	*CAR(Earnings Ann. Window)*	*CAR(Drift)*	Drift Ratio Mean	Drift Ratio Median
1984-1986 (10,595)	*DSUE*	0.0897	0.0325	0.0572	0.62	0.68
	DSUEAF	0.0623	0.0284	0.0339	0.53	0.55
	Test-of-difference				*p*=0.3160	*p*=0.1289
1987-1989 (14,333)	*DSUE*	0.0840	0.0359	0.0481	0.52	0.57
	DSUEAF	0.0903	0.0338	0.0565	0.60	0.60
	Test-of-difference				*p*=0.1588	*p*=0.1294
1990-1992 (17,778)	*DSUE*	0.0943	0.0499	0.0444	0.47	0.53
	DSUEAF	0.1149	0.0564	0.0586	0.55	0.57
	Test-of-difference				*p*=0.1429	*p*=0.2754
1993-1995 (25,703)	*DSUE*	0.0847	0.0380	0.0467	0.53	0.59
	DSUEAF	0.1156	0.0549	0.0607	0.51	0.46
	Test-of-difference				*p*=0.8140	*p*=0.4648
1996-1998 (33,092)	*DSUE*	0.0673	0.0382	0.0290	0.47	0.51
	DSUEAF	0.1127	0.0608	0.0519	0.48	0.49
	Test-of-difference				*p*=0.8186	*p*=1.0000
1999-2001 (30,254)	*DSUE*	0.0692	0.0381	0.0311	0.59	0.60
	DSUEAF	0.1024	0.0674	0.0351	0.39	0.43
	Test-of-difference				*p*=0.0502	*p*=0.0625
2002-2004 (30,085)	*DSUE*	0.0664	0.0324	0.0340	0.50	0.57
	DSUEAF	0.0982	0.0715	0.0267	0.34	0.38
	Test-of-difference				*p*=0.1122	*p*=0.2500
2005-2007 (31,806)	*DSUE*	0.0924	0.0465	0.0459	0.45	0.49
	DSUEAF	0.1183	0.0889	0.0294	0.24	0.24
	Test-of-difference				*p* <.0001	*p*=0.0010
2008-2010 (30,766)	*DSUE*	0.0423	0.0491	-0.0068	0.47	0.47
	DSUEAF	0.1199	0.1076	0.0122	0.23	0.26
	Test-of-difference				*p*=0.0196	*p*=0.0313

This table reports the coefficients in the regression of three different *CAR*s (i.e., *CAR(Total), CAR(Earnings Announcement Window),* and *CAR(Drift)*) on *DSUE* and *DSUEAF*, respectively.
Drift ratio is calculated by the slope coefficient in the regression of *CAR(Drift)* on the earnings surprise decile rank (*DSUE* or *DSUEAF*) divided by the slope coefficient in the regression of *CAR(Total)* on the earnings surprise decile rank (*DSUE* or *DSUEAF*).
Mean (Median) drift ratio is the mean (median) quarterly drift ratios over the sample period.
t-statistics (Wilcoxon signed rank-statistics) is used for the test of mean (median) difference.
See Table 1 for the definitions of variables.

TABLE 4
The Effect of Time Horizon on the Relation between Earnings Surprises and the Market Responses

Panel A. *Regression of CARs on DSUE and its interaction with recency*

	Dependent Variable		
	CAR(Total)	*CAR(Earnings Ann. Window)*	*CAR(Drift)*
	(1)	(2)	(3)
Intercept	-0.0088	0.0018	-0.0106
	(-17.48)	(10.49)	(-22.68)
DSUE	0.0958	0.0349	0.0609
	(22.19)	(23.52)	(15.18)
*DSUE*Recency*	-0.0003	0.0001	-0.0004
	(-5.60)	(4.26)	(-7.60)
n	224,412	224,412	224,412
Adj. R^2 (%)	0.81	2.03	0.21

Panel B. *Regression of CARs on DSUEAF and its interaction with recency*

	Dependent Variable		
	CAR(Total)	*CAR(Earnings Ann. Window)*	*CAR(Drift)*
	(1)	(2)	(3)
Intercept	-0.0092	0.0015	-0.0107
	(-18.43)	(9.25)	(-23.04)
DSUEAF	0.0923	0.0237	0.0686
	(23.89)	(18.25)	(19.00)
*DSUEAF*Recency*	0.0003	0.0007	-0.0005
	(4.47)	(38.32)	(-8.99)
n	224,412	224,412	224,412
Adj. R^2 (%)	2.04	7.53	0.34

This table reports the coefficients in the regression of three different *CAR*s (i.e., *CAR(Total), CAR(Earnings Announcement Window),* and *CAR(Drift)*) on the earnings surprise and its interaction with recency factor (i.e., (*DSUE* and *DSUE*Recency*) or (*DSUEAF* and *DSUEAF*Recency*).

Recency equals zero if a firm-quarter belongs to Q1/1984 and increases by one as the firm-quarters move on to the following quarters, and thus its maximum value is 107 when the firm-quarters belong to the most recent quarter (i.e., Q4/2010).

See Table 1 for the definitions of variables.

TABLE 5
The Effect of Informativeness of Earnings Forecasts on the Relation between Earnings Surprises and the Market Responses

Panel A. *Regression of CARs on DSUE and its interaction with mean absolute SUE of the past 12 quarters*

	Dependent Variable			Drift ratio (excluding interaction term)	Drift ratio (including interaction term)†
	CAR(Total) (1)	*CAR(Earnings Ann. Window)* (2)	*CAR(Drift)* (3)		
Intercept	-0.0080	0.0019	-0.0099		
	(-15.84)	(10.95)	(-21.10)		
DSUE	0.0762	0.0419	0.0344	0.45	
	(42.01)	(67.02)	(20.37)		
*DSUE** *D_Mean Abs.* $SUE_{(t-12,\ t-1)}$	0.0371	0.0146	0.0225		0.50
	(6.11)	(6.97)	(3.99)		
n	219,196	219,196	219,196		
Adj. R^2 (%)	0.81	2.05	0.19		

Panel B. *Regression of CARs on DSUEAF and its interaction with mean absolute SUEAF of the past 12 quarters*

	Dependent Variable			Drift ratio (excluding interaction term)	Drift ratio (including interaction term)†
	CAR(Total) (1)	*CAR(Earnings Ann. Window)* (2)	*CAR(Drift)* (3)		
Intercept	-0.0085	0.0018	-0.0103		
	(-16.81)	(10.27)	(-21.70)		
DSUEAF	0.1113	0.0725	0.0388	0.35	
	(66.20)	(127.53)	(24.71)		
*DSUEAF** *D_Mean Abs.* $SUEAF_{(t-12,\ t-1)}$	0.0371	0.0316	0.0055		0.26
	(6.67)	(16.82)	(1.06)		
n	215,609	215,609	215,609		
Adj. R^2 (%)	2.05	7.15	0.30		

This table reports the coefficients in the regression of three different *CAR*s (i.e., *CAR(Total)*, *CAR(Earnings Announcement Window)*, and *CAR(Drift)*) on the earnings surprise and its interaction with informativeness proxy (i.e., (*DSUE* and *DSUE** *D_Mean Abs.* $SUE_{(t-12,\ t-1)}$) or (*DSUEAF* and *DSUEAF** *D_Mean Abs.* $SUEAF_{(t-12,\ t-1)}$)).

D_Mean Abs. $SUE_{(t-12,\ t-1)}$ (*D_Mean Abs.* $SUEAF_{(t-12,\ t-1)}$) is an adjusted decile rank of *Mean Abs.* $SUE_{(t-12,\ t-1)}$ (*Mean Abs.* $SUEAF_{(t-12,\ t-1)}$). It is calculated by multiplying negative one to *Mean Abs.* $SUE_{(t-12,\ t-1)}$ (*Mean Abs.* $SUE_{(t-12,\ t-1)}$), and then it is transformed into a decile rank by sorting firms according to every quarter. The measure is then divided by 9 minus 0.5.

†Drift Ratio (including interaction term) is calculated by the sum of the slope coefficient in the regression of *CAR(Drift)* on the earnings surprise decile rank and its interaction with informativeness proxy (i.e., (*DSUE* and *DSUE** *D_Mean Abs.* $SUE_{(t-12,\ t-1)}$) or (*DSUEAF* and *DSUEAF** *D_Mean Abs.* $SUEAF_{(t-12,\ t-1)}$)) divided by the sum of the slope coefficient in the regression of *CAR(Total)* on the earnings surprise decile rank and its interaction with informativeness proxy (i.e., (*DSUE* and *DSUE** *D_Mean Abs.* $SUE_{(t-12,\ t-1)}$) or (*DSUEAF* and *DSUEAF** *D_Mean Abs.* $SUEAF_{(t-12,\ t-1)}$))

See Table 1 for the definitions of variables.

TABLE 6
The Market Responses at Different Levels of Informativeness of Earnings Forecasts

Panel A. *The Earnings Response Coefficients at Different Levels of Informativeness of Time-series based Earnings Forecasts*

(-)*Mean Abs.* $SUE_{(t\text{-}12,\ t\text{-}1)}$ Quintile Rank		n	*CAR (Total)* (1)	*CAR(Earnings Ann. Window)* (2)	*CAR (Drift)* (3)	Drift Ratio
Rank1 (Least informative)	*DSUE*	43795	0.0649	0.0380	0.0269	0.41
Rank2	*DSUE*	43860	0.0693	0.0378	0.0315	0.45
Rank3	*DSUE*	43866	0.0762	0.0423	0.0338	0.44
Rank4	*DSUE*	43860	0.0899	0.0474	0.0425	0.47
Rank5 (Most informative)	*DSUE*	43815	0.0954	0.0536	0.0418	0.44

Panel B. *The Earnings Response Coefficients at Different Levels of Informativeness of Analyst-based Earnings Forecasts*

(-)*Mean Abs.* $SUEAF_{(t\text{-}12,\ t\text{-}1)}$ Quintile Rank		n	*CAR (Total)* (1)	*CAR(Earnings Ann. Window)* (2)	*CAR (Drift)* (3)	Drift Ratio
Rank1 (Least informative)	*DSUEAF*	43076	0.0964	0.0605	0.0359	0.37
Rank2	*DSUEAF*	43142	0.1092	0.0676	0.0416	0.38
Rank3	*DSUEAF*	43147	0.1092	0.0731	0.0360	0.33
Rank4	*DSUEAF*	43145	0.1242	0.0828	0.0414	0.33
Rank5 (Most informative)	*DSUEAF*	43099	0.1368	0.0916	0.0452	0.33

This table reports the coefficients in the regression of three different *CAR*s (i.e., *CAR(Total)*, *CAR(Earnings Announcement Window)*, and *CAR(Drift)*) on *DSUE* and *DSUEAF* at different informativeness levels (i.e., (-)*Mean Abs.* $SUE_{(t\text{-}12,\ t\text{-}1)}$ or (-)*Mean Abs.* $SUEAF_{(t\text{-}12,\ t\text{-}1)}$).

(-)*Mean Abs.* $SUE_{(t\text{-}12,\ t\text{-}1)}$ is *Mean Abs.* $SUE_{(t\text{-}12,\ t\text{-}1)}$ multiplied by negative one.

(-)*Mean Abs.* $SUEAF_{(t\text{-}12,\ t\text{-}1)}$ is *Mean Abs.* $SUEAF_{(t\text{-}12,\ t\text{-}1)}$ multiplied by negative one.

See Table 1 for the definitions of variables.

TABLE 7
The Effect of Firm Characteristics on the Relation between Earnings Surprises and the Market Responses

Panel A. *Firm size and drift ratios*

		n	*CAR(Total)*	*CAR(Earnings Ann. Window)*	*CAR(Drift)*	Drift ratio
MCAP is less than median	*DSUE*	112,179	0.0912	0.0494	0.0419	0.46
	DSUEAF	112,179	0.1165	0.0703	0.0462	0.40
MCAP is greater than median	*DSUE*	112,233	0.0430	0.0262	0.0168	0.39
	DSUEAF	112,233	0.0917	0.0667	0.0250	0.27

Panel B. *Number of analyst following and drift ratios*

		n	*CAR(Total)*	*CAR(Earnings Ann. Window)*	*CAR(Drift)*	Drift ratio
NUMEST is less than median	*DSUE*	111,580	0.0947	0.0486	0.0461	0.49
	DSUEAF	111,580	0.1143	0.0660	0.0482	0.42
NUMEST is greater than median	*DSUE*	112,832	0.0484	0.0310	0.0174	0.36
	DSUEAF	112,832	0.0985	0.0734	0.0250	0.25

Panel C. *Price and drift ratios*

		n	*CAR(Total)*	*CAR(Earnings Ann. Window)*	*CAR(Drift)*	Drift ratio
PRICE is less than median	*DSUE*	112167	0.0791	0.0444	0.0348	0.44
	DSUEAF	112167	0.1103	0.0688	0.0415	0.38
PRICE is greater than median	*DSUE*	112245	0.0611	0.0328	0.0282	0.46
	DSUEAF	112245	0.1029	0.0695	0.0334	0.32

Panel D. *Trading volumes and drift ratios*

		n	*CAR(Total)*	*CAR(Earnings Ann. Window)*	*CAR(Drift)*	Drift ratio
VOLUME is less than median	*DSUE*	112136	0.0876	0.0458	0.0418	0.48
	DSUEAF	112136	0.1059	0.0615	0.0444	0.42
VOLUME is greater than median	*DSUE*	112189	0.0619	0.0364	0.0256	0.41
	DSUEAF	112189	0.1105	0.0771	0.0334	0.30

This table reports the coefficients in the regression of three different *CAR*s (i.e., *CAR(Total), CAR(Earnings Announcement Window),* and *CAR(Drift)*) on *DSUE* and *DSUEAF* at different levels of firm characteristics such as firm size, number of analyst following, share price, and trading volumes.
See Table 1 for the definitions of variables.