Expected Earnings and the Post-Earnings-Announcement Drift*

Yaniv Konchitchki, Xiaoxia Lou, Gil Sadka, and Ronnie Sadka†

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Abstract

This paper studies competing explanations for the Post-Earnings-Announcement Drift (PEAD) anomaly. We decompose analyst-forecast error into a component predictable by prior stock returns and a surprise component, with the predictable component interpreted as expected earnings. Under the investment-based asset-pricing explanation for PEAD, both components are related to future earnings and thus to expected returns. In contrast, under the investor underreaction explanation, PEAD is driven only by the surprise component. We find that purging the expected earnings component reduces PEAD profits by up to 54%, which suggests that a substantial part of the PEAD is consistent with investment-based asset pricing.

JEL classification: G12, G14, M41

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†Yaniv is from the University of California at Berkeley, Haas School of Business email: yaniv@haas.berkeley.edu; Xiaoxia is from University of Delaware, email: lous@udel.edu; Gil is from Columbia University, email: gs2235@columbia.edu; and Ronnie is from Boston College, Carroll School of Management, email: ronnie.sadka@bc.edu.

1 Introduction

The Post-Earnings-Announcement Drift (PEAD) anomaly refers to the positive association between unexpected earnings and post-announcement returns (Ball and Brown, 1968). The literature proposes that PEAD can be explained by investor underreaction (e.g., Foster, Olsen, and Shevlin, 1984; Bernard and Thomas, 1989; Bernard and Thomas, 1990) and investment-based asset-pricing theory (Liu and Zhang, 2011). This paper provides empirical evidence suggesting that a substantial part of the PEAD is consistent with investment-based asset pricing by using two insights. These insights allow us to develop an empirical framework to differentiate between the two competing explanations for the PEAD. The first insight is that investors' expectations are incorporated into stock prices, and the second insight is derived from the investment-based asset pricing theory. That is, expected returns and expected earnings are proportionate in equilibrium. We document that proxies of earnings surprises such as analyst-forecast errors are predictable by prior stock returns.[1] The predictable component is interpreted as part of expected earnings since investors' expectations should have been incorporated in stock prices. We then demonstrate that the underreaction hypothesis and the investment-based explanation generate different predictions for PEAD returns after the predictable component of earnings surprises is taken into consideration.

A simplified version for the intuition behind our hypothesis development, for which a separate section is devoted in the paper, is as follows. As we notice that proxies of earnings surprises are predictable by prior stock returns (which reflect investor expectations), one can purge the expected component (expected by investors) such that the remaining component is an improved measure of earnings surprise. The underreaction hypothesis implies that the expected component does not contribute to the PEAD, because investors should not underreact to what they had already expected and incorporated into stock prices. There-

[1] One of the main measures of investor expectations of earnings is analyst forecasts. Brown and Rozeff (1978) show that analyst forecasts represent a superior expectation model for earnings compared with time-series models. Based on these results, many studies use analyst forecasts as a proxy for investor expectations of earnings. In a recent example, Chen and Zhao (2009) use analyst-forecast revisions to proxy for changes in expected future cash flows (cash-flow news). Other studies use analyst forecasts to infer the cost of capital (e.g., Gode and Mohanram, 2003; Easton, 2004; Barth, Konchitchki, and Landsman, 2013).

fore, removing the expected component of an earnings surprise proxy is essentially reducing the noise, thereby increasing the signal-to-noise ratio. Subsequently, PEAD returns should increase as the earnings surprise measure is estimated with less error (see, e.g., Livnat and Mendenhall, 2006).

Investment-based theory implies that expected returns and expected earnings are proportionate in equilibrium, as firms optimally choose investment until the discount rate (future stock returns) equals the marginal benefit of investment (future earnings) divided by the marginal cost of investment (see, e.g., Cochrane ,1991; Liu and Zhang, 2011; Lin and Zhang, 2012). Therefore, investment-based asset pricing provides an alternative explanation for PEAD, insofar as both components of an earnings surprise proxy, the expected and unexpected components, are related to future earnings and thus to expected returns. The high persistence of earnings implies a positive relation between the first component and expected return, while the second component affects investors' expectation about future earnings, which is, again, positively related to future expected return. Therefore, investment-based asset-pricing theory implies that purging the expected component of the earnings surprise proxy may either increase or decrease the PEAD depending on which of the two components—the expected component or the true earnings surprise proxy—has a stronger relation with expected returns. That is, the investment-based explanation does not provide a clear prediction for the effects of purging the expected component of the earnings surprise on PEAD returns. If purging the expected component of the earnings surprise results in higher PEAD returns, then it is not possible to distinguish between an investment-based explanation and an underreaction explanation. However, a decline in PEAD returns is consistent strictly with the PEAD driven in part by expected earnings, not with the underreaction explanation. Our empirical analysis shows that PEAD returns decline after purging the expected component of the earnings surprise, thereby providing supporting evidence for the investment-based asset-pricing explanation for the PEAD.

Our empirical analysis includes two parts. Prior studies have shown that analyst-forecast errors are predictable using pre-forecast stock returns. For example, Abarbanell (1991) documents that analyst forecasts do not fully reflect information in prior stock returns, leading to predictable forecast errors. Similarly, Lys and Sohn (1990) show that analysts incorporate approximately 66% of the information in stock prices (see also Ali, Klein, and Rosenfeld, 1992; Hughes, Liu, and Su, 2008). These studies examine the correlation between analyst-forecast errors and stock returns compounded over a few months or less prior to the forecast release date.[2] However, because we are interested in drawing inferences with respect to the PEAD, we cannot rely on the results in prior studies. This is because Chordia and Shivakumar (2006) show that such short-run returns, i.e., price momentum (see, Jegadeesh and Titman, 1993), are related to PEAD returns. To avoid the confounding effects of price momentum, we extend the analysis to test whether analyst forecasts incorporate information available in prior returns measured over longer periods prior to the release date. Specifically, our findings suggest that a high (low) stock return in year y–1 implies that year y earnings will be above (below) the mean analyst forecast released during year y. Moreover, we show that the stock return during year y–1 is more highly correlated with the forecast error in year y than with the earnings forecast itself.[3]

Next, we study the implications of the predictability of earnings surprise proxies for the PEAD anomaly. To purge the effects of past returns, we use the error term from a regression of forecast errors on returns accumulated during the prior year, y–1 (the twelve-month period beginning 24 months and ending 13 months prior to the earnings announcement). As noted above, we do not employ the returns immediately before the earnings announcement, (i.e., the twelve-month period beginning 12 months and ending one month prior to the earnings announcement) because we would like to demonstrate our incremental contribution beyond the documented short-term momentum effect depicted in Jegadeesh and Titman (1993). We

[2] For example, Lys and Sohn (1990) employ stock returns during a short period that begins at the release date of the prior forecast and ends two days prior to the release date of the new forecast—an average period of two months.

[3] In sum, our findings emphasize that analyst forecasts are a poor measure of investor expectations because the analyst forecast errors can be predicted using prior stock returns. Our findings are consistent with those reported by Bradshaw, Drake, Myers, and Myers (2009) who find that, in some cases, time-series-based earnings forecasts are superior to analyst forecasts. The results also suggest that the extent to which analysts incorporate public information is even lower than previously shown in the literature (e.g., Lys and Sohn, 1990). Prior studies infer the limited extent to which analysts incorporate information in stock prices through examining stock returns of only a few months prior to the earnings announcement. We show that analysts fail to incorporate information in stock prices even from two years prior to the earnings announcement.

also show that our findings are robust to controlling for a momentum factor. We find that using a better expectation model (one that purges the predictability of forecast errors using past returns) reduces the PEAD returns by up to 54%. We also find that the association between earnings news and future earnings growth declines when we improve the measure of earnings surprise. The results suggest that purging expected earnings from measures of earnings surprises reduces the relation between these measures and both future profitability (earnings) and future stock returns, consistent with the investment-based explanation. Note that while our results are inconsistent with underreaction-to-earnings-news being the full explanation for the PEAD, they do not suggest that the PEAD returns are unaffected by other behavioral biases. In particular, the positive association between expected earnings and expected returns may be driven by such behavioral biases.

Our main analysis is conducted using one measure of earnings surprise, analyst forecast errors. As robustness, we test whether our results hold for earnings growth. Consistent with our main findings, when we purge the expected component of earnings growth, PEAD returns declines. In addition, we test whether our results hold after controlling for earnings announcement returns (see Brandt, Kishore, Santa-Clara, and Venkatachalam, 2008). We first sort stocks into five portfolios based on earnings announcement returns. Within each portfolios, stocks are further sorted into five portfolios based on various measures of earnings surprises. Consistent with the investment-based explanation, PEAD returns decline when we improve the measure of earnings surprise. Finally, since price momentum exhibits similar characteristics as PEAD, we test wether our hypothesis applies to price momentum as well. Consistent with our PEAD results, we find that momentum returns decline when we purge the expected component of the returns during the formation period.

The remainder of the paper is organized as follows. Section 2 develops the hypotheses and describes the testing methodology. Section 3 describes the data and variables. Section 4 tests whether analyst forecasts incorporate the information in prior stock returns. Section 5 tests the implications of the predictability of forecast errors for the PEAD. Section 6 provides additional analysis. Section 7 concludes.

2 Hypotheses Development

We provide evidence that earnings surprise proxies, such as analyst-forecast error, are predictable by prior stock returns. Therefore, it is possible to decompose any proxy for earnings surprise, $\widehat{\mu}$, into two orthogonal components: an expected component, e, and an unexpected component (the true earnings surprise or shock), μ, where

$$\widehat{\mu}_{i,t} = e_{i,t} + \mu_{i,t}. \tag{1}$$

2.1 Alternative Explanations for the PEAD

The relation between returns and a proxy for earnings surprise, $\widehat{\mu}$, can be expressed as the relation of returns with each of the two components of $\widehat{\mu}$. Using a regression approach, this relation can be formulated as

$$R_{i,t+1} = a + \beta_e e_{i,t} + \beta_\mu \mu_{i,t} + \xi_{i,t+1}. \tag{2}$$

2.1.1 Underreaction Explanation

Since the discovery of the PEAD (Ball and Brown, 1968), the prevalent hypothesis for its existence was of a behavioral nature—investors underreact to the information in earnings.[4] For example, Bernard and Thomas (1990) suggest that investors fail to incorporate the implications of current earnings surprises into their earnings expectations, resulting in a price drift. Similarly, Abarbanell and Bernard (1992) suggest that analyst fail to incorporate the implications of current earnings surprises into their earnings expectations. Under the underreaction explanation, investors underreact to earnings news insofar as some of the information in earnings surprises, measured at time t, with respect to future cash flows are not entirely incorporated in stock prices at time t. Instead, after earnings are announced,

[4] While a behavioral hypothesis can explain the existence of the drift, it cannot explain its persistence over time. Some studies hypothesize that limits to arbitrage can explain the persistence of asset pricing anomalies (e.g., Pontiff, 1996), and PEAD in particular (e.g., Bhushan, 1994; Mendenhall, 2004; Ng, Rusticus, and Verdi, 2008; Chordia, Goyal, Sadka, Sadka, and Shivakumar, 2009).

investors slowly revise their expectations of future cash flows. This suggests that the coefficient on $e_{i,t}$ is zero and there is no relation between expected earnings and future returns. Investors would not react to information they already incorporated into prices.

In a regression format, the underlying relation between returns at time $t+1$ and unexpected earnings can be described as

$$R_{i,t+1} = a + \beta_{\mu,1}\mu_{i,t} + \varepsilon_{i,t+1}, \tag{3}$$

where

$$\beta_{\mu,1} = \frac{Cov(\mu_{i,t}, R_{i,t+1})}{\sigma_{\mu}^{2}}, \tag{4}$$

and $\mu_{i,t}$ is unexpected earnings. The underreaction hypothesis advances that the coefficient for $\mu_{i,t}$ is positive.

2.1.2 Investment-Based Explanation

The investment-based explanation for the PEAD is based on models that focus on firms' optimal investment decisions, such as those in Cochrane (1991), Liu and Zhang (2011), and Lin and Zhang (2012). More formally, Lin and Zhang (2012) show that the optimal investment condition in the q-theory model with two periods and constant returns is

$$r_{i,1}^{s} = \frac{\Pi_{i,1}}{1 + a(I_{i,0}/K_{i,0})}, \tag{5}$$

where $r_{i,1}^{s}$ is firm i's stock return from time zero to time one, $\Pi_{i,1}$ is future earnings (today is date 0), $I_{i,0}/K_{i,0}$ is investment-to-capital, and $a > 0$ is a constant. Intuitively, firm i keeps investing until the marginal cost of investment at date 0, $1 + a(I_{i,0}/K_{i,0})$, is equated to the marginal benefit of investment at date 1, $\Pi_{i,1}$, discounted to date 0 with the stock return, $r_{i,1}^{s}$, as the discount rate. Taking expectation on both sides of Equation (5) yields the relation that high expected earnings imply high expected return, conditional on investment (see also Liu, Whited, and Zhang, 2009).

Overall, the above logic suggests that earnings surprise proxies, $\widehat{\mu}_{i,t}$, can be positively correlated with future returns through two channels. The first channel is through the true unexpected earnings; that is, $cov\left(\mu_{i,t}, R_{i,t+1}\right)$ can be positive. This is because earnings surprise of current period increases investors' expectation for future earnings, which is positively related to future expected returns. That is, earnings surprise does not necessarily contain a cash-flow shock alone, but it also potentially includes a discount-rate shock. A high $\mu_{i,t}$ could imply that a company's projects are riskier than expected by investors, and investors consequently revise their expected returns upward. The second channel is through the expected component of earnings surprise proxies, $e_{i,t}$. $Cov\left(e_{i,t}, R_{i,t+1}\right) > 0$ because expected earnings are persistent. High expected earnings for time t is based on the riskiness of the projects undertaken by the company (i.e., a high discount rate), and expected returns of a company are quite persistent as the compositions of assets (and hence systematic risk) of a company are persistent (e.g., Berk, Green, and Naik, 1999). That is, unlike the underreaction hypothesis, the observed PEAD profits using an earnings surprise proxy potentially contains two sources, one for each of the two components of the earnings surprise proxy, $\widehat{\mu}_{i,t}$.

In a regression format, the relation between future return and the two components of $\widehat{\mu}_{i,t}$ is given by

$$R_{i,t+1} = a + \beta_e e_{i,t} + \beta_{\mu,2} \mu_{i,t} + u_{i,t+1}, \tag{6}$$

where

$$\beta_e = \frac{Cov(e_{i,t}, R_{i,t+1})}{\sigma_e^2}, \tag{7}$$

$$\beta_{\mu,2} = \frac{Cov(\mu_{i,t}, R_{i,t+1})}{\sigma_\mu^2}, \tag{8}$$

$e_{i,t}$ is the expected component of the earnings surprise proxy, and $\mu_{i,t}$ is the unexpected component (the two components of the earnings surprise proxy are orthogonal). Both β_e and $\beta_{\mu,2}$ are possibly positive, because $e_{i,t}$ and $\mu_{i,t}$ might be both positively correlated with future expected earnings, and thus expected returns. That is, the investment-based explanation allows both components to be related to future returns, and they can differentially impact future returns.

2.1.3 The Role of Expected Earnings in Testing the Two Hypotheses

The different sources of PEAD profits under the underreaction- and investment-based explanations suggest that one could test the two hypotheses by improving the proxies for earnings surprises. Particularly, we explore the role of the expected component of an earnings surprise proxy by removing it from the earnings surprise proxy and thereby arriving at a better measure for the true surprise. We show below that the use of such a measure for surprise yields different predictions for PEAD returns under the underreaction hypothesis and the investment-based hypothesis. Our paper is related to Vuolteenaho (2002), who finds that cash-flow news and discount-rate news are negatively correlated after decomposing news into a cash-flow component and a discount-rate component. However, since Vuolteenaho (2002) focuses on cash-flow news, that paper cannot differentiate between the underreaction and investment-based explanations. Specifically, $cov\left(\mu_{i,t}, R_{i,t+1}\right)$ can be positive, because either investors underreact to μ_t, or μ_t is associated with expected earnings at time $t+1$. Thus, focusing solely on the news component of the earnings announcements is inappropriate for testing the different explanations.

In contrast to Vuolteenaho (2002), we use the expected component of earnings growth in the analysis. The advantage of focusing on the expected component is that underreaction does not suggest a positive $cov\left(e_{i,t}, R_{i,t+1}\right)$. To illustrate, consider an underreaction explanation for this covariance to be positive. Assume investors expect a 1% earnings growth in a given period. A positive $cov\left(e_{i,t}, R_{i,t+1}\right)$ implies that, when a 1% earnings growth is realized during the period, investors are surprised, thus a positive cash-flow news, and investors also underreact to the news as reflected by a positive relation between $e_{i,t}$ and $R_{i,t+1}$, even though the outcome meets their expectations. We find this underreaction scenario highly unlikely, as it requires investors to underreact to their expectations, which are already incorporated in prices. We note, however, that the analysis does not preclude the possibility of a behavioral hypothesis for the PEAD. Specifically, the positive hypothesized relation between expected earnings and expected returns can be affected by behavioral biases.

2.2 Estimation of PEAD

Prior literature estimates PEAD returns using the following model:

$$R_{i,t+1} = a + \beta_{\widehat{\mu}}\widehat{\mu}_{i,t} + \omega_{i,t+1}, \tag{9}$$

where

$$\beta_{\widehat{\mu}} = \frac{Cov(\widehat{\mu}_{i,t}, R_{i,t+1})}{\sigma^2_{\widehat{\mu}}} \tag{10}$$

and $\widehat{\mu}_{i,t}$ is a proxy for earnings surprise. A positive estimated $\beta_{\widehat{\mu}}$ reflects PEAD profits.

Under the underreaction explanation, comparing Equation (3) and Equation (9), one observes that the estimated Equation (9) can be econometrically interpreted as a case of measurement error insofar as $\mu_{i,t}$ is measured with error using $\widehat{\mu}_{i,t}$ (such as in the case of using analyst-forecast errors to measure earnings growth unexpected by investors) and therefore the observed PEAD drift, i.e. the estimate of $\beta_{\widehat{\mu}}$ in Equation (9) is not an unbiased estimate of $\beta_{\mu,1}$. Formally,

$$\beta_{\widehat{\mu}} = \frac{\sigma^2_{\mu}}{\sigma^2_{\widehat{\mu}}}\beta_{\mu,1} < \beta_{\mu,1}. \tag{11}$$

That is, the PEAD reflects a shrunken $\beta_{\mu,1}$ (recall e and μ are orthogonal). If we improve our measure of earnings surprise, then the observed drift should increase, and if the surprise is perfectly measured, then the drift should be an unbiased estimate of $\beta_{\mu,1}$.

Under the investment explanation, given that $\widehat{\mu}_{i,t} = e_{i,t} + \mu_{i,t}$, in estimating Equation (9), one is estimating a constrained version of Equation (6), where $\beta_{\mu,2} = \beta_e$. The $\beta_{\widehat{\mu}}$ estimate of Equation (9) can be expressed as

$$\beta_{\widehat{\mu}} = \frac{\sigma^2_e}{\sigma^2_e + \sigma^2_{\mu}}\beta_e + \frac{\sigma^2_{\mu}}{\sigma^2_e + \sigma^2_{\mu}}\beta_{\mu,2}, \tag{12}$$

that is, $\beta_{\widehat{\mu}}$ is a weighted average of β_e and $\beta_{\mu,2}$. Therefore, the PEAD as documented in the literature reflects a weighted average of β_e and $\beta_{\mu,2}$.

2.3 Purging Expected Earnings

In this subsection, we show that when we purge $e_{i,t}$ (the component predictable by prior stock returns), which in turn improves the measure of earnings surprise, the two explanations yield different predictions on the impact of this purging on PEAD returns.

Specifically, to investigate the implications of purging the effect of $e_{i,t}$ on the PEAD, we estimate the coefficient for $\mu_{i,t}$ in the following regression:

$$R_{i,t+1} = a + \beta_\mu \mu_{i,t} + \nu_{i,t+1.} \tag{13}$$

In the case of underreaction, if we improve our measure of earnings surprise, then the observed drift will increase, and, if the surprise is perfectly measured, then the drift will be an unbiased estimate of $\beta_{\mu,1}$. In contrast, under the investment-based explanation, after purging the expected component of the earnings surprise proxy, the remaining drift is determined by $\beta_{\mu,2}$. Comparing the drift before purging, $\frac{\sigma_e^2}{\sigma_e^2+\sigma_\mu^2}\beta_e + \frac{\sigma_\mu^2}{\sigma_e^2+\sigma_\mu^2}\beta_{\mu,2}$, with $\beta_{\mu,2}$, we can conclude that whether we observe a higher drift after purging the expected component depends on the relative magnitudes of β_e and $\beta_{\mu,2}$. If β_e is higher than $\beta_{\mu,2}$, then we should observe a lower drift and vice versa.

2.4 Summary of Predictions

In sum, in our empirical analysis, we remove the expected component of earnings surprise proxies and estimate PEAD returns. An increase in PEAD returns is consistent with both an investment-based explanation and an underreaction explanation. However, a decline in PEAD returns is consistent only with an investment-based explanation, not with an underreaction explanation. This is because the underreaction hypothesis implies that, upon removing the expected component of the earnings surprise, PEAD returns should increase as the earnings surprise measure is estimated with less error.

In contrast, the investment-based explanation does not provide a clear prediction for the effects of purging the expected component of the earnings surprise on PEAD returns. If the observed PEAD returns decline when we purge the expected component of the earnings surprise, it suggests that $\beta_e > \beta_{\mu,2} \geqslant 0$. This is consistent with the investment-based explanation, i.e., higher discount rate will result in higher expected earnings growth. Our empirical analysis below shows that PEAD returns decline after purging the expected component of the earnings surprise, thereby providing supporting evidence for our hypothesis that expected earnings are a significant driver of the PEAD.

The table below summarizes the empirical predictions.

Decomposition of Earnings Surprise Proxy: $\widehat{\mu}_{i,t} = e_{i,t} + \mu_{i,t}$		
Summary of Predictions		
	Investors Underreaction	Investment-Based Asset Pricing
True Model:		
	$R_{i,t+1} = a + \beta_{\mu,1}\mu_{i,t} + \varepsilon_{i,t+1}$	$R_{i,t+1} = a + \beta_e e_{i,t} + \beta_{\mu,2}\mu_{i,t} + u_{i,t+1}$
PEAD Before Purging $e_{i,t}$: $R_{i,t+1} = a + \beta_{\widehat{\mu}}\widehat{\mu}_{i,t} + \omega_{i,t+1}$		
	$\beta_{\widehat{\mu}} = \frac{\sigma_\mu^2}{\sigma_{\widehat{\mu}}^2}\beta_{\mu,1}$	$\beta_{\widehat{\mu}} = \frac{\sigma_e^2}{\sigma_e^2+\sigma_\mu^2}\beta_e + \frac{\sigma_\mu^2}{\sigma_e^2+\sigma_\mu^2}\beta_{\mu,2}$
PEAD After Purging $e_{i,t}$: $R_{i,t+1} = a + \beta_\mu \mu_{i,t} + \nu_{i,t+1}$		
	$\beta_\mu = \beta_{\mu,1}$	$\beta_\mu = \beta_{\mu,2}$
Change in Drift $(\beta_\mu - \beta_{\widehat{\mu}})$:		
	Positive	Positive if $\beta_e < \beta_{\mu,2}$
		Negative if $\beta_e > \beta_{\mu,2}$

3 Data and Variable Definitions

Data on stock returns, prices, and shares outstanding are obtained from the Center for Research in Security Prices (CRSP). We obtain analyst earnings forecasts from the IBES Summary History—Summary Statistics with Actuals (EPS for U.S. Region) dataset. We use a firm's analyst mean earnings-per-share consensus forecast as the analyst forecast of the firm, which is then multiplied by the number of shares outstanding, adjusted for stock splits and stock dividends, on the last day of the period for which the forecast is calculated. For robustness, we also use the firm's analyst median earnings-per-share consensus forecast. The accounting data are for all U.S. firms, obtained from the Compustat North America Merged Fundamentals, XPF Tables, datasets. Earnings used in the paper are either Compustat's Earnings Before Extraordinary Items (Compustat data item IB) or IBES' Actual Earnings. For brevity, because IBES earnings and Compustat earnings yield similar results, we only tabulate the results using IBES earnings. Year y earnings change, denoted as $E_{i,y}–E_{i,y-1}$, is the difference between current earnings and last period's earnings. For quarterly analysis, Quarter q earnings change is defined as the earnings of Quarter q minus the earnings of Quarter q–4 (q denotes quarters).

Analyst forecast error, $E_{i,y}–F_{i,y}$, is the difference between the earnings of Year y and the consensus analyst forecast ($F_{i,y}$) for the period. Analyst forecasted earnings growth, $F_{i,y}–E_{i,y-1}$, is the analyst consensus forecast for the current period minus the previous period's earnings. We scale all three terms—$E_{i,y}–E_{i,y-1}$, $E_{i,y}–F_{i,y}$, and $F_{i,y}–E_{i,y-1}$—by the market capitalization at the end of the previous period. Earnings-price ratio, $E_{i,y}/P_{i,y}$, is Compustat earnings during Year y divided by the market capitalization at the end of that year. We calculate market value of equity by multiplying number of shares by stock prices, adjusted for stock splits and stock dividends, and we calculate annual returns by compounding each firm's CRSP monthly raw returns over the period. The sample period varies depending on the data availability. Our tests are based on 26 sample years over the period from 1985 through 2010.

Figure 1 plots the timeline for the analysis. In our annual analysis, annual return is the compounded return over the 12 months from April of calendar year y to March of calendar year y+1. Analyst forecasts for fiscal year y are made after March of calendar year y. Because we define year y as the 12 months from April of calendar year y to March of calendar year y+1, we use IBES and CRSP data from 1984 through 2010.

Table 1, Panel A, reports the summary statistics for the main variables used in our analysis. Panel A reports the mean, standard deviation, and various percentiles of earnings change, analyst forecast error, and analyst forecasted earnings growth, defined using earnings from both Compustat and IBES, as well as of earnings-price ratio and annual return. We calculate these statistics each year and then average across years from 1985 to 2010. The terms $E_{i,y}$–$E_{i,y-1}$, $E_{i,y}$–$F_{i,y}$, and $F_{i,y}$–$E_{i,y-1}$ have similar levels of standard deviation, all around 0.125-0.160 for the Compustat earnings group and 0.071-0.096 for the IBES earnings group. Both $E_{i,y}$–$E_{i,y-1}$ and $F_{i,y}$–$E_{i,y-1}$ have positive medians, while the median for $E_{i,y}$–$F_{i,y}$ is negative, suggesting that analysts are, on average, overly optimistic. Mean and median lagged earnings-price ratio are positive and equal 0.021 and 0.060, respectively, reflecting 2.1% and 6.0% accounting return on market value of equity. Mean and median annual return, Ret_y, are 19.4% and 11.7%, with a standard deviation of 53.4%, which indicates large variation of annual return over our sample period.

Table 1, Panel B, presents the correlation between returns (Ret_y), lagged returns (Ret_{y-1}), lagged earnings-price ratio (E_{y-1}/P_{y-1}), earnings change ($E_{i,y}$–$E_{i,y-1}$), earnings forecast error ($E_{i,y}$–$F_{i,y}$), and forecasted earnings growth ($F_{i,y}$–$E_{i,y-1}$). For each variable, we calculate Pearson and Spearman correlations by pooling observations across all firms and years in the sample. The total number of observations in the pooled correlations varies between 27,011 and 29,022 depending on the variable. Earnings changes and returns are contemporaneously positively correlated. There is evidence that price changes lead earnings changes because earnings changes and lagged returns are generally positively correlated. Lagged return is correlated with earnings change—the correlation varies between -0.02 and 0.25 across the different definitions of earnings. Lagged return is also correlated with $E_{i,y}$–$F_{i,y}$ (the correlation varies between 0.11 and 0.22), implying that analyst forecast errors can be predicted by prior year's stock returns. This result suggests that we can improve our estimates of investor expectations for future earnings by incorporating the information in historical stock prices. In addition, since the correlation between forecast errors and lagged stock returns is generally higher than the correlation between earnings growth and lagged stock returns, it is not clear that forecast errors provide a better measure of earnings surprise compared with earnings growth.

Our investigation on PEAD uses quarterly earnings announcements. Our monthly PEAD strategy starts from 1986. In each month from 1986 to 2010, we use the most recent quarterly announcement made in the previous three months. Therefore, our quarterly announcements start from 1985:3. There are 158,479 quarterly announcements in our sample period.

4 Do Analyst Forecasts Reflect Investor Expectations?

In this section, we test whether a common expected earnings proxy—analyst forecasts—fully reflect investor expectations by examining the predictability of forecast errors using past returns. To differentiate our effect from the well-studied intermediate momentum effect (e.g., Jegadeesh and Titman, 1993), we are mostly interested in the predictability of earnings surprise proxies using past stock returns that are measured over the one year that begins two years prior to the earnings release date. Our empirical analysis below reveals that analysts do not fully incorporate the information in stock prices when making their forecasts. Past stock returns (prior to the end of the prior period) predict analyst forecast errors.

Also, our tests below allow relating the sign and magnitude of the forecast error to the market's expectations prior to the end of the forecasting period. Specifically, our finding that lagged returns predict forecast errors suggests that analysts underestimate economic gains and losses embedded in stock returns. This is because, given a reported earnings, a positive return is associated with higher future forecast error. Also, the decreasing magnitude of the coefficient on lagged return as the forecasting period moves closer to the year-end illuminates the way analysts process information throughout the year, and it reveals a learning effect on the part of analysts—they gradually, yet only partially, process past information.

4.1 Firm-Level Cross-Sectional Regressions

We begin our empirical analysis by testing how well analyst forecasts represent investor expectations, as reflected in stock prices. Specifically, we estimate the following equation:

$$E_{i,y} - F_{i,y} = a_1 + c_1 \cdot Ret_{i,y-1} + \mu_{1,y}, \tag{14}$$

where $E_{i,y}$ is earnings for firm i in year y; $F_{i,y}$ is the earliest analyst forecast for firm i in the year y for the earnings at year y. The dependent variable is scaled by P_{y-1}, where P_{y-1} is the market capitalization at the end of fiscal year y–1. This regression model tests whether analyst forecasts represent investor expectations. The intuition underlying the model is as follows. If analyst forecasts fully reflect the information in prior stock prices, then prior stock returns will not predict forecast errors. Focusing on the return in the previous fiscal year, this would suggest that $c_1 = 0$. But, if analysts fail to incorporate all information reflected in prior stock prices, then prior stock return will predict forecast errors, i.e., $c_1 > 0$. Alternatively, if investors overreact to information, one would expect the coefficient on prior returns to be negative, i.e., $c_1 < 0$.

Note that prior studies suggest that non-stock-price-based variables can also predict analyst-forecast errors (e.g., Bradshaw, Richardson, and Sloan, 2001). However, investors may "miss" the same variables or be optimistic or pessimistic in the same way that analysts can be. In other words, analysts may be biased and inefficient yet still reflect investor expectations if investors are also similarly biased and inefficient. Because our focus is on the difference in efficiency between analysts and investors, our tests do not include non-price-based measures to forecast earnings.

The estimation results for Equation (14) are reported in Table 2, Panel A. We estimate the models using IBES actual earnings. The results using Compustat earnings are similar and therefore not reported for brevity. We estimate cross-sectional regressions each year using individual-firm observations. We report the mean, median, standard deviation, 5^{th} percentile, 25^{th} percentile, 75^{th} percentile, and 95^{th} percentile. Following Fama and MacBeth (1973), the table also reports the time-series t-statistic of the coefficients. Our findings suggest that analyst forecasts do not fully reflect the information in prior stock prices. The mean coefficient on lagged returns is positive and significant in Equation (14). Specifically, c_1 is 0.041 with the t-statistic of 6.01. The results shed light on the extent to which analyst forecasts fail to represent investor expectations.

Moreover, unreported results indicate that the stock return prior to the forecast is more associated with the forecast error than with the growth in earnings. For example, the average adjusted R^2 when regressing earnings growth on lagged stock returns is 2.3% compared with a 4.2% adjusted R^2 when regressing the forecast errors on lagged stock returns. These findings suggest that prior stock returns are more highly correlated with "unexpected earnings growth" (based on analyst forecasts) than with overall growth in earnings. While expectations using analyst forecasts are more accurate, on average, than time-series models, our findings suggest that they may not provide a superior measure of investor expectations. Because analyst forecast errors are more highly correlated with past stock returns, it is not clear whether the enhanced PEAD reported in Livnat and Mendenhall (2006) is due to an improvement in the measure of surprise.

4.2 Expanding the Interval between Stock Returns and Analyst Forecast Dates

The analysis in Table 2, Panel A, examines analyst forecasts that are measured shortly after the past return window and several months before the earnings release dates. Following prior studies documenting that analyst forecast precision improves as the forecast approaches the announcement date (see, e.g., Brown, Griffin, Hagerman, and Zmijewski, 1987; Brown, Richardson, and Schwager, 1987; Kross, Ro, and Schroeder, 1990), we repeat our tests in Table 2, Panel A, using more updated forecasts. Specifically, we regress analyst forecasts on lagged returns, sequentially changing the date of the analyst forecast, $F_{i,y}$, to include analyst forecasts that approach the earnings announcement at year y. This procedure expands the time interval between past stock returns and the analyst forecast dates because the return is computed over the prior fiscal year, y–1, and it will be useful for our next analysis of the PEAD. The results are reported in Table 2, Panel B.

The findings are consistent with prior studies insofar as the evidence suggests that analyst forecasts become more accurate as they approach the announcement date. The average estimate for c_1 declines from 0.041 for April forecasts to 0.011 for December forecasts. These results imply that as the forecast date approaches the earnings announcement date, analysts better incorporate the information in one-year-prior stock returns. In unreported results, we find similar evidence with respect to the intercept of the regression model, suggesting that the bias in analyst forecasts declines as we approach the reporting date.

However, most notably, analysts do not fully incorporate the information in stock prices even though they seem to update their forecasts over time. The relation between lagged stock returns and forecast errors remains positive. The coefficient c_1 for December forecasts has a t-statistic of 4.12. Our findings suggest that the extent to which analysts incorporate information already reflected in stock prices is even lower than previously revealed in prior studies (e.g., Lys and Sohn, 1990). These prior studies commonly use short window returns (of up to a few months) prior to the forecasts. Our findings reveal that a longer return window is appropriate when assessing the extent to which analysts incorporate public information reflected in stock prices.

4.3 Asymmetric Association between Lagged Stock Returns and Forecast Errors

Basu (1997) documents that accounting earnings are more significantly related to stock returns when stock returns are negative. Basu attributes his findings to accounting conservatism, which requires firms to recognize increases in value when they are realized and declines in value when they are anticipated. In addition, prior studies (e.g., Keane and Runkle, 1998; Bradshaw and Sloan, 2002) document that analysts tend to miss, or perhaps ignore, nonrecurring items, which tend to be negative. Accordingly, we extend our analysis to test whether positive and negative returns differ insofar as predicting forecast errors. Specifically, we estimate an extended version of Equation (14), as follows:

$$E_{i,y} - F_{i,y} = a + a_2 \cdot Dum_{i,y} + c_2 \cdot Ret_{i,y-1} + \delta_2 \cdot Dum_{i,y} \cdot Ret_{i,y-1} + \mu_{2,y}, \tag{15}$$

where $Dum_{i,y}$ is an indicator variable that receives the value of one if $Ret_{i,y-1} < 0$ and zero otherwise. Following the analysis in Table 2, Panel B, we change the analyst forecast, $F_{i,y}$, every month as it approaches the earnings announcement date of fiscal year y, while using the stock returns accumulated over the twelve months of year y–1. If analyst forecasts "miss" negative information more often than positive information, then we expect δ_2 to be positive.

The results are reported in Table 3. We report the distribution of the coefficient on lagged returns, c_2, and on the incremental slope, δ_2. The estimation results of the c_2 coefficient are consistent with the findings in Table 2, Panels A and B. The coefficient on lagged returns, c_2, is positive, and it declines when more recent forecasts are used. The average coefficient declines from 0.014 to 0.003. Our findings also reveal that analyst forecasts are generally more likely to "miss" bad news (measured by negative stock returns) than good news (measured by positive stock returns). Specifically, Table 3 shows that the incremental slope, δ_2, is positive and statistically significant in all models. Similar to our findings on the c_2 coefficient, the incremental coefficient on negative returns declines as we approach the announcement date. The average coefficient declines from 0.133 to 0.041. This positive slope suggests that analysts do not fully incorporate the information in stock prices for both favorable and unfavorable news (as measured by positive and negative returns, respectively).[5]

In addition to cross-sectional specifications employed throughout the paper, we estimate the models using firm-level, time-series regressions (e.g., Teets and Wasley, 1996; Sadka and Sadka, 2009). The results, unreported for brevity, show that the firm-level, time-series estimates for Equations (14) and (15) are consistent with the cross-sectional estimates reported in Tables 2 and 3. Moreover, following prior studies showing that the earnings-to-price ratio is associated with expected earnings growth (e.g., Easton, 2004), we examine whether the earnings-to-price ratio predicts analyst forecast errors and find that after controlling for contemporaneous and lagged returns, earnings-to-price ratio does not predict analyst forecast errors.

4.4 Quarterly Analysis

In addition to the analysis at the annual frequency, we also test whether quarterly analyst forecasts represent investor expectations. For the quarterly analysis, Quarter q is defined as the three months from the last month of calendar quarter q to the two months after the end of the calendar quarter q. As with the annual analysis, analyst forecasts for quarter q are made during the same time period, i.e., after the beginning of the last month of calendar quarter q. The results are reported in Table 4.

The quarterly results resemble the annual results described above. The relation between

[5] Our analysis employs the mean analyst forecast as a proxy for the consensus analyst forecast. We re-estimate the models in Tables 2 and 3, using the median instead of the mean analyst forecast as the measure for analyst consensus forecast. The resulting coefficient estimates resemble those reported in Tables 2 and 3.

earnings changes and lagged returns is positive. Specifically, in terms of Equation (14), the results that $c_1 > 0$ imply that analysts do not fully incorporate the information in prior stock returns when making their forecasts. In addition, our findings suggest that analysts mostly fail to incorporate bad news as reflected in negative stock returns. When estimating Equation (15), we find that the incremental slope, δ_2, is positive and statistically significant. Finally, consistent with our annual tests, in unreported quarterly analysis we find that prior quarter stock returns are more significantly related to the analyst forecast errors than to the forecasted earnings growth.

5 Earnings Surprises and PEAD

The previous section shows that analyst forecasts do not fully impound investor expectations reflected in past stock prices. Thus, in this section, we create a new expectation model that incorporates the information contained in past stock prices. We then proceed to examine the impact on PEAD returns after improving our measure of earnings surprises. The underreaction hypothesis implies that, upon removing the expected component of an earnings surprise proxy, PEAD returns should increase because the earnings surprise measure is estimated with less error. In contrast, the investment-based explanation does not provide a clear prediction on the effects of purging the expected component of forecast errors on PEAD returns. As developed in Section 2, when we improve our measure of earnings surprise, if $\beta_e < \beta_{\mu,2}$, that is, the impact of the predictable component of an earnings surprise proxy on discount rates is lower than the impact of earnings surprises on discount rates, then the PEAD returns will increase; conversely, if $\beta_e > \beta_{\mu,2}$, the observed PEAD returns should decline. Therefore, an increase in PEAD returns is consistent with both the investment-based explanation and the underreaction explanation, while a decrease in PEAD returns in consistent only with the investment-based explanation.

5.1 An Expectation Model for Forecast Errors

Our improved investor expectation model incorporates prior stock returns.[6] Specifically, we use the following model, which is estimated using firm-level, cross-sectional regressions:

$$E_{i,q} - F_{i,q} = a_1 + c_1 \cdot Ret_{i,q-7\rightarrow q-4} + \mu_{1,i,q}, \tag{16}$$

where $E_{i,q}$ denotes actual earnings for firm i in quarter q. The variable $F_{i,q}$ denotes the analyst forecast of quarter q earnings for firm i in quarter q. The dependent variable in the regressions is scaled by P_{q-4}, where P_{q-4} is the market capitalization at the end of fiscal quarter q-4. The return variable, $Ret_{i,q-7\rightarrow q-4}$, denotes the cumulative return of firm i for the period that begins 24 months and ends 13 months prior to the fiscal quarter end (i.e., from q-7 quarter-end until q-4 quarter-end).

Given the results in Table 4 about a differential effect for positive and negative returns, we include the following model as well:[7]

$$\begin{aligned} E_{i,q} - F_{i,q} &= a + a_2 \cdot Dum_{i,q} + c_2 \cdot Ret_{i,q-7\rightarrow q-4} + \\ &\quad + \delta_2 \cdot Dum_{i,q} \cdot Ret_{i,q-7\rightarrow q-4} + \mu_{2,i,q}, \end{aligned} \tag{17}$$

where the variable $Dum_{i,q}$ is an indicator variable that receives the value of one if $Ret_{i,q-7\rightarrow q-4} < 0$ and zero otherwise. Because Chordia and Shivakumar (2006) demonstrate that the PEAD and price momentum are related, our return accumulation period is determined such that our results would not be driven by the overlap between PEAD and the momentum effect (i.e., the return during the twelve-month period prior to the fiscal quarter end, $Ret_{i,q-3\rightarrow q}$). Figure 2 plots the timeline for this analysis.

[6] Note that it is not our goal to specify the perfect model for expected earnings. Our aim is to construct a parsimonious model for earnings expectations that better reflects investor expectations than one that uses analyst forecasts alone. Therefore, we only include stock-price-based variables to capture investor expectations reflected in stock prices.

[7] Both expectation models are estimated monthly when we sort stocks into portfolios using the most recent quarterly earnings announcement made in the previous three months.

5.2 Expected Earnings

Our expected earnings hypothesis implies that the PEAD represents a positive relation between expected earnings and expected returns. Since returns are measured at $t+1$, we test the extent to which our improved earnings measures predict earnings growth at $t+1$ as well as returns. The expected earnings hypothesis implies that as we improve the measure of earnings news, the associations of earnings news with future earnings and future returns will either (1) both decline, or (2) both increase. The latter result is consistent with the underreaction hypothesis as well.

Section 4 provides evidence suggesting that adding past returns provides a more accurate expectation model for earnings. Consequently, Equations (16) and (17) provide expectation models that better reflect investor expectations for earnings. We use the residuals from estimating Equations (16) and (17), $\mu_{1,i,q}$, and $\mu_{2,i,q}$, as proxies for earnings surprises. Specifically, at the beginning of each month t, we estimate Equations (16) and (17) using a firm's most recent earnings announcement made in months [t-3, t-1]. Our surprise measures provide better proxies for the surprise in earnings compared with analyst forecast errors ($E_{i,q}$–$F_{i,q}$). We then sort firms into five portfolios based on each of the measures of earnings surprises, $E_{i,q}$–$F_{i,q}$, $\mu_{1,i,q}$, and $\mu_{2,i,q}$. Table 5 reports the average future earnings growth for each of the five portfolios.

The results in Table 5 suggest that a better measure of earnings surprise is associated with a weaker relation with future earnings growth. For example, for the most positive earnings news (Portfolio 5), future earnings growth declines from 1.85% to 1.47% as we improve our measure of earning surprise from analyst forecast errors to $\mu_{2,i,q}$. The earnings growth difference between the most positive news and the most negative news declines from 3.02% to 2.20%. The last four columns of the table shows that these declines in future average profitability are statistically significant as well.

Our findings in Table 5 have implications for the PEAD returns. The investment-based explanation implies that as we improve the measure of earnings news, the associations of earnings news with future earnings and future returns will either (1) both decline, or (2) both increase. The evidence in Table 5—that improving the earnings surprise measure reduces the association between earnings surprises and future earnings growth—implies that we will also observe lower associations between earnings surprise and future returns as we move from forecast errors to μ_1 and μ_2. That is, we will observe lower drifts using the better measures of earnings surprises.

5.3 Revisiting the Post-Earnings-Announcement Drift

In this section, we proceed to investigate the association of earnings surprises with future returns as we improve the measure of earnings surprise. We use a portfolio approach to test the abnormal returns that the PEAD strategy generates. Specifically, at the beginning of each month t, we estimate Equations (16) and (17) using a firm's most recent earnings announcement made in months [t-3, t-1]. We then sort firms into five portfolios based on each of the three measures of earnings surprises, $E_{i,q}$–$F_{i,q}$, $\mu_{1,i,q}$, and $\mu_{2,i,q}$. As a benchmark asset-pricing model, we use the CAPM, Fama and French (1993) three-factor model (FF3), including the market return in excess of the risk-free rate (MKT–RF), the book-to-market portfolio return spread (HML), and the size return spread (SMB). In addition, we examine a model (FF4) that includes a momentum factor, UMD (see Fama and French, 1996; Carhart, 1997). To abstract from any potential influence of the above asset-pricing models on the earnings effect, Table 6 also includes average returns in excess of the risk-free rate.

Table 6 reports the results. When portfolios are sorted based on analyst-forecast errors, the average monthly excess returns, the CAPM, FF3, and FF4 alphas of the long-short portfolio spread of earnings surprise are significant (1.19, 1.21%, 1.29%, and 1.06%, respectively). This finding reflects the PEAD anomaly in our sample, and it is consistent with prior literature. When we include prior stock returns in our expectation model and create five portfolios using $\mu_{1,i,q}$, we find that the abnormal returns difference between the most positive earnings surprise and the most negative earnings surprise decline to 0.76%, 0.79%, 0.78%, and 0.56% for the average return, CAPM, FF3, and FF4 models, respectively. Using $\mu_{2,i,q}$ to sort stocks, the alphas further decline: 0.73%, 0.74%, 0.73%, and 0.48% for the average return, CAPM, FF3, and FF4 models, respectively. This reflects a reduction of approximately 38%-54% in PEAD returns. These results are also highlighted in Figure 3. This figure plots the abnormal returns for five earnings surprise portfolios for the three different earnings-surprise measures considered in Table 6. The figure shows that the abnormal returns decline as we improve the expectation model to better reflect investor expectations. The last four columns of Table 6 test the significance of these declines. The results are that all the declines in PEAD profits are statistically significant.

In sum, we find that as one improves the measurement of earnings surprises, the PEAD declines significantly and this decline is economically and statistically significant. Our findings, that the PEAD returns decline when we purge the expected component of earnings growth, offer additional insight into the PEAD anomaly. These findings contrast the hypothesis that investors underreact to earnings surprises, which suggests that better measures of earnings surprises generate higher drifts. However, as explained in Section 2, the findings are consistent with an investment-based explanation for the PEAD anomaly. The declines in PEAD returns are consistent with the declines in future earnings growth shown in Table 5. Taken together, the results in Table 5 and 6 show that improving the measure of earnings surprise results in weaker associations with both future earnings growth and future stock returns. These results are consistent with a positive association between expected earnings and expected returns.

6 Additional Analysis

6.1 An Analysis of Earnings Growth

One of the common expectation models for earnings growth is the random walk model. For robustness, we replicate the tests in Tables 2-6 using earnings growth instead of forecast errors. For this purpose, we employ the following improved expectation models:

$$
\begin{aligned}
E_{i,q} - E_{i,q-4} &= a_3 + c_3 \cdot Ret_{i,q-7\to q-4} + d_3 \cdot (F_{i,q} - E_{i,q-4}) + \mu_{3,i,q}, \qquad (18) \\
E_{i,q} - E_{i,q-4} &= a + a_4 \cdot Dum_{i,q} + c_4 \cdot Ret_{i,q-7\to q-4} + \delta_4 \cdot Dum_{i,q} \cdot Ret_{i,q-7\to q-4} \\
&\quad + d_4 \cdot (F_{i,q} - E_{i,q-4}) + \mu_{4,i,q}.
\end{aligned}
$$

The first model tests whether stock returns predict earnings growth, after controlling for forecasted growth. The second model accounts for the asymmetric association between lagged stock returns and earnings growth. The coefficients on forecasted growth, d_3 and d_4, signify whether analyst forecasts tend to be optimistic ($d < 1$) or pessimistic ($d > 1$). Prior studies (e.g., Butler and Lang, 1991) suggest the former, which implies that analyst forecasts tend to be positively biased. The coefficients on lagged returns signify whether lagged returns can predict earnings change after controlling for forecasted growth (Keane and Runkle, 1998).

For brevity, we do not tabulate the estimation results of Equations (18). Our findings are consistent with those in Table 2—past returns predict future earnings growth. Consistent with the findings reported in Table 2, the relation between prior stock returns and forecast errors declines as we approach the reporting date.

For robustness, we replicate the analysis in Table 6 using earnings growth. We employ $E_{i,q}$–$E_{i,q-4}$, $\mu_{3,i,q}$, and $\mu_{4,i,q}$ as our measures of earnings surprise. Specifically, at the beginning of each month t, we estimate Equations (18) using a firm's most recent earnings announcement made in months [t-3, t-1]. We then sort firms into five portfolios based on each of the three measures of earnings surprises, $E_{i,q}$–$E_{i,q-4}$, $\mu_{3,i,q}$, and $\mu_{4,i,q}$. The results, reported in Table 7, are consistent with those in Table 6. The PEAD declines when we purge the expected component of earnings growth. The profits of the long-short strategy decline from 1.04%, 1.07%, 1.12%, and 0.80% to 0.76%, 0.78%, 0.75%, and 0.50% for the average return, CAPM, FF3, and FF4 models, respectively. This reflects a reduction of approximately 27%–38% in PEAD profits.

6.2 Earnings Announcement Returns

Brandt, Kishore, Santa-Clara, and Venkatachalam (2008) document a significant drift following significant earnings announcement returns (EAR). While EAR reflects news across many dimensions of a company in addition to the news in earnings, we test whether our results are robust to the EAR returns. In the beginning of each month, we first sort stocks into five portfolios based on EAR, the market-adjusted cumulative returns in the three days surrounding an earnings announcement made in the previous three months. Within each EAR portfolio, stocks are further sorted into five portfolios based on various measures of earnings surprises. Table 8 reports the profits of an EAR-neutral zero-cost strategy that is long in stocks of the top quintile of earnings surprise measure and short in stocks in the bottom quintile of earnings surprise, averaged across the five EAR-sorted portfolios.

The results in Table 8 show that the returns of EAR-neutral zero-cost portfolios are generally slightly lower than those in Table 6 and 7. Most importantly, the PEAD returns decline when we improve the measure of earnings surprise after controlling for the effect of EAR. For example, the FF3 alphas of the PEAD returns drop from 1.13% to 0.73%, which reflects a drop of 35% when we move from forecast error to $\mu_{2,i,q}$. The decline is slightly lower than that reported in Table 6. Similarly, for example, when one moves from earnings change to $\mu_{4,i,q}$, the FF3 alphas of the PEAD strategy drop from 1.02% to 0.70%. The declines in PEAD returns within each EAR-neutral zero cost portfolio are similar in magnitude compared with the results in Table 7. These findings suggest that the decline in PEAD returns due to the improvement in earnings surprise measures is robust to the EAR effect.

6.3 Price Momentum and Expected Returns

Similar to the PEAD, Jegadeesh and Titman (1993) document a robust price momentum effect—returns for past winners are higher than the returns for past losers. The underreaction hypothesis argues that the momentum anomaly is a result of underreaction to the news in the portfolio formation period, the period over which past returns are measured. The rational hypothesis argues that past winners continue to outperform past losers because they have higher expected returns. To test whether the expected return hypothesis applies to the price momentum as well, we follow the same methodology employed in Tables 6 and 7 to the price momentum. The intuition is as follows. If the momentum returns are due to underreaction to news during the formation period, we should observe higher momentum profits when the momentum strategy is based on a better measure of surprise. Therefore, by decomposing the returns during the formation period into the expected and unexpected components and comparing the momentum anomaly between the basic return measure and the enhanced measure of surprise, we can test the underreaction hypothesis of the momentum anomaly. We use two models of expected returns for the formation period. The first model includes the 12-month return before the formation period, $Ret_{i,m-24\to m-13}$. The second model adds two more characteristics: size, and the book-to-market ratio, both measured before the beginning of the formation period. Specifically, for each month m, we estimate the following regression models:

$$Ret_{i,m-12\to m-2} = \xi_0 + \xi_1 \cdot Ret_{i,m-24\to m-13} + \kappa_{i,1,m} \qquad (19)$$

$$Ret_{i,m-12\to m-2} = \xi_0 + \xi_1 \cdot Ret_{i,m-24\to m-13} + \xi_2 \cdot Size_{m-13} + \xi_3 \cdot \frac{B}{M}_{m-13} + \kappa_{i,2,m}, \qquad (20)$$

where $Ret_{i,m-12\to m-2}$ is the cumulative return of a stock in the 11 months from month m-12 to month m-2; $Ret_{i,m-24\to m-13}$ is the cumulative return of a stock in the 12 months from month m-24 to month m-13. After estimating these two expected return models, we sort stocks based on $Ret_{i,m-12\to m-2}$, $\kappa_{i,1,m}$, and $\kappa_{i,2,m}$, and examine whether the momentum returns drop when we use $\kappa_{i,1,m}$ or $\kappa_{i,2,m}$ instead of $Ret_{i,m-12\to m-2}$. The results are reported in Table 9.

Table 9 reveals that the momentum returns decline consistently when we purge the expected returns component from $Ret_{i,m-12\to m-2}$. For example, the CAPM abnormal returns for momentum portfolios decline from 1.59% to 1.36% per month when we purge the expected returns component from $Ret_{i,m-12\to m-2}$, which represents a 15% decline in abnormal returns. These findings suggest that momentum returns do not fully represent an underreaction to news, because our findings imply that the price momentum returns are associated, in part, with past expected returns.

7 Conclusion

This paper studies competing explanations for the PEAD anomaly. We develop an empirical framework that can distinguish between an underreaction explanation and an investment-based explanation for PEAD, based on the implications of using an improved measure of earnings surprises. The PEAD anomaly, as posited by the literature, reflects a positive correlation between earnings surprise proxies and future (expected) returns in the cross-section of stocks. However, previous studies (e.g., Abarbanell ,1991; and Lys and Sohn, 1990) suggest that analyst forecasts do not fully incorporate the information in stock prices and, thus, analyst forecasts may not provide an appropriate measure for investor expectations of earnings. This paper shows that analyst-forecast errors are even more predictable than previously shown. Specifically, we demonstrate that returns for year y–1 predict forecast errors for forecasts made during year y, including forecasts made as late as December of year y. We also demonstrate that this predictability of forecast errors exists in quarterly data.

In light of the predictability of earnings surprise proxies, we devise an improved measure of surprises in earnings growth, utilizing returns in the year prior to the fiscal period. Forming portfolios using the improved measure of earnings surprises reduces PEAD profits by up to 54%, which is consistent with the investment-based explanation. While we do not preclude the possibility that the PEAD reflects behavioral biases, our results suggest that the PEAD returns are not fully driven by an underreaction to earnings news.

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Table 1. Summary Statistics and Correlations

The table presents summary statistics and correlations for the main variables used in the analysis. In Panel A for each variable, various percentiles (e.g., p5 is the 5th percentile), mean, and standard deviation (std) are calculated in each year y, and these statistics are then averaged across years in the sample. Panel B presents correlations among the main variables used in the analysis. For each variable, correlations are calculated by pooling observations across all firms and years in the sample. Year y is defined as the 12 months from April of calendar year y to March of calendar year $y+1$. Variable Ret_y is the compounded return in year y. Variable E_y denotes earnings, either from Compustat or IBES. Variable F_y denotes the earliest analyst mean consensus forecast made in April of year y for fiscal year y. Variables E_y-E_{y-1}, E_y-F_y, and F_y-E_{y-1} are scaled by P_{y-1}, the market capitalization at the end of fiscal year y-1. Variable E_{y-1} / P_{y-1} is the earnings-price ratio, calculated as Compustat earnings for year y-1 divided by year y-1 market capitalization. We require that the earnings of year y-1 are already announced before the beginning of year y. Our sample includes all NYSE, AMEX, and NASDAQ stocks that are in the intersection of CRSP, Compustat, and IBES datasets, with stock price higher than one dollar and December fiscal year-end. The earnings growth, forecast error, and forecasted growth variables, using Compustat and IBES earnings, are winsorized each period at one and ninety nine percentiles. The sample period is 1985 to 2010.

Panel A: Summary Statistics

Variable		Mean	std	p25	Median	p75
Compustat Earnings	$E_y - E_{y-1}$	0.012	0.160	-0.016	0.006	0.026
	$E_y - F_y$	-0.028	0.125	-0.029	-0.003	0.008
	$F_y - E_{y-1}$	0.040	0.147	0.000	0.010	0.030
IBES Earnings	$E_y - E_{y-1}$	0.003	0.096	-0.011	0.006	0.020
	$E_y - F_y$	-0.015	0.076	-0.017	-0.002	0.005
	$F_y - E_{y-1}$	0.019	0.071	0.001	0.009	0.020
	E_{y-1} / P_{y-1}	0.021	0.283	0.029	0.060	0.086
	Ret_y	0.194	0.534	-0.077	0.117	0.341

Panel B: Correlations (Pearson/Spearman Above/Below Diagonal)

		Compustat Earnings			IBES Earnings					
		$E_y - E_{y-1}$	$E_y - F_y$	$F_y - E_{y-1}$	$E_y - E_{y-1}$	$E_y - F_y$	$F_y - E_{y-1}$	E_{y-1} / P_{y-1}	Ret_y	Ret_{y-1}
Compustat Earnings	$E_y - E_{y-1}$	1.00	0.23	0.82	0.40	0.26	0.29	-0.73	0.33	-0.02
	$E_y - F_y$	0.58	1.00	-0.29	0.35	0.62	-0.15	0.15	0.09	0.13
	$F_y - E_{y-1}$	0.49	-0.20	1.00	0.26	-0.09	0.38	-0.75	0.29	-0.09
IBES Earnings	$E_y - E_{y-1}$	0.72	0.47	0.40	1.00	0.53	0.60	-0.15	0.20	0.08
	$E_y - F_y$	0.53	0.74	-0.05	0.64	1.00	-0.21	0.08	0.15	0.11
	$F_y - E_{y-1}$	0.39	-0.07	0.69	0.58	-0.03	1.00	-0.28	0.10	-0.01
	E_{y-1} / P_{y-1}	-0.29	0.08	-0.49	-0.16	-0.01	-0.23	1.00	-0.23	0.08
	Ret_y	0.30	0.30	0.05	0.30	0.36	0.05	0.10	1.00	-0.13
	Ret_{y-1}	0.16	0.22	0.00	0.25	0.21	0.12	-0.03	-0.09	1.00

Table 2. Analyst Forecasts Inefficiency: Annual Firm-Level Cross-Sectional Regression Results

The table reports estimation results of Equation (14) using firm-level cross-sectional regressions. Specifically, in Panel A, analyst forecast error, E_y-F_y, is regressed on lagged return in year y-1. Year y is defined as the 12 months from April of calendar year y to March of calendar year y+1. Variable E_y-F_y is scaled by P_{y-1}, the market capitalization at the end of year y-1. Variable Ret_{y-1} is the compounded return in year y-1. Variable E_y denotes earnings obtained from IBES. Variable F_y denotes the analyst consensus forecast made in April year y for fiscal year. Panel B reports the estimation results of Equation (14) as the time of the forecasts moves closer to the earnings announcement date. We require that the earnings of year y-1 are already announced before the beginning of year y, and that each regression has at least 10 observations to be included in the analysis. Our sample includes all NYSE, AMEX, and NASDAQ stocks that are in the intersection of CRSP, Compustat, and IBES datasets, with stock price higher than one dollar and December fiscal year-end. The earnings growth, forecast error, and forecasted growth variables are winsorized each period at one and ninety nine percentiles. The sample period is 1985-2010.

Panel A: $E_{i,y}$-$F_{i,y}$ $= a_1 + c_1 \cdot Ret_{i,y-1} + \mu_{i,y}$

	p5	p25	p50	p75	p95	mean	std	T-stat
c_1	0.004	0.020	0.030	0.070	0.099	0.041	0.034	6.01
R^2	0.007	0.020	0.038	0.055	0.100	0.043	0.031	
adj. R^2	0.006	0.019	0.036	0.054	0.099	0.042	0.031	

Panel B: Move Closer to Announcement Day

				c_1				
Month	p5	p25	p50	p75	p95	mean	std	t-stat
April	0.004	0.020	0.030	0.070	0.099	0.041	0.034	6.01
May	0.003	0.013	0.022	0.043	0.071	0.029	0.024	6.07
June	0.003	0.011	0.019	0.041	0.068	0.027	0.023	5.95
July	0.003	0.009	0.014	0.039	0.062	0.023	0.020	5.75
August	0.002	0.006	0.012	0.035	0.053	0.020	0.018	5.40
September	0.001	0.005	0.012	0.033	0.052	0.018	0.018	5.02
October	0.000	0.004	0.010	0.028	0.049	0.017	0.019	4.46
November	0.000	0.002	0.007	0.024	0.037	0.013	0.014	4.49
December	0.000	0.002	0.005	0.020	0.033	0.011	0.013	4.12

Table 3. Analyst Forecasts Inefficiency: The Basu Model

The table reports estimation results of Equation (15) using firm-level cross-sectional regressions. Year y is defined as the 12 months from April of calendar year y to March of calendar year $y+1$. Variable E_y-F_y is scaled by P_{y-1}, the market capitalization at the end of year y-1. Variable Ret_{y-1} is the compounded return in year y-1. Dum_{iy} is a dummy variable taking the value of one if $Ret_{i,y-1}$ is negative and zero otherwise. Variable E_y denotes earnings obtained from IBES. Variable F_y denotes the analyst consensus forecast made in each month from April to December of year y for fiscal year y. We require that the earnings of year y-1 are already announced before the beginning of year y, and that each regression has at least 10 observations to be included in the analysis. Our sample includes all NYSE, AMEX, and NASDAQ stocks that are in the intersection of CRSP, Compustat, and IBES datasets, with stock price higher than one dollar and December fiscal year-end. The earnings growth, forecast error, and forecasted growth variables are winsorized each period at one and ninety nine percentiles. The sample period is 1985-2010.

$$(E_{i,y} - F_{i,y}) = a + a_2 \cdot Dum_{i,y} + c_2 \cdot Ret_{i,y-1} + \delta_2 \cdot Dum_{i,y} \cdot Ret_{i,y-1} + \mu_{2,y}$$

Panel A: Coefficient on $Ret_{i,y-1}$ (c_2)

Month	p5	p25	p50	p75	p95	mean	std	t-stat
April	-0.002	0.004	0.013	0.020	0.037	0.014	0.014	5.10
May	-0.009	0.003	0.009	0.015	0.030	0.010	0.013	3.78
June	-0.005	0.001	0.009	0.013	0.028	0.009	0.012	3.61
July	-0.006	0.001	0.006	0.011	0.025	0.007	0.010	3.39
August	-0.005	0.000	0.004	0.008	0.020	0.004	0.008	2.72
September	-0.006	0.000	0.003	0.007	0.018	0.004	0.007	2.64
October	-0.004	0.000	0.001	0.006	0.017	0.003	0.006	2.48
November	-0.001	0.000	0.001	0.003	0.010	0.002	0.004	2.98
December	-0.001	0.000	0.001	0.003	0.009	0.002	0.003	3.21

Panel B: Coefficient on $Dum_{i,y} \cdot Ret_{i,y-1}$ (δ_2)

Month	p5	p25	p50	p75	p95	mean	std	t-stat
April	0.003	0.054	0.097	0.178	0.334	0.133	0.135	4.90
May	-0.003	0.030	0.074	0.140	0.284	0.098	0.097	5.04
June	-0.009	0.033	0.068	0.144	0.257	0.088	0.086	5.10
July	-0.006	0.019	0.067	0.092	0.237	0.074	0.073	5.09
August	-0.006	0.015	0.048	0.087	0.226	0.068	0.067	5.06
September	-0.006	0.012	0.045	0.091	0.171	0.061	0.060	5.06
October	-0.013	0.014	0.042	0.075	0.159	0.056	0.057	4.92
November	-0.013	0.012	0.032	0.072	0.119	0.045	0.046	4.95
December	-0.011	0.008	0.032	0.065	0.102	0.041	0.040	5.23

Table 4. Analyst Forecasts Inefficiency: Quarterly Firm-Level Cross-Sectional Regression Results

The table reports estimation results of analyst forecaste inefficiency using quarterly firm-level cross-sectional regressions. Specifically, in Panel A, analyst forecast error, E_q-F_q, is regressed on the lagged return. Variable E_q -F is scaled by P_{q-4}, the market capitalization at the end of fiscal quarter q-4. Variable $Ret_{q-7\rightarrow q-4}$ is the compounded return in Quarter q-7 through q-4. Variable E_q denotes earnings obtained from IBES. Variable F_q denotes the analyst consensus forecast made before the quarterly earnings announcement. In Panel B, we consider the asymmetric relation between forecast error and lagged returns. Our sample includes all NYSE, AMEX, and NASDAQ stocks that are in the intersection of CRSP, Compustat, and IBES datasets, with stock price higher than one dollar and December fiscal year-end. The sample period is 1986-2010.

	p5	p25	p50	p75	p95	mean	std	T-stat
	Panel A: E_q - F_q $= a_1 + c_1 \cdot Ret_{q-7\rightarrow q-4} + \mu_{1,q}$							
c_1	-0.002	0.001	0.003	0.009	0.028	0.006	0.010	6.47
R^2	0.000	0.001	0.002	0.007	0.019	0.005	0.007	
adj. R^2	-0.001	0.000	0.002	0.006	0.018	0.004	0.007	

Panel B: $(E_{i,q}$-$F_{i,q}) = a + a_2 \cdot Dum_{i,q} + c_2 \cdot Ret_{q-7\rightarrow q-4} + \delta_2 \cdot Dum_{i,q} \cdot Ret_{q-7\rightarrow q-4} + \mu_{2,q}$								
c_2	-0.007	0.000	0.000	0.001	0.009	0.001	0.006	0.91
δ_2	-0.037	-0.001	0.016	0.040	0.129	0.025	0.056	4.51
R^2	0.001	0.003	0.008	0.018	0.053	0.014	0.018	
adj. R^2	-0.001	0.001	0.005	0.016	0.050	0.012	0.017	

Table 5. Future Earnings Growth

The table reports the future earnings growth for portfolios sorted by three measures of earnings surprises: Forecast Error, $\mu_{1,i,q}$, and $\mu_{2,i,q}$. Measure $\mu_{1,i,q}$ is the residual of the following regression : $(E_{i,q}-F_{i,q}) = a_1 + c_1 \cdot Ret_{i,q-7\rightarrow q-4} + \mu_{1,i,q}$. Measure $\mu_{2,i,q}$ is the residual obtained from estimating the following model: $(E_{i,q}-F_{i,q}) = a + a_2 \cdot Dum_{i,q} + c_2 \cdot Ret_{i,q-7\rightarrow q-4} + \delta_2 \cdot Dum_{i,q} \cdot Ret_{i,q-7\rightarrow q-4} + \mu_{2,i,q}$, where variable $Ret_{q-7\rightarrow q-4}$ is the compounded return in Quarter q - through q-4; $Dum_{i,q}$ is an indicator variable that is equal to one if $Ret_{i,q-7\rightarrow q-4}$ is negative and zero otherwise; and $Dum_{i,q} \cdot Ret_{i,q-7\rightarrow q-4}$ is an interaction variable. Variable $E_{i,q}$ denotes quarter q IBES earnings of firm i, and Variable $F_{i,q}$ denotes analyst mean consensus earnings-per-share forecast of firm i for fiscal quarter q. Forecast error, $E_{i,q}-F_{i,q}$, is scaled by $P_{i,q-4}$, the market capitalization at the end of fiscal quarter q-4. These regressions are estimated each month using the quarterly earnings announcement made in the previous three months. We then sort stocks into portfolios based on the monthly residuals and most recent observed forecast error. We calculate average portfolio earnings growth from Quarter q-3 to Quarter q+1. Our sample includes all NYSE, AMEX, and NASDAQ stocks that are in the intersection of CRSP, Compustat, and IBES datasets, with stock price higher than one dollar and December fiscal year-end. Measures $\mu_{1,i,q}$ and $\mu_{2,i,q}$ are truncated each period at the 1% and 99% level. The sample period is 1986 to 2010.

	Sorting Variable						Difference		Difference	
	$(E_{i,q}-F_{i,q})$		$\mu_{1,i,q}$		$\mu_{2,i,q}$		$(E_{i,q}-F_{i,q}) - \mu_{1,i,q}$		$(E_{i,q}-F_{i,q}) - \mu_{2,i,q}$	
Portfolios	$(E_{i,q+1}-E_{i,q-3})$	T-stat	$(E_{i,q+1}-E_{i,q-3})$	T-stat	$(E_{i,q+1}-E_{i,q-3})$	T-stat	$\Delta(E_{i,q+1}-E_{i,q-3})$	T-stat	$\Delta(E_{i,q+1}-E_{i,q-3})$	T-stat
1 (most negative news)	-1.17%	-4.81	-0.84%	-5.1	-0.73%	-5.18	-0.33%	-2.06	-0.44%	-2.26
2	-0.04%	-0.96	-0.01%	-0.3	0.01%	0.44	-0.03%	-1.01	-0.06%	-2.01
3	0.25%	3.09	0.17%	6.6	0.18%	7.72	0.07%	0.91	0.07%	0.88
4	0.35%	10.72	0.28%	7.51	0.31%	7.48	0.07%	2.59	0.04%	1.47
5 (most positive news)	1.85%	8.51	1.56%	7.51	1.47%	7.09	0.29%	2.19	0.38%	2.77
Dif (5-1)	3.02%	11.45	2.40%	10.17	2.20%	11.71	0.62%	3.57	0.82%	4.61

Table 6. Revisiting Post-Earnings-Announcement Drift: Decomposing Forecast Errors

The table reports results from estimating time-series monthly portfolio regressions. Measure $\mu_{1,i,q}$ is the residual of regression of the following model : $(E_{i,q} - F_{i,q}) = a_1 + c_1 \cdot Ret_{i,q-7\to q-4} + \mu_{1,i,q}$. Measure $\mu_{2,i,q}$ is the residual obtained from estimating the following model: $(E_{i,q} - F_{i,q}) = a + a_2 \cdot Dum_{i,q} + c_2 \cdot Ret_{i,q-7\to q-4} + \delta_2 \cdot Dum_{i,q} \cdot Ret_{i,q-7\to q-4} + \mu_{2,i,q}$, where $Dum_{i,q}$ is an indicator variable that is equal to one if $Ret_{i,q-7\to q-4}$ is negative and zero otherwise; and $Dum_{i,q} \cdot Ret_{i,q-7\to q-4}$ is an interaction variable. Variable $E_{i,q}$ denotes quarter q earnings of firm i , using either IBES or Compustat, and Variable $F_{i,q}$ denotes analyst mean consensus earnings-per-share forecast of firm i for fiscal quarter q . Forecast error, $E_{i,q} - F_{i,q}$ is scaled by $P_{i,q-4}$, the market capitalization at the end of fiscal quarter $q-4$. These regressions are estimated each month using the quarterly earnings announcement made in the previous three months. At the beginning of each month, we sort stocks into portfolios based on these residuals and most recent observed forecast error. We calculate average portfolio returns in excess of the risk free rate, rf, each month, and regress these monthly excess portfolio returns on varioius factors. The intercepts from these regressions are reported as α in the table. Our sample includes all NYSE, AMEX, and NASDAQ stocks that are in the intersection of CRSP, Compustat, and IBES datasets, with stock price higher than one dollar and December fiscal year-end. Measure $\mu_{1,i,q}$ and $\mu_{2,i,q}$ are truncated each period at the 1% and 99% level. The sample period is 1986 to 2010. The risk free rate, rf, is the one-month Treasury bill rate. We obtain rf, and the Fama-French three facot and the momentum factor (MKTRF, SMB, HML, UMD) from the Fama-French Portfolios and Factors dataset.

	Sorting Variable						Difference		Difference	
	$(E_{i,q} - F_{i,q})$		$\mu_{1,i,q}$		$\mu_{2,i,q}$		$(E_{i,q} - F_{i,q}) - \mu_{1,i,q}$		$(E_{i,q} - F_{i,q}) - \mu_{2,i,q}$	
	α	t-statistic	α	t-statistic	α	t-statistic	$\Delta\alpha$	t-statistic	$\Delta\alpha$	t-statistic
Excess Return										
1 (most negative news)	0.37%	0.95	0.58%	1.50	0.47%	1.25	-0.21%	-2.82	-0.10%	-1.26
2	0.54%	1.73	0.68%	2.25	0.68%	2.24	-0.15%	-2.22	-0.15%	-2.01
3	0.71%	2.46	0.71%	2.55	0.80%	2.81	0.00%	-0.04	-0.09%	-1.47
4	0.99%	3.39	0.90%	3.07	1.06%	3.60	0.09%	1.41	-0.07%	-1.02
5 (most positive news)	1.56%	4.43	1.34%	3.74	1.20%	3.29	0.23%	3.57	0.36%	4.24
Zero-cost Portfolio(5-1):	1.19%	8.41	0.76%	5.01	0.73%	4.24	0.44%	3.67	0.47%	3.18
CAPM Alpha										
1 (most negative news)	-0.32%	-1.48	-0.12%	-0.58	-0.21%	-1.06	-0.20%	-2.67	-0.11%	-1.31
2	-0.04%	-0.31	0.10%	0.82	0.10%	0.79	-0.15%	-2.18	-0.14%	-1.96
3	0.14%	1.37	0.17%	1.59	0.24%	2.40	-0.02%	-0.51	-0.09%	-1.59
4	0.42%	3.99	0.34%	2.83	0.50%	3.99	0.08%	1.26	-0.08%	-1.16
5 (most positive news)	0.90%	5.73	0.67%	4.07	0.53%	2.98	0.23%	3.58	0.37%	4.26
Zero-cost Portfolio(5-1):	1.21%	8.50	0.79%	5.17	0.74%	4.26	0.43%	3.58	0.48%	3.22
FF3 Alpha										
1 (most negative news)	-0.54%	-3.86	-0.27%	-2.02	-0.39%	-2.55	-0.27%	-3.88	-0.16%	-2.08
2	-0.23%	-2.23	-0.04%	-0.36	-0.03%	-0.33	-0.20%	-3.04	-0.20%	-2.79
3	0.02%	0.21	0.01%	0.10	0.12%	1.59	0.01%	0.20	-0.10%	-1.64
4	0.30%	3.94	0.16%	2.10	0.33%	3.99	0.14%	2.31	-0.03%	-0.42
5 (most positive news)	0.75%	8.04	0.51%	4.89	0.34%	3.14	0.25%	3.82	0.41%	4.78
Zero-cost Portfolio(5-1):	1.29%	9.32	0.78%	5.13	0.73%	4.16	0.52%	4.48	0.57%	4.03
FF4 Alpha										
1 (most negative news)	-0.26%	-2.47	-0.01%	-0.10	-0.09%	-0.77	-0.25%	-3.61	-0.18%	-2.27
2	-0.03%	-0.40	0.16%	1.98	0.16%	1.83	-0.19%	-2.87	-0.19%	-2.61
3	0.11%	1.42	0.09%	1.27	0.17%	2.39	0.02%	0.35	-0.06%	-1.06
4	0.35%	4.55	0.22%	2.91	0.38%	4.61	0.13%	2.06	-0.03%	-0.49
5 (most positive news)	0.79%	8.44	0.55%	5.32	0.39%	3.58	0.24%	3.67	0.40%	4.60
Zero-cost Portfolio(5-1):	1.06%	9.14	0.56%	4.15	0.48%	3.07	0.49%	4.23	0.58%	4.02

Table 7. Revisiting Post-Earnings-Announcement Drift: Decomposing Earnings Change

The table reports results from estimating time-series monthly portfolio regressions. At the beginning of each month t, we sort firms into five portfolios based on each of the three measures of earnings surprises, $E_{i,q}$-$E_{i,q-4}$, $\mu_{3,i,q}$, and $\mu_{4,i,q,}$ where earnings change, $E_{i,q}$-$E_{i,q-4}$, is the benchmark earnings surprise measure. Measure $\mu_{3,i,q}$ is the residual of regression of the following model : $(E_{i,q} - E_{i,q-4}) = a_3 + c_3 \cdot Ret_{i,q-7\rightarrow q-4} + d_3 \cdot (F_{i,q} - E_{i,q-4}) + \mu_{3,i,q}$, where $F_{i,q}$-$E_{i,q-4}$ is the forecasted growth, and $Ret_{i,q-7\rightarrow q-4}$ is the compounded return of firm i over the four quarters (q–7 through q–4) that end at fiscal quarter q–4. Measure $\mu_{4,i,q}$ is the residual obtained from estimating the following model: $(E_{i,q} - E_{i,q-4}) = a + a_4 \cdot Dum_{i,q} + c_4 \cdot Ret_{i,q-7\rightarrow q-4} + \delta_4 \cdot Dum_{i,q} \cdot Ret_{i,q-7\rightarrow q-4} + d_4 \cdot (F_{i,q} - E_{i,q-4}) + \mu_{4,i,q}$, where $Dum_{i,q}$ is an indicator variable that is equal to one if $Ret_{i,q-7\rightarrow q-4}$ is negative and zero otherwise; and $Dum_{i,q} \cdot Ret_{i,q-7\rightarrow q-4}$ is an interaction variable. Variable $E_{i,q}$ denotes quarter q earnings of firm i, using either IBES or Compustat, and variable $F_{i,q}$ denotes analyst mean consensus earnings-per-share forecast of firm i for fiscal quarter q. Forecast error, $E_{i,q}$-$F_{i,q}$, as well as the earnings growth and forecasted growth variables are scaled by $P_{i,q-4}$, the market capitalization at the end of fiscal quarter q–4. These regressions are estimated each month using the quarterly earnings announcement made in the previous three months. We then sort stocks into portfolios based on the residuals and earnings growth. We calculate average portfolio returns in excess of the risk free rate, rf, each month, and regress these monthly excess portfolio returns on various factors. The intercepts from these regressions are reported as α in the table. Our sample includes all NYSE, AMEX, and NASDAQ stocks that are in the intersection of CRSP, Compustat, and IBES datasets, with stock price higher than one dollar and December fiscal year-end. Measure $\mu_{3,i,q}$ and $\mu_{4,i,q}$ are truncated each period at the 1% and 99% level. The sample period is 1986 to 2010.

	Sorting Variable						Difference		Difference	
	$(E_{i,q} - E_{i,q-4})$		$\mu_{3,i,q}$		$\mu_{4,i,q}$		$(E_{i,q} - E_{i,q-4}) - \mu_{3,i,q}$		$(E_{i,q} - E_{i,q-4}) - \mu_{4,i,q}$	
	α	t-statistic	α	t-statistic	α	t-statistic	$\Delta\alpha$	t-statistic	$\Delta\alpha$	t-statistic
Excess Return										
1 (most negative news)	0.32%	0.78	0.51%	1.31	0.52%	1.35	-0.19%	-2.80	-0.20%	-2.86
2	0.63%	2.04	0.76%	2.52	0.71%	2.38	-0.13%	-2.02	-0.08%	-1.12
3	0.75%	2.73	0.73%	2.61	0.76%	2.72	0.02%	0.43	-0.01%	-0.10
4	1.11%	3.87	0.84%	2.89	0.92%	3.12	0.26%	4.01	0.19%	2.84
5 (most positive news)	1.36%	3.71	1.34%	3.76	1.28%	3.56	0.02%	0.26	0.08%	1.11
Zero-cost Portfolio(5-1):	1.04%	6.09	0.83%	5.43	0.76%	4.84	0.21%	1.92	0.29%	2.36
CAPM Alpha										
1 (most negative news)	-0.40%	-1.75	-0.19%	-0.92	-0.17%	-0.84	-0.21%	-3.02	-0.23%	-3.16
2	0.05%	0.37	0.19%	1.45	0.14%	1.12	-0.14%	-2.12	-0.09%	-1.27
3	0.22%	1.99	0.19%	1.72	0.21%	2.07	0.03%	0.59	0.01%	0.14
4	0.55%	5.19	0.28%	2.43	0.35%	2.96	0.27%	4.05	0.20%	2.95
5 (most positive news)	0.67%	4.01	0.67%	4.22	0.61%	3.70	0.01%	0.09	0.07%	0.96
Zero-cost Portfolio(5-1):	1.07%	6.22	0.86%	5.55	0.78%	4.92	0.21%	1.95	0.30%	2.42
FF3 Alpha										
1 (most negative news)	-0.60%	-3.84	-0.35%	-2.47	-0.33%	-2.31	-0.25%	-3.72	-0.27%	-3.89
2	-0.12%	-1.17	0.05%	0.49	0.00%	0.02	-0.17%	-2.72	-0.13%	-1.82
3	0.07%	0.80	0.04%	0.43	0.08%	1.04	0.03%	0.68	-0.01%	-0.20
4	0.43%	5.46	0.11%	1.35	0.18%	2.26	0.33%	5.24	0.25%	4.01
5 (most positive news)	0.51%	4.87	0.51%	5.38	0.42%	4.14	0.01%	0.13	0.10%	1.33
Zero-cost Portfolio(5-1):	1.12%	6.52	0.86%	5.55	0.75%	4.77	0.26%	2.36	0.36%	3.02
FF4 Alpha										
1 (most negative news)	-0.28%	-2.43	-0.07%	-0.66	-0.04%	-0.38	-0.21%	-3.14	-0.24%	-3.48
2	0.10%	1.30	0.25%	3.31	0.18%	2.31	-0.15%	-2.39	-0.08%	-1.21
3	0.18%	2.14	0.12%	1.50	0.16%	2.18	0.05%	1.08	0.01%	0.27
4	0.44%	5.42	0.16%	2.09	0.23%	2.92	0.27%	4.52	0.21%	3.33
5 (most positive news)	0.52%	4.81	0.53%	5.50	0.46%	4.49	-0.01%	-0.13	0.06%	0.83
Zero-cost Portfolio(5-1):	0.80%	5.86	0.60%	4.61	0.50%	3.70	0.20%	1.85	0.30%	2.50

Table 8. EAR-Neutral Portfolios

At the beginning of each month, stocks are first sorted into five portfolios based on EAR, the three-day cumulative market-adjusted return surrounding an earnings announcement made in the previous three months. Within the each EAR portfolio, stocks are further sorted into five portfolios based on various measures of earnings surprises: forecast error, u_1, u_2, earnings change, u_3, and u_4. The table reports the average returns and various alphas of the EAR-neutral zero-cost portfolio that is long in stocks in the top quintile of earnings surprise and short in stocks in the bottom quintile of earnings surprise (averaged across the five EAR-sorted portfolios). The sample period is 1986 to 2010.

	Sorting Variable						Difference		Difference	
	$(E_{i,q}-F_{i,q})$		$\mu_{1,i,q}$		$\mu_{2,i,q}$		$(E_{i,q}-F_{i,q}) - \mu_{1,i,q}$		$(E_{i,q}-F_{i,q}) - \mu_{2,i,q}$	
	α	t-statistic	α	t-statistic	α	t-statistic	$\Delta\alpha$	t-statistic	$\Delta\alpha$	t-statistic
Average Returns	1.05%	7.67	0.76%	5.30	0.73%	4.52	0.28%	2.61	0.31%	2.35
CAPM	1.06%	7.71	0.78%	5.39	0.74%	4.54	0.28%	2.54	0.32%	2.35
FF3 alpha	1.13%	8.36	0.77%	5.29	0.73%	4.42	0.36%	3.39	0.40%	3.12
FF4 Alpha	0.91%	7.91	0.57%	4.34	0.50%	3.38	0.34%	3.19	0.41%	3.11

	Sorting Variable						Difference		Difference	
	$(E_{i,q}-E_{i,q-4})$		$\mu_{3,i,q}$		$\mu_{4,i,q}$		$(E_{i,q}-E_{i,q-4}) - \mu_{3,i,q}$		$(E_{i,q}-E_{i,q-4}) - \mu_{4,i,q}$	
Portfolios	α	t-statistic	α	t-statistic	α	t-statistic	$\Delta\alpha$	t-statistic	$\Delta\alpha$	t-statistic
Average Returns	0.96%	5.89	0.73%	4.83	0.71%	4.70	0.23%	2.31	0.25%	2.17
CAPM	0.98%	6.01	0.75%	4.93	0.72%	4.75	0.24%	2.35	0.26%	2.25
FF3 alpha	1.02%	6.29	0.75%	4.92	0.70%	4.60	0.27%	2.71	0.32%	2.81
FF4 Alpha	0.73%	5.53	0.50%	3.87	0.47%	3.53	0.23%	2.29	0.26%	2.30

Table 9. Price Momentum

The table reports results from estimating time-series monthly portfolio regressions. Measure κ_{1m} is the firm-month residual of the following regression estimated in each month m : $Ret_{m-12\rightarrow m-2} = \xi_0 + \xi_1 \cdot Ret_{m-24\rightarrow m-13} + \kappa_{1m}$. Measure κ_{2m} is the firm-month residual of the following regression : $Ret_{m-12\rightarrow m-2} = \xi_0 + \xi_1 \cdot Ret_{m-24\rightarrow m-13} + \xi_2 \cdot Size + \xi_3 \cdot B/M + \kappa_{2m}$, where $Ret_{m-12\rightarrow m-2}$ is the cumulative return for a stock in months m -12 through m -2; $Ret_{m-24\rightarrow m-13}$ is the cumulative return in months m -24 through m -13. Size is the log of market cap measured at month m -13, and B/M is the most recent available book-to-market ratio before the end of month m -13 assuming that it takes four months for investors to obtain information about B/M after the end of a fiscal year. We sort stocks into five portfolios based on $Ret_{m-12\rightarrow m-2}$, κ_{1m} and κ_{2m} , respectively. We calculate average portfolio returns in excess of the risk free rate each month, and regress these monthly excess portfolio returns on varioius factors. The intercepts from these regressions are reported as α in the table. Our sample includes all NYSE, AMEX, and NASDAQ stocks with stock price higher than one dollar. The sample period is 1986 to 2010. The risk free rate, *rf* , is the one-month Treasury bill rate. We obtain *rf* and the Fama-French three facot and the momentum factor (MKTRF, SMB, HML, UMD) from the Fama-French Portfolios and Factors dataset.

Alpha		Sorting Variable						Difference		Difference	
		$Ret_{m-12\rightarrow m-2}$		κ_1		κ_2		$Ret_{m-12\rightarrow m-2} - \kappa_1$		$Ret_{m-12\rightarrow m-2} - \kappa_2$	
		α	t-statistic	α	t-statistic	α	t-statistic	$\Delta\alpha$	t-statistic	$\Delta\alpha$	t-statistic
Excess Return	1 (Losers)	-0.16%	-0.34	0.05%	0.12	0.07%	0.16	-0.21%	-4.51	-0.23%	-3.94
	5 (Winners)	1.27%	3.67	1.27%	3.71	1.27%	3.72	0.00%	0.08	0.01%	0.17
	Winners-Losers	1.43%	4.42	1.22%	3.98	1.20%	3.96	0.21%	3.92	0.23%	2.98
CAPM	1 (Losers)	-0.97%	-3.26	-0.74%	-2.60	-0.73%	-2.50	-0.23%	-4.99	-0.24%	-4.14
	5 (Winners)	0.62%	3.01	0.62%	3.08	0.60%	3.23	-0.01%	-0.28	0.02%	0.54
	Winners-Losers	1.59%	4.96	1.36%	4.50	1.33%	4.43	0.22%	4.15	0.26%	3.34
FF3	1 (Losers)	-1.09%	-4.37	-0.91%	-3.90	-0.89%	-3.81	-0.18%	-4.37	-0.20%	-3.64
	5 (Winners)	0.62%	4.84	0.62%	5.02	0.60%	5.33	0.00%	-0.05	0.02%	0.44
	Winners-Losers	1.71%	5.35	1.53%	5.13	1.49%	5.05	0.18%	3.52	0.22%	2.99
FF4	1 (Losers)	-0.46%	-3.10	-0.33%	-2.32	-0.32%	-2.17	-0.13%	-3.40	-0.14%	-2.65
	5 (Winners)	0.33%	3.68	0.35%	3.93	0.34%	4.49	-0.02%	-0.81	-0.01%	-0.14
	Winners-Losers	0.79%	6.25	0.68%	5.66	0.66%	5.17	0.12%	2.45	0.14%	1.96

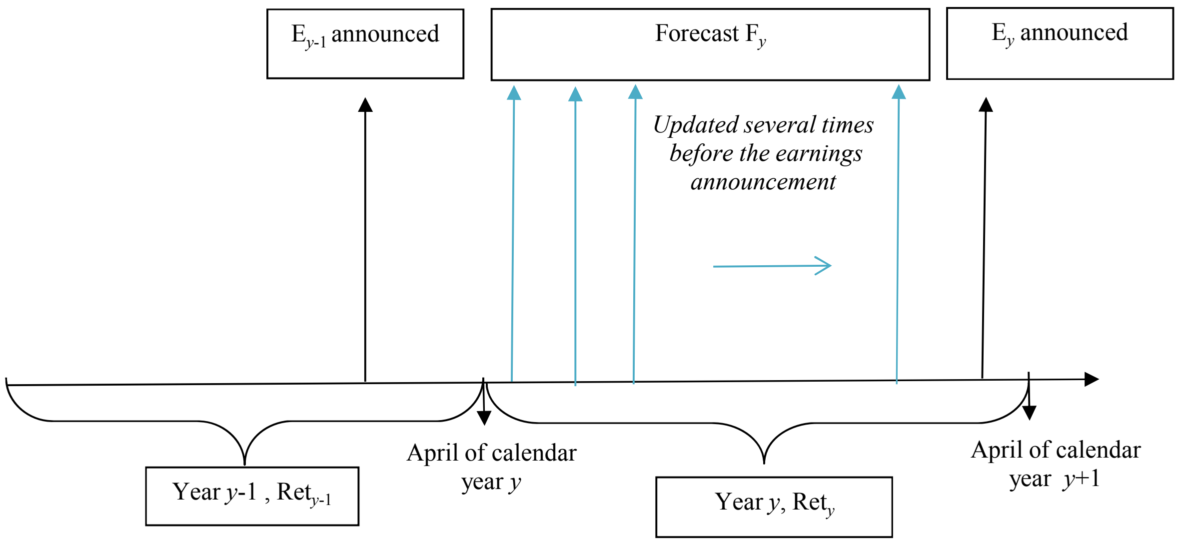

Figure 1. Timeline for Analysis of Predictability of Analyst-Forecast Errors. The figure plots the timeline for the analysis at the annual frequency for December fiscal year-end firms. Annual returns (Ret) of fiscal year y are cumulated from April of calendar year y through March of calendar year $y+1$. Annual firm earnings (E_y) for fiscal year y are announced shortly before April of calendar year $y+1$, while analyst forecasts for fiscal year y earnings are released after the earnings announcement of fiscal year y -1, and may be updated several times before the announcement of fiscal year y earnings. Ret_{y-1} is a 12-month return that begins accumulating two years prior to fiscal year y earnings announcement.

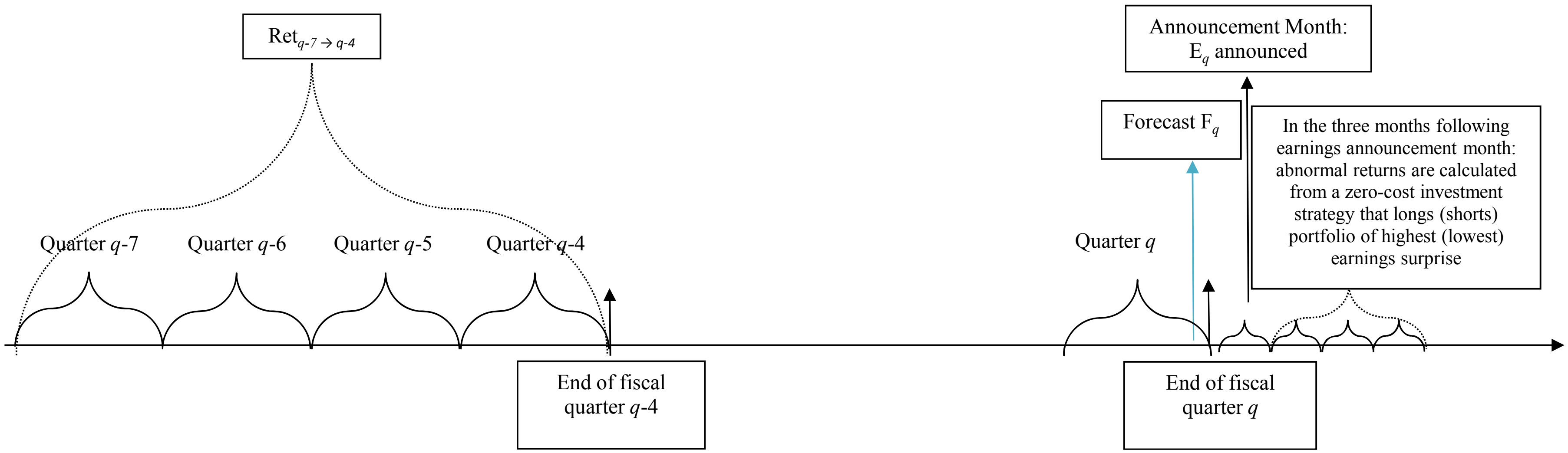

Figure 2. Timeline for Analysis of the Effects of Predictability of Analyst-Forecast Errors on the Post-Earnings-Announcement Drift. The figure plots the timeline for the analysis of the implications of predictable analyst-forecast errors for the post-earnings-announcement drift. $Ret_{q-7 \rightarrow q-4}$ is a 12-month stock return, cumulated over the four quarters that end at fiscal quarter q -4, thus it contains the returns for quarters q -7 through q -4. Quarterly firm earnings for fiscal quarter q (E_q) are announced after the fiscal quarter end of quarter q. Analyst consensus earnings-per-share forecasts for fiscal quarter q , F_q, are released after the end of fiscal quarter q -1. Fama-French and momentum adjusted returns are calculated over the three months subsequent to the month during which the earnings for quarter q are announced, using a zero-cost investment strategy that longs (shorts) the portfolio with highest (lowest) earnings surprise measure, which is either without or after purging out the predictable part of analyst-forecast errors.

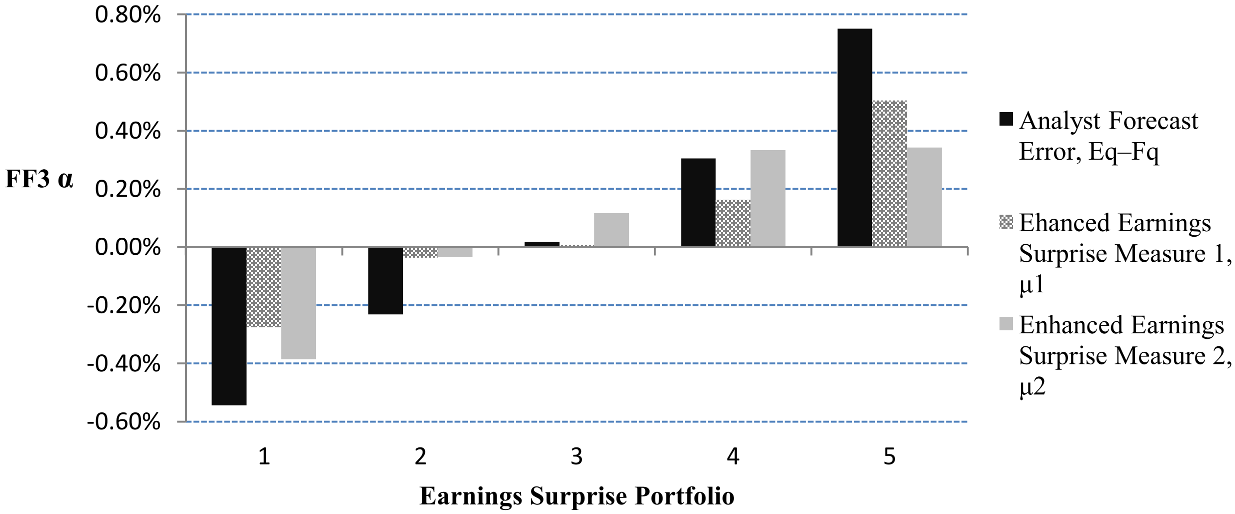

Figure 3. The Decline in PEAD Returns Using Enhanced Measures of Earnings Surprises. The figure plots the Fama-French three-factor alphas for five earnings surprise portfolios for three different earnings-surprises measures. Measure $\mu_{1,i,q}$ is the residual of regression of the following model: $(E_{i,q} - F_{i,q}) = a_1 + c_1 \cdot Ret_{i,q-7 \to q-4} + \mu_{1,i,q.}$ Measure $\mu_{2,i,q}$ is the residual obtained from estimating the following model: $(E_{i,q} - F_{i,q}) = a + a_2 \cdot Dum_{i,q} + c_2 \cdot Ret_{i,q-7 \to q-4} + \delta_2 \cdot Dum_{i,q} \cdot Ret_{i,q-7 \to q-4} + \mu_{2,i,q}$, where $Dum_{i,q}$ is an indicator variable that is equal to one if $Ret_{i,q-7 \to q-4}$ is negative and zero otherwise; and $Dum_{i,q} \cdot Ret_{i,q-7 \to q-4}$ is an interaction variable. Variable $E_{i,q}$ denotes quarter q earnings of firm i, using either IBES or Compustat, and Variable $F_{i,q}$ denotes analyst mean consensus earnings-per-share forecast of firm i for fiscal quarter q. Forecast error, $E_{i,q} - F_{i,q}$ is scaled by $P_{i,q-4}$, the market capitalization at the end of fiscal quarter q-4. These regressions are estimated each month using the most recent quarterly earnings announcement made in the previous three months. At the beginning of each month, we then sort stocks into portfolios based on these residuals and most recent observed forecast error. We calculate average portfolio returns in excess of the risk free rate, rf, each month, and regress these monthly excess portfolio returns on varioius factors. The intercepts from these regressions are reported as α in the table. Our sample includes all NYSE, AMEX, and NASDAQ stocks that are in the intersection of CRSP, Compustat, and IBES datasets, with stock price higher than one dollar and December fiscal year-end. Measure $\mu_{1,i,q}$ and $\mu_{2,i,q}$ are truncated each period at the 1% and 99% level. The sample period is 1986 to 2010. The risk free rate, rf, is the one-month Treasury bill rate. We obtain rf, and the Fama-French three facot and the momentum factor (MKTRF, SMB, HML, UMD) from the Fama-French Portfolios and Factors dataset.