Can Cash Flow Expectations Explain Momentum and Reversal?

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Abstract

This paper uses the model-implied patterns of cash flow expectations to differentiate among the three most prominent behavioral theories explaining stock return momentum and reversal. Using analyst earnings forecasts as a proxy for cash flow expectations, I trace the dynamics of the expectation errors for winner and loser stocks in a 24-month holding period, during which returns are characterized by a momentum phase followed by a reversal phase. The large positive cross-sectional difference in expectation errors between winner and loser stocks gradually shrinks to zero over the holding period. This pattern is most consistent with the underreaction hypothesis in Hong and Stein (1999), in which cash flow expectation errors can only explain momentum, and price extrapolation is needed to explain reversal.

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1 Introduction

Momentum and reversal are two of the best-established return predictabilities in asset pricing. Momentum is a phenomenon in which stocks with relatively stronger/weaker recent performance—that is, winner/loser stocks—continue to outperform/underperform other stocks in the short to medium run (Jegadeesh and Titman (1993)). Reversal is a phenomenon in which winner/loser stocks begin underperforming/outperforming other stocks in the long run (e.g., DeBondt and Thaler (1985); Jegadeesh and Titman (2001)). According to recent research, momentum and reversal exist not only in the U.S. equity market but also in others, such as the U.K. and Continental Europe equity markets, as well as in other asset classes, such as commodities and currencies (e.g., Moskowitz, Ooi, and Pedersen (2012); Menkhoff, Sarno, Schmeling, and Schrimpf (2012); Asness, Moskowitz, and Pedersen (2013)). Not surprisingly, a large body of literature has been devoted to explaining these two important regularities. However, since models have mostly been built to generate momentum and/or reversal, researchers have had a difficult time discriminating among the competing mechanisms by only examining the implied moment conditions of returns. In this study, I adopt a different approach by examining the implied moment conditions of expected cash flows, and in doing so, I am able to sharpen the investigation of the mechanisms behind momentum and reversal.

I categorize the existing theories of momentum and reversal into two types. The first type resides within the rational expectations paradigm and argues that predictable returns are compensation for taking covariance risk.[2] The second type deviates from the rational expectations framework and attributes momentum and reversal to systematic biases in expectations. In this paper, I focus primarily on three models of the second type—Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), and Barberis, Shleifer, and Vishny (1998) (hereafter, DHS, HS, and BSV)—because they are able to offer coherent explanations for momentum *and* reversal in a unified framework,[3] while a unified explanation

[2] An incomplete list of risked-based explanations for momentum includes Johnson (2002); Sagi and Seasholes (2007) ; Bansal, Dittmar, and Lundblad (2005); Chordia and Shivakumar (2002); Liu and Zhang (2011). An incomplete list of risked-based explanations for reversal, which is closely related to value premium, includes Zhang (2005); Hansen, Heaton, and Li (2008); Lettau and Wachter (2007); Carlson, Fisher, and Giammarino (2004); and Bansal, Dittmar, and Lundblad (2005).

[3] I emphasize both momentum and reversal because, as Fama (1998) states, "Any alternative model (to

remains difficult to achieve in risk-based theories.[4] Nevertheless, DHS, HS, and BSV emphasize distinctively different behavioral biases: DHS postulate that agents overreact to cash flow news, HS postulate that agents underreact to available cash flow news,[5] and BSV postulate a combination of both. Existing literature has documented several characteristics associated with the strength of momentum and reversal (Hong, Lim, and Stein (2000); Avramov, Jostova, and Philipov (2007); Cooper, Gutierrez, and Hameed (2004); Zhang (2006)), but these characteristics of returns are of little help in differentiating one model from another.

I propose to distinguish among the models by examining the model-implied pattern of cash flow expectations. Models under rational expectations do not rely on cash flow expectations to generate momentum or reversal. Nevertheless, they imply that the expectation errors should always be zero, on average, and thus are not correlated with past returns. On the other hand, models under the behavioral view use cash flow expectations as the main mechanism to generate momentum and reversal; therefore, they impose more structural restrictions of cash flow expectations. I show that these models imply diametrically opposed moment conditions of cash flow expectations, and I nest these moment conditions in one specification test.

To empirically study cash flow expectations, we need a proxy. Among a limited set of available candidates, earnings forecasts of financial analysts are the most appropriate proxy for three reasons.[6] First, earnings forecasts are arguably the "benchmark" for expected earnings, since earnings surprises reported in financial outlets are calculated as actual earnings minus the average earnings forecasts. Second, earnings forecasts are practically public information as they are accessible through various brokerage accounts. Third, in accounting literature, earnings forecasts have been found to outperform a large class of time series models in terms

market efficiency)... must specify biases in information processing that cause the same investors to underreact to some types of events and overreact to others." Moreover as Hong and Stein (1998) states, "There seems to be broad agreement that to be successful, any candidate theory should, at a minimum: ...(2) explain the existing evidence in a parsimonious and unified way."

[4]The transition from momentum to reversal occurs approximately six months to one year after sorting (e.g., Jegadeesh and Titman (1993); Lewellen (2002)). To offer a joint explanation of momentum and reversal, risk-based theories need to generate a covariance structure that reverses the cross-sectional pattern at a frequency of six months to one year. Recently, Vayanos and Woolley (2013) use a time-varying agency cost to achieve this, and Li (2012) proposed an investment-based model in which the expiration of investment commitments helps to reverse the covariance structure.

[5]Other than the underreaction to cash flow news, HS also features price extrapolation.

[6]I pay special attention to some known issues regarding analyst forecast data when I conduct the empirical test. I discuss these in the data section.

of predicting annual earnings.[7]

Using earnings forecasts as a proxy for cash flow expectations, my research demonstrates that winner stocks have more positive cash flow expectation errors than loser stocks throughout a two-year holding period, during which returns are characterized by a momentum phase followed by a reversal phase. This systematic expectation bias lends support to the behavioral view. Furthermore, the pattern of expectation errors implies that the cash flow expectations of winner (loser) stocks do not incorporate the information in past good (bad) returns sufficiently, thereby pinpointing underreaction to information as the dominant bias in cash flow expectations underlying both momentum and reversal. Although the literature has generally appreciated underreaction in cash flow expectations as an important mechanism for momentum, what has been much less appreciated is that underreaction in cash flow expectations is also associated with reversal. This is because reversal is perceived to be associated with overreaction. In this regard, I highlight the distinction between overreaction in cash flow expectations and overreaction in price expectations. I find a large positive cross-sectional difference in cash flow expectation errors between winner and loser stocks, and I find that this difference gradually shrinks to zero over the holding period. Thus, this pattern is thus most consistent with HS's hypothesis that cash flow expectations exhibit underreaction, thereby suggesting that overreaction is more likely to exist in price expectations. In sum, the identified pattern of cash flow expectation errors provides an informative restriction for future theories that attempt to explain momentum and reversal via a mechanism involving cash flow expectations.

2 Literature Review

This study belongs to the literature that confronts competing explanations of momentum and reversal with new empirical findings. Jegadeesh and Titman (2001) cite the reversal that follows the return momentum as support for behavioral models over Conrad and Kaul (1998).

[7] See Brown, Hagerman, Griffin, and Zmijewski (1987). Bradshaw, Drake, Myers, and Myers (2012) offer a re-examination and confirm that analyst forecasts are a superior predictor for the current fiscal year and the next fiscal year.

Nevertheless, their results cannot discriminate among the competing behavioral models because they only examine the dynamics of returns. Kothari, Lewellen, and Warner (2006) attempt to reject a broad class of behavioral theories–including DHS, HS, and BSV–by showing the theories to be inconsistent with the empirical relation between aggregate earnings and aggregate returns. However, this conclusion is disputed by Sadka and Sadka (2009). The disagreement stems from the fact that the seasonal change in aggregate earnings is strongly predictable, and Sadka and Sadka (2009) claim that the change is not an appropriate proxy for earnings surprises. These contradictory results indicate that the dynamics of expectations are at the heart of behavioral theories. Avramov, Jostova, and Philipov (2007), Cooper, Gutierrez, and Hameed (2004), Chan (2003), and Vega (2006), among others, find various firm characteristics that are associated with the strength of momentum and reversal, but these patterns of returns cannot differentiate one behavioral theory from another. The current study contributes to this literature in two respects. Methodologically, it shows that the three most prominent behavioral theories are distinct in their predictions of cash flow expectation errors and that the predictions can be tested under one nesting specification. Empirically, it documents the full dynamics of cash flow expectation errors for stocks undergoing the momentum and reversal phases.[8]

Two earlier studies—Chui, Titman, and Wei (2003) and Hwang (2010)—explicitly attempt to differentiate Daniel, Hirshleifer, and Subrahmanyam (1998) from Hong and Stein (1999). Chui, Titman, and Wei (2003) examine the strength of momentum within real estate investment trusts (REITs) before and after 1990. They assume that REITs in the post-1990 period experienced more severe overconfidence but faster information diffusion. Since it is difficult to evaluate this additional assumption, it is unclear whether they reject only the additional assumption or the entire model. Hwang (2010) finds that momentum strength is positively correlated with the cross-sectional average correlation of earnings forecast errors. This is inconsistent with the form of information diffusion assumed in Hong and Stein (2007), that is, analysts underreact to independent information. However, an alternative information

[8] To be clear, the main objective of this study is to identify the most powerful test of the existing behavioral theories of momentum and reversal. It is possible that the empirical results documented here are consistent with alternative theories.

diffusion process, under which most analysts underreact to similar information, can conform to Hwang's empirical finding while keeping the main theory predictions.

This study differs from Chui, Titman, and Wei (2003) and Hwang (2010) in two ways. First, by examining the dynamics of cash flow expectations, I target the main mechanisms of the theories, thereby offering a direct test that is robust to possible model modifications. Second, I not only test the theories in the momentum phase, as done in the two abovementioned papers, but it also simultaneously tests the theories in the reversal phase.

3 Cash Flow Expectations in the Three Theories

In this section, I formally lay out the moment conditions of cash flow expectations imposed by DHS, HS, and BSV. I find that moment conditions predicted by BSV are indistinguishable from those predicted by DHS, while moment conditions predicted by HS are very different from those of the former two.

3.1 Daniel, Hirshleifer, and Subrahmanyam (1998)

In the DHS model, a risk-neutral representative investor receives news about future cash flows and prices stocks according to discounted cash flow model:

$$P_t = \Sigma_{j\geq 1}\frac{E_t\left(CF_{t+j}\right)}{(1+r)^j}.$$

Because discount rates are assumed to be constant, the cash flow expectations determine the stock prices in this model. The investor initially receives a noisy private signal about future cash flows, followed by noisy public signals in subsequent periods. Public signals will eventually reveal the true cash flows. In this model, due to overconfidence and self-attribution biases, the investor's cash flow expectations show increasing overreaction initially and then revert to the rational level, thereby resulting in momentum and reversal.

Consider a loser stock as an example. Initially, the investor receives a private signal about a permanent decrease in future cash flows. Under rational expectations, the investor's cash flow expectations will fall once and for all upon receiving the signal. However, due to the overconfidence bias, the investor in this model overestimates the precision of this negative private signal. Then, this signal has a disproportionately large influence in dragging down the investor's expectation to a level below the rational one, that is, there is overreaction.[9] Due to the self-attribution bias, when subsequent public signals confirm the private signal, the investor believes that his private signal is truly superior and further raises his confidence in the private signal; when subsequent public signals disapprove the private signal, the investor believes it is due to bad luck and maintains his confidence in the private signal. On average, the arrival of public signals increases the investor's confidence in the negative private signal. For a while, the private signal acquires greater influence and thus pushes the cash flow expectations progressively lower, i.e., a continuing overreaction. Eventually, despite the fact that the private signal carries a disproportionate weight, the amassed public news will lift the expectation back to the rational level. Note that the cash flow expectations determine the price in this model. Hence, after the initial price drop, the model predicts a continuous decline in the price due to the continuing overreaction in cash flow expectations, that is, a momentum phase. This is followed by price recovery due to the correction of cash flow expectations, that is, a reversal phase.

The upper panel of Figure 1 features the prediction regarding expected earnings in the DHS model. The dashed line represents rational expectations, an unbiased estimate of future cash flows. The investor's expectation, which experiences continuing overreaction and subsequent correction, is represented by the black line with an arrow.

[Insert Figure 1 here]

Defining expectation errors as actual cash flows minus expectations, I test the following two key hypotheses of the DHS model, presented in the lower panel of Figure 1:

1. The cross-sectional difference between winner and loser stocks in expectation errors is

[9] Daniel, Hirshleifer, and Subrahmanyam (1998) assume that the representative investor is overly confident in the first period. However, overconfidence at the beginning of the momentum phase is not indispensable to the model's main results. Hence, I avoid testing the sign of forecast errors in the initial momentum phase.

negative: it is most negative around the turning point from the momentum phase to the reversal phase.

2. The cross-sectional difference between winner and loser stocks in expectation errors will decline progressively to a negative value in the momentum phase but increase toward zero in the reversal phase.

3.2 Hong and Stein (1999)

The HS model features two heterogeneous groups of investors: news watchers and momentum traders. Momentum traders only observe past prices, and their trading positions are positively related to past returns. News watchers observe information on future cash flows and their trading positions are positively related to expected cash flows. Together, demands from momentum traders and news watchers determine the price. In this model, news watchers' cash flow expectations incorporate the available information with a delay. This delay causes underreaction in cash flow expectations, which initiates the momentum and thus attracts momentum trading. Momentum trading then fuels further momentum and results in eventual reversal.

Take a loser stock as an example. Initially, news about a permanent drop in future cash flows arrives in the market. The model assumes that each news watcher is able to obtain only a portion of the news, and although others' portions can be deduced from the price, news watchers fail to do so. Consequently, the average cash flow expectations of news watchers do not drop sufficiently, thereby resulting in an overly optimistic expectation. In subsequent periods, each news watcher will obtain additional pieces of the original bad news, correcting his/her initial underreaction, thereby lowering the expectation gradually toward the rational level. Thus, a momentum of price decline is formed. Then, the negative momentum attracts momentum traders to take short positions, thereby exacerbating the fall in price. Since momentum traders blindly trade on serial correlations, eventually they cause an excessive drop in the price. As more information on future cash flows is revealed, the demand of news watchers increases the price, momentum traders close their short positions, and the price increases back to the rational level.

The upper panel of Figure 2 presents the prediction of expected earnings under the HS model. The dashed line represents rational expectations, an unbiased estimate of future cash flows. News watchers' cash flow expectations, which manifest the gradually corrected underreaction, are represented by the black line with an arrow.

[Insert Figure 2 here]

Comparing the lower panel of Figure 2 to that of Figure 1, it is evident that the HS model predicts different dynamics of expectation errors:

1. The cross-sectional difference between winner and loser stocks in expectation errors is positive (rather than negative in the DHS model).

2. The cross-sectional difference between winner and loser stocks in expectation errors shrinks from a positive number toward zero (rather than a U-shaped pattern in the DHS model).

3.3 Barberis, Shleifer, and Vishny (1998)

The BSV model was not originally designed to generate momentum and reversal in sequence, but it can do so under certain parameter configurations. Similar to DHS, BSV assume a risk-neutral representative investor who sets prices by discounting expected cash flows. BSV assume that the true cash flow dynamics are a random walk, but the representative investor nevertheless believes that cash flows follow a regime-switching model with two Markov regimes: a trending regime, in which positive shocks are followed by positive shocks; and a mean-reverting regime, in which positive shocks are followed by negative shocks. The investor first believes in the mean-reverting regime and then Bayesian updates the probability of each regime upon new shocks.

Consider a loser stock whose the price falls because of a negative cash flow shock initially. Under rational expectations, the negative shock will cause a permanent fall in the expectations of all future cash flows because the true dynamics are assumed to be a random walk in this model. However, believing in mean-reversion, the investor expects a positive shock in the next period. Thus, the investor's cash flow expectations are too optimistic relative to what the random walk process implies in the first period. In the second period, the average shock is zero under the random walk process, thereby leading to a negative surprise for the investor because the investor expects a positive shock. In addition, the investor will also lower his expectation of future cash flows. To understand this, consider that negative and positive shocks have equal probability of occurrence under the random walk process. If the investor observes negative shocks again in the second period, he switches his belief from mean-reverting to trending under certain model configurations. Consequently, the investor expects negative shocks to occur in the third period. For the other half of the chance, the investor observes positive shocks in the second period and then believes that he is still in the mean-reverting regime (note that this stock has a negative shock in the first period). Consequently, the investor again expects negative shocks for the third period. Thus, in the second period, the investor will experience a negative earnings surprise and lower the expectation for future earnings. Consequently, the price will continue its fall from the first period, thereby resulting in a momentum phase. Finally, since the second period's expectations of negative shocks are overly pessimistic compared to the random walk process, the subsequent returns will be positive, thereby resulting in a reversal phase.

The upper panel of Figure 3 presents the prediction regarding expected earnings under the BSV model, and the lower panel of Figure 3 summarizes the two key predictions of BSV. Although BSV are motivated by different behavioral biases from those in DHS, comparing Figures 2 and 3, it is evident that BSV actually have predictions on cash flow expectations that are indistinguishable from the predictions in DHS.

Finally, I summarize the different patterns of cash flow expectation errors implied by the three models in Figure 4. In a nutshell, the three behavioral theories disagree on whether there should be an overreaction in cash flow expectations (DHS/BSV) or not (HS) when the return pattern shifts from momentum to reversal. In addition, models under rational expectations predict that both winner and loser stocks should have zero cash flow expectation errors throughout the holding period.

[Insert Figure 4 here]

4 Data

4.1 Data Description

My data encompass the period from 1985 to 2012 and include all nonfinancial common stocks traded on NYSE, AMEX, and NASDAQ from the CRSP database.

Stock prices, total shares outstanding, and market values are taken from CRSP. Book values are taken from COMPUSTAT. Monthly returns are adjusted by delisting returns when applicable. Annual earnings forecasts and actual earnings are taken from I/B/E/S unadjusted detail files. I use actual earnings reported in I/B/E/S rather than those in COMPUSTAT because I/B/E/S actual earnings use an earnings definition that is closer to what is used by analysts.[10] I use forecasts for the current fiscal year end and the next fiscal year end, because these are the two most frequently issued annual forecasts. Then, I merge CRSP data with I/B/E/S earnings forecasts by matching CUSIPs. I follow Payne and Thomas (2003) by adjusting the effect of changes in shares on EPS (earnings per share) that occurred between the portfolio formation date and the dates of interest.

To minimize the attrition effect, I only include firms that satisfy the following characteristics when I form the portfolios: positive book equity, price per share higher than $5, market value larger than NYSE bottom size decile, more than two analysts providing coverage, and no missing returns in the past 18 months. Table 1 provides a step-by-step description of the data cleaning process.

[Insert Table 1 here]

Table 2 presents the distribution of firm size, number of analysts, and book-to-market ratios averaging over portfolio formation dates for each of the momentum quintile portfolios.[11] In my sample, stocks in the loser portfolio (the lowest momentum quintile) have the smallest

[10] See Bradshaw and Sloan (2002) and Livnat and Mendenhall (2006) for a discussion on the difference between the COMPUSTAT earnings definition and the I/B/E/S earnings definition.

[11] At the end of each month t, I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Then, stocks are sorted into momentum quintile portfolios based on these breakpoints.

average market capitalization. The mean is $3.1 billion and the median is $611 million. Stocks in the winner portfolio (the highest momentum quintile) have the second-smallest average market capitalization. The mean is $4.8 billion and the median is $1 billion. Loser stocks have the highest average book-to-market ratio. The mean is 0.64 and the median is 0.49, which are approximately twice as large as the mean and the median of the book-to-market ratio of winner stocks, respectively. With regard to the number of analysts providing coverage for one particular stock, the distribution appears rather even across momentum portfolios. For stocks in the loser or winner portfolios, the mean number of analysts providing coverage is approximately 7.5 and the median is approximately 6.

[Insert Table 2 here]

4.2 Proxy for Cash Flow Expectations

Although earnings forecasts of financial analysts are the best available proxy for cash flow expectations, there are several known issues related to earnings forecasts. I pay special attention to avoiding them when I construct the proxy for cash flow expectations. First, the analyst forecasts database I/B/E/S does not specify the time frame for its consensus forecasts, so the consensus forecasts can include stale forecasts. Stale forecasts are founded to reduce the accuracy of forecasts (O'Brien (1988)) and may complicate the use of predictive regressions. Second, the distribution of earnings forecast errors is left skewed, and the distribution may have a discrete jump from small negative errors to small positive errors (Abarbanell and Lehavy (2003)). Third, the literature disagrees on whether an average optimism bias exists in earnings forecasts (Chen and Jiang (2006)) or not (Gu and Wu (2003)). To avoid these issues, I work with individual forecasts and construct my own consensus forecasts to ensure that forecasts used in the left-hand side of predictive regressions are newly issued after the portfolio formation date. Thus, under rational expectations, the momentum rankings should not predict future forecast errors. Second, aware of the skewness effect in the data, I show that the main results are robust to the choice of median or mean errors, as well as to the different choices of winsorization. Third, I focus on cross-sectional differences in forecast errors to avoid statistical issues surrounding the estimate of the average forecast bias. As long as the potential optimism is symmetric across portfolios, the results of cross-sectional differences are robust to average biases.

In the robustness section, I also address the concern that earnings forecasts may systematically differ from the cash flow expectations of the market.

5 Main Analysis

In this section, I first show how I construct the proxy for cash flow expectations. Then, I identify the momentum and reversal phases in my sample. Finally, I check whether the empirical pattern of cash flow expectation errors in the momentum and reversal phases is consistent with model predictions.

5.1 Construction of the Proxy for Cash Flow Expectations

Figure 5 illustrates how I construct the portfolios and associated cash flow expectations.

[Insert Table 5 here]

At the end of each month t, I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Then, stocks are sorted into momentum quintile portfolios based on these breakpoints and held for 24 months. I use mom_t^i to denote the resultant quintile rankings. To calculate the consensus forecast for stock i in the $k+1$ month after the portfolio formation month t, in a quarter-long window from month $t+k+1$ to $t+k+3$, I collect all newly issued earnings forecasts made for the fiscal year end that is closest to month $t+k+1$ but still at least six months away from month $t+k+1$. Thus, the forecast horizon ranges from 6 months to 18 months. If one analyst issues more than one such forecast in the quarter long window, I choose the latest one. I calculate the median of these forecasts for stock i and call it the consensus forecast $AF^i_{t,t+k+1\to t+k+3,T_k}$. Note that t signifies that stocks are sorted on momentum at time t, $t+k+1 \to t+k+3$ signifies that the forecasts are issued between month $t+k+1$ and month $t+k+3$, and T_k signifies the fiscal year forecasted. I use $AF^i_{t,t+k+1\to t+k+3,T_k}$ as the proxy for cash flow expectations in this study. While the window of a quarter ensures that there are sufficient forecasts to compute the consensus forecasts, it nevertheless leads to some overlapping. I take account of the resulting serial correlation in the calculation of standard errors throughout the paper by using Newey-West heteroskedasticity and autocorrelation consistent standard errors (Newey and West (1987)). I use $Act^i_{T_k}$ to denote the actual realized earnings for $AF^i_{t,t+k+1\to t+k+3,T_k}$, which is usually announced approximately three to six months after the fiscal year end. The forecast errors are defined as actual earnings minus the consensus forecasts. Then, I normalize the forecast errors by the absolute value of forecasts to convert them into percentage errors, thereby conforming closer to a normal distribution. The percentage errors are denoted as $FE^i_{t+k+1\to t+k+3} = \frac{Act^i_{T_k} - AF^i_{t,t+k+1\to t+k+3,T_k}}{|AF^i_{t,t+k+1\to t+k+3,T_k}|}$.[12] For each stock i and portfolio-formation month t, I calculate 24 $FE^i_{t+k+1\to t+k+3}$'s for the holding period, $k = 0,\ 1, ...,\ 23$.

Finally, I repeat the calculations for each portfolio formation month t from 1988/1 to 2008/6,[13] thereby generating a time series of monthly observations for $FE^i_{t+k\to t+k+2}$, $k = 1,\ 1, ...,\ 24$.

5.2 Momentum and Reversal in the Sample

[Insert Figure 6 here]

Figure 6 depicts the differences in the cumulative returns over the holding period between stocks in the lowest momentum quintile (loser stocks) and stocks in the highest quintile (winner stocks). The dots are the time series average across portfolio formation dates. The k^{th} dot represents the average winner-minus-loser cumulative return over the first k months after sorting. From Figure 6, it is evident that the winner-minus-loser portfolio generates a gain of approximately 3.5% per dollar in the first six months and then a loss of approximately 4.8% in the following 18 months. Thus, I categorize months 1 to 6 as the momentum phase and the remainder as the reversal phase. Momentum is significant in months 1 to 6, and reversal

[12] Earnings per share are much less correlated with the size of the firm than the total earnings. Similar results are attained with forecast errors without normalization and with forecast errors normalized by price or standard deviations of changes in quarterly earnings.

[13] For years before 1988, too few firms are available for sorting because of the limited coverage of analyst earnings forecasts. The portfolio formation stops in 2008/6 because the holding period is 24 months. This implies that the last forecasts for stocks sorted into portfolios in 2008/6 are made in 2010/6 for the fiscal year ending in 2011. The 2011 earnings are announced in 2012, which is the end of my data sample.

is significant in months 9 to 13, as shown in the table within Figure 6. The return pattern of a momentum phase followed by a reversal phase is well documented in the literature, such as Lewellen (2002) and Jegadeesh and Titman (2001).[14] As discussed in Section 3, the dynamics of forecast errors in the two phases will convey critical information to distinguish among the different explanations of momentum and reversal.

5.3 Main Tests

Once I identify the momentum and reversal phases, I go directly to the main test. DHS and BSV predict the difference in forecast errors between winner and loser portfolios to be *negative* at the end of the momentum phase, whereas HS predicts this difference to be *positive.* Furthermore, DHS and BSV predict the difference to decrease in the momentum and increase in the reversal phase, whereas HS predicts the difference to decrease monotonically throughout both phases. See Figure 4 for an illustration.

5.3.1 Dynamics of Forecast Errors

[Insert Figure 7 here]

Figure 7 depicts the pattern of forecast errors for winner and loser portfolios in the holding period. The line with dots (triangles) is the time series average pattern for the winner portfolio (loser portfolio). The asterisks indicate the 95% confidence interval. The winner portfolio has positive forecast errors initially at an approximate level of 0.7% in the first month, which then gradually decline to -3.2% at the end of the holding period.[15] The forecast errors for the loser portfolio gradually shrink from -17.4% at the beginning of the holding period to -5.1% at the end of the holding period. With regard to the key moment conditions that

[14]As Jegadeesh and Titman (2001) note, hereafter JT, the switch of momentum and reversal at a frequency of less than one year is very challenging for a risk-based model to explain. My results are more similar to Lewellen (2002), which sorts stocks by the past 12-month returns. JT sort stocks by the past six-month returns, so readers should compare the holding period in this paper with the holding period from the sixth month onwards in JT. The magnitude of momentum is 0.6% per month in my sample, which is similar to Lewellen's results but a little lower than JT's results. The magnitude of reversal is -0.25% per month in my sample, which is between Lewellen's results and JT's results.

[15]Forecast errors are defined as actual earnings minus forecasts. Recall that I use a quarter-long window to calculate the consensus forecasts, so the first month is really the quarter-long window starting from the first month.

differentiate the HS model from the DHS and BSV models: around the transition period from the momentum phase to the reversal phase, i.e., months 6 to 9 in the holding period, the cross-sectional differences in forecast errors between winner and loser portfolios are all significantly positive; in addition, these differences decrease gradually from approximately 18% to 2% through the momentum and reversal phases. These results indicate that the cash flow expectations for winner stocks are less optimistic relative to those for loser stocks, and the cross-sectional difference in expectation errors diminishes over the holding period. Comparing Figure 7 with Figure 4, it is evident that the dynamics of forecast errors fit the prediction of the underreaction mechanism postulated in Hong and Stein (1999) very well. Table 4 confirms that the winner-minus-loser differences in forecast errors remain significantly positive for approximately 13 to 15 months. Thus the pattern of forecast errors is consistent with the underreaction hypothesis, which helps to explain the return momentum, but runs counter to the subsequent return reversal. This finding highlights the important role of momentum traders in the HS model: without momentum traders, cash flow expectation errors can only cause return momentum. Because momentum traders exploit the return momentum by extrapolating prices blindly,[16] they inevitably push the prices too far from the fundamental value, thereby causing return reversal.

[Insert Figure 7 Here]

The economic magnitude of the cross-sectional differences in forecast errors between winner and loser portfolios should be interpreted with additional assumptions. I use the forecasts for the current fiscal year and the next fiscal year to construct consensus forecasts. Thus, if the cross-sectional differences in forecast errors are similar for these annual forecasts and forecasts beyond the next fiscal year, the correction of forecast errors will generate a 16% to 18% difference in cumulative returns between winner and loser stocks over the two-year holding period. In contrast, if the cross-sectional differences in forecast errors for forecasts beyond the next fiscal year are much smaller, e.g., zero, then the correction of forecast errors will only generate a 1.6% to 1.8% difference in cumulative returns, assuming a P/E ratio of

[16]HS show that it is not a suboptimal strategy because momentum traders actually front-run traders who are slowly incorporating cash flow news.

10.[17] Therefore, gauging the exact impact of forecast errors on returns can be difficult.

Previous studies have examined the relation between forecast errors and past returns (e.g., Abarbanell (1991); Easterwood and Nutt (1999); Doukas, Kim, and Pantzalis (2002); Piotroski and So (2012));[18] however, to my knowledge, this study is the first to examine the full dynamics of the forecast errors simultaneously in the momentum and reversal phases and to connect these dynamics to a test of three prominent behavioral theories. Taking advantage of sharp predictions from the theories also grants my tests extra robustness and power in distinguishing between the underreaction and overreaction mechanisms. First, all three theories can predict more positive forecast errors for winner stocks at the beginning of the momentum phase. Thus, the evidence that winner stocks have positive forecasts errors in the momentum phase may not be sufficient to support the underreaction mechanism. My tests avoid this problem by explicitly utilizing the information from returns to identify the transition period from the momentum phase to the reversal phase, during which different mechanisms generate diametrically opposite predictions. I show that the cross-sectional difference in cash flow expectation errors persists into the reversal phase. Second, on the one hand, winner stocks have positive forecast errors at the beginning of the holding period and negative forecast errors at the end of the holding period; on the other hand, if researchers decide to adjust the forecast errors for winner and loser stocks by subtracting the average forecast errors, then winner stocks will have positive adjusted forecast errors throughout the holding period. Disagreements on the average forecast errors will thus lead to different conclusions. My tests, in contrast, focus on the predicted pattern of cross-sectional differences in forecast errors, thereby avoiding the thorny issues of identifying the average forecast errors.

[17] Under the discounted cash flow model, assuming discount rates are the same between earnings forecast days and earnings announcement days, I obtain $P_{realized} = \frac{CF_1}{1+r_1} + \frac{CF_2}{1+r_2} + ... + \frac{CF_\infty}{1+r_\infty}$ and $P_{expected} = \frac{AF_1}{1+r_1} + \frac{AF_2}{1+r_2} + ... + \frac{AF_\infty}{1+r_\infty}$. If percentage forecast errors for winner stocks are 16% higher for all earnings CF_1 to CF_∞, i.e., $\frac{CF_n - AF_n}{|AF_n|} = 16\%$ for all n, then $\frac{P_{realized} - P_{expected}}{P_{expected}} = 16\%$. In contrast, if $\frac{CF_n - AF_n}{|AF_n|} = 0\%$ for all $n > 1$, assuming $\frac{P_{expected}}{|AF_n|} = 10$, then $\frac{P_{realized} - P_{expected}}{P_{expected}} = \frac{CF_1 - AF_1}{AF_1} / \frac{P_{expected}}{|AF_n|} = 1.6\%$.

[18] Please see Ramnath, Rock, and Shane (2008) for a more comprehensive review.

5.3.2 Panel Regression

To formally test the implied moment conditions of cash flow expectation errors from the theories, I run the following panel regression:

$$FE^i_{t+k\rightarrow t+k+2} \quad = \quad c^k_1 + \lambda_k mom^i_t + Yearmon_t + \epsilon^i_{t+k}. \tag{1}$$

The models under rational expectations predict that all $\lambda_k^{\prime}s$ are equal to zero, i.e., momentum rankings in month t cannot predict the errors for forecasts made between months $t+k$ and $t+k+2$. The main difference between the three behavioral models is that DHS and BSV predict that $\lambda_k^{\prime}s$ are *negative* in the transition period from momentum to reversal as well as in the reversal phase. DHS and BSV also predict that $\lambda_k^{\prime}s$ grow more negative in the momentum phase and then gradually return to zero in the reversal phase, a U-shaped trend. In contrast, HS predict that $\lambda_k^{\prime}s$ are *positive* throughout the momentum phase and reversal phases and the $\lambda_k^{\prime}s$ will decrease from a positive number to zero. The intuition is that underreaction (overreaction) is associated with positive (negative) $\lambda_k^{\prime}s$. In the DHS and BSV models, overreaction in cash flow expectations peaks at the transition period, and its subsequent abatement generates return reversal. In the HS model, underreaction in cash flow expectations subsides over time.

[Insert Table 5 here]

Table 5 presents the regression results. The 24 $\lambda_k^{\prime}s$ are all significantly positive, and the magnitude of $\lambda_k^{\prime}s$ declines throughout the momentum and reversal phases. The t-statistics of $\lambda_k^{\prime}s$ clearly reject the hypothesis that $\lambda_k^{\prime}s$ are zero, thereby suggesting that the consensus earnings forecasts systematically deviate from rational expectations. The t-statistics also reject the hypothesis that $\lambda_k^{\prime}s$ are negative around the turning point from the momentum phase to the reversal phase. I can also easily reject the hypothesis that $\lambda_k^{\prime}s$ are jointly negatively for months 9 to 13, the return reversal is significant. Therefore, I conclude that the pattern of the forecast errors is most consistent with Hong and Stein (1999).

6 Robustness

6.1 Control for Analyst-Specific Sluggishness

In the main results, I use earnings forecasts as a proxy for cash flow expectations in the tested models. I now discuss how the proxy error may affect the regression results.

I formally denote the cash flow expectations in the model as MF, i.e., marginal investors' expectations, earnings forecasts as AF, and the actual earnings as CF. This yields

$$AF_{t+k} \quad = \quad MF_{t+k} + \eta^{A}_{t+k}, \tag{2}$$

where η^{A}_{t+k} is the difference between the cash flow expectations in the model and the consensus forecasts. Under the null hypotheses derived from the three theories, cash flow expectation errors can be forecasted by past returns. Thus, the following relation between the errors for forecasts made in months k to $k+2$ after portfolio formation and momentum ranking upon the portfolio formation is obtained for each firm i and each portfolio formation month t:

$$CF_{i,t+k} - MF_{i,t+k} \quad = \quad c_k + \lambda_k mom_{i,t} + \epsilon_{i,t+k}. \tag{3}$$

$CF_{i,t+k} - MF_{i,t+k}$ is the cash flow expectation error in the model. λ_k is the parameter of interest to distinguish among models. However, since I do not observe MF_{t+k} , I replace it with AF_{t+k}. Combining equations 2 and 3, I obtain

$$CF_{i,t+k} - AF_{i,t+k} \quad = \quad c_k + \hat{\lambda}_k mom_{i,t} + \epsilon_{i,t+k} - \eta^{A}_{i,t+k}, \tag{4}$$

where $CF_{i,t+k} - AF_{i,t+k}$ is the forecast errors. I do not need zero proxy error $\eta^{A}_{i,t+k}$ to obtain a consistent estimate of the key coefficient λ_k. For consistency, I only need the proxy error $\eta^A_{i,t+k}$ to be orthogonal to the momentum ranking $mom_{i,t}$. Nevertheless, there is a concern that $\eta^A_{i,t+k}$ is correlated with $mom_{i,t}$. For example, consider a loser stock that has had several disappointing quarterly earnings. It is possible that, while the marginal investor has already incorporated the firm's deteriorating business prospects into its price, the analysts are reluctant to lower their forecasts fully, thereby generating a positive proxy error $\eta^A_{i,t+k}$. As a result, this loser stock will have zero market expectation errors, but negative forecast errors. In this case, the momentum ranking can predict forecast errors but not market expectation errors. Consequently, the estimate of λ_k in regression equation 4 will be biased upward in favor of the underreaction mechanism.[19] In research on market expectations, because market expectations cannot be observed, one cannot eliminate the possible correlation between $\eta^A_{i,t+k}$ and $mom_{i,t}$ completely. However, given a concrete conjecture of the *analyst-specific* forecast bias, I can control $\eta^A_{i,t+k}$. Below I posit that $\eta^A_{i,t+h}$ is a linear function of past forecast revisions, past earnings announcement returns, and past standardized earnings surprises. This conjecture implies that the marginal investor efficiently uses the information contained in these control variables even though under the null hypotheses of the three theories, the marginal investor does not use information efficiently. Though this additional conjecture is probably not realistic, it is a strong restriction against ascertaining the predictive power of past returns, thereby serving as a stress test for the main results.

Thus, I run regression 4 again with the following control variables:

$$\begin{aligned} FE_{i,t+k} \quad &= \quad \hat{\lambda}_k mom_{i,t} + \rho_{1,k} SUE_{i,t} + \rho_{2,k} SUE_{i,t,L1} + \rho_{3,k} EAR_{i,t} \\ &\quad + \rho_{4,k} EAR_{i,t,L1} + \rho_{5,k} REV_{i,t} + \rho_{6,k} REV_{i,t,L1} + \rho_{7,k} REV_{i,t,L2} + \eta_{i,t+h}, \end{aligned} \tag{5}$$

where $SUE_{i,t}$ is the last quarterly earnings surprise before month t, defined as IBES actual earnings minus analyst consensus forecasts divided by prices at the fiscal quarter-end;[20] $EAR_{i,t}$ is the three-day return centered around the last quarterly earnings announcement;

[19] The correlation between $\eta^A_{i,t+k}$ and $mom_{i,t}$ could be positive, and in that case, the estimate of λ_{t+k} will be biased downward.

[20] I follow the approach outlined in Livnat and Mendenhall (2006).

and $REV_{i,t}$ is the percentage forecast change in the last calendar quarter, defined as the difference between the median annual forecast over months $t-2$ to t and the median annual forecast over months $t-5$ to $t-3$ scaled by the absolute value of the latter. $L1$ denotes the same variable with one lag. $L2$ denotes the same variable with two lags.

These variables are correlated with the past 11-month returns for obvious reasons; e.g., past earnings announcement returns EAR_t and lagged EAR_t are a mechanical part of the past 11-month return. Thus, I expect that including these correlated variables in the control variables will reduce the significance of the momentum ranking mom_t, generating a conservative estimate of the coefficient $\hat{\lambda}_{t+k}$.

Tables 6 and 7 present the regression results for equation 5. Comparing the coefficients of momentum rankings in this regression to those in regression 4, it is evident that the magnitude of the coefficients is reduced by approximately 50% when using control variables. Nevertheless, the important pattern of the loadings on momentum rankings does not change. The coefficients λ_k's remain significantly positive well into the reversal phase, and the magnitude of these coefficients declines consistently after the portfolio formation. Both are consistent with the pattern found in regression 4. Most control variables emerge as statistically significant. Variables such as past forecast revisions predict the forecast errors as strongly as the momentum rankings do. As discussed before, it is difficult to gauge whether the forecast errors predicted by control variables only pertain to analysts or if they are part of market expectation errors. Nevertheless, even assuming the former, I reach the same conclusion.

[Insert Table 6 here]

6.2 A Further Test

In this section, I probe the validity of the HS model and the appropriateness of using analyst forecasts as a proxy for cash flow expectations in an alternative manner. In the HS model, momentum originates from news watchers' underreaction in cash flow expectations. The more severe the underreaction is, the stronger the momentum is. Therefore, I create a bottom-up measure of underreaction for each firm only using earnings forecasts. Then, I check whether sorting on this underreaction measure can generate the predicted variation in the pattern of earnings forecast errors. Finally, I check whether the same sorting can generate the predicted variation in the pattern of returns. If the HS model does not conform to the data or the analyst forecasts are a bad proxy for cash flow expectations in the model, one will not observe the predicted variation in forecast errors or returns across the portfolios sorted on the underreaction measure.

6.2.1 Construction of the Underreaction Measure

To capture the tendency of analysts' underreaction, I construct the following measure. I trace each analyst's forecast revision history for a particular firm-fiscal year. For concreteness, consider a situation in which one analyst n makes three forecasts for a particular firm-fiscal year i: $AF^n_{i,t}$, $AF^n_{i,t-1}$, and $AF^n_{i,t-2}$. The corresponding revisions are $Rev^n_{i,t} = AF^n_{i,t} - AF^n_{i,t-1}$ and $Rev^n_{i,t-1} = AF^n_{i,t-1} - AF^n_{i,t-2}$. If one analyst uses information efficiently, no information before time $t-1$ can predict $Rev^n_{i,t}$, including $Rev^n_{i,t-1}$. However, if one analyst underreacted to information at time $t-1$, which affected the previous revision $Rev^n_{i,t-1}$, then as the analyst incorporates more of the time $t-1$ information subsequently, his/her revision $Rev^n_{i,t}$ will be forecastable by $Rev^n_{i,t-1}$. Therefore, at the end of each month t, for each analyst n, I run a simple pooled regression of $Rev^n_{i,t-h}$ on $Rev^n_{i,t-h-1}$ for all the forecast revisions that one analyst made in the past 24 months,

$$Rev^n_{i,t-h} = c + \beta^n_t Rev^n_{i,t-h-1} + \epsilon^n_{i,t-h}, \ 0 \le h \le 24, \ i = 1, 2, ...I. \quad (6)$$

A positive β^n_t indicates that analyst n is sluggish in revising his/her forecasts. To see why, consider a stock that is hit with bad news. If one analyst underreact to this bad news, the forecast is revised downward insufficiently. Subsequently, the analyst incorporates more of this bad news when he/she issues the next forecast, thereby resulting in another negative revision. A negative previous revision $Rev^n_{i,t-h-1}$ followed by a negative revision $Rev^n_{i,t-h}$ will result in a positive regression coefficient β^n_t. A more positive β^n_t implies that lesser information was incorporated initially and thus indicates more severe underreaction.

With the measure of underreaction at the analyst level, the HS model predicts that, if a stock is covered by analysts who underreact more severely, the momentum phase for this stock will be stronger. Thus, for each firm i, at the end of month t, I calculate the median β_t^n of all analysts who cover firm i, and this is the underreaction measure for firm i at the portfolio formation month t. Based on the underreaction measure, the median β_t^n, I assign firms into quintile groups and term the quintile rankings "the underreaction rankings." A high underreaction ranking implies that a firm is covered by analysts who underreact severely. For firms within each quintile underreaction ranking, I further sort them into tertile portfolios based on returns of the past 11 months independently and again hold them for 24 months.[21] Then, I trace out the dynamics of the forecast errors and the dynamics of the returns in the holding period, similar to what I did in the main analysis. Under the HS model, I expect the winner-minus-loser momentum portfolio within the highest underreaction ranking to exhibit the most severe underreaction in cash flow expectations and the strongest momentum phase.

6.2.2 Dynamics of Forecast Errors for Firms Covered by Sluggish Analysts

Figure 8 depicts the pattern of the forecast errors for the winner and loser portfolios in the holding period across different underreaction quintiles. First, I observe that sorting on underreaction rankings indeed induces a variation in the dynamics of earnings forecast errors. In the upper-left panel, stocks with the lowest underreaction ranking have an initial difference of approximately 13%, and the gap shrinks to 1% after one year. In contrast, in the lower-left panel, stocks with the highest underreaction ranking exhibit a larger difference, from 17% at the beginning to 5% after one year.

[Insert Figure 8 here]

To formally test whether underreaction in cash flow expectations is more severe in firms with the highest underreaction ranking, I run the following regression:

[21] I sort stocks into tertile momentum portfolios to ensure I have sufficient stocks within each of the 5-by-3 portfolios.

$$\begin{aligned} FE^i_{t+k\to t+k+2} &= c^k_1 + c^k_2 I\left(Under^i_{t+k} = 5\right) + \lambda_k mom_{i,t} + \\ \ldots &\quad \beta^k I\left(Under^i_{t+k} = 5\right) \times mom_{i,t} + \epsilon^i_{t+k}. \end{aligned} \tag{7}$$

The results in Table 8 indicate that the coefficient of the product term β^k is positive for approximately 22 months, with the first 18 months being statistically significant. These results confirm that our empirical underreaction measures capture the tendency of underreaction in earnings forecasts with of firms.[22]

6.2.3 Return Momentum and Reversal for Firms Covered by Sluggish Analysts

If analyst forecasts were a poor proxy for the cash flow expectations in the HS model, then the variation in the dynamics of forecast errors would not cause a variation in the pattern of momentum and reversal. Figure 9 shows that this is not the case. In the upper-left panel, for stocks with the least underreaction, momentum lasts approximately six months. Thereafter, reversal kicks in. This is consistent with the pattern of the full sample. In contrast, in the lower-left panel, for stocks with the most severe underreaction, momentum is stronger and lasts three months longer, and reversal is weaker.

[Insert Figure 9 here]

To formally test whether the momentum phase is stronger in the firms with the highest underreaction ranking, I compare the average returns in the momentum and reversal phases across the underreaction rankings. As Table 9 shows, in months 1 to 6, the winner-minus-loser portfolio in the highest underreaction ranking achieves stronger momentum than the winner-minus-loser portfolios in the other underreaction quintiles. The difference is approximately 0.24% per month and significant at the 5% level, which is a noticeable amount given that

[22] The results of a version with control variables is also available upon request.

$$\begin{aligned} FE^i_{t+k\to t+k+2} &= c^k_1 + c^k_2 I\left(Under^i_{t+k} = 5\right) + \lambda_k mom_{i,t} + \\ \ldots &\quad \beta^k I\left(Under^i_{t+k} = 5\right) \times mom_{i,t} + X^i_t + \epsilon^i_{t+k} \end{aligned}$$

The results do not change much in the regression with control variables.

the average winner-minus-loser profit of the momentum tertile portfolios is approximately 0.44% per month among stocks in the underreaction quintiles 1-4. The winner-minus-loser portfolio with the highest underreaction ranking also has a more persistent momentum phase. For months 7 to 9, while this portfolio still exhibits some momentum, the winner-minus-loser portfolios in other underreaction quintiles have begun reversal. The difference is 0.41% per month and is significant at the 5% level. Finally, from month 7 to month 24, the general reversal phase for the momentum portfolios in the full sample, the winner-minus-loser portfolio in the highest underreaction ranking exhibits little reversal, -0.1% per month, while the winner-minus-loser portfolios in other underreaction quintiles exhibit a reversal -0.28% per month. The difference is 0.17% and is significant at the 10% level. The results are consistent with the prediction in the HS model that more severe underreaction leads to a prolonged momentum phase. The variations generated in return patterns also validate the use of earnings forecast as a proxy for cash flow expectations.

In summary, I find that the stocks exhibit prolonged momentum and little reversal if they are covered by analysts who underreact severely to past information. This evidence supports the underreaction mechanism postulated by HS and validates the use of analyst forecasts as a proxy for the cash flow expectations.

7 Methodological Alternatives

In this section, I address potential questions regarding several methodological alternatives to my main test. First, I discuss one caveat of this study and its implication. Second, I discuss a similar test using forecast revisions. Third, I discuss how to reconcile the dynamics of earnings forecast errors with the patterns of earnings announcement returns documented in previous literature. Finally, I discuss the applicability of the methodology.

7.1 Cash Flow Expectations: Long-Term vs. Short-Term

Due to the limitations of the data, I have good proxies for the earnings expectation up to two years at a point of time.[23] Still, in DHS, BSV, and HS, long-term cash flow expectations should have similar expectation errors as those of the short-term cash flow expectations because all three models do not distinguish long-term expectations from short-term ones. Under this embedded auxiliary assumption or as long as long-term expectations do not have opposite errors, my findings regarding the dynamics of annual forecast errors suggest that cash flow expectations cannot explain momentum and reversal simultaneously. Nevertheless, empirically, there is a possibility that long-term cash flow expectations have opposite errors; i.e., long-term expectations exhibit the overreaction bias, while annual expectations exhibit the underreaction bias. In this case, models beyond DHS, BSV, and HS are needed.[24] To investigate whether there is a difference in the dynamics of expectation errors for short-term and long-term forecasts, I repeat the main analysis for the nearest quarterly forecasts and two-year-ahead forecasts. If the underreaction bias, i.e., the positive difference in forecast errors between winner and loser stocks, is smaller for the two-year-ahead forecasts, then the underreaction bias may turn to an overreaction bias for forecasts exceeding two years. However, in results shown in the appendix, I fail to find such a tendency—the two-year-ahead forecasts actually exhibit a similar underreaction pattern to the pattern of the nearest quarterly forecasts.

[23]One may propose using analysts' forecasts of long-term growth, but I caution against it for several reasons. First, analysts actually do not specify the exact forecasting horizons for long-term growth forecasts. Therefore, it is almost impossible to evaluate the accuracy of these forecasts precisely. Second, because the median analyst tenure is approximately three to five years, it is not practical to evaluate an analyst based on the accuracy of his/her long-term forecasts. Third, analysts update their long-term forecasts much less frequently. Consequently, analysts' long-term growth forecasts are a poor predictor for the actual long-term growth rate (Chan, Karceski, and Lakonishok (2003)) and not a good proxy for corresponding market expectations.

[24]This is not completely unforeseen by previous researchers; e.g., BSV (1998) page 332 says, "One possible way to extend the model *is to allow investors to estimate the level and the growth rate of earnings separately*"(italic emphasis added). I can interpret the "level" as near-term earnings and the "growth" as long-term earnings.

The results using analysts' long-term forecasts are consistent with the overreaction mechanism. However, the statistical significance is marred by the infrequent updates and the long-run characteristic. In addition, as discussed in the previous footnote, analysts' long-term forecasts are not widely taken as a good proxy for market expectations of long-term earnings.

7.2 Forecast Errors vs. Forecast Revisions

The focus in the main test is on forecast errors but not forecast revisions because the predicted dynamics of forecast revisions in the momentum phase in the three tested models are indistinguishable: winner stocks have positive forecast revisions and loser stocks have negative forecast revisions. This is not surprising because the theories are created to fit the same return patterns, and as revisions are changes in expectations, revisions are a mechanical part of returns. In contrast, the key difference among the theories, that is, whether the cash flow expectations underreact or overreact to past information, manifests in the level of cash flow expectations relative to the level of rational expectations. Therefore, taking the actual earnings as the benchmark of rational expectations and examining the forecast errors, i.e., actual minus forecasts, yields sharper tests of the models.

Nevertheless, the three models still have distinctively different predictions of forecast revisions in the reversal phase. The HS model predicts that winner stocks will have more positive revisions in the reversal phase, while the DHS and BSV models predict the opposite. Empirically, taking the first difference in the forecasts to calculate revisions offers two unique features. First, I can explicitly eliminate the analyst-specific fixed effect. Second, I restrict the comparisons to forecasts issued by the same analysts. McNichols and O'Brien (1997) find that analysts tend to self-censor negative views. This is not a problem for forecast revisions, because revisions can only be calculated for analysts who are still issuing forecasts. Thus, checking whether the dynamics of revisions also support the underreaction mechanism postulated by the HS model can offer corroborating evidence.

I provide the results of forecast revisions in the appendix. The dynamics of forecast revisions are consistent with conclusions drawn from examining the dynamics of forecast errors. Winner stocks have significantly more positive forecast revisions than loser stocks more than 13 months into the holding period, which is consistent with the underreaction hypothesis in Hong and Stein (1999). I also experiment with different normalization schemes, such as normalizing by past prices or standard deviations of past changes in quarterly earnings. I also examine the pattern of revisions for nearest quarterly forecasts and two-year-ahead forecasts.

Nevertheless, I find that the dynamics of the portfolio median forecast revisions are consistent across these variations.

7.3 Earnings Forecast Errors vs. Earnings Announcement Returns

Occasionally, earnings announcement returns are used to approximate changes in cash flow expectations. However, examining the earnings announcement returns is not optimal for this study because earnings announcement returns are not a direct measure of cash flow news. As with any other returns, earnings announcement returns have three components: expected returns, cash flow news, and discount rate news (Campbell and Shiller (1988)). Admittedly, more cash flow news is revealed around earnings announcement days than normal days, but expected returns and discount rate news can still be important around earnings announcement days (Kishore, Brandt, Santa-Clara, and Venkatachalam (2008); Dubinsky and Johannes (2006)).[25] Earnings announcement returns conflate all three components, so it is not well suited for the purpose of this study, which is to discriminate among models that predict similar return dynamics but different dynamics of cash flow expectations.

Nevertheless, in the appendix, I report the dynamics of earnings announcement returns after the portfolio formation to connect with prior studies and to highlight the difficulty of distinguishing different theories by examining return dynamics. I split all stocks into two groups. One group includes stocks that are covered by two analysts and satisfy all the data-cleaning criteria (the stock sample used in the main results), and the other group includes stocks that are *not* covered by two analysts but otherwise satisfy all the data-cleaning criteria employed in this paper. Across both groups, I find that winner stocks generally have higher earnings announcement returns than loser stocks in the first six months of the holding period. Interestingly, the positive cross-sectional difference in earnings announcement returns between winner and loser stocks is statistically significant for six months among stocks that are covered

[25]Kishore, Brandt, Santa-Clara, and Venkatachalam (2008) show that the earnings announcement returns include more information than cash flow news. One interpretation of their results is that earnings announcements release a great deal of information regarding the riskiness of the business prospects, which affects the discount rate. Dubinsky and Johannes (2006)) find that market participants expect a large amount of uncertainty to be resolved around scheduled announcement windows using option data. Thus, expected returns are also likely to play a non-negligible role in announcement returns.

by two analysts, but it is only statistically significant for three months among stocks that are not covered by two analysts. This discrepancy between two groups is consistent with my main finding that winner stocks have more positive cash flow expectation errors.

In the reversal phase from month 7 to month 24, among stocks covered by two analysts, winner stocks have significantly more negative earnings announcement returns most of the time, which is consistent with earlier studies, such as Chopra, Lakonishok, and Ritter (1992) and Porta, Lakonishok, Shleifer, and Vishny (1997). In contrast, among stocks covered by two analysts, the cross-sectional difference in earnings announcement returns between winner and loser stocks is not always negative, and except for the last three months, the cross-sectional difference is statistically significant from zero. For example, if one examines months 9 to11, among stocks covered by two analysts, winner stocks underperform by approximately 0.39% during the three-day earnings announcement windows, while among stocks covered by two analysts, winner stocks only underperform by approximately 0.06%. This interesting discrepancy between the two groups is consistent with all three models. In the HS model, the price extrapolation causes winner stocks to underperform in the reversal phase. For stocks followed by analysts, because earnings forecast errors are still more positive for winner stocks in the reversal phase, the earnings surprises will be more positive for winner stocks, thereby reducing the return reversal around the earnings announcements. In contrast, in the DHS and BSV models, cash flow extrapolations cause return reversal. For stocks followed by analysts, because the forecasts do not exhibit an overreaction bias, the return reversal is insignificant around announcements. For stocks that are not followed by analysts, although I do not observe forecasts for these stocks, it is possible that there is overreaction in cash flow expectations: an explanation for the strong return reversal around announcements. This again highlights the difficulty of distinguishing different theories by examining return dynamics and the necessity of directly studying the dynamics of cash flow expectations.

7.4 Applicability of the Methodology

The test design I propose in this study is a general one. For any asset pricing model that relies on the dynamics of cash flow expectations to generate specific return regularities, I can test the implied moment conditions of cash flow expectations. These moment conditions are particularly informative when models are designed to fit return patterns and thus are difficult to test by examining the moment conditions of returns.

8 Conclusion

Despite voluminous research on momentum and reversal, discriminating among competing explanations of momentum and reversal has remained an unresolved challenge. In this study, I propose to distinguish among the three most prominent behavioral models by examining their predicted pattern of cash flow expectation errors. I carefully construct the proxy for cash flow expectations from earnings forecasts and trace the dynamics of expectation errors over a two-year holding period, during which returns are characterized by a momentum phase followed by a reversal phase. I find that winner stocks have significantly more positive cash flow expectation errors than loser stocks over both the momentum phase and the beginning of the reversal phase. The large positive cross-sectional difference in cash flow expectation errors between winner and loser stocks gradually shrinks to zero over the holding period. I obtain similar results either by examining the portfolio median expectation errors or by examining the expectation errors at the individual stock level in a regression setting. The results are robust to whether I use nearest quarterly forecasts or two-year-ahead forecasts. The results are also robust to a regression setting that controls for analyst-specific sluggishness. When I rank stocks by the underreaction severity of the analysts who cover them, I find momentum is stronger among stocks with the highest underreaction ranking. Taken together, the results are most consistent with the prediction of Hong and Stein (1999), in which underreaction in cash flow expectations drive return momentum, but price extrapolation is needed to generate reversal. I also examine the dynamics of forecast revisions and the dynamics of earnings announcement returns in the holding period. Both results corroborate the main conclusion.

While the results are most consistent with Hong and Stein (1999), direct evidence on the price extrapolation behavior of momentum traders is needed to further validate the model. Greenwood and Shleifer (2013) find direct evidence for price extrapolation at the aggregate market level, but evidence at the stock level is scant. Future research on this front will complement this study in providing the empirical basis for behavioral theories that use extrapolative expectations to generate reversal-like return predictability.

The methodology used in this paper can be directly applied to study the patterns of cash flow expectation errors underlying other return regularities in the equity market. The identified patterns could shed light on the plausible unified mechanism involving cash flow expectations behind these phenomena, and could provide informative moment conditions to pin down the parameters of behavioral biases in related structural estimations.

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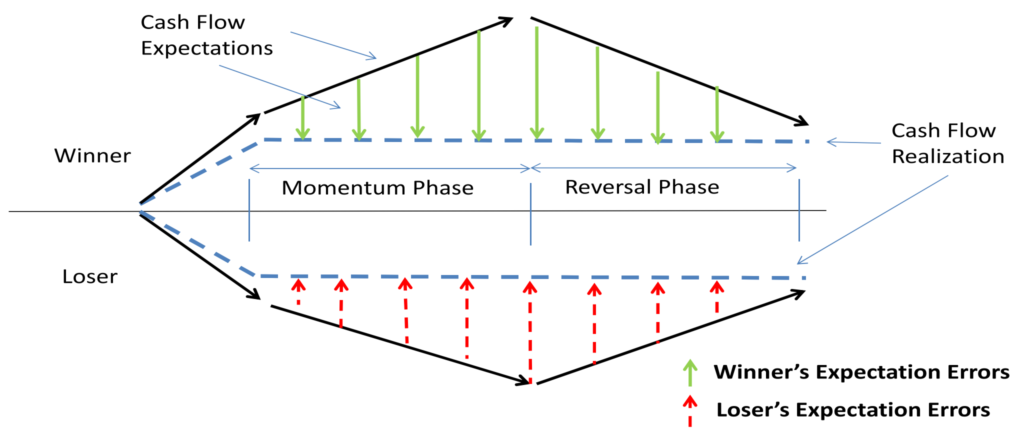
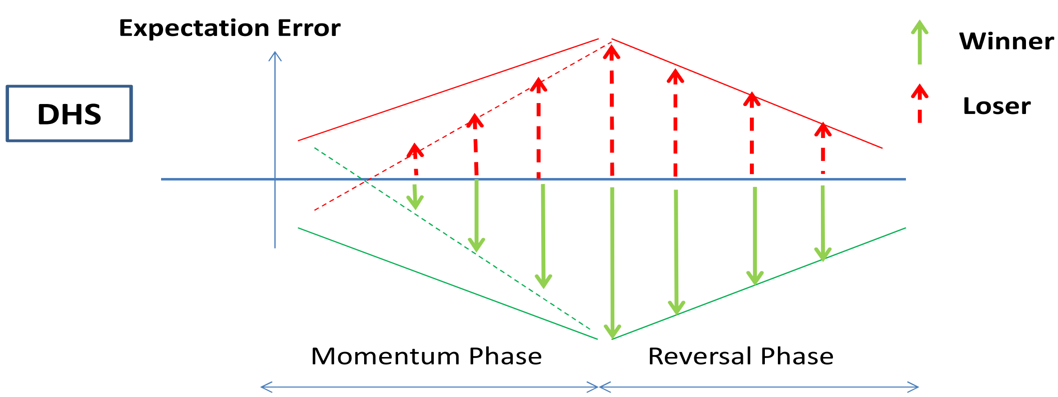


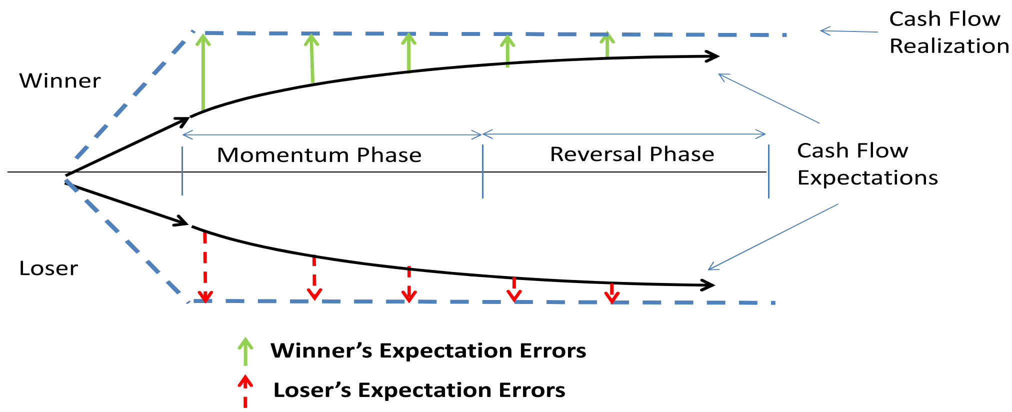
(a) Cash Flow Expectations



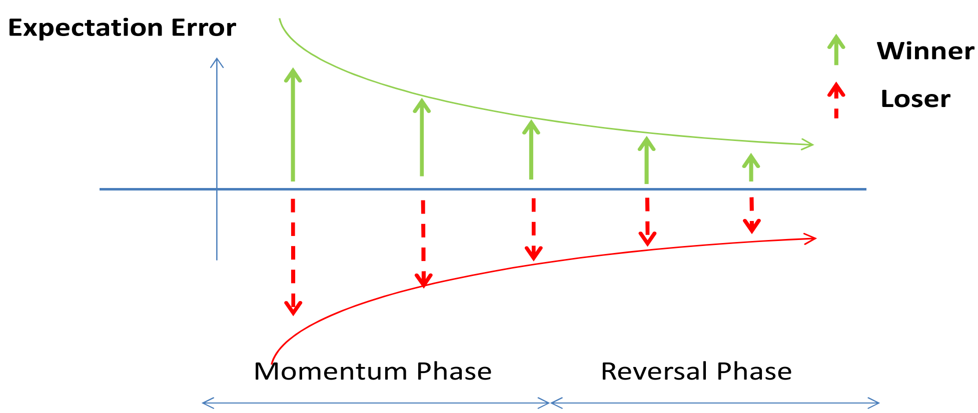
(b) Cash Flow Expectation Errors

Figure 1: Illustration of Model 1–Daniel, Hirshleifer, and Subrahmanyam (1998)

In the upper panel, the dashed line represents rational expectations, an unbiased estimate of future cash flows; the black line with an arrow represents the cash flow expectations in the model. The momentum (reversal) phase is the phase in the holding period in which winner stocks outperform (underperform) loser stocks. In the lower panel, the green (lighter) line represents the dynamics of cash flow expectation errors for winner stocks; the red (darker) line represents the dynamics of cash flow expectation errors for loser stocks. The dashed line represents the other possible prediction of the model (see footnote 9).



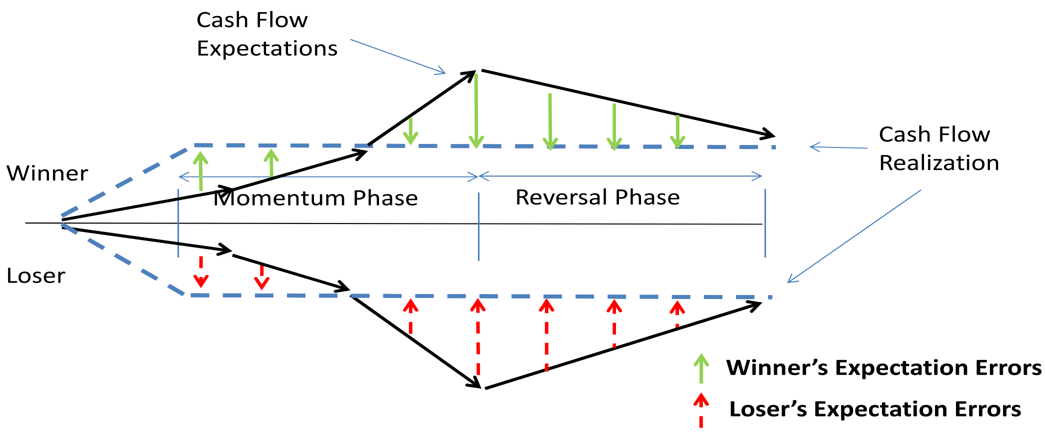
(a) Cash Flow Expectations



(b) Cash Flow Expectation Errors

Figure 2: Illustration of Model 2–Hong and Stein (1999)

In the upper panel, the dashed line represents rational expectations, an unbiased estimate of future cash flows; the black line with an arrow represents the cash flow expectations in the model. The momentum (reversal) phase is the phase in the holding period in which winner stocks outperform (underperform) loser stocks. In the lower panel, the green (lighter) line represents the dynamics of cash flow expectation errors for winner stocks; the red (darker) line represents the dynamics of cash flow expectation errors for loser stocks.



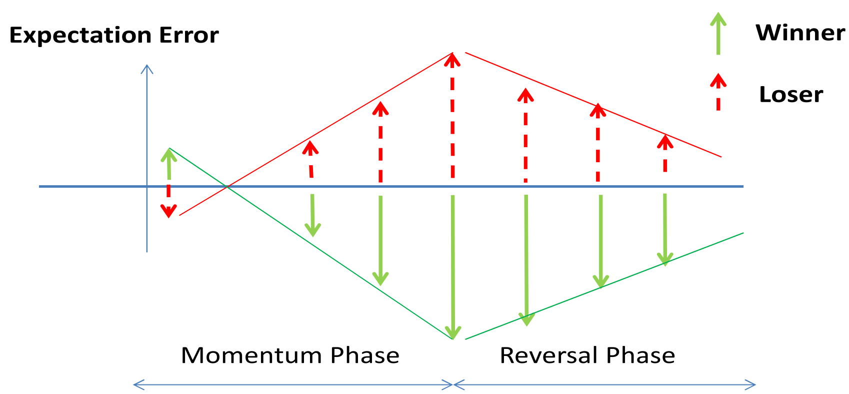


Figure 3: Illustration of Model 3–Barberis, Shleifer, and Vishny (1998)

In the upper panel, the dashed line represents rational expectations, an unbiased estimate of future cash flows; the black line with an arrow represents the cash flow expectations in the model. The momentum (reversal) phase is the phase in the holding period in which winner stocks outperform (underperform) loser stocks. In the lower panel, the green (lighter) line represents the dynamics of cash flow expectation errors for winner stocks; the red (darker) line represents the dynamics of cash flow expectation errors for loser stocks.

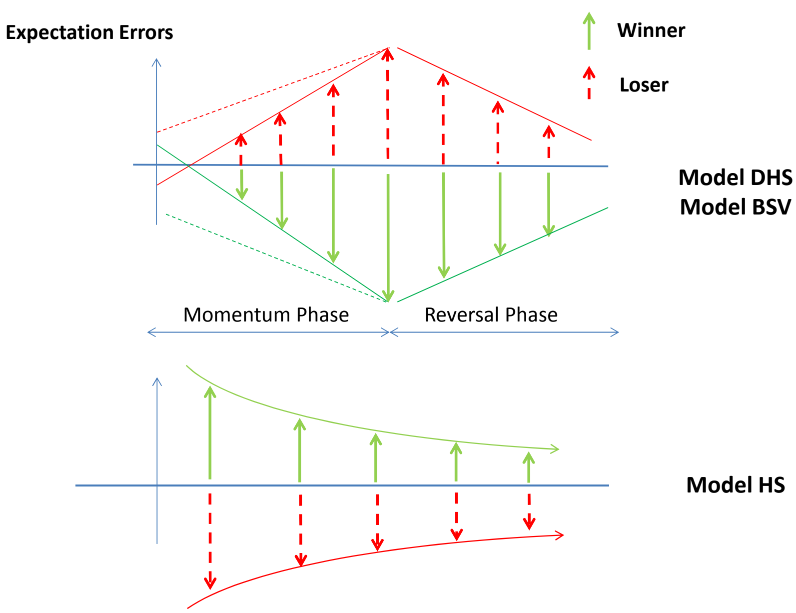


Figure 4: Summary of the Competing Predictions

The green (lighter) line represents the dynamics of cash flow expectation errors for winner stocks; the red (darker) line represents the dynamics of cash flow expectation errors for loser stocks. The dashed line represents the other possible prediction of the DHS model (see footnote 9).

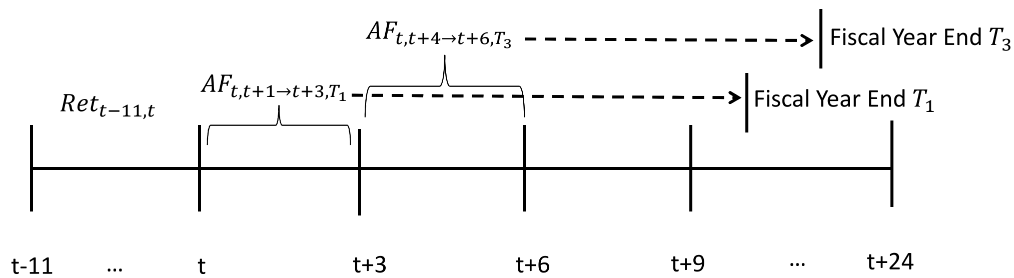
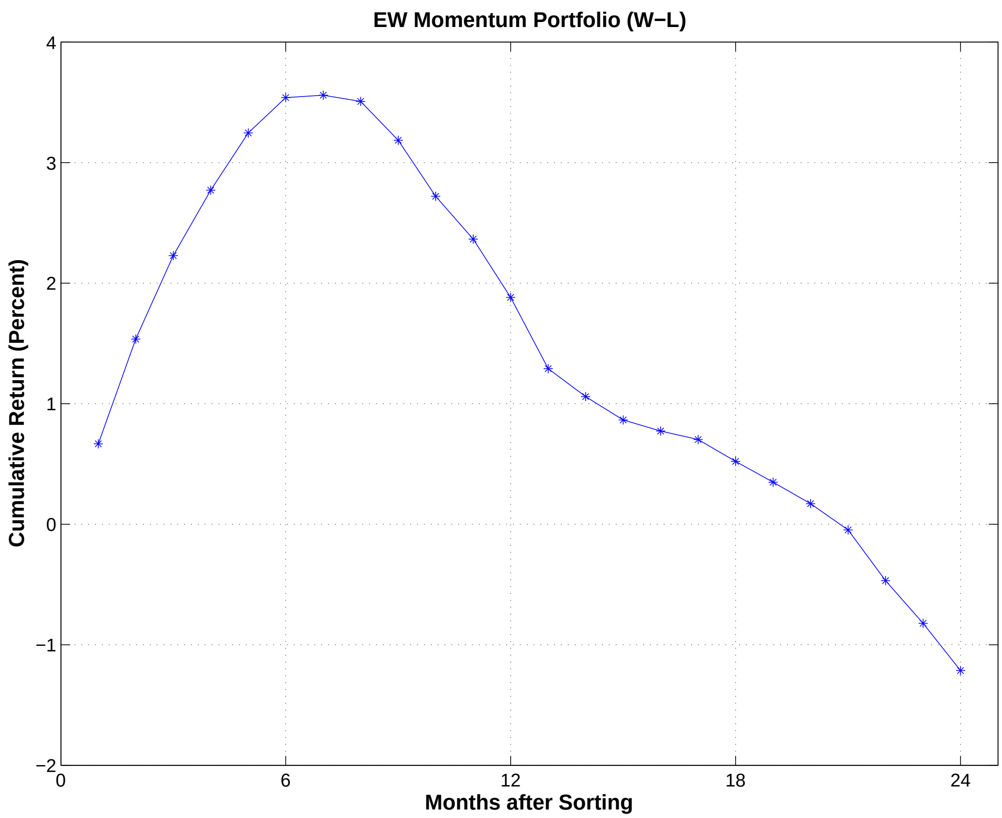


Figure 5: Timeline for Portfolio Construction

At the end of each month t, I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Then, I sort all stocks into momentum quintile portfolios based on these breakpoints and held for 24 months. To calculate the consensus forecast for stock i in the first month after the portfolio formation month t, in a quarter-long window from month $t+1$ to $t+3$, I collect all newly issued analyst earnings forecasts made for the fiscal year end that is closest to month $t+1$ but still at least six months away from month $t+1$. The forecast horizon thus ranges from 6 months to 18 months, with the average approximately one year. If one analyst issues more than one such forecast in the quarter-long window, I choose the latest one. I calculate the median of these forecasts for stock i and call it the consensus forecast $AF^i_{t,t+1\to t+3,T_1}$. Note that t signifies that stocks are sorted on momentum at time t, $t+1 \to t+3$ signifies that the forecasts are issued between month $t+1$ and month $t+3$, and T_1 signifies forecast for the fiscal year end.



Winner-minus-loser Average Returns				
Months in the holding period	1–6	7–8	9–13	14–24
Ave. Ret	0.60	0.01	-0.45	-0.24
T Stat	2.43	0.02	-1.99	-1.22
N	246	246	246	246

Figure 6: Differences in Cumulative Returns between Winner and Loser Portfolios

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Then, I sort all stocks into momentum quintile portfolios based on these breakpoints and held for 24 months. The winner-minus-loser portfolio is formed by taking a long position in the highest quintile portfolio and a short position in the lowest quintile portfolio. Sorting is done monthly between 1988/1-2008/6. Returns are equally weighted returns. Average returns in each month of the holding period are calculated by averaging over different portfolio-formation months. Cumulative returns are calculated by summing the average monthly returns over the holding period.

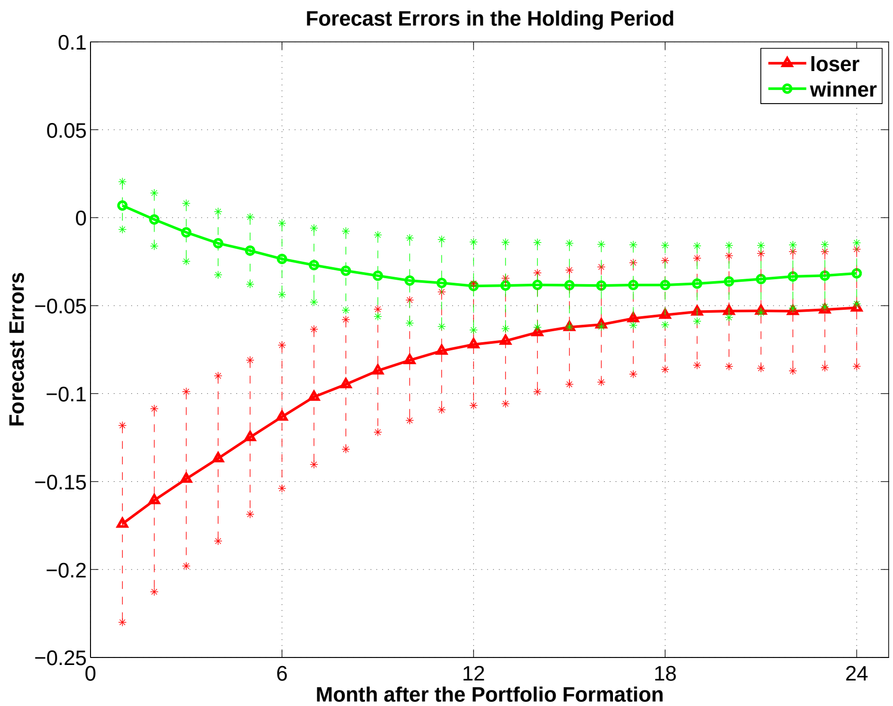


Figure 7: Dynamics of Forecast Errors for Winner and Loser Portfolios in the Holding Period
I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Then, I sort all stocks into momentum quintile portfolios based on these breakpoints and held for 24 months. In overlapping quarter-long windows within the holding period, I calculate the consensus forecast by taking the median of the newly issued forecasts for the closest fiscal year end that is at least six-month away. Forecast errors are actual earnings minus the consensus forecast. I calculate the portfolio median forecast errors for each of the overlapping quarter-long windows and then take the time series average of these forecast errors. The first dot represents the time series average of the forecast errors for forecasts made in the first quarter-long window (month 1 to month 3) in the holding period. The second dot represents the time series average of forecast errors for forecasts made in the second quarter-long window (month 2 to month 4) in the holding period. Asterisks connected by dashed lines represent the 95% confidence interval for the time series average forecast errors, using Newey-West standard errors with 18 lags.

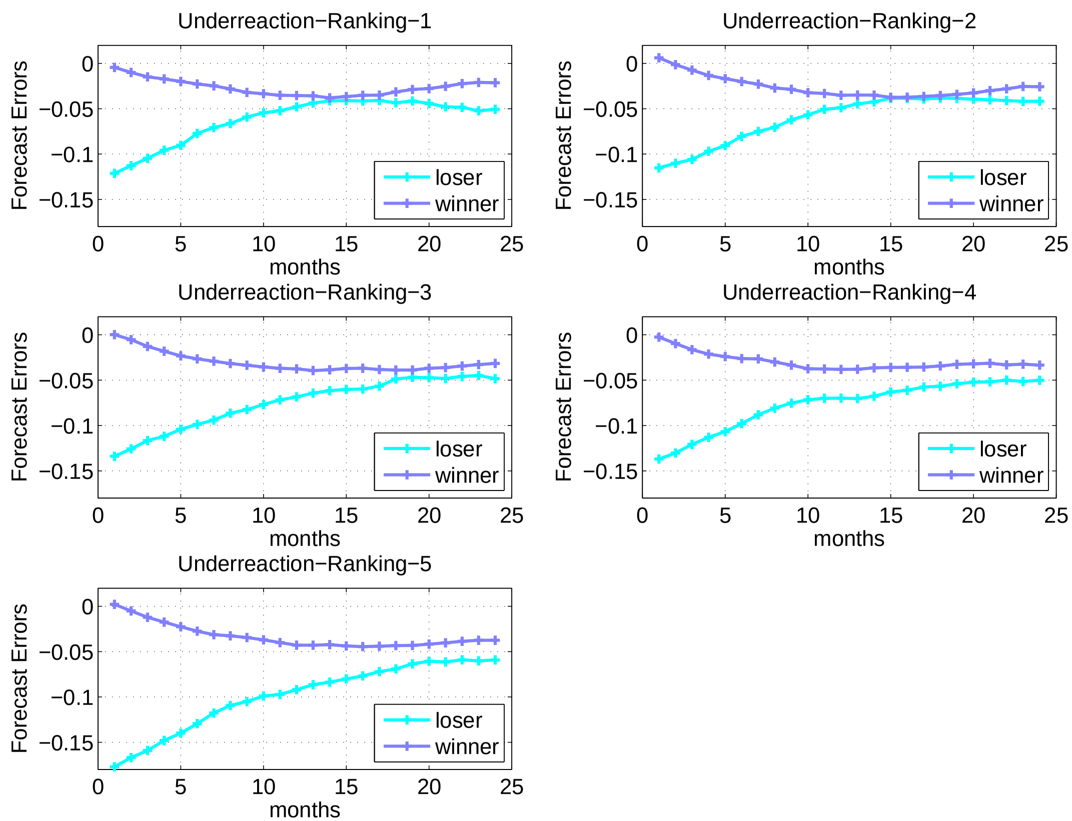


Figure 8: Time Series Mean of the Portfolio Median Forecast Errors for Winner and Loser Portfolios within Underreaction Ranking Quintiles

I form momentum tertile breakpoints from all NYSE firms based on their past 11-month returns. I form underreaction quintile breakpoints from stocks in my sample based on their underreaction betas. Stocks are then sorted into three momentum groups and five underreaction groups based on these breakpoints. Winner stocks are stocks within the highest momentum tertile, and loser stocks are stocks within the lowest momentum tertile. Stocks with high underreaction rankings are stocks with higher underreaction betas. Portfolio median forecast errors for the holding period are calculated in a similar way as before.

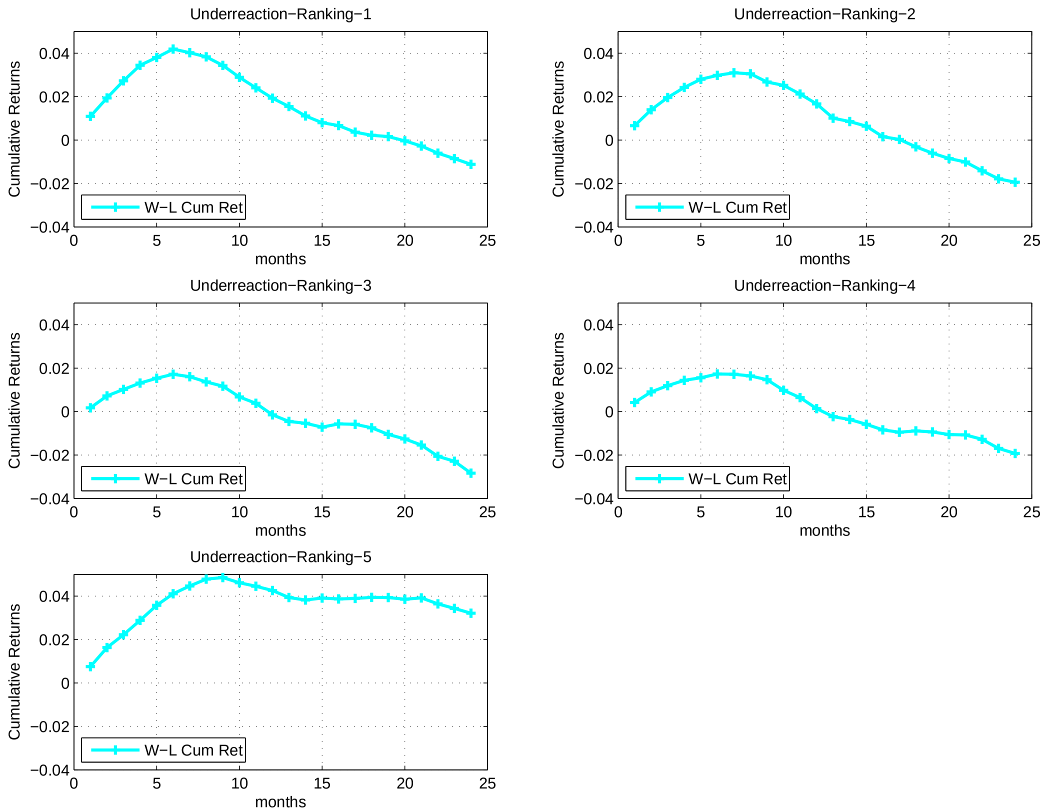


Figure 9: Time Series Mean of Winner-minus-loser Cumulative Returns across Underreaction Quintiles

I form momentum tertile breakpoints from all NYSE firms based on their past 11-month returns. I form underreaction-ranking quintile breakpoints from stocks in my sample based on their underreaction betas. Stocks are then sorted into three momentum groups and five underreaction-ranking groups based on these breakpoints. Winner stocks are stocks within the highest momentum tertile, and loser stocks are stocks within the lowest momentum tertile. Stocks with high underreaction rankings are stocks with higher underreaction betas. Within each underreaction-ranking group, the winner-minus-loser portfolio is formed by taking a long position in the highest tertile portfolio and a short position in the lowest tertile portfolio. Sorting is done monthly from 1988/1-2008/6. Returns are equally weighted returns. Average returns in each month of the holding period are calculated by averaging over different portfolio-formation months. Cumulative returns are calculated by summing the average monthly returns over the holding period.

Table 1: Data Filters (1985-2012)

Sample	Cleaning Criteria (Additive)	Ave. Firms per Month	Ave. % of CRSP Mkt Cap
CRSP	All CRSP common stocks in NYSE, AMEX, and NASDAQ	5,702	100%
	Nonmissing returns for the past 18 months	5,275	98%
Merge w/Comp	Book equity>0 and COMPUSTAT history≥3 years	4,453	94%
	Price per share > $5 and Market value > NYSE bottom size decile	2,298	93%
CRSP/COMP	Exclude financial firms (SIC between 6000 and 6999)	1,880	77%

Sample	Cleaning Criteria (Additive)	Ave. Firms per Month	Ave. % of CRSP/COMP Mkt Cap
CRSP/COMP	See above	1,880	100%
Merge w/ IBES	Within the past quarter, No. of analysts FY1(FY2) forecasts ≥ 2	1,215	92%

Table 2: Characteristics for Momentum Quintile Portfolios

Stocks in the sample are non-financial common stocks in NYSE, AMEX, and NASDAQ with nonmissing returns for the past 18 months, price per share greater than \$5, market value larger than the NYSE bottom size decile, positive book equity, more than three year COMPUSTAT records, and at least two analysts' forecasts for the current fiscal year and two analysts' forecasts for the next fiscal year within the past quarter. Every month, stocks are sorted into momentum quintile portfolios by the past 11-month returns. Quintile breakpoints are calculated based on NYSE stocks only. Sorting is done monthly from 1988/1-2008/6. P1-P99 are variable values at corresponding percentiles. Market capitalization is measured at the end of the portfolio-formation month. Book-to-market ratios for July year t to June year $t+1$ are the ratio of book equity of fiscal year $t-1$ over the market value at December year $t-1$. The number of following analysts are the number of analysts who issue annual forecasts in the last quarter for the nearest fiscal year that is at least six months away.

	Market Capitalization (\$Millions)					
Mom_Quintile	Mean	P1	P25	P50	P75	P99
1	3,104	69	282	611	1,658	51,286
2	5,385	75	441	1,111	3,222	78,893
3	6,333	90	579	1,448	4,162	87,930
4	6,314	94	590	1,491	4,377	84,842
5	4,867	84	434	1,029	2,904	72,328
All	5,129	79	429	1,067	3,122	74,586

	Book-to-market Ratio					
Mom_Quintile	Mean	P1	P25	P50	P75	P99
1	0.64	0.04	0.29	0.49	0.80	2.96
2	0.58	0.05	0.28	0.46	0.75	2.29
3	0.53	0.04	0.26	0.43	0.69	2.04
4	0.46	0.03	0.22	0.36	0.59	1.76
5	0.31	0.01	0.12	0.23	0.39	1.40
All	0.49	0.02	0.21	0.38	0.64	2.19

	Number of Following Analysts					
Mom_Quintile	Mean	P1	P25	P50	P75	P99
1	7.83	2	4	6	10	26
2	7.82	2	4	6	10	26
3	7.72	2	4	6	10	25
4	7.58	2	4	6	10	25
5	7.36	2	4	6	9	26
All	7.65	2	4	6	10	25

Table 3: Momentum and Reversal

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Stocks are then sorted into momentum quintile portfolios based on these breakpoints and held for 24 months. The winner-minus-loser portfolio is formed by taking a long position in the highest quintile portfolio and a short position in the lowest quintile portfolio. Sorting is done monthly from 1988/1-2008/6. Returns are equally weighted returns. Average monthly returns in the months after sorting are shown in the following table.

EW Portfolio Average Monthly Return (Percent)												
n^{th} Month after Sorting	1	2	3	4	5	6	7	8	9	10	11	12
Ave. Monthly Return	0.67	0.86	0.71	0.55	0.49	0.32	0.05	-0.04	-0.32	-0.48	-0.39	-0.49
T-stat	1.9	2.6	2.3	1.9	1.7	1.1	0.2	-0.1	-1.2	-1.7	-1.5	-1.9
n^{th} Month after Sorting	13	14	15	16	17	18	19	20	21	22	23	24
Ave. Monthly Return	-0.59	-0.24	-0.20	-0.10	-0.08	-0.19	-0.17	-0.20	-0.24	-0.45	-0.38	-0.40
T-stat	-2.2	-0.9	-0.8	-0.4	-0.3	-0.8	-0.7	-0.9	-1.1	-2.1	-1.8	-1.9

Table 4: Dynamics of Forecast Errors

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Stocks are then sorted into momentum quintile portfolios based on these breakpoints and held for 24 months. $FE^i_{t+k \to t+k+2}$ is the forecast error for firm i between month k and month $k+3$ in the holding period, and t signifies the portfolio-formation month (for the detailed description of forecast error calculation, please refer to 5.1). T-statistics are calculated based on Newey-West standard errors with 18 lags.

Portfolio Median Forecast Errors												
Months in the Holding Period	1-3	2-4	3-5	4-6	5-7	6-8	7-9	8-10	9-11	10-12	11-13	12-14
Ave. Winner-Loser Diff.	18.1%	16.0%	14.0%	12.2%	10.6%	9.0%	7.5%	6.5%	5.4%	4.5%	3.9%	3.3%
T-stat	8.1	8.1	7.7	7.3	7.0	6.7	6.1	5.4	4.6	3.8	3.2	2.6
Months in the Holding Period	13-15	14-16	15-17	16-18	17-19	18-20	19-21	20-22	21-23	22-24	23-25	24-26
Ave. Winner-Loser Diff.	3.1%	2.7%	2.4%	2.2%	1.9%	1.7%	1.6%	1.7%	1.8%	2.0%	1.9%	2.0%
T-stat	2.3	2.1	2.0	1.9	1.7	1.6	1.6	1.7	1.7	1.9	2.0	2.0

Table 5: Regression of Forecast Errors

$$FE_{i,t+k \to t+k+2} \quad = \quad c_k + \lambda_k mom_{i,t} + Yearmon_t + \epsilon_{i,t+k \to t+k+2}$$

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Stocks are then sorted into momentum quintile portfolios based on these breakpoints and held for 24 months. $mom_{i,t}$ is the quintile momentum ranking for firm i. $FE^i_{t+k \to t+k+2}$ is the forecast error for the median forecast made for firm i between month k and month $k+3$ in the holding period, and t signifies the portfolio-formation month. $Yearmon_t$ is the year-month dummy to control for the time fixed effect. Standard errors are clustered at the firm level to account for the serial correlation. Forecast errors are winsorized at the 2.5% level at both tails.

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.073***	0.068***	0.061***	0.056***	0.050***	0.045***	0.041***	0.038***	0.034***	0.031***	0.029***	0.027***
	(32.82)	(29.13)	(25.89)	(22.82)	(20.13)	(17.93)	(16.21)	(14.64)	(13.07)	(11.94)	(11.10)	(10.35)
N	246164	244829	243289	241752	240322	238976	237737	236465	235063	233865	231458	229630
R^2	0.061	0.056	0.052	0.049	0.047	0.046	0.045	0.044	0.042	0.041	0.041	0.041
N_clust	4465	4440	4399	4355	4323	4265	4207	4190	4159	4128	4094	4064
k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.025***	0.024***	0.023***	0.022***	0.021***	0.020***	0.019***	0.019***	0.018***	0.018***	0.017***	0.017***
	(9.67)	(9.15)	(8.52)	(7.99)	(7.63)	(7.28)	(7.02)	(6.78)	(6.55)	(6.34)	(6.03)	(5.97)
N	227989	226516	225011	223578	222313	221235	220143	218933	217635	216478	214436	212980
R^2	0.041	0.041	0.04	0.04	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041
N_clust	4024	3993	3964	3928	3878	3820	3761	3740	3730	3707	3690	3661

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 6: Regressions of Forecast Errors (w/controls)

$$FE^i_{t+k\to t+k+2} \quad = \quad \hat{\lambda}_{t+k} mom_{i,t} + \rho_{1,k} SUE_{i,t} + \rho_{2,k} SUE_{i,t,L1} + \rho_{3,k} EAR_{i,t} + \rho_{4,k} EAR_{i,t,L1} + \rho_{5,k} REV_{i,t} + \rho_{6,k} REV_{i,t,L1} + \rho_{7,k} REV_{i,t,L2} + Yearmon_t + \eta_{i,t+h}$$

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Stocks are then sorted into momentum quintile portfolios based on these breakpoints and held for 24 months. $mom_{i,t}$ is the quintile momentum ranking for firm i. $FE^i_{t+k\to t+k+2}$ is the forecast error for the median forecast made for firm i between month k and month $k+3$ in the holding period, and t signifies the portfolio-formation month.
$SUE_{i,t}$ is the last quarterly earnings surprise before month t, defined as IBES actual earnings minus analyst forecasts divided by prices at the fiscal quarter-end; $EAR_{i,t}$ is the three-day returns at the last quarterly earnings announcement before month t; and $REV_{i,t}$ is the percentage forecast changes in the last calendar quarter, defined as the difference between the median annual forecast over month $t-2$ to t and the median annual forecast over month $t-5$ to $t-3$, scaled by the absolute value of the latter. $L1$ signifies one lag. $L2$ signifies two lags. Forecast errors and other non-return variables are winsorized at the 2.5% level at both tails.

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.035***	0.033***	0.030***	0.027***	0.024***	0.022***	0.020***	0.018***	0.016***	0.014***	0.013***	0.011***
	(14.9)	(13.4)	(12.1)	(10.6)	(9.1)	(8.0)	(7.3)	(6.6)	(5.7)	(5.1)	(4.6)	(3.8)
EAR_t	0.149***	0.136***	0.114***	0.090**	0.059	0.036	0.023	0.033	0.02	0.015	0.021	0.026
	(4.0)	(3.6)	(2.9)	(2.1)	(1.4)	(0.9)	(0.6)	(0.8)	(0.5)	(0.3)	(0.5)	(0.6)
lag EAR_t	-0.047	-0.063*	-0.085**	-0.093**	-0.079**	-0.082**	-0.089**	-0.085**	-0.067	-0.052	-0.051	-0.043
	(-1.29)	(-1.73)	(-2.26)	(-2.33)	(-2.01)	(-2.03)	(-2.12)	(-2.08)	(-1.62)	(-1.22)	(-1.26)	(-1.04)
sue	8.631***	7.895***	7.346***	6.729***	5.546***	5.085***	5.122***	5.674***	6.464***	6.713***	6.170***	5.488***
	(9.7)	(8.7)	(7.8)	(6.9)	(5.9)	(5.4)	(5.3)	(6.0)	(6.6)	(6.7)	(6.2)	(5.4)
lag sue	1.994**	1.451*	1.299	1.328	2.123**	2.876***	3.490***	3.257***	2.867***	2.861***	3.009***	3.153***
	(2.5)	(1.8)	(1.6)	(1.6)	(2.5)	(3.3)	(3.8)	(3.6)	(3.1)	(3.0)	(3.3)	(3.6)
rev1	0.466***	0.457***	0.438***	0.429***	0.427***	0.400***	0.365***	0.316***	0.264***	0.222***	0.199***	0.205***
	(21.1)	(20.2)	(18.9)	(17.5)	(17.5)	(16.9)	(15.5)	(14.1)	(12.0)	(10.1)	(9.4)	(9.8)
rev2	0.258***	0.269***	0.262***	0.236***	0.188***	0.144***	0.112***	0.114***	0.131***	0.151***	0.150***	0.143***
	(12.9)	(13.5)	(13.1)	(11.3)	(9.8)	(8.0)	(6.1)	(6.2)	(7.0)	(7.7)	(7.8)	(7.5)
rev3	0.176***	0.141***	0.123***	0.117***	0.122***	0.142***	0.162***	0.168***	0.168***	0.158***	0.147***	0.135***
	(8.9)	(7.4)	(6.5)	(5.9)	(6.2)	(7.1)	(7.8)	(8.4)	(8.5)	(7.5)	(6.9)	(6.4)
R^2	0.125	0.112	0.1	0.089	0.08	0.071	0.065	0.061	0.057	0.055	0.053	0.053

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Regressions of Forecast Errors (w/controls) Continued

k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.010***	0.010***	0.009***	0.009***	0.008***	0.008**	0.009***	0.009***	0.009***	0.009***	0.008**	0.009**
	(3.5)	(3.3)	(3.1)	(2.9)	(2.6)	(2.5)	(2.9)	(2.9)	(2.8)	(2.7)	(2.5)	(2.6)
EAR_t	0.014	-0.001	-0.015	-0.029	0	0.024	0.032	0.02	0.009	0.005	0.023	0.028
	(0.3)	(-0.02)	(-0.35)	(-0.65)	(0.0)	(0.6)	(0.7)	(0.5)	(0.2)	(0.1)	(0.5)	(0.7)
lag EAR_t	-0.039	-0.018	0.003	0.017	0.01	-0.003	-0.022	0.004	0.011	0.017	-0.005	-0.039
	(-0.90)	(-0.45)	(0.1)	(0.4)	(0.3)	(-0.07)	(-0.51)	(0.1)	(0.3)	(0.4)	(-0.13)	(-0.91)
sue	5.035***	4.478***	4.492***	4.567***	4.593***	4.552***	4.289***	3.699***	3.278***	2.729***	2.363**	2.311**
	(4.8)	(4.5)	(4.5)	(4.7)	(4.8)	(4.8)	(4.5)	(4.0)	(3.4)	(2.8)	(2.5)	(2.4)
lag sue	3.454***	3.688***	3.754***	3.473***	3.298***	2.739***	2.492**	2.195**	2.147**	2.056**	2.241**	2.005**
	(3.9)	(4.2)	(4.0)	(3.6)	(3.4)	(2.9)	(2.5)	(2.3)	(2.1)	(2.0)	(2.2)	(2.0)
rev1	0.207***	0.217***	0.218***	0.215***	0.216***	0.209***	0.194***	0.164***	0.135***	0.111***	0.098***	0.093***
	(9.7)	(9.9)	(9.8)	(9.2)	(9.1)	(8.8)	(8.1)	(7.1)	(5.9)	(4.9)	(4.4)	(4.2)
rev2	0.129***	0.124***	0.122***	0.108***	0.080***	0.057***	0.037*	0.035*	0.041**	0.055***	0.078***	0.091***
	(6.4)	(6.0)	(5.8)	(5.1)	(4.1)	(3.0)	(1.9)	(1.9)	(2.1)	(2.6)	(3.7)	(4.3)
rev3	0.116***	0.083***	0.056***	0.048**	0.051**	0.064***	0.073***	0.101***	0.118***	0.137***	0.133***	0.122***
	(5.6)	(4.1)	(2.8)	(2.3)	(2.5)	(3.0)	(3.2)	(4.2)	(4.9)	(5.7)	(5.8)	(5.3)
R^2	0.052	0.05	0.05	0.048	0.047	0.047	0.046	0.045	0.045	0.045	0.046	0.046

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Forecast Errors for Momentum/Underreaction Ranking Portfolios

I form momentum tertile breakpoints from all NYSE firms based on their past 11-month returns. I form underreaction quintile breakpoints from stocks in my sample based on their underreaction betas (see equation 6 in the text). Stocks are then sorted into three momentum groups and five underreaction groups based on these breakpoints. $Under_{i,t+k}$ is the quintile underreaction ranking for firm i. $mom_{i,t}$ is the tertile momentum ranking for firm i. $FE_{i,t+k\rightarrow t+k+2}$ is the forecast error for the median forecast made between holding months $t+k$ and $t+k+3$ for firm i. The following regression tests whether the gap in the forecast errors across momentum rankings is significantly wider for stocks with the highest underreaction ranking. Standard errors are clustered at the firm level to account for the serial correlation. Forecast errors are winsorized at the 2.5% level at both tails. A year-month dummy is added to control for time fixed effect.

$$FE_{i,t+k\rightarrow t+k+2} \quad = \quad c_1^k + c_2^k I\left(Under_{i,t+k}=5\right) + \lambda_k mom_{i,t} + \beta^k I\left(Under_{i,t+k}=5\right) \times mom_{i,t} + Yearmon_t + \epsilon_{i,t+k}$$

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.118***	0.109***	0.100***	0.092***	0.082***	0.073***	0.067***	0.061***	0.054***	0.049***	0.045***	0.042***
	29.06	26.10	23.30	20.79	18.17	16.03	14.46	12.88	11.23	10.00	9.24	8.47
β^k	0.057***	0.058***	0.054***	0.051***	0.049***	0.048***	0.045***	0.044***	0.043***	0.042***	0.039***	0.037***
	5.74	5.58	5.14	4.70	4.54	4.41	3.96	3.85	3.80	3.65	3.45	3.35
R^2	0.061	0.056	0.052	0.048	0.044	0.041	0.04	0.039	0.038	0.038	0.038	0.039
k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.039***	0.037***	0.036***	0.035***	0.035***	0.033***	0.033***	0.033***	0.034***	0.033***	0.034***	0.034***
	7.76	7.35	6.89	6.59	6.52	6.24	6.07	6.05	6.12	6.06	6.14	6.18
β^k	0.036***	0.035***	0.031***	0.027**	0.023**	0.021*	0.017	0.012	0.006	0.001	-0.007	-0.009
	3.29	3.28	2.84	2.45	2.14	1.93	1.54	1.09	0.52	0.05	-0.63	-0.91
R^2	0.039	0.039	0.039	0.039	0.039	0.039	0.04	0.04	0.04	0.04	0.04	0.041

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Monthly Returns of Momentum Portfolios across Underreaction Ranking Quintiles

I form momentum tertile breakpoints from all NYSE firms based on their past 11-month returns. I form underreaction quintile breakpoints from stocks in my sample based on their underreaction betas (see equation 6 in the text). Stocks are then sorted into three momentum groups and five underreaction groups based on these breakpoints. The average monthly returns (in percent) of winner-minus-loser momentum portfolios are calculated for months in the holding period. Standard errors are Newey-West standard errors with lags.

Underreaction Ranking Quintile	Months	1-6	7-9	7-24
5 (High)	Ave. Ret	0.68***	0.25	-0.11
	T stat	2.8	1.0	-0.6
1 to 4 (Low)	Ave. Ret	0.44**	-0.16	-0.28
	T stat	2.2	-0.8	-1.6
High-minus-Low	Ave. Ret	0.24**	0.41**	0.17*
	T stat	2.1	2.3	1.8

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

9 Appendix

Table A.1: Winner-Loser Three-Day Earnings Announcement Returns (Stocks with Analyst Forecasts)

Stocks here are non-financial common stocks in NYSE, AMEX, and NASDAQ with non-missing returns for the past 18 months, price per share larger than \$5, market value larger than the NYSE bottom size decile, positive book equity, and more than three year COMPUSTAT records. Within these stocks, I put them into two groups: "stocks with analyst forecasts" are stocks that have at least two analyst forecasts for the current fiscal year and two analyst forecasts for the next fiscal year within the past quarter, and "stocks without analyst forecasts" are stocks that do not satisfy this criteria.
Stocks in these two groups are separately sorted into momentum quintile portfolios by the past 11-month returns. Momentum quintile breakpoints are calculated from all NYSE firms based on their past 11-month returns. Sorting is done monthly from 1988/1-2008/6. Winner-minus-loser portfolio is formed by taking a long position in the highest quintile portfolio and a short position in the lowest quintile portfolio. Average three-day earnings announcement returns centered on the announcement date for winner-minus-loser portfolio in the months after sorting are shown in the following table. Returns are equally weighted returns. Standard errors are Newey-West standard errors with 3 lags.

Winner-Loser Three-Day Earnings Announcement Returns (Stocks with Analyst Forecasts)												
Months in the Holding Period	1-3	2-4	3-5	4-6	5-7	6-8	7-9	8-10	9-11	10-12	11-13	12-14
Ave. Three-Day Return	0.28%	0.20%	0.18%	0.18%	0.19%	0.11%	0.03%	-0.03%	-0.06%	-0.12%	-0.17%	-0.15%
T-stat	2.5	1.9	1.8	1.9	2.0	1.1	0.3	-0.3	-0.5	-1.0	-1.4	-1.1
Months in the Holding Period	13-15	14-16	15-17	16-18	17-19	18-20	19-21	20-22	21-23	22-24	23-25	24-26
Ave. Three-Day Return	-0.05%	0.07%	0.09%	0.05%	0.02%	0.04%	0.04%	-0.02%	-0.12%	-0.20%	-0.29%	-0.30%
T-stat	-0.4	0.5	0.6	0.4	0.2	0.3	0.3	-0.2	-1.0	-1.6	-2.4	-2.5

Table A.2: Winner-Loser Three-Day Earnings Announcement Returns (Stocks without Analyst Forecasts)

Please refer to the description in Table A.1.

EW Winner-Loser Average Three-Day Earnings Announcement Returns												
Months in the Holding Period	1-3	2-4	3-5	4-6	5-7	6-8	7-9	8-10	9-11	10-12	11-13	12-14
Ave. Three-Day Return	0.37%	0.24%	0.07%	0.08%	0.02%	-0.01%	-0.16%	-0.40%	-0.39%	-0.42%	-0.30%	-0.35%
T-stat	2.3	1.5	0.4	0.4	0.1	-0.1	-1.0	-2.3	-2.3	-2.5	-1.8	-2.4
Months in the Holding Period	13-15	14-16	15-17	16-18	17-19	18-20	19-21	20-22	21-23	22-24	23-25	24-26
Ave. Three-Day Return	-0.28%	-0.16%	-0.21%	-0.23%	-0.22%	-0.24%	-0.31%	-0.36%	-0.31%	-0.28%	-0.26%	-0.27%
T-stat	-1.7	-0.9	-1.1	-1.2	-1.3	-1.4	-2.0	-2.3	-2.1	-1.6	-1.6	-1.7

Table A.3: Dynamics of Forecast Revisions (Nearest quarterly forecasts)

Analysts do not issue forecasts regularly. To calculate the relevant forecast revision for one stock in the k^{th} month after portfolio formation month t, i.e., month $t+k$, I use the revisions around month $t+k$ to approximate it. I collect forecasts that are newly issued within the last quarter ending in month $t+k$, I then track the revisions of these forecasts that occur between months $t+k$ and $t+k+3$. I call the period between forecasts and their revisions the revision period. I then multiply the revisions by the ratio of the revision period that falls within month $t+k$ to the total length of revision period. These are the approximate revisions in month $t+k$. I then take the median of the revisions as the estimated revision for the stock in month $t+k$.
To compare the estimated revisions across stocks, I need to normalize the revisions, which are in the unit of earnings-per-share. In the main test, I normalize by the absolute value of forecasts. Here I choose to normalize by different variables for the robustness purpose: the price or the standard deviations of one-year changes in quarterly earnings. Because the average revisions of all forecasts are negative and the non-zero average effect will bias the normalization results, I need to take out the average effect. To do so, I subtract from the revisions their average value between year -7 to year -5 and year +3 to year +5. Then I scale the demeaned revisions by the price at the formation month t or the standard deviations of one-year changes in quarterly earnings during the last eight quarters before the formation month t.
Also for the robustness purpose, I investigate the revisions for the nearest quarterly forecasts that are at least three months away and the revisions for two-year-ahead forecasts. Winner and loser portfolios are formed in the same way as conducted in the main test.

Portfolio Median Forecast Revisions for the nearest quarterly forecasts (Demeaned/Scaled by Price)												
n^{th} Month after Sorting	1	2	3	4	5	6	7	8	9	10	11	12
Ave. Winner-Loser Diff.	0.069%	0.060%	0.051%	0.044%	0.040%	0.034%	0.029%	0.024%	0.021%	0.018%	0.014%	0.010%
T-stat	9.41	8.13	8.26	8.47	7.49	6.67	5.85	5.86	5.33	4.32	3.64	2.89
n^{th} Month after Sorting	13	14	15	16	17	18	19	20	21	22	23	24
Ave. Winner-Loser Diff.	0.007%	0.006%	0.005%	0.002%	0.003%	0.002%	0.002%	0.000%	0.000%	0.001%	0.001%	0.000%
T-stat	2.09	1.74	1.28	0.60	0.65	0.56	0.38	0.02	0.01	0.25	0.23	0.02

Table A.4: Dynamics of Forecast Revisions (Two-year-ahead forecasts)

Portfolio Median Forecast Revisions for Two-year-ahead forecasts (Demeaned/Scaled by Price)												
n^{th} Month after Sorting	1	2	3	4	5	6	7	8	9	10	11	12
Ave. Winner-Loser Diff.	0.235%	0.201%	0.172%	0.151%	0.131%	0.116%	0.100%	0.084%	0.071%	0.059%	0.048%	0.036%
T-stat	9.57	9.72	9.20	9.01	8.85	8.31	7.93	7.43	6.68	5.86	5.17	4.52
n^{th} Month after Sorting	13	14	15	16	17	18	19	20	21	22	23	24
Ave. Winner-Loser Diff.	0.030%	0.028%	0.022%	0.017%	0.014%	0.010%	0.005%	0.003%	0.001%	0.002%	0.000%	0.000%
T-stat	3.72	3.41	2.41	1.89	1.45	1.03	0.51	0.28	0.11	0.22	-0.03	0.02

Table A.5: Forecast Errors Regression (winsorized at 5%)

$$FE^i_{t+k\to t+k+2} = \hat{\lambda}_{t+k} mom_{i,t} + \rho_{1,k} SUE_t + \rho_{2,k} SUE_{t,L1} + \rho_{3,k} EAR_t + \rho_{4,k} EAR_{t,L1} + \rho_{5,k} REV_t + \rho_{6,k} REV_{t,L1} + \rho_{7,k} REV_{t,L2} + Yearmon_t + \eta_{i,t+h}$$

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.031***	0.028***	0.025***	0.021***	0.018***	0.016***	0.014***	0.012***	0.010***	0.009***	0.008***	0.006***
	(19.05)	(16.84)	(14.66)	(12.45)	(10.53)	(9.09)	(7.93)	(6.91)	(5.81)	(4.96)	(4.30)	(3.38)
EAR_t	0.125***	0.112***	0.094***	0.074***	0.053*	0.036	0.024	0.027	0.018	0.009	0.014	0.022
	(4.90)	(4.43)	(3.53)	(2.68)	(1.96)	(1.36)	(0.89)	(1.01)	(0.67)	(0.32)	(0.52)	(0.78)
lag EAR_t	-0.027	-0.038	-0.050**	-0.059**	-0.052**	-0.056**	-0.057**	-0.051*	-0.039	-0.032	-0.026	-0.021
	(-1.11)	(-1.57)	(-1.99)	(-2.25)	(-2.01)	(-2.14)	(-2.15)	(-1.94)	(-1.47)	(-1.17)	(-0.98)	(-0.76)
sue	6.213***	5.649***	5.239***	4.834***	4.122***	3.754***	3.716***	4.066***	4.456***	4.703***	4.512***	4.212***
	(10.48)	(9.48)	(8.62)	(7.79)	(6.78)	(6.06)	(5.98)	(6.62)	(7.19)	(7.35)	(7.06)	(6.40)
lag sue	1.756***	1.468***	1.497***	1.530***	1.965***	2.463***	2.861***	2.823***	2.677***	2.670***	2.537***	2.472***
	(3.20)	(2.70)	(2.64)	(2.58)	(3.31)	(4.10)	(4.61)	(4.53)	(4.27)	(4.15)	(4.16)	(4.17)
rev1	0.302***	0.293***	0.285***	0.279***	0.277***	0.259***	0.235***	0.203***	0.168***	0.145***	0.133***	0.135***
	(21.66)	(21.04)	(19.88)	(18.60)	(18.56)	(17.60)	(16.15)	(14.78)	(12.59)	(10.62)	(9.82)	(9.98)
rev2	0.167***	0.169***	0.165***	0.148***	0.118***	0.089***	0.071***	0.073***	0.085***	0.096***	0.096***	0.087***
	(13.40)	(13.91)	(13.30)	(11.49)	(10.07)	(8.07)	(6.21)	(6.21)	(7.08)	(7.70)	(7.99)	(7.46)
rev3	0.109***	0.084***	0.073***	0.072***	0.079***	0.094***	0.104***	0.107***	0.104***	0.096***	0.092***	0.084***
	(8.76)	(7.13)	(6.18)	(5.70)	(6.27)	(7.36)	(7.94)	(8.41)	(8.29)	(7.37)	(7.00)	(6.48)
R^2	0.143	0.13	0.119	0.108	0.099	0.09	0.084	0.08	0.077	0.076	0.075	0.074
k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.006***	0.005***	0.005***	0.005**	0.004**	0.004**	0.005**	0.005**	0.005**	0.005**	0.005**	0.005**
	(3.02)	(2.87)	(2.65)	(2.52)	(2.23)	(2.22)	(2.49)	(2.51)	(2.46)	(2.55)	(2.42)	(2.40)
EAR_t	0.015	0.01	0	-0.012	-0.005	-0.003	0.002	-0.001	0.003	0.005	0.015	0.013
	(0.53)	(0.35)	(-0.01)	(-0.40)	(-0.19)	(-0.10)	(0.09)	(-0.02)	(0.09)	(0.17)	(0.56)	(0.47)
lag EAR_t	-0.022	-0.013	-0.007	-0.004	-0.004	-0.005	-0.01	0.005	0.004	0.002	-0.004	-0.016
	(-0.76)	(-0.48)	(-0.26)	(-0.14)	(-0.16)	(-0.18)	(-0.38)	(0.17)	(0.14)	(0.09)	(-0.17)	(-0.57)
sue	3.923***	3.483***	3.381***	3.427***	3.488***	3.484***	3.350***	2.981***	2.638***	2.425***	2.274***	2.259***
	(5.76)	(5.37)	(5.37)	(5.38)	(5.61)	(5.65)	(5.36)	(4.88)	(4.26)	(3.76)	(3.58)	(3.50)
lag sue	2.636***	2.796***	2.878***	2.834***	2.713***	2.241***	2.021***	1.862***	1.960***	1.915***	2.030***	1.878***
	(4.41)	(4.76)	(4.77)	(4.47)	(4.37)	(3.69)	(3.23)	(2.98)	(3.01)	(2.92)	(3.20)	(3.03)
rev1	0.134***	0.136***	0.132***	0.127***	0.127***	0.122***	0.114***	0.095***	0.076***	0.058***	0.052***	0.050***
	(9.63)	(9.77)	(9.45)	(8.85)	(8.80)	(8.44)	(7.83)	(6.77)	(5.55)	(4.30)	(3.97)	(3.90)
rev2	0.078***	0.073***	0.071***	0.062***	0.044***	0.030***	0.017	0.017	0.020*	0.028**	0.038***	0.047***
	(6.37)	(6.05)	(5.78)	(5.06)	(3.86)	(2.61)	(1.50)	(1.52)	(1.77)	(2.36)	(3.09)	(3.76)
rev3	0.074***	0.053***	0.035***	0.027**	0.030**	0.038***	0.043***	0.058***	0.071***	0.083***	0.086***	0.086***
	(5.69)	(4.30)	(2.81)	(2.12)	(2.34)	(2.85)	(3.10)	(3.99)	(4.88)	(5.61)	(5.98)	(6.01)
R^2	0.075	0.074	0.074	0.073	0.072	0.071	0.071	0.071	0.071	0.071	0.072	0.073

Table A.6: Forecast Errors Regression (winsorized at 5%/Scaled by Price)

$$FE^i_{t+k\to t+k+2} = \hat{\lambda}_{t+k} mom_{i,t} + \rho_{1,k} SUE_t + \rho_{2,k} SUE_{t,L1} + \rho_{3,k} EAR_t + \rho_{4,k} EAR_{t,L1} + \rho_{5,k} REV_t + \rho_{6,k} REV_{t,L1} + \rho_{7,k} REV_{t,L2} + Yearmon_t + \eta_{i,t+h}$$

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.227***	0.201***	0.175***	0.152***	0.132***	0.116***	0.103***	0.091***	0.077***	0.068***	0.059***	0.049***
	(24.90)	(22.11)	(19.28)	(16.82)	(14.56)	(12.90)	(11.62)	(10.27)	(8.66)	(7.56)	(6.50)	(5.31)
EAR_t	0.491***	0.432***	0.357***	0.313**	0.254**	0.166	0.107	0.118	0.112	0.108	0.163	0.221*
	(3.95)	(3.61)	(2.98)	(2.57)	(2.19)	(1.44)	(0.94)	(1.05)	(0.96)	(0.87)	(1.34)	(1.78)
lag EAR_t	-0.13	-0.159	-0.168	-0.173	-0.103	-0.074	-0.022	0.035	0.075	0.072	0.049	0.067
	(-1.10)	(-1.41)	(-1.47)	(-1.45)	(-0.89)	(-0.64)	(-0.19)	(0.31)	(0.65)	(0.59)	(0.41)	(0.56)
sue	0.654***	0.574***	0.509***	0.469***	0.407***	0.381***	0.368***	0.385***	0.405***	0.418***	0.400***	0.378***
	(10.11)	(9.10)	(8.17)	(7.49)	(6.75)	(6.33)	(6.28)	(6.74)	(7.14)	(7.12)	(6.82)	(6.43)
lag sue	0.241***	0.238***	0.248***	0.251***	0.274***	0.294***	0.306***	0.298***	0.280***	0.285***	0.284***	0.266***
	(4.15)	(4.14)	(4.28)	(4.27)	(4.76)	(5.14)	(5.35)	(5.29)	(5.03)	(5.05)	(5.18)	(4.96)
rev1	1.506***	1.418***	1.346***	1.277***	1.200***	1.052***	0.868***	0.693***	0.555***	0.446***	0.400***	0.431***
	(16.15)	(15.31)	(14.46)	(13.53)	(12.84)	(11.51)	(9.86)	(8.41)	(6.87)	(5.43)	(4.76)	(4.95)
rev2	0.583***	0.547***	0.467***	0.352***	0.230***	0.137**	0.067	0.091	0.172**	0.242***	0.292***	0.276***
	(7.66)	(7.32)	(6.40)	(4.91)	(3.49)	(2.12)	(1.01)	(1.33)	(2.38)	(3.24)	(4.01)	(3.75)
rev3	0.236***	0.157**	0.160**	0.184**	0.233***	0.330***	0.417***	0.454***	0.442***	0.403***	0.360***	0.335***
	(3.23)	(2.25)	(2.29)	(2.54)	(3.16)	(4.31)	(5.36)	(5.99)	(5.73)	(4.99)	(4.40)	(4.16)
R^2	0.146	0.132	0.121	0.112	0.104	0.098	0.096	0.093	0.091	0.092	0.091	0.09
k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.042***	0.040***	0.036***	0.032***	0.030***	0.028***	0.031***	0.033***	0.034***	0.038***	0.041***	0.045***
	(4.55)	(4.36)	(3.87)	(3.44)	(3.19)	(2.99)	(3.33)	(3.58)	(3.60)	(3.90)	(4.17)	(4.43)
EAR_t	0.198	0.181	0.165	0.145	0.102	0.066	0.066	0.029	-0.01	-0.044	-0.073	-0.141
	(1.56)	(1.47)	(1.34)	(1.14)	(0.83)	(0.53)	(0.53)	(0.24)	(-0.08)	(-0.33)	(-0.56)	(-1.05)
lag EAR_t	0.071	0.072	0.051	0.04	0.044	-0.003	-0.079	-0.072	-0.118	-0.136	-0.158	-0.191
	(0.57)	(0.61)	(0.42)	(0.32)	(0.37)	(-0.02)	(-0.65)	(-0.61)	(-0.96)	(-1.05)	(-1.26)	(-1.49)
sue	0.360***	0.343***	0.325***	0.311***	0.310***	0.294***	0.269***	0.246***	0.216***	0.189***	0.182***	0.177***
	(6.07)	(5.97)	(5.79)	(5.51)	(5.68)	(5.32)	(4.84)	(4.52)	(3.94)	(3.37)	(3.31)	(3.30)
lag sue	0.255***	0.248***	0.249***	0.236***	0.227***	0.206***	0.183***	0.169***	0.184***	0.194***	0.203***	0.183***
	(4.73)	(4.75)	(4.57)	(4.13)	(4.12)	(3.83)	(3.42)	(3.27)	(3.48)	(3.60)	(3.86)	(3.54)
rev1	0.456***	0.463***	0.449***	0.447***	0.440***	0.441***	0.431***	0.378***	0.339***	0.277***	0.279***	0.310***
	(5.16)	(5.27)	(5.06)	(4.87)	(4.72)	(4.75)	(4.69)	(4.34)	(3.99)	(3.29)	(3.42)	(3.79)
rev2	0.241***	0.208***	0.206***	0.175**	0.128*	0.111	0.089	0.099	0.128*	0.181**	0.228***	0.262***
	(3.13)	(2.68)	(2.66)	(2.31)	(1.84)	(1.64)	(1.31)	(1.50)	(1.89)	(2.58)	(3.09)	(3.42)
rev3	0.300***	0.260***	0.226***	0.227***	0.248***	0.287***	0.318***	0.384***	0.430***	0.468***	0.459***	0.433***
	(3.85)	(3.54)	(3.08)	(3.02)	(3.30)	(3.75)	(4.01)	(4.63)	(4.97)	(5.17)	(5.08)	(4.78)
R^2	0.09	0.089	0.089	0.089	0.091	0.091	0.092	0.092	0.093	0.094	0.096	0.098

Table A.7: Forecast Errors Regression (winsorized at 2.5%)

$$FE^i_{t+k\rightarrow t+k+2} \quad = \quad \hat{\lambda}_{t+k} mom_{i,t} + \rho_{1,k} SUE_t + \rho_{2,k} SUE_{t,L1} + \rho_{3,k} EAR_t + \rho_{4,k} EAR_{t,L1} + \rho_{5,k} REV_t + \rho_{6,k} REV_{t,L1} + \rho_{7,k} REV_{t,L2} + Yearmon_t + \eta_{i,t+h}$$

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.035***	0.033***	0.030***	0.027***	0.024***	0.022***	0.020***	0.018***	0.016***	0.014***	0.013***	0.011***
	(14.9)	(13.4)	(12.1)	(10.6)	(9.1)	(8.0)	(7.3)	(6.6)	(5.7)	(5.1)	(4.6)	(3.8)
EAR_t	0.149***	0.136***	0.114***	0.090**	0.059	0.036	0.023	0.033	0.02	0.015	0.021	0.026
	(4.0)	(3.6)	(2.9)	(2.1)	(1.4)	(0.9)	(0.6)	(0.8)	(0.5)	(0.3)	(0.5)	(0.6)
lag EAR_t	-0.047	-0.063*	-0.085**	-0.093**	-0.079**	-0.082**	-0.089**	-0.085**	-0.067	-0.052	-0.051	-0.043
	(-1.29)	(-1.73)	(-2.26)	(-2.33)	(-2.01)	(-2.03)	(-2.12)	(-2.08)	(pd.62)	(-1.22)	(-1.26)	(-1.04)
sue	8.631***	7.895***	7.346***	6.729***	5.546***	5.085***	5.122***	5.674***	6.464***	6.713***	6.170***	5.488***
	(9.7)	(8.7)	(7.8)	(6.9)	(5.9)	(5.4)	(5.3)	(6.0)	(6.6)	(6.7)	(6.2)	(5.4)
lag sue	1.994**	1.451*	1.299	1.328	2.123**	2.876***	3.490***	3.257***	2.867***	2.861***	3.009***	3.153***
	(2.5)	(1.8)	(1.6)	(1.6)	(2.5)	(3.3)	(3.8)	(3.6)	(3.1)	(3.0)	(3.3)	(3.6)
rev1	0.466***	0.457***	0.438***	0.429***	0.427***	0.400***	0.365***	0.316***	0.264***	0.222***	0.199***	0.205***
	(21.1)	(20.2)	(18.9)	(17.5)	(17.5)	(16.9)	(15.5)	(14.1)	(12.0)	(10.1)	(9.4)	(9.8)
rev2	0.258***	0.269***	0.262***	0.236***	0.188***	0.144***	0.112***	0.114***	0.131***	0.151***	0.150***	0.143***
	(12.9)	(13.5)	(13.1)	(11.3)	(9.8)	(8.0)	(6.1)	(6.2)	(7.0)	(7.7)	(7.8)	(7.5)
rev3	0.176***	0.141***	0.123***	0.117***	0.122***	0.142***	0.162***	0.168***	0.168***	0.158***	0.147***	0.135***
	(8.9)	(7.4)	(6.5)	(5.9)	(6.2)	(7.1)	(7.8)	(8.4)	(8.5)	(7.5)	(6.9)	(6.4)
R^2	0.125	0.112	0.1	0.089	0.08	0.071	0.065	0.061	0.057	0.055	0.053	0.053

k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.010***	0.010***	0.009***	0.009***	0.008***	0.008**	0.009***	0.009***	0.009***	0.009***	0.008**	0.009**
	(3.5)	(3.3)	(3.1)	(2.9)	(2.6)	(2.5)	(2.9)	(2.9)	(2.8)	(2.7)	(2.5)	(2.6)
EAR_t	0.014	-0.001	-0.015	-0.029	0	0.024	0.032	0.02	0.009	0.005	0.023	0.028
	(0.3)	(-0.02)	(-0.35)	(-0.65)	(0.0)	(0.6)	(0.7)	(0.5)	(0.2)	(0.1)	(0.5)	(0.7)
lag EAR_t	-0.039	-0.018	0.003	0.017	0.01	-0.003	-0.022	0.004	0.011	0.017	-0.005	-0.039
	(-0.90)	(-0.45)	(0.1)	(0.4)	(0.3)	(-0.07)	(-0.51)	(0.1)	(0.3)	(0.4)	(-0.13)	(-0.91)
sue	5.035***	4.478***	4.492***	4.567***	4.593***	4.552***	4.289***	3.699***	3.278***	2.729***	2.363**	2.311**
	(4.8)	(4.5)	(4.5)	(4.7)	(4.8)	(4.8)	(4.5)	(4.0)	(3.4)	(2.8)	(2.5)	(2.4)
lag sue	3.454***	3.688***	3.754***	3.473***	3.298***	2.739***	2.492**	2.195**	2.147**	2.056**	2.241**	2.005**
	(3.9)	(4.2)	(4.0)	(3.6)	(3.4)	(2.9)	(2.5)	(2.3)	(2.1)	(2.0)	(2.2)	(2.0)
rev1	0.207***	0.217***	0.218***	0.215***	0.216***	0.209***	0.194***	0.164***	0.135***	0.111***	0.098***	0.093***
	(9.7)	(9.9)	(9.8)	(9.2)	(9.1)	(8.8)	(8.1)	(7.1)	(5.9)	(4.9)	(4.4)	(4.2)
rev2	0.129***	0.124***	0.122***	0.108***	0.080***	0.057***	0.037*	0.035*	0.041**	0.055***	0.078***	0.091***
	(6.4)	(6.0)	(5.8)	(5.1)	(4.1)	(3.0)	(1.9)	(1.9)	(2.1)	(2.6)	(3.7)	(4.3)
rev3	0.116***	0.083***	0.056***	0.048**	0.051**	0.064***	0.073***	0.101***	0.118***	0.137***	0.133***	0.122***
	(5.6)	(4.1)	(2.8)	(2.3)	(2.5)	(3.0)	(3.2)	(4.2)	(4.9)	(5.7)	(5.8)	(5.3)
R^2	0.052	0.05	0.05	0.048	0.047	0.047	0.046	0.045	0.045	0.045	0.046	0.046

Table A.8: Forecast Errors Regression (winsorized at 5%/Scaled by Price)

$$FE^i_{t+k\rightarrow t+k+2} \quad = \quad \hat{\lambda}_{t+k} mom_{i,t} + \rho_{1,k} SUE_t + \rho_{2,k} SUE_{t,L1} + \rho_{3,k} EAR_t + \rho_{4,k} EAR_{t,L1} + \rho_{5,k} REV_t + \rho_{6,k} REV_{t,L1} + \rho_{7,k} REV_{t,L2} + Yearmon_t + \eta_{i,t+h}$$

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.280***	0.248***	0.217***	0.190***	0.165***	0.146***	0.131***	0.118***	0.102***	0.092***	0.082***	0.070***
	(24.4)	(21.9)	(19.2)	(16.8)	(14.6)	(13.0)	(11.8)	(10.7)	(9.3)	(8.4)	(7.4)	(6.4)
EAR_t	0.655***	0.605***	0.521***	0.444***	0.367**	0.243*	0.167	0.167	0.137	0.109	0.176	0.26
	(4.1)	(4.0)	(3.4)	(2.9)	(2.5)	(1.7)	(1.1)	(1.2)	(0.9)	(0.7)	(1.1)	(1.6)
lag EAR_t	-0.14	-0.188	-0.204	-0.204	-0.126	-0.118	-0.06	0.005	0.036	0.03	-0.005	0.033
	(-0.93)	(-1.30)	(-1.40)	(-1.34)	(-0.85)	(-0.80)	(-0.40)	(0.0)	(0.3)	(0.2)	(-0.03)	(0.2)
sue	0.660***	0.583***	0.518***	0.479***	0.426***	0.399***	0.386***	0.392***	0.412***	0.419***	0.399***	0.387***
	(9.9)	(9.0)	(8.1)	(7.6)	(6.9)	(6.5)	(6.4)	(6.8)	(7.1)	(7.0)	(6.6)	(6.3)
lag sue	0.261***	0.249***	0.258***	0.258***	0.273***	0.287***	0.297***	0.294***	0.280***	0.296***	0.296***	0.270***
	(4.5)	(4.3)	(4.5)	(4.4)	(4.8)	(5.0)	(5.2)	(5.1)	(5.0)	(5.2)	(5.3)	(5.0)
rev1	1.311***	1.254***	1.207***	1.164***	1.117***	0.985***	0.817***	0.669***	0.551***	0.456***	0.414***	0.412***
	(13.4)	(12.7)	(12.1)	(11.6)	(11.3)	(10.5)	(9.1)	(8.0)	(6.7)	(5.5)	(4.8)	(4.6)
rev2	0.599***	0.562***	0.481***	0.367***	0.254***	0.184***	0.123*	0.135*	0.194**	0.233***	0.264***	0.258***
	(7.2)	(7.1)	(6.5)	(5.2)	(3.9)	(2.9)	(1.8)	(1.9)	(2.6)	(3.1)	(3.6)	(3.5)
rev3	0.265***	0.183**	0.183**	0.202***	0.239***	0.304***	0.370***	0.390***	0.378***	0.346***	0.307***	0.284***
	(3.5)	(2.6)	(2.6)	(2.7)	(3.1)	(3.8)	(4.6)	(5.0)	(4.9)	(4.3)	(3.8)	(3.7)
R^2	0.126	0.114	0.103	0.096	0.088	0.082	0.078	0.075	0.073	0.073	0.073	0.072

k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.064***	0.061***	0.056***	0.051***	0.049***	0.045***	0.047***	0.048***	0.049***	0.052***	0.055***	0.059***
	(5.8)	(5.5)	(5.0)	(4.6)	(4.3)	(4.1)	(4.2)	(4.2)	(4.1)	(4.2)	(4.4)	(4.6)
EAR_t	0.242	0.225	0.199	0.181	0.128	0.098	0.102	0.086	0.054	-0.017	-0.071	-0.156
	(1.5)	(1.4)	(1.3)	(1.1)	(0.8)	(0.6)	(0.6)	(0.5)	(0.3)	(-0.10)	(-0.42)	(-0.93)
lag EAR_t	0.Fil	0.062	0.056	0.051	0.063	0.01	-0.091	-0.08	-0.157	-0.188	-0.233	-0.278*
	(0.3)	(0.4)	(0.4)	(0.3)	(0.4)	(0.1)	(-0.58)	(-0.52)	(-1.00)	(-1.14)	(-1.46)	(-1.73)
sue	0.376***	0.349***	0.324***	0.314***	0.317***	0.307***	0.287***	0.275***	0.252***	0.237***	0.232***	0.234***
	(6.1)	(5.8)	(5.5)	(5.2)	(5.6)	(5.4)	(5.1)	(4.9)	(4.4)	(4.0)	(4.0)	(4.1)
lag sue	0.254***	0.254***	0.262***	0.268***	0.261***	0.245***	0.231***	0.220***	0.235***	0.242***	0.243***	0.215***
	(4.7)	(4.9)	(4.9)	(4.7)	(4.7)	(4.5)	(4.2)	(4.0)	(4.2)	(4.2)	(4.4)	(4.0)
rev1	0.408***	0.415***	0.421***	0.419***	0.402***	0.404***	0.388***	0.351***	0.299***	0.261***	0.251***	0.280***
	(4.5)	(4.6)	(4.7)	(4.6)	(4.4)	(4.6)	(4.6)	(4.4)	(3.8)	(3.3)	(3.2)	(3.5)
rev2	0.233***	0.209***	0.207***	0.172**	0.141**	0.118*	0.092	0.085	0.114*	0.164**	0.220***	0.253***
	(3.1)	(2.8)	(2.9)	(2.5)	(2.2)	(1.8)	(1.4)	(1.3)	(1.7)	(2.3)	(2.9)	(3.1)
rev3	0.260***	0.231***	0.196***	0.202***	0.213***	0.244***	0.292***	0.378***	0.428***	0.452***	0.430***	0.404***
	(3.6)	(3.3)	(2.8)	(2.7)	(2.9)	(3.2)	(3.7)	(4.4)	(4.7)	(4.7)	(4.5)	(4.3)
R^2	0.071	0.07	0.07	0.07	0.071	0.071	0.072	0.073	0.073	0.074	0.076	0.078

Table A.9: Dynamics of Forecast Errors (Two-year-ahead forecasts)

Portfolio Median Forecast Errors for Two-year-ahead forecasts												
n^{th} Month after Sorting	1	2	3	4	5	6	7	8	9	10	11	12
Ave. Winner-Loser Diff.	22.1%	19.2%	16.4%	14.0%	12.1%	10.4%	8.7%	7.3%	6.2%	5.1%	4.7%	4.0%
T-stat	9.5	8.7	7.5	6.4	5.6	4.6	4.0	3.3	2.8	2.3	2.1	1.8
n^{th} Month after Sorting	13	14	15	16	17	18	19	20	21	22	23	24
Ave. Winner-Loser Diff.	3.3%	3.2%	3.1%	2.9%	2.9%	2.7%	2.9%	3.2%	3.2%	3.0%	2.8%	2.6%
T-stat	1.4	1.4	1.3	1.4	1.4	1.4	1.6	1.8	1.8	1.6	1.5	1.3

Table A.10: Dynamics of Forecast Errors (Nearest quarterly forecasts)

	Portfolio Median Forecast Errors for the nearest quarterly forecasts											
n^{th} Month after Sorting	1	2	3	4	5	6	7	8	9	10	11	12
Ave. Winner-Loser Diff.	9.0%	8.0%	6.8%	5.9%	5.1%	4.2%	3.4%	2.7%	2.0%	1.6%	1.4%	1.2%
T-stat	6.5	6.2	6.3	5.6	4.9	4.7	4.4	3.8	3.5	3.3	3.1	2.5
n^{th} Month after Sorting	13	14	15	16	17	18	19	20	21	22	23	24
Ave. Winner-Loser Diff.	1.0%	0.5%	0.2%	0.2%	0.1%	-0.2%	0.1%	-0.2%	-0.4%	-0.5%	-0.4%	-0.4%
T-stat	2.0	1.2	0.4	0.3	0.3	-0.4	0.1	-0.5	-0.8	-1.1	-0.9	-1.0

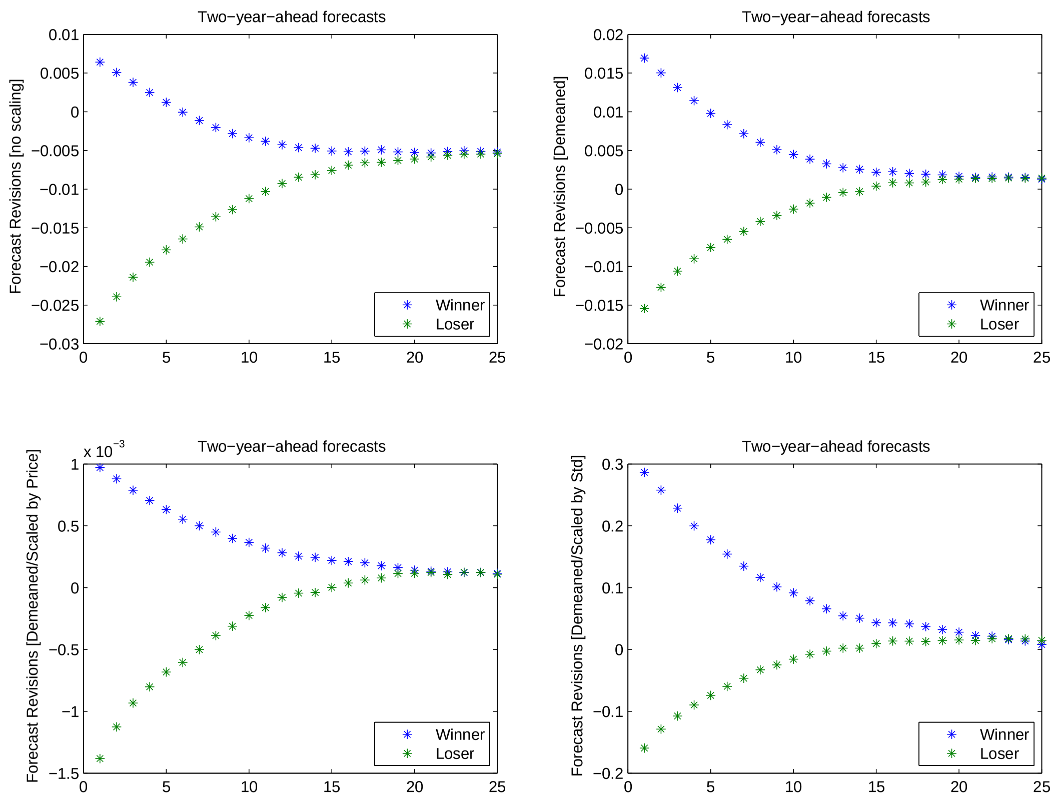


Figure A.1: Dynamics of Forecast Revisions for Two-year-ahead Forecasts

Please refer to the description in Table A.3.

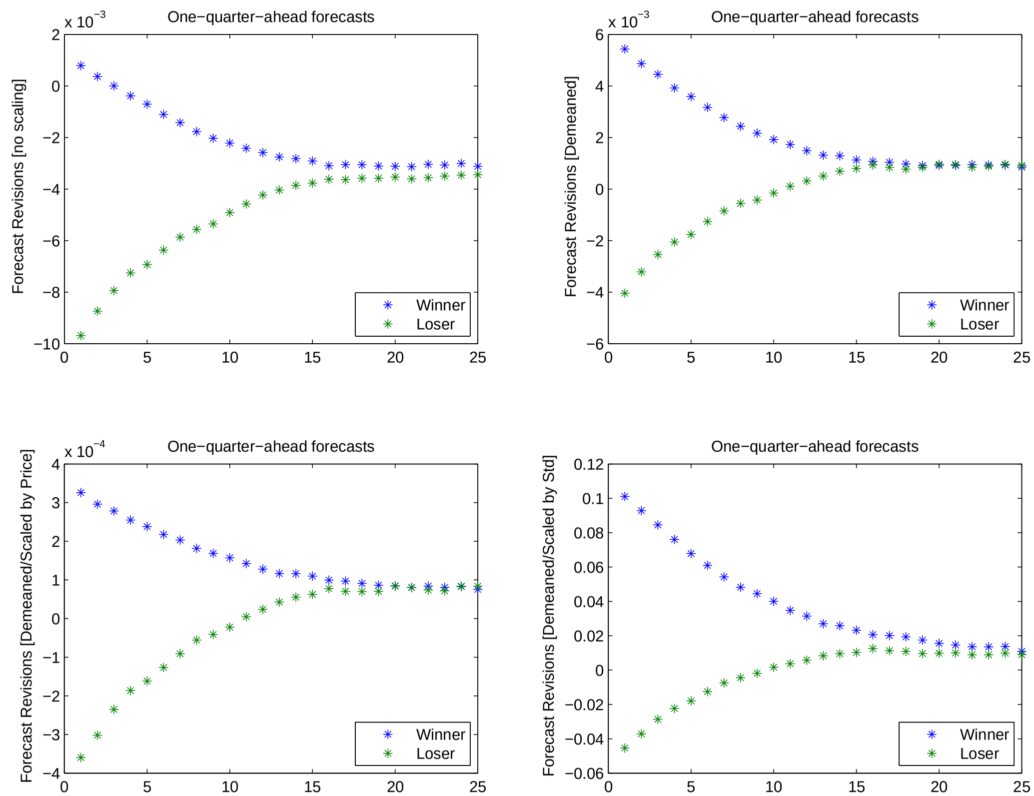


Figure A.2: Dynamics of Forecast Revisions for the Nearest Quarterly Forecasts)

Please refer to the description in Table A.3.