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Analyst Coverage and the Profitability of Earnings Momentum Strategies

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ABSTRACT

It is a well documented finding that stock prices drift in the direction of unexpected earnings changes, a phenomenon known as post-earnings announcement drift. In my thesis, I study the stock prices' reaction to quarterly earnings news. This thesis will show that the timeframe in which the drift occurs is related to the size of a company and is limited in time after the earnings announcement. Furthermore, I analyze the effect of the number of analysts following a firm on the magnitude and persistence of post-earnings announcement drift. I document that recent analyst coverage predicts large drifts after the earnings announcements. Relatively low analyst coverage indicates a negative momentum stock that has a long way to go before it turns the corner. Relatively high analyst coverage signals a stock that has "bottomed out" and has a bigger upside potential. These patterns are, however, mainly observed in larger stocks. Market risk partially explains the drifts. Book-to-market effects and transactions costs do not justify the abnormal returns. I suggest several possible explanations, but the evidence seems most consistent with recent analyst coverage providing information about investor (or analyst) expectations regarding firm's future earnings.

Keywords: post-earnings announcement drift, analyst coverage, market efficiency, momentum

I. Introduction

Financial academics have spent much of the past decades debating how stock prices react to important news about their fundamental value. Believers in market efficiency say that the price of a financial asset reflects all available information that is relevant to its fundamental value. Any deviations from fundamental values cannot last for long. On the other hand, behavioral economists are much more skeptical about markets' rationality. They challenge the traditional view of the "Efficient Market Hypothesis" that the market price is the right price.

The main focus of this thesis is on the stock prices' reaction to earnings news. Prior research documents that stock prices drift in the direction of unexpected earnings changes, a phenomenon known as post-earnings announcement drift. Although firms' stock prices respond positively to earnings news, they fail to fully reflect implications of current earnings for future earnings and require several quarters to fully incorporate this information. The delayed market response to earnings news is one of the most puzzling anomalies to emerge from capital market research over the past decades.

If the sluggishness in the response of prices to earnings announcements causes the drift, we need to better understand the price discovery process: how the market processes information and how this all relates to the earnings momentum. This calls for an appropriate proxy for the rate of information flow. Prior research recommends financial analyst coverage[1], but lacks to relate it to the post-earnings announcement phenomenon. This paper empirically links drift to analyst coverage. My investigation focuses on the effect of the number of analysts following a firm on the magnitude and persistence of the post-earnings announcement drift.

There are two main motivations for my research. First, I set out to provide an out-of-sample test of recent behavioral theories (presented in the literature overview). These studies attribute the delayed price response to earnings news to investors' information processing bias. I am interested in whether the predictions of these models can explain the patterns emerging from analyst coverage analysis on drift. Second, examining the relation between drift and analyst coverage I intend to follow up on the prior research on the prediction of intermediate horizon returns following the earnings announcement. The basic motivation here stems from McNichols and O'Brien's (1997) evidence that analyst coverage contains some return-predictive power.

The results show that the earnings momentum is highly pronounced and persists longest among the smallest stocks on the NYSE (stocks below the 40^{th} percentile of the NYSE/AMEX stocks' universe).

[1] For more details, see Brennan et al. (1993), Hong, Lim and Stein (2000), Elgers et al. (2001) or Gleason and Lee (2003).

I show that post-announcement drifts in security returns are mainly associated with firms with negative unexpected earnings, suggesting that bad news travels slowly. These findings remain mostly unchanged even when I control for beta risk, book-to-market factors and short-selling restrictions. This evidence is consistent with previous research.

More interestingly, there is an intriguing and consistent pattern in the results. Bad-news stocks with relatively low analyst coverage continue to lose while their peers with relatively high analyst coverage do not. Similarly, prices of good-news stocks with low analyst coverage initially drift and then strongly rebound, whereas good-news stocks with high analyst coverage still continue to drift, though moderately. In other words, a strategy of buying good-news firms with high analyst coverage and selling bad-news firms with low analyst coverage yields higher abnormal results in comparison with simple earnings momentum strategy, which buys good-news firms and sells bad-news firms without conditioning on analyst coverage .

These results are difficult to reconcile using the set of available behavioral models. In my thesis, I present an interesting suggestion for my results by adopting a framework of the "Earnings Expectation Life Cycle" proposed by Bernstein (1993). If the firms are of approximately the same size, the number of analysts can be seen as a proxy for investor expectation and investor interest in a firm. This interpretation comes from McNichols and O'Brien (1997) who report that initiating and dropping coverage is associated with analyst optimism and pessimism, respectively, about the firm's future prospects. Therefore, analysts will report on stocks about which they have favorable views, and vice versa. It implies that relatively low coverage predicts negative returns and relatively high coverage predicts positive returns, hence high-coverage stocks outperform low-coverage stocks. One might object that analyst coverage can proxy for other factors such as beta risk, book-to-market ratio, constraints on short-selling or trading volume. I conduct some robustness tests and show that the profitability of this strategy still carries over. Note that these patterns are, however, mainly observed in larger stocks. Analyst coverage does not tell us much about post-earnings announcement drift in the smaller stocks.

In my analysis, I construct earnings momentum portfolios based on a measure of unexpected earnings changes. Specifically, I employ two ways of forming such portfolios. The first method closely follows Bernard and Thomas (1989) and requires taking positions in stocks almost daily (always the day after firm's earnings announcement). The second method replicates Chan, Jegadeesh and Lakonishok (1996) and portfolios are formed at the beginning of every month. The latter method might be easier to implement but understates the returns on earnings momentum strategies. Unlike Bernard and Thomas (1989) and Chan, Jegadeesh and Lakonishok (1996), who compute the measure of unexpected earnings changes based on a simple model of expected earnings, I obtain this measure using analyst forecasts of quarterly earnings[2]. When looking for the effects of analyst coverage on drift, I further decompose portfolios based on their analyst coverage. Instead of using a raw number of analysts, I apply residual coverage after controlling for a size effect. Lo and MacKinlay (1990) find a positive relation between size and the speed of adjustment and Bhushan (1989) points out the relation between size and the number of analysts. Controlling for size, any results found in my analysis can be attributed to a pure analyst coverage effect and will not be tainted by differences in firm's size.

The remainder of this thesis is structured as follows. Section II provides the motivation for my paper from prior studies' perspective. Section III elaborates on the data sources and methodological issues employed in the paper. Section IV reviews the results of my analysis. Finally, section V concludes and summarizes the implications of my findings.

II. Related Literature

The literature on anomalies is very large and covers topics of broad areas. A summary of old papers documenting post-earnings announcement drifts in security returns is presented in Ball (1978) or Joy and Jones (1979). Foster, Olsen and Shevlin (1984) use 4 models of estimating unexpected earnings to form their portfolios. The first two models estimate unexpected earnings from time-series models of past earnings and the other two use security returns prior to the release of earnings. Forecast earnings errors are then determined from these models for each quarter. Based on the distribution of these forecast errors, each firm is assigned to one of the ten portfolios in the quarter subsequent to that in which the cut-off points were determined. Then they show that the portfolio with ten percent most negative earnings forecast error yields -3.08 percent and another portfolio with ten percent most positive forecast error has an abnormal return of +3.23 percent, both within 60 trading days over the 1974 to 1981 period. They also find that the drift is stronger in the smallest stocks. Their firm size variable explains 66 percent of the variation in abnormal returns.

To compute the drift, Foster, Olsen and Shevlin (1984) use abnormal returns in excess of the return to the portfolio of stocks of the same size. Bernard and Thomas (1989) argue that this strategy requires an investor to take new positions in size-control portfolios, containing hundreds of stocks, almost every day, making the strategy more difficult to implement. Therefore they construct the "continuously balanced" strategy which buys good news firms and shorts bad news firms, while short positions must equal long positions all the time. This zero-investment strategy is easier to implement but still yields comparable returns. Indeed, for the 1974 to 1981 period, they obtain an annualized return of 19%. Bernard and Thomas also confirm the relation of drift to firm size. The strategy has an

[2] See Liang (2003)

abnormal return of approximately 5.3% over the 60 days after the earnings announcement among small firms, compared to 4.5% and 2.8% for medium and large firms, respectively. Almost the full magnitude of the drift occurs within nine months for small firms and within six months for large firms.

Researchers have presented several competing explanations to justify these abnormal returns. One possible explanation suggests that if stocks are priced rationally, any systematic differences in average returns are due to differences in risk. Bernard and Thomas (1989) argue that if the abnormal returns on this strategy yield a positive return because of its riskiness, that risk should periodically results in losses. Surprisingly, the mean return on their zero-investment strategy is negative only 8% or 12% of the time. Furthermore, they show that differences in beta risk, between firms with the most negative and firms with the most positive unexpected earnings, is too small to explain the magnitude of the drift.

Fama (1998) suggests that this anomaly could simply represent a chance deviation. This explanation is difficult to reconcile with the findings of Chan, Jegadeesh and Lakonishok (1996) that momentum and earnings strategies persist in both up- and down-markets. By and large, it is doubtful to believe that risk alone explains the existence of the post-earnings announcement drift. Even Fama and French (1993,1996) concede that their three factor model does poorly to rationalize the empirical evidence on profitability of momentum strategies.

Another branch of the EMH' explanation is that post-event prices drift due to limits of arbitrage (high trading costs). Bhushan (1993) shows that transaction costs are an important determinant of the post-announcement drift. In contrast, Lee and Swaminathan (2000) found that price and earnings momentum is more pronounced among high volume stocks. Hence, this evidence runs counter to the transaction costs' explanation of the phenomenon. Bernard and Thomas (1989) refute this possibility by showing that restrictions on short sales do not attenuate the return on their zero-investment strategy based on past unexpected earnings.

Another class of explanations suggests that at least part of the drift arises from a delayed price response. Most studies document an initial underreaction to important news that must be corrected at some point in the future. For example, Bernard and Thomas (1989) show that a market is again surprised in a quarter subsequent to the one when the portfolio is formed. The finding of high abnormal returns (1.3% for small good news firms and -0.8% for small bad news firms) around the announcement subsequent to the announcement when portfolios were formed suggests a delayed response. However, they lack a plausible explanation why this delay would occur.

Bernard and Thomas (1990) offer a model in which prices react slowly to earnings news. They argue that investors do not fully recognize the impact information in today's earnings has on future earnings. They document an intriguing and persistent relation between current and future earnings. Particularly, they find a positive relation between unexpected earnings for the current quarter and abnormal returns around the subsequent release of earnings, but also a negative relation between unexpected earnings for quarter t and post-announcement drift for quarter t+4. Bernard and Thomas conjecture that investors ignore this pattern in earnings and thus are surprised in subsequent quarters. Their model is consistent with empirical evidence on underreaction to public news.

Chan, Jegadeesh and Lakonishok (1996) provide evidence that post-earnings announcement drift is distinct from price momentum. An interesting result in this regard is that momentum strategies based on past returns (price momentum) and on earnings surprises (earnings momentum) underreact to different pieces of information. The very low correlation (0.236) between abnormal returns on a price momentum strategy and abnormal returns around earnings announcements demonstrate this finding. They hypothesize that an earnings momentum strategy may spark from underreaction to short-term earnings, whereas a price momentum strategy arises from the market's sluggish response to a broader set of information. That is why the post-earnings announcement drift tends to be smaller and seems to be more short-lived. In addition, they find that almost half of the drift in the first six months occurs around the release of earnings, when the portfolio is created, and at the subsequent release of earnings. Consistent with previous studies, their results imply the market is slow to incorporate past earnings news, especially if these were bad.

More recent studies of post-earnings announcement drift[3] use analysts' forecasts to estimate earnings surprises. Analysts' forecasts have been widely used in previous research as a proxy for investor's information because analysts play a crucial role in the stock market as information intermediaries. Using analysts' forecasts, Liang (2003), Gleason and Lee (2003) and others further show that information processing biases must partially justify drift. Without any doubts, the delayed market response to earnings news is one of the most puzzling anomalies to emerge from capital market research over the past decades. If the underreaction story is right the following question arises: why does the market underreact to earnings news and why does it take months to correct this mistake?

Barberis, Schleifer and Vishny (1998) present a model of how a representative agent (investor) forms his or her beliefs. The model captures two cognitive biases identified by psychological research. Conservatism, or the tendency of investors to only slowly update their beliefs in the presence of new evidence and representativeness, or the tendency of investors to view events as typical and ignore the

[3] See, for example, Liang (2003), Livnat (2003 a,b) or Mendenhall (2004)

probability with which these events occur. Combining both biases together, investors put too much weight on the strength of the evidence and too little on its statistical weight. Thus investors underreact to current earnings (conservatism) but overreact to a series of either good or bad earnings announcements (representativeness). This hypothesis also suggests that investors underreact more to information that is relatively more reliable. The fact that investors subject to conservatism disregard the full information contained in current earnings links this model to a model of Bernard and Thomas (1990) who show that investors ignore the autocorrelation pattern in earnings and thus underreact to the earnings announcement. This mistake is corrected in subsequent quarters when more evidence on sustainability of current earnings is revealed.

The first out-of-sample test of BSV model was conducted by Dische (2001). He finds higher abnormal returns on the earnings momentum strategy among stocks with a low dispersion in analysts' consensus forecasts. The low dispersion suggests that analysts are surer about the firms' future prospects, or in other words investors weigh more on forecasts with a low dispersion, resulting on average in a stronger impact on stock prices.

Daniel, Hirhleifer and Subrahmanyam (1998) point out two different psychological biases: investor overconfidence about the precision of private information; and self-attribution, which implies that investors tend to attribute success to their superior skills and failure to bad luck. Applying the two biases to the model, they show that prices overreact to private information but underreact to public news. If public news arrives after private information and confirms it, then attribution bias leads to even stronger overreaction. Thus the model justifies both under- and over-reaction. The model suggests the drift to be most pronounced in stocks with the greatest information asymmetry. This implies that the model predicts greater inefficiencies for small stocks than for large stocks. According to the model, mispricing should also be more severe among stocks that are hard to value such as glamour stocks because more private information- causing more overreaction- is needed to resolve the uncertainty about the value of these stocks.

The previously described models assume a representative investor subject to psychological biases. A model of Hong and Stein (1999) introduces two classes of boundedly rational investors who receive different pieces of private information at different points in time. Investors are boundedly rational in a sense that each type of investors can only process part of the available public information, which is not identified by the other class of investors. The first group, the so called "newswatchers", trade only on their privately observed information about fundamentals, but they fail to extract information from historical prices. Assuming that information diffuses gradually across investors, newswatchers generate underreaction in the short run. The second group of investors, trend chasers or momentum traders, condition on historical prices, however, their limitation is that they can only implement simple chartists' rules and they do not observe private information about the stock's fundamental value. Acting upon recent price movements, trend chasers cause prices to move in the direction of fundamentals in the short run. As more chartists start to trade, prices eventually overshoot in the long run. Trend chasers exploit the underreaction induced by newswatchers and those acting early in the "momentum cycle"- shortly after the news arrival- make a profit. Those who jump on a "momentum bandwagon" too late lose money because prices have already overshot their fundamental values.[4] Hence, the model predicts short-term underreaction and long-term overreaction. Hong and Stein embellish their model for such phenomenon where information is observable by everyone simultaneously, as it is in the case of post-earnings announcement drift. They state, that "it is easy to embellish our model so that it also generates short-run undereaction to public news. For example, one might argue that although the news announcement itself is public, it requires some other, private, information to convert this news into a judgment about value. If this is true, the market's response to public news involves the aggregation of private signals, and our previous underreaction results continue to apply". However, it is not clear whether prices overshoot in the longer run after public news announcements. Recall that with private news trend chasers couldn't know whether they were acting early or late, but with public news they can make their strategy time dependent and act only shortly after the release of information and not later on. Therefore it does not necessarily lead to overreaction. This suggested absence of overreaction to public news could also explain why the earnings momentum is short-lived compared to the price momentum, as shown in Chan, Jegadeesh and Lakonishok (1996). Also, one can think of investors as not very sophisticated and assume that they do not base their investment decisions on recently released public news. If this was the case, implications of the model would equally hold for the price momentum as well as for the earnings momentum. The bottom line here is that Hong and Stein admit that the response to public news might look different from that to private information.

In contrast with Daniel et al. (1998) and Barberis et al. (1998), under- and over-reaction in Hong and Stein (1999) are triggered from the interaction between heterogeneous agents rather than triggered from biases to their behavior. Both Daniel et al. (1998) and Hong and Stein (1999) predict stronger drift in stocks with the greater information asymmetry. Greater information asymmetry means more heterogeneous information is available in the market, implying more private information among investors and hence stronger price drift.

Prior empirical research in this field shows mixed evidence for these models. For instance, Dische (2001) finds higher drift for firms with smaller information asymmetry, proxied by the dispersion in analysts' consensus forecasts. Results of Lee and Swaminathan (2000) indicate a higher momentum

[4] Bear in mind that trend chasers cannot recognize whether they act early or late in the momentum cycle since they fail to observe private information.

effect among high volume winners. If we assume that higher volume results in greater information diffusion, then, according to Daniel et al. (1998) and Hong and Stein (1999), high volume stocks should have less momentum. The empirical tests of Liang (2003) show that drift has a significantly positive relationship with heterogonous information. To derive a proxy for investor's information, he uses the correlation in forecast errors. The higher the correlation the less heterogeneous information is in the market, resulting in smaller drift. Hong, Lim and Stein (2000) use analyst coverage in their analysis, possibly another proxy for information asymmetry. They find evidence that momentum strategies work better in stocks with low analyst coverage and the effect is further enhanced for stocks that did poorly in the past. Brennan et al. (1993) show that low coverage stocks tend to lag high coverage stocks. Their interpretation is that analysts play an important role in helping to disseminate common (market) information whereas in Hong, Lim and Stein (2000), the focus is on the diffusion of firm-specific information. Similarly, Gleason and Lee (2003) document that the price drift is lower for firms followed by more analysts, further supporting the evidence on the role of analysts in the price discovery process.

Another model of heterogeneous agents, fundamentalists and chartists, was laid out by DeLong et al. (1990). They propose a "frontrunning" effect, whereby rational speculators buy more aggressively ahead of noise traders since they know that it will kick off a series of momentum trades, thereby driving up prices even more. These rational speculators exploit momentum-driven price swings. By buying early, they stimulate noise traders' demand and at later point they sell these stocks (book a profit) to noise traders who buy stocks in response to price movements (in their model noise traders are also called positive feedback traders). The model also relates to post-earnings announcement drift. For example, if a good public news announcement causes prices to rise today, prices might further increase tomorrow in response to buying demand from positive feedback traders. In contrast with previous models, here the drift occurs due to market overreaction, suggesting that prices should reverse at some point in the future. In this sense, the model is very distinct from a model of heterogeneous investors presented in Hong and Stein (1999), where such frontrunning effect is not possible and it is the group of trend chasers who benefit, not the group of newswatchers (rational traders).

Chan, Jegadeesh and Lakonishok (1996) lack direct evidence on price reversals in momentum anomalies, casting doubts on the prediction that the profitability of these strategies stems from overreaction induced by positive feedback trading strategies. Only the model of Hong and Stein (1999) admits, even strongly suggests, the possibility that there need be no overreaction to public news. All other models predict overreaction at some point after the release of earnings.

Clearly, the previous research provides a lot of evidence that stock prices underreact to news about future earnings but none of the current models in behavioral finance sufficiently justify this evidence. Fama (1998) ask whether the theories can "explain the big picture". He states that "any alternative model must specify biases in information processing that cause the same investors to under-react to some types of events and over-react to others. The alternative must also explain the range of observed results better than the simple market efficiency story; that is, the expected value of abnormal returns is zero, but chance generates deviations from zero in both directions". Apparently, this is a tough task. Different out-of-sample tests of behavioral models are consistent with some models but inconsistent with others. Despite the puzzling evidence in financial markets, the EMH is still relevant. Myron Scholes, one of the founders of LTCM (Long-Term Capital Management), says: "to claim something has failed you have to have something to replace it, and so far we do not have a new paradigm to replace efficient markets."

III. Sample and Methodology

The data used in my analysis comes from three main sources:

First, I obtained the stock return data and the number of shares outstanding from the Center for Research in Security Prices (CRSP) databases. Observations for American Depository Receipts, Real Estate Investment Funds, closed-end funds, and primes and scores are excluded from my sample. In terms of CRSP codes, only stocks having share type code 10 or 11 are included. This approach is identical to Hong, Lim and Stein (2000).

Second, the data on analyst coverage can be retrieved from the I/B/E/S Historical Summary File, and is available on monthly bases. As it will be discussed in section III.A, analysts' earnings forecasts are measured as the median of forecasts reported to I/B/E/S within 90 days before the firm's earnings announcement, thus I set analyst coverage for any given firm in any given quarter to the number of I/B/E/S analysts who provide fiscal year 1 earnings estimates at least 90 days before the earnings announcement. Actual and forecasted (median of forecasts) quarterly earnings-per-share are extracted from the same database.

Finally, earnings announcement dates are obtained from the Compustat combined quarterly files. As I will explain later, I sort the data by firm-quarters and firm-months. Any of the firm-quarter or firm-month observations lacking one of the above data will be excluded from my sample.

In addition to the above three sources, I will need the data on beta excess returns, trading volume, options listing and book-to-market ratio to conduct sensitivity tests. I obtain daily beta excess returns and the number of trades a day from the CRSP database. The data on options listing are available through Ivy DB OptionMetrics starting from January 1996. Finally, the book-to-market data comes from Compustat. This file contains all information for the year 1998 to 2006 and excludes data after 2006.

The centre of my focus is a contemporaneous sample period that runs from 1998 to 2007. The sample period is thus more recent than the data used in previous studies. I did not include the crisis year 2008 due to the missing data on analysts' forecasts of earnings in the I/B/E/S Historical Summary File. In my analysis, I exclude NASDAQ firms and use only NYSE and AMEX firms because NASDAQ firms tend to be smaller and more difficult to trade in momentum-based strategies[5]. Table 1 (columns 6 and 7) provides some overview of the sample employed in my research. The number of firms in each quarter (column 6), after excluding firms that lack the data on one or more variables, ranges roughly from 1000 to 1300, which is sufficient for my analysis. The number of analysts per firm (column 7), on average, does not change throughout the sample period, but is much higher than in prior studies. For example, Hong, Lim and Stein (2000) - henceforth HLS (2000) - report that there is a marked increase in coverage around 1980. This documents the increasing relevance of analysts' forecasts, making recent research on analyst coverage more appealing.

The sample includes mainly larger firms above the 40^{th} percentile NYSE/AMEX breakpoint. Firms below the 40^{th} percentile represent less than 20% of my sample (and below the 30^{th} percentile represent only 10%). Firms above the 80^{th} percentile account for almost 30% (see Table 6). This is simply because analysts tend to cover larger and actively traded firms. The median of analysts covering firms above the 80^{th} percentile is 15, while it is 9, 5 and 3 for firms in the 60^{th}-80^{th} percentile, 40^{th}-60^{th} percentile and below the 40^{th} percentile, respectively (see Table 7). HLS (2000) point out that 77.3% of all firms were not covered in 1976, declining to 36.9% in 1996, mostly consisting of the smallest firms (below the 20^{th} percentile). Since my measure of unexpected earnings changes requires a firm to have at least one analyst to forecast its earnings, I lose some observations among the smallest stocks where I expect the drift to be most pronounced. Further noteworthy fact is that the relation between analyst coverage and the momentum effect is strongest between firms with no-coverage and firms with at-least-some coverage (HLS (2000)). I conjecture that my results might somewhat understate this relation since I exclude firms with no coverage. Nevertheless, the main implications of analyst coverage should still be present.

[5] For more details, see Lee and Swaminathan (2000)

A. Post-Earnings Announcement Drift

Older studies, including Foster, Olsen and Shevlin (1984) or Bernard and Thomas (1989), use time-series models of past earnings to estimate standardized unexpected earnings (henceforth SUE) for each firm. Based on the distribution of SUE, each firm is assigned to one of the ten portfolios in the quarter subsequent to that in which the cut-off points were determined. For the purpose of my analysis of the post-earnings-announcement drift, I adopt two distinct approaches to construct earnings-momentum portfolios. Both deploy analysts' consensus forecasts to determine the SUE portfolios rather than time-series models used in older studies.

The first approach (I label this approach the "quarterly method") follows the methodology of Liang (2003), Mendenhall (2004) and Livnat (2003 a, b). Consistent with these studies, my measure of unexpected earnings is given by the following equation:

$$(1)\ SUE_{jq} = \frac{EPS_{jq} - E(EPS_{jq})}{P_{jq}}$$

SUE_{jq} denotes firm j's standardized unexpected earnings in quarter q. EPS_{jq} represents firm j's Earnings Per Share before extraordinary items in quarter q. $E(EPS_{jq})$ is analysts' consensus forecast, measured as the median of forecasts reported to I/B/E/S within 90 days before earnings announcement q, for firm j. The measure for $E(EPS_{jq})$ varies per study, but the one just proposed is like in Livnat and Mendenhall (2006) or Abarbanell and Bernard (1992). P_{jq} is the firm j's adjusted closing price per share at the end of quarter q.

Most studies assign firms into ten portfolios based on the SUE ranking[6]. By sorting firms into deciles, they reduce the influence of outliers in SUE. I proceed as HLS (2000) and classify firms for each quarter into only three portfolios based on SUE rankings: SUE1 contains the lowest 30 percent SUE firms, SUE2 includes the middle 40 percent and SUE3 represents the highest 30 percent firms. Each of these portfolios will be further subdivided into another three portfolios on the basis of their standings relative to residual analyst coverage (see the next section). I use this sort of thinner breakdown in order to capture the desired effect of analyst coverage. If I were to use ten SUE portfolios (and further break them into analyst coverage sub-portfolios) I would end up with too many undiversified portfolios creating larger standard errors in the test statistics.

Foster, Olsen and Shevlin (1984) as well as Bernard and Thomas (1989) assigned firms on the basis of SUE cutoffs from quarter t-1. If firms were assigned according to the distribution of SUE from the

6 See Bernard and Thomas (1989) or Foster, Olsen and Shevlin (1984)

current quarter, there would be a hindsight bias because the distribution would also include companies that have not yet released earnings for the current quarter. Take two companies announcing earnings for the same quarter but on different dates. The firm releasing earnings earlier would have to be assigned to one of the SUE portfolios formed on a basis of the entire distribution of SUE for that quarter, including the firm announcing earnings later. However, Bernard and Thomas (1990) report that post-earnings announcement drift is insensitive to using a current quarter or prior quarter SUE ranking. I tried both ways and both yield approximately same results. For the sake of a precaution, I use the distribution of SUE in the prior quarter.

Now I turn to computing abnormal returns for each observation (firm-quarter). In doing this, I follow the method used in most drift studies:

$$(2)\ AR_{jt} = R_{jt} - R_{pt}$$

R_{jt} is the raw return on security j on day t and R_{pt} is the equally weighted mean return on day t of the NYSE/AMEX firm size decile that firm j is a member of in the quarter examined. Firm size deciles are formed by sorting all firms based on market capitalization on the last trading day of each quarter (Liang (2003)). Then, ten equally populated portfolios (following HLS (2000)) are formed. The benefit of this approach is that it controls for the firm size effects in security returns. It assumes homogeneity within a firm size decile but allows for heterogeneity across deciles.

To examine how prices respond to earnings news over different periods, one can average (AARs) or sum (CARs) the abnormal returns. AARs and CARs are considered as a common approach. Fama (1998) suggests using cumulative abnormal returns for a number of statistical reasons. Thus the next step is to calculate the cumulative abnormal returns for different time intervals after earnings announcement q for firm j:

$$(3)\ CAR_{jq} = \sum_{t=q}^{q+\pi} AR_{jt}$$

In equation 3 CAR_{jq} denotes the firm j's cumulative abnormal return after earnings announcement q. Greek letter Π represents a period over which I sum the abnormal returns. Bernard and Thomas (1989) found that drift still carries over when the abnormal returns are compounded rather than summed. An interval of 60, 120, 240, 360 trading days is examined to capture both short- and long-term behaviour of price drift.

CARs can be interpreted as returns in excess of the return to the portfolio consisting of stocks of approximately the same size. If one wants to materialize the CARs obtained from equation 3, Bernard and Thomas (1989) argue that this “strategy requires an investor to take new positions in size-control portfolios every day, with each control portfolio containing hundreds of stocks. Thus, results based on this approach leave open the question of whether similar returns could be generated by an easily implemented, zero-investment strategy”. Therefore, they construct the “continuously balanced” strategy which buys good news firms and shorts bad news firms, while short positions must equal long positions all the time. This zero-investment strategy is easier to implement and, as Bernard and Thomas show, still yields comparable returns.

The second method[7], which I label the “monthly method”, ranks stocks at the beginning of every month from January 1998 to December 2007. A measure of SUE remains as in equation (2) except that is adjusted to suit the monthly method:

$$(4)\ SUE_{jm} = \frac{EPS_{jq} - E(EPS_{jq})}{P_{jm}}$$

where EPS_{jq} is firm j’s quarterly earnings per share most recently announced as of month m, reported within the previous three months. In this regard, I consider a complete cycle of earnings releases. $E(EPS_{jq})$ is analysts’ consensus forecast for the most recently released earnings as of month m, measured as the median of forecasts reported to I/B/E/S within 90 days before earnings announcement q for firm j. P_{jm} is the firm j’s adjusted closing price per share at the end of month m.

In the given month, all stocks are suitable for inclusion in my earnings momentum portfolios. Since the measure of earnings (EPS) is a quarterly released item, the portfolios based on SUE will also select earnings for firms not announcing earnings in the given month of portfolio formation, thus including firms with out-of-date earnings. I could simply use only firms announcing earnings in the given month of portfolio formation, but by doing this, my sample would dramatically shrink. This would result in undiversified portfolios, thereby decreasing the statistical power of my tests. Furthermore, picking up firms at the beginning of every month cause investors to miss out on the gains generated shortly after the earnings news release. As confirmed in many studies, a surprisingly large bulk of returns to the earnings anomaly occurs within a few days after the earnings news has been announced. This inevitably leads to an understatement of the drift. Nevertheless, I am able to compare the main results of these two methods. The monthly strategy might be easier to implement because it does not require offsetting positions in individual firms with the position in a size-control portfolio every day, but only at the beginning of every month. However, if one is able to construct the “continuously balanced”

[7] For more details, see Chan, Jegadeesh and Lakonishok (1996)

strategy of Bernard and Thomas (1989), which earns returns comparable to the quarterly method, using the monthly method will unnecessarily attenuate my results.

ARs for the monthly method are computed using equation 2. To obtain CARs using equation 3, I start to cumulate ARs on the first day of the portfolio formation- always the first day of the given month for each firm in the portfolio. This differs from the quarterly method, where the first day varies per firm because I assign firms to the SUE portfolios on the day of their earnings announcement. I measure CARs for the 3-, 6-, 12-, 18-month interval (corresponding to the 60-, 120-, 240-, 360-day interval used in the quarterly method).

Another noteworthy difference relates to the number of firms that are candidates for inclusion in the SUE based portfolios. When I apply the quarterly method, I only include firms for which the fiscal quarters end on March 31st, June 30th, September 30th and December 31st for the 1st, 2nd, 3rd and 4th quarter, respectively. This selection criterion accounts for about 95% of all firms having at least one analyst reporting to I/B/E/S. I use this criterion to simplify the quarterly portfolio formation when running the program in EViews. For example, imagine a firm releasing earnings for fiscal quarter ending on February 28th. I would face a problem whether to assign the firm when forming SUE portfolios for quarter ending on December 31st or for quarter ending on March 31st and I cannot form separate SUE portfolios for quarter ending on February 28th owing to very few observations. Due to losing only a minor fraction of my sample, I do not expect this to alter my conclusions. On the other hand, I do not omit these firms when I use the monthly method. Recall, when creating SUE portfolios for the given month, I consider all firms that released earnings in the prior three months. This also takes into account firms with fiscal quarters ending on "non-regular" dates. For example, again think of the firm with fiscal quarter ending on February 28th and releasing earnings for that quarter, say, in March. I will consider this firm when forming momentum portfolios at the beginning of April. From this point on, all results presented in the text are for the quarterly method. Selected results are replicated for the monthly method and are reported in the Appendix. All tables in the Appendix are adjusted for the monthly method and tables' numbering between the text and the Appendix is consistent, thus Table 1 in the text for the quarterly method corresponds to Table 1 in the Appendix for the monthly method.

B. Residual Analyst Coverage

Previous research suggests few proxies for the rate of information flow. Dische (2001) uses the dispersion in analysts' consensus forecasts; Liang (2003) prefers the correlation in forecast errors. Brennan et al. (1993), Gleason and Lee (2003) suggest analyst coverage. Furthermore, Lo and MacKinlay (1990) find a positive relation between the speed of information and size. HLS (2000) consider size and analyst coverage as proxies for information diffusion. It is conceivable that information about small firms gets out more slowly, but the size measure is likely to capture other effects as well, that may confound the final outcome and leads to overwhelming conclusions about the hypothesis. It seems that the number of analysts covering a stock contains some incremental information about future stock returns.

The drawback of using coverage ratio as a proxy for information diffusion was first detected by Bhushan (1989), who points out that analyst coverage is highly correlated with firm size. Therefore, my methodology replicates HLS (2000) to solve this obstacle. When I construct investment strategies in section IV.A., based on residual analyst coverage, I use residuals obtained from regressing size on the number of analysts, rather than the raw number of analysts. Thus for each quarter, I run cross-sectional regression of the following form:

$$(5)\quad Log\left(1 + Analysts_{jq}\right) = b_0 + b_1 \log\left(Size_{jq}\right) + \varepsilon$$

In formula 5, $Analysts_{jq}$ denotes the number of analysts for firm j in quarter q. I employ the variable log (1 + Analysts), rather than a widely used simple number of analysts, because, as stated in H&S (2000), "we ultimately want to use the residuals from our analyst-coverage regressions to explain momentum, and it seems plausible that one extra analyst should matter much more in this regard if a firm has few analysts than if it has many." $Size_{jq}$ is measured as firm j's market capitalization (shares outstanding * closing price) on its last trading day in current quarter q. The Greek letter ε denotes an error term. Results of these quarterly regressions are presented in Table 1.

As it can be seen, the size variable is positively correlated with analyst coverage, yielding an R^2 of approximately 0.60 in most examined quarters, and generating high t-statistics of above 40. These results are very similar to those obtained by HLS (2000) who studied the 1980 to 1996 period. They also suspect other variables to be correlated with analyst coverage. Thus, they add other variables on the right-hand side of equation (5). Particularly, they experiment with the firm's book-to-market ratio, beta, industry-dummy variables, a turnover measure, the options-listing dummy, 1/P ratio and the variance of daily returns. As it turns out, most of the variables are significantly related to analyst coverage. I will turn to a detailed discussion of the most influential variables when I conduct sensitivity tests in section IV.C. Nonetheless, the size variable appears to be the most dominant factor. Thus, I will use the simple size-based regression 5 as a baseline for computing residual analyst coverage. The basic size-based regression assumes a linear form of the relationship between size and analyst coverage for the entire sample. However, as I make it clear in the next section, after certain point the number of analysts peaks, and no longer increases with size. To tackle this deficiency, I run a

Table 1
Size as a Determinant of Analyst Coverage

This table illustrates the results of regressions of the form of equation 5. I rerun the regression for each quarter starting in 1998 Q1 and ending in 2007 Q4. Table includes the numbers for coefficient b_1 estimation, its t-statistic, R^2, adjustedR^2 and the number of observations included in each regression. The last column documents the mean number of analysts per firm. The number of observations represents all stocks that are suitable for inclusion in my earnings momentum portfolios in each given quarter.

Period	Coef. b_1	T-statistic	R^2	Adjusted R^2	No.obs	No. analyst
1998Q1	0.35	47.2	0.64	0.64	1227	9.26
1998Q2	0.34	47.5	0.63	0.63	1280	8.96
1998Q3	0.33	46.6	0.62	0.62	1290	9.14
1998Q4	0.32	45.7	0.62	0.62	1281	9.19
1999Q1	0.32	48.0	0.61	0.64	1260	9.49
1999Q2	0.33	48.6	0.64	0.64	1283	9.36
1999Q3	0.33	48.4	0.64	0.64	1268	9.38
1999Q4	0.33	46.7	0.63	0.63	1228	9.52
2000Q1	0.31	41.5	0.59	0.59	1171	9.69
2000Q2	0.32	42.4	0.60	0.60	1164	9.13
2000Q3	0.31	41.0	0.62	0.62	994	9.98
2000Q4	0.31	42.0	0.61	0.61	1094	8.87
2001Q1	0.33	44.0	0.64	0.64	1050	9.20
2001Q2	0.34	42.4	0.62	0.62	1083	9.18
2001Q3	0.32	39.4	0.59	0.59	1065	8.74
2001Q4	0.34	40.3	0.61	0.61	1033	8.64
2002Q1	0.34	39.8	0.60	0.60	1047	8.35
2002Q2	0.34	38.8	0.58	0.58	1081	8.37
2002Q3	0.32	37.3	0.56	0.56	1087	8.45
2002Q4	0.33	39.5	0.59	0.59	1076	8.83
2003Q1	0.32	38.8	0.58	0.57	1093	8.68
2003Q2	0.35	40.7	0.60	0.60	1098	8.95
2003Q3	0.36	40.3	0.59	0.59	1106	9.23
2003Q4	0.36	39.6	0.58	0.58	1101	9.43
2004Q1	0.36	39.2	0.58	0.58	1102	9.48
2004Q2	0.37	40.9	0.59	0.59	1144	9.10
2004Q3	0.36	41.2	0.59	0.59	1156	9.03
2004Q4	0.36	39.0	0.57	0.57	1149	9.03
2005Q1	0.36	42.4	0.60	0.60	1178	9.25
2005Q2	0.35	41.6	0.59	0.59	1174	8.94
2005Q3	0.35	44.4	0.62	0.62	1191	8.87
2005Q4	0.35	44.8	0.63	0.63	1162	8.63
2006Q1	0.34	43.9	0.62	0.62	1179	9.10
2006Q2	0.33	42.3	0.59	0.59	1199	8.99
2006Q3	0.32	41.3	0.58	0.58	1201	8.91
2006Q4	0.32	38.5	0.55	0.55	1194	8.76
2007Q1	0.32	42.8	0.60	0.60	1202	9.23
2007Q2	0.30	38.5	0.55	0.55	1168	8.52
2007Q3	0.29	36.5	0.54	0.54	1110	8.43
2007Q4	0.27	29.8	0.47	0.47	982	8.82

separate cross-sectional analyst regression for each quarter for firms in different size classes (below the 40^{th} NYSE/AMEX percentile, in the 40^{th}-60^{th} percentile, so on and so forth), hoping to obtain a more precise relationship between size and analyst coverage. In section IV.C, I will undertake sensitivity tests by adding some of the variables considered in HLS (2000) into regression 5 to erase any doubts arising from using a simple model. Specifically, I examine the effect of the firm's book-to-market ratio, beta risk, turnover and the options-listing dummy.

C. Residual Coverage-Based Earnings Momentum Portfolios

Now, I need to define how I divide the whole universe of stocks based on residual analyst coverage. I continue to replicate H&S (2000). I form three new sub-portfolios on the basis of sample distributions of the residuals obtained from quarter-by-quarter regressions (equation 5). When applying this portfolio formation technique, I use the residual analyst coverage 2 quarters (6 months) before the actual quarter for which the earnings announcement has been released. Loosely speaking, when 3Q 2001 is being examined, I first create portfolios based on residual coverage observed at the beginning of 1Q 2001. Then, independently of the residual coverage ranking, I sort firms based on the standing of their SUE in the current quarter (3Q 2001) relative to the distribution of SUE obtained in the prior quarter (2Q 2001). The technique mimics H&S (2000) who used stale data on analyst coverage in order to address a potential bias discussed in their paper. They believe that by using stale data, the results presented in their paper would be driven by the permanent component of coverage, and not by recent (perhaps return-predicting) innovations in coverage. Although they show that the results are insensitive to when they measure analyst coverage, I adopt their methodology so that I can directly compare their results with my results. While their focus is on the price momentum, I test the residual coverage effect on the post-earnings announcement drift. I emphasize that the conclusions in my thesis still hold no matter if I use actual or stale data on residual coverage. The three sub-portfolios are formed as follows: RC1 consists of 30 percent firms with the lowest residual coverage; RC2 portfolio gathers the middle 40 percent; and RC3 portfolio includes the highest 30 percent.

If I am to assess the effect of analyst coverage on drift and draw conclusions from this relationship, I would like to obtain a healthy variation in coverage across portfolios RC1-RC3. I further hope that each subsample will contain stocks of about the same size, so that any patterns that I now find cannot be attributed to differences in size. HLS (2000) were concerned about the variation in coverage due to having too many firms with zero analysts in their sample, whereas this is not the concern in my analysis, since the way I examine post-announcement drift requires firms to have at least one analyst. Indeed, as Table 2 shows, the median (mean) of analysts increases from 3 (5.24) in the portfolio consisting of firms with the lowest residual coverage to 12 (12.89) in the portfolio consisting of firms with the highest residual coverage.

Table 2
Mean and Median Analyst Coverage

This table reports the mean (median) of I/B/E/S analysts per firm who provide fiscal year 1earnings estimates, across the three residual coverage portfolios. The mean (median) numbers are aggregated for the 40 quarters studied in the paper.

Residual Coverage Class	Mean Coverage	Median Coverage
Low: RC1	5.24	3.00
Medium: RC2	9.44	8.00
Large: RC3	12.89	12.00
All	9.25	8.00

However, the problem with size matching seems inevitable. HLS (2000) demonstrate that after certain point, the number of analysts peaks, and no longer increases with size. Hence, the very large firms seem to have relatively low residual analyst coverage. Consequently, they happen to fall in the lowest coverage class (RC1) and thereby pushing mean size in RC1 higher relative to RC3. Table 3 shows mean and median statistics for size across residual coverage portfolios. The disproportion in size between the low- and high- coverage portfolio is large. The mean size of low coverage firms is almost \$11 billion, while it is only \$3.6 billion for high coverage firms. Size differences in terms of median statistics are much lower. The medians are \$1 billion and \$1.55 billion for the low- and high -coverage firms, respectively. HLS (2000) obtain similar patterns in size differences across the residual coverage portfolios, but generally the mean and median size of their sample is much smaller owing to the inclusion of NASDAQ firms and firms with no coverage that tend to be much smaller. The size differences stems from applying overly simple linear structure to the entire sample when regressing size on analyst coverage. I will resolve this caveat very shortly, but for the purpose of analysis in this section I will neglect this deficiency.

Table 3
Mean and Medium Size

This table reports mean (median) firm size in thousands of dollars in market capitalization across the three residual coverage portfolios. The mean (median) numbers are aggregated for the 40 quarters examined in the paper.

Residual Coverage Class	Mean Size	Median Size
Low: RC1	10940531	1028770.
Medium: RC2	7533733.	1871272.
Large: RC3	3636638.	1556721.
All	7360412.	1486225.

Before turning to the discussion of my results, I will first elaborate on how I proceed when analysing the relation between drift and analyst coverage. The methodology closely resembles Clare and Thomas (1995) who use it to find evidence for overreaction of stock prices in the U.K. As described above, I classify stocks into nine portfolios for each of the 40 quarters (120 months for the monthly method) in my sample. Three portfolios are formed based on stocks' standings relative to SUE and these are further subdivided into three different portfolios that are cut relative to the residual coverage breakpoints, thereby resulting in nine portfolios. Having formed nine portfolios, the mean cumulative abnormal return for each portfolio formation period (40 quarters or 120 months, respectively) over the 60, 120, 240, and 360 trading day intervals (3, 6, 12, 18 and 24 month intervals for the monthly method) for the nine portfolios are then computed. It is just an average of the CAR_{jq}-s of the stocks used to form each portfolio. This gives me 40 observations (or 120 in the case of the monthly method)[8] for my regression tests. Running simple regressions of the mean cumulative abnormal return on a constant (equation 6), one can test the sign and significance of the excess return of the nine portfolios. Results are presented in Table 4.

$$(6)\quad CAR_{pt}^{\pi} = \alpha + \varepsilon$$

In equation 6, CAR_{pt} denotes the mean cumulative abnormal return for portfolio *p* formed in portfolio formation period *t* over period *Π* and α is a constant. Greek letter ε denotes an error term.

Denote the mean cumulative abnormal return of the winner – SUE3 – and loser – SUE1 – portfolios (the top 30% and bottom 30% of firms based on the SUE ranking in portfolio formation period t) as $CAR_{SUE3,t}$ and $CAR_{SUE1,t}$, respectively. Define the difference between these as $CAR_{SUE3,t\ -\ SUE1,t} = CAR_{SUE3,t} - CAR_{SUE1,t}$. The regression to be performed is of the excess return of the winners over the losers on a constant only (equation 7).

$$(7)\quad CAR_{SUE3,t-SUE1,t}^{\pi} = \alpha + \varepsilon$$

The test is of whether alpha is significant and positive. Alpha indicates the magnitude of post-announcement drift. Next, denote the mean cumulative abnormal return of the winner – SUE3 – and loser – SUE1 – portfolios consisting of stocks with the lowest residual coverage (RC1) as $CAR_{SUE3RC1,t}$ and $CAR_{SUE1RC1,t}$, respectively. Then, the difference between these equals $CAR_{SUE3RC1,t\ -\ SUE1RC1,t} = CAR_{SUE3RC1,t} - CAR_{SUE1RC1,t}$. The next regression in my analysis is of the excess return of the winners with the lowest analyst coverage over the losers with the lowest coverage on a constant (equation 8).

[8] All regressions on a constant in my analysis have 40 observations (120 for the monthly method), each representing the portfolio mean cumulative abnormal return in each portfolio formation period. I am fully aware of the fact that having only 40 observations, I should be cautious not to overwhelm the results of my analysis. I remark that I could not extend the sample period owing to computational constraints of the software used for my analysis. Nonetheless, my results are confirmed when I employ the monthly method with 120 observations. Furthermore, I rerun all tests for the 1987 to 1996 period (unreported), yielding similar results.

$$(8)\ CAR^{\pi}_{SUE3RC1,t-SUE1RC1,t} = \alpha + \varepsilon$$

The magnitude of alpha represents the drift generated by firms with low residual coverage. I look for positive and significant alpha. I run the same regressions for stocks with the medium ($CAR_{SUE3RC2,t - SUE1RC2,t}$) and highest analyst coverage ($CAR_{SUE3RC3,t - SUE1RC3,t}$) and then I compare the drift generated by stocks in the lowest and highest coverage class by running the following regression:

$$(9)\ (CAR_{SUE3RC1,t-SUE1RC1,t} - CAR_{SUE3RC3,t-SUE1RC3,t})^{\pi} = \alpha + \varepsilon$$

The test is of whether alpha is significant to see if there is a significant difference between abnormal returns to the low- and high-coverage portfolios after the earnings announcement. The sign of the alpha coefficient will indicate whether low coverage stocks exhibit higher drift than high coverage stocks or vice versa.

Furthermore, I am interested in whether analyst coverage has something to say about the drift following bad news and good news. As before, denote the mean cumulative abnormal return of the low coverage – RC1 – and high coverage – RC3 – portfolios (the top 30% and bottom 30% of firms based on the residual coverage ranking in portfolio formation period t) consisting of bad news firms as $CAR_{RC1SUE1,t}$ and $CAR_{RC3SUE1,t}$, respectively. Define the difference between these as $CAR_{RC1SUE1,t - RC3SUE1,t} = CAR_{RC1SUE1,t} - CAR_{RC3SUE1,t}$. The regression to be performed is of the excess return of the low-coverage losers over the high-coverage losers on a constant only (equation 10).

$$(10)\qquad CAR^{\pi}_{RC1SUE1,t-RC3SUE1,t} = \alpha + \varepsilon$$

I rerun this regression for good news firms (winners) as well ($CAR_{RC1SUE3,t - RC3SUE3,t}$). Significant alpha will signal that analyst coverage have some predictive power for the price drift after the earnings announcement. The sign of the alpha coefficient will suggest the direction of the relationship between drift and analyst coverage. I also repeat all the tests for different *Π* holding periods. All results are summarized in Table 4.

Prior to reviewing the results, one final comment on an econometric issue. In regression equations 6 to 10, the dependent variable is an abnormal return measured over overlapping intervals (the CARs are sampled from common periods). Thus, standard t-tests applied to mean cumulative abnormal returns are suspected to be biased due to correlation in the data. In other words, the regression residuals are certainly correlated. However, ordinary least squares method may still be used to estimate equations above, since the coefficients will be consistent even in the presence of autocorrelation. To deal with it, the t-statistics in all tables[9] are calculated using the Newey-West variance-covariance estimator that is consistent in the presence of both heteroscedasticity and autocorrelation.

IV. Results

A. *Cuts on Residual Analyst Coverage*

The first column in Table 4 confirms that there is a significant earnings momentum in the full sample. Indeed, the strategy of buying good news firms and selling bad news firms (SUE3-SUE1) yields an abnormal return of 3.4% (t-statistic 19.34) and 4.5% (t-statistic 11) within the 20 and 60 trading days after the earnings release, which are the outcomes of estimation of equation 7. From Table 4 emerges that the earnings anomaly is a short-lived phenomenon – the abnormal returns after 60 trading days add only a little to the overall drift. The drift peaks after 240 trading days (5.9% with t-statistic 4.57) and then slightly reverses. Apparently, most of the drift occurs within few days following the earnings announcement (abnormal returns generated within 20 trading days account for more than half of the drift). The findings are consistent with prior studies, although the abnormal returns after 120 days are somewhat smaller. I conjecture that this difference arises owing to the more contemporaneous sample period employed in my paper and owing to the inclusion of mostly larger stocks. As it soon will be shown, the drift's longevity and strength varies with size.

Turning to the relationship between analyst coverage and earnings momentum, some intriguing patterns emerge from Table 4. Considering first the results for up to 60 trading days, one can see that relatively low coverage firms exhibit stronger drift than their peers with relatively high coverage. Indeed, the drift in the low-coverage portfolio is 3.7%, 4.8% compared to 2.8%, 3.5% for the high-coverage portfolio, over the 20- and 60-day horizon, respectively. The difference of 0.9%, 1.2% is marginally significant with t-statistics 1.99 and 1.61. These results are consistent with the findings of HLS (2000). Implications of their model, developed in 1999 (see the literature overview), predict the price inefficiencies to be more severe among stocks with slower information diffusion.[10] If analyst coverage is deemed to be a good proxy for the rate of information flow, one would expect higher drift to occur in the low coverage portfolio. Their second important finding is that the effect of residual coverage on their momentum measure is almost entirely driven by what is happening in the loser stocks. They call it the "loser-analyst-spread-trade", or "LAST" strategy. The LAST strategy buys the high-coverage losers and shorts low-coverage losers without dealing in the winners portfolios. If my results confirm their findings, the difference RC1-RC3 for SUE1 (bad news stocks) in Table 4 should be significantly negative. Examining the 20- and 60-day horizon, I obtained similar patterns.

[9] Except for cases when the abnormal return is not measured over overlapping intervals, such as the 30-day return (only included in Table 4) or the 60-day return (included in all tables)
[10] Note, Daniel et al. (1998) outlined a different model that would predict the same results

Table 4

Earnings Momentum Strategies, Q1/1998-Q4/2007, Using Abnormal Returns, Sorting By Equation 5 Analyst Residuals

This table reports the average cumulative abnormal returns on portfolios based on the SUE measure and portfolios formed using an independent sort on equation 5 analyst residuals of log size over different holding periods. Portfolio SUE1 consists of stocks in the 30 percent most negative unexpected earnings changes, portfolio SUE2 includes the middle 40 percent, and portfolio SUE3 contains stocks in the 30 percent most positive unexpected earnings changes. The least-covered stocks are in RC1 portfolio, the medium covered stocks in RC2 portfolio, and the most covered stocks in RC3 portfolio. The numbers are α coefficients of regressions of the form of equations 6-10. T-statistics are in parentheses.

		Residual Coverage Class			
Past	all stocks	Low: RC1	Medium: RC2	High: RC3	RC1-RC3
20 trading days					
SUE1	-0.01653	-0.01937	-0.01621	-0.01066	-0.00871
	(-9.67)	(-7.34)	(-6.67)	(-2.61)	(-1.63)
SUE2	-0.00031	-0.00426	0.001414	0.001257	-0.00552
	(-0.26)	(-2.29)	(0.79)	(0.78)	(-1.88)***
SUE3	0.017061	0.017313	0.019287	0.017098	0.000215
	(14.00)	(9.37)	(11.58)	(6.13)	(0.06)
SUE3 - SUE1	0.033594	0.036681	0.035495	0.027756	0.008926
	(19.34)*	(11.43)*	(17.11)*	(7.91)*	(1.99)***
60 trading days					
SUE1	-0.02613	-0.02978	-0.02887	-0.01412	-0.01566
	(-7.05)	(-6.74)	(-6.51)	(-1.97)	(-1.92)***
SUE2	-0.01163	-0.01797	-0.01215	-0.00673	-0.01123
	(-6.70)	(-5.31)	(-5.70)	(-1.78)	(-1.93)***
SUE3	0.018709	0.017834	0.020044	0.021242	-0.00341
	(8.34)	(4.62)	(7.14)	(4.70)	(-0.56)
SUE3 - SUE1	0.044842	0.047618	0.048909	0.035362	0.012256
	(11.00)*	(7.73)*	(10.43)*	(5.43)*	(1.61)
120 trading days					
SUE1	-0.03643	-0.04476	-0.04378	-0.01153	-0.03323
	(-5.23)	(-5.55)	(-6.73)	(-0.86)	(-2.30)**
SUE2	-0.01867	-0.02855	-0.02201	-0.00804	-0.02051
	(-6.66)	(-4.28)	(-6.66)	(-1.39)	(-1.87)***
SUE3	0.011929	0.007209	0.012940	0.022614	-0.0154
	(2.88)	(1.27)	(3.15)	(2.80)	(-1.78)***
SUE3 - SUE1	0.048356	0.051972	0.056724	0.034148	0.017824
	(6.06)*	(5.00)*	(6.74)*	(2.94)*	(1.30)
240 trading days					
SUE1	-0.05419	-0.07031	-0.06209	-0.01888	-0.05143
	(-4.61)	(-5.80)	(-6.11)	(-0.88)	(-2.35)**
SUE2	-0.03597	-0.05699	-0.036	-0.02044	-0.03655
	(-8.22)	(-5.66)	(-6.10)	(-2.64)	(-2.39)**
SUE3	0.004977	-0.00703	0.002641	0.025886	-0.03291
	(0.91)	(-1.18)	(0.39)	(1.93)	(-2.29)**
SUE3 - SUE1	0.059162	0.063281	0.064730	0.044768	0.018514
	(4.57)*	(4.89)*	(4.89)*	(2.46)**	(1.09)
360 trading days					
SUE1	-0.0559	-0.06895	-0.06802	-0.01509	-0.05385
	(-4.24)	(-4.93)	(-6.30)	(-0.55)	(-2.01)***
SUE2	-0.05277	-0.0812	-0.05459	-0.02982	-0.05138
	(-9.12)	(-6.93)	(-6.87)	(-2.78)	(-2.74)*
SUE3	-0.00858	-0.03036	-0.00974	0.025005	-0.05536
	(-1.27)	(-4.04)	(-1.43)	(1.68)	(-3.97)*
SUE3 - SUE1	0.047317	0.038590	0.058282	0.040098	-0.00151
	(3.55)*	(3.14)*	(4.53)*	(1.77)***	(-0.07)

* Significant at the 1% level (reported only for SUE3-SUE1 differential and RC1-RC3 differential)
** Significant at the 5% level (reported only for SUE3-SUE1 differential and RC1-RC3 differential)
*** Significant at the 10% level (reported only for SUE3-SUE1 differential and RC1-RC3 differential)

Almost the entire difference of 0.9%, 1.2% between the low- and high-coverage stocks' performance subsequent to the earnings announcements is due to the bad news firms with low coverage – SUE1RC1 – performing worse (-1.9%, -3% over 20 and 60 trading days) than bad news firms with high coverage – SUE1RC3 – (-1.1%, -1.4% over 20 and 60 trading days), hence creating the difference of -0.8% (t-statistic -1.63), -1.6% (t-statistic -1.92) over the 20- and 60-day horizon, respectively. The LAST strategy in my case would earn, on average 0.8 % over the 20-day horizon. HLS (2000) attribute this evidence to bad news travelling more slowly.

On the other hand, there is not much of a difference once I look at the winner portfolios for up to 60 days. According to HLS (2000), winners should do better if they have relatively low analyst coverage compared to winners with more analysts, resulting in a positive difference RC1-RC3 for the winner portfolios (SUE3). However, the abnormal return to the winners with low-coverage compared to the winners with high-coverage is almost identical over the 20-day interval (the difference of 0.02 % with t-statistic 0.06 is negligible) and even slightly negative over the 60-day interval, though insignificantly (-0.03%, t-statistic -0.56). This potentially contradicts the model of Hong and Stein, but not necessarily, as I will show later. HLS (2000) also document this contradictory evidence that the returns among winners go the opposite way to what the model predicts. The continuing performance of low-coverage winners is worse than that of high-coverage winners, although it fades away when they use beta-adjusted returns.

When I include longer-term horizons in my analysis, a few things become apparent. The effect of analyst coverage (RC1-RC3) on the earnings momentum (SUE3-SUE1) appears to gradually disappear, even becoming negative after 360 trading days. This is due to a different effect analyst coverage has on good news firms and bad news firms than suggested by HLS (2000). What emerges from Table 4 is that the low-coverage stocks (RC1) with bad news (SUE1) still continue to lose, while high-coverage stocks (RC3) with bad news (SUE1) stay flat over the next 360 days. The difference RC1-RC3 for the bad news firms (SUE1) is significantly negative over all horizons. I call this the "Loser-Analyst-Spread". On the other hand, the low-coverage winners strongly rebound after 60 days subsequent to the earnings releases, while high-coverage winners still exhibit a moderate drift even after 60 days. This causes the significantly negative residual coverage differential (RC1-RC3) for the good news stocks, labeled the "Winner-Analyst-Spread", that is at odds with the Hong and Stein model. For example, consider the portfolio of low-coverage losers (RC1SUE1) and compare it with the high-coverage losers (RC3SUE1). RC1SUE1 portfolio loses -1.9% (t-statistic=-7.3) in the first 20 trading days, and -7% (t-statistic=-5.8) after 240 trading days, while the performance of RC3SUE1 hardly changes (-1.1% with t-statistic=-2.6 after 20 days, -1.9% with t-statistic=-0.9 after 240 days). The difference between RC1SUE1 and RC3SUE1 – the loser analyst spread – is -5.1% (t-statistic=-2.4) for the 240-day horizon. Turning to the winners portfolios, RC1SUE3 – low-coverage winners –

gain 1.7% (t-statistic=9.4) in the first 20 days and after that lose ground and yields an abnormal return of -3% (t-statistic=-4) after 360 trading days. However, the winner portfolio with high-analyst coverage – RC3SUE3 – performs similarly to RC1SUE3 portfolio in the first 20 days, gaining 1.7% (t-statistic=6.1), but later the returns of the two decouples and RC3SUE3 still continues to earn 2.5% (t-statistics 1.7). The difference between the two – the winner analyst spread – is -3.3% (t-statistic=2.3), -5.5% (t-statistic=-4) over the 240- and 360-day period.

Taken together, these patterns suggest an investment strategy of buying good news firms covered by many analysts and selling bad news firms covered by few analysts. To examine the strategy, denote the mean cumulative abnormal return of the high-coverage winners and the low-coverage losers in portfolio formation period t as $CAR_{RC3SUE3,t}$ and $CAR_{RC1SUE1,t}$, respectively. Then the difference between these two ($CAR_{RC3SUE3,t\ -\ RC1SUE1,t} = CAR_{RC3SUE3,t} - CAR_{RC1SUE1,t}$) represents the mean cumulative abnormal return on the zero-investment strategy. Consequently, I run a regression of the mean abnormal return on the zero-investment strategy with 40 observations, one for each portfolio formation period (120 observations for the monthly strategy), on a constant:

(11) $$CAR^{\pi}_{RC3SUE3,t-RC1SUE,t} = \alpha + \varepsilon$$

Furthermore, I wish to compare the abnormal returns on the earnings momentum strategy obtained from equation 7 – labeled the "SUE3-SUE1 strategy" or "Simple Earnings Momentum Strategy" – to the strategy represented by equation 11 – labeled the "RC3SUE3-RC1SUE1 strategy" or "Analyst-Earnings Momentum Strategy". For that purpose, I run a regression of the CARs' differential of the two strategies on a constant:

(12) $$\left(\mathrm{CAR}_{\mathrm{SUE3RC3,t-SUE1RC1,t}} - CAR_{SUE3,t-SUE1,t}\right)^{\pi} = \alpha + \varepsilon$$

I hope to find the difference to be significantly positive to prove that the analyst-earnings momentum strategy, on average, earns more than the simple earnings momentum strategy. The results of equations 11 and 12 are reported in Table 5 for different holding periods.

As seen in Table 5, the strategy of buying high-coverage winners and selling low-coverage losers outperforms the simple earnings momentum strategy. To be more specific, the analyst-earnings strategy returns 6.7% (9.6%) over the 120-day horizon (240-day horizon) compared to 4.8% (5.9%) produced by the simple earnings momentum strategy. The difference of 1.9%, 3.7%, and 4.7% for the 120-, 240-, and 360-day holding period, respectively, is statistically significant, yielding corresponding t-statistics of 1.72, 2.04, and 2.55. The difference between the two strategies is

Table 5
Simple Earnings Momentum Strategies and Earnings Momentum Strategies Based on Equation 5 Analyst Residuals, Using Abnormal Returns

The first row of this table reports the mean cumulative abnormal returns on strategies that buy stocks with the most positive unexpected earnings changes and sell stocks with the most negative unexpected earnings changes over different holding periods. The numbers are α coefficients of regressions of the form of equation 7. The second row reports the cumulative abnormal returns on strategies that buy high-coverage stocks with the most positive unexpected earnings changes and sell low-coverage stocks with the most negative unexpected earnings changes over different holding periods. The numbers are α coefficients of regressions of the form of equation 11. The last row (difference) reports the average difference in the mean cumulative abnormal returns between the two strategies. The numbers are α coefficients of regressions of the form of equation 12. T-statistics are in parentheses.

	Holding Period			
Strategy	60 days	120 days	240 days	360 days
"Simple Earnings momentum" SUE3-SUE1	0.04484	0.04835	0.05916	0.04731
	(11.00)	(6.06)	(4.57)	(3.55)
"Analyst Earnings Momentum" RC3SUE3-RC1SUE1	0.05102	0.06737	0.09619	0.09395
	(7.92)	(5.53)	(5.11)	(4.21)
Difference				
(P3RC3-P1RC1)-(P3-P1)	0.00618	0.01902	0.03703	0.04663
	(1.03)	(1.72)***	(2.04)**	(2.56)**

* Significant at the 1% level (reported only for the difference of the two strategies)
** Significant at the 5% level (reported only for the difference of the two strategies)
*** Significant at the 10% level (reported only for the difference of the two strategies)

insignificant and negligible over very short horizons due to the weaker residual coverage effect among good news firms (the winner-analyst spread is weaker) within the first 60 days. While the gap between the returns to the low- and high-coverage loser portfolios – the loser analyst spread – arises already shortly after including these stocks into the portfolios, both the low- and high-coverage winners initially drift and the gap – the winner analyst spread – arises only after 60 days when low-coverage winners rebound and high-coverage winners continue to drift. Shorting loser stocks in the lowest residual coverage class contributes more to the overall difference between these strategies than buying the winner stocks in the highest residual coverage class.

How can the results presented thus far be reconciled with the implications of the theoretical models? Hong and Stein (1999) and Daniel et al. (1998) proposed a model that can justify the “loser-analyst-spread”. More analysts help disseminate information about the firm’s future prospects contained in current earnings. Thus, the underreaction is more severe and it takes longer for prices to adjust if a firm has fewer analysts. This is especially true for bad news firms because managers are more reluctant to communicate bad news to investors, thereby making analysts more important in disseminating bad news. When firms are releasing good earnings, managers have more incentives to provide their investors with this information and thus attenuating the importance of analysts. This evidence, also known as “bad news travels slowly”, was also documented by Chan (2003). What seems to run counter to the “information asymmetry” explanation is that prices exhibit reversals among low-coverage winners, whereas high-coverage winners slightly continue to gain. The model of Hong and Stein (1999) would predict the opposite to happen.

As discussed in section III.C., Hong, Lim and Stein assumed that by using stale data on analyst coverage (number of analysts 6 months prior to the portfolio formation), they would circumvent the possibility that analyst coverage has some return-predictive power and thus using analyst coverage as a clear proxy for information asymmetry. I also used the same analyst coverage measure and it seems that firm's analyst coverage might be a proxy for investor expectation and investor interest in firm, possibly confounding the analyst's effect as examined in HLS (2000). In this regard, an interesting study of McNichols and O'Brien (1997) documents that analysts report on firms based on their expectations of the firm's performance. Analysts initiate coverage when investors' expectations are favorable and drop coverage once the firm falls into their disfavor. Taking this view, relatively low analyst coverage is an indication of a firm that is believed to perform badly in the near future, while relatively high analyst coverage is an indication that a firm is considered to deliver good results in the near future.

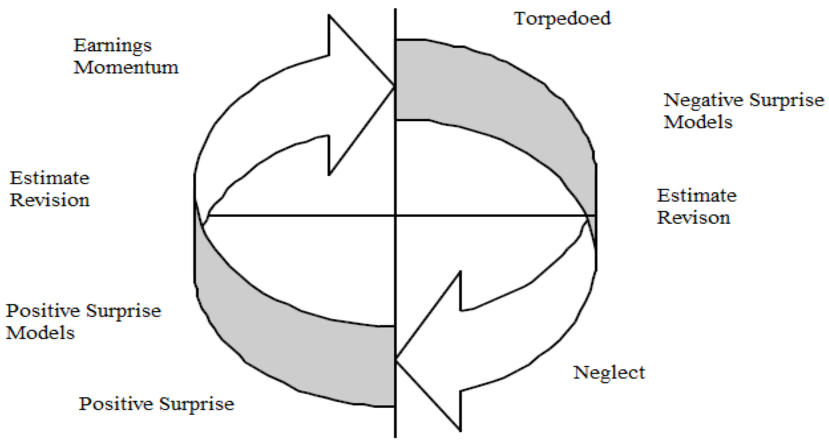

Figure 1 Earnings Expectation Life Cycle.[11] This figure depicts the salient features of my results. I document that high-coverage stocks generally outperform low-coverage stocks. Low residual coverage indicates a negative momentum stock that has a long way to go before it turns the corner. Relatively high residual coverage signals a stock that has bottomed out and has a bigger upside potential.

To better understand this point, I adopt a framework of the "Earnings Expectation Life Cycle" proposed by Bernstein (1993). This framework gives an idea how the expectation for a stock changes over time. A stock travels through a cycle as follows (depicted in Figure 1). A stock at the bottom of the momentum cycle starts to signal more optimistic information. When a stock is becoming popular, analysts start to report more on that stock and analyst coverage increases. The stock regains attention of momentum investors who search for stocks with positive earnings surprises. When the stock approaches the top of the cycle, earnings expectations might be becoming very high. At this point, the earnings momentum strategy becomes more risky. The risk is that an earnings disappointment might occur in a very short time. Put it differently, an investor faces the risk of jumping on the "momentum bandwagon" too late. At some point, the stock is "torpedoed" and the stock falls into investors'

[11] Source: Bernstein, Richard, 1995, *Style Investing*, page 36.

disfavor. Consequently, analysts begin to drop coverage. The stock becomes a potential candidate for momentum traders seeking firms with lower-than-expected earnings. Bernstein points out that not every stock follows this path. Each stock travels at its own speed and may stagger between different stages. The main point here is that the salient features of the model should hold at portfolio level.

The framework suggests that good momentum traders buy a stock shortly after 6 o'clock (when a stock has bottomed out) and sell a stock past 12 o'clock (after a stock has reached the top of the cycle). Conversely, bad momentum traders buy a stock just before 12 o'clock (when a stock is about to reach the top and rebound shortly) and sell a stock shortly before 6 o'clock (when a stock is about to enjoy a positive earnings surprise in the near future). However, the model is silent on how to make the momentum strategies time-dependent or in other words how to identify where a stock currently is located in a cycle. Loosely speaking, momentum traders do not ask how long the stock has been winning (losing) but how much longer it is going to last.

My results suggest that analyst coverage is a potential candidate to be such indicator. Consider two firms A and B of approximately the same size. Firm A has more analysts than firm B. Given the framework above and evidence that analysts base their coverage on their expectations of the firm's performance (McNichols and O'Brien (1997)), firm A is expected to perform well in the near future, while analysts are skeptical about firm B's ability to generate high earnings in the coming time. Thus, if firm A delivers better-than-expected earnings, the firm A's stock will exhibit drift after the release. If it reports worse-than-expected earnings, the stock might initially lose, but should regain the loss as it delivers better results in the future. On the other hand, relatively low-coverage firm B will continue to lose after the negative earnings surprise because analysts' expectations for future earnings are very low. A positive earnings surprise will boost firm B's price shortly after the announcement, but the price will exhibit a strong reversal as firm B performs poorly in the future. This explanation can justify the results presented thus far. Low residual coverage indicates a negative momentum stock that has a long way to go before it turns the corner. Relatively high residual coverage signals a stock that has bottomed out and has a bigger upside potential. The limitation of the model is that it lacks explanation for why the negative earnings momentum among low-coverage losers is much more pronounced than the positive earnings momentum among high-coverage winners. It is also puzzling why the loser-analyst spread becomes evident shortly after the earnings release, while it takes longer (at least 120 trading days) for the winner-analyst spread to become statistically significant.

I also replicated Table 4 and Table 5 for the monthly method (results are presented in the Appendix). The drift is much weaker compared to the quarterly method. The strategy yields 0.77% (t-statistics=3.8), 0.49% (t-statistics=2.23) per month for the low- and high-coverage stocks, respectively. Recall that the portfolios in the monthly method also contains firms not announcing earnings in the given month of portfolio formation, thus including firms with out-of-date earnings. Moreover, this method involves buying and selling firms at the beginning of every month what causes investors to miss out on the gains generated shortly after the earnings news release that accounts for more than half of the drift.[12] The bottom line here is that the main findings persist. The relation between analyst coverage and drift is confirmed and is even more significant. As illustrated in Table 5 in the Appendix, the analyst-earnings strategy earns 3.5% (6.1%) over the 6-month horizon (12-month horizon) in comparison with 1.5% (2%) generated by the simple earnings momentum strategy. The difference of 2%, 4.1%, and 5.7% for the 6-, 12-, and 18-month holding period, respectively, is statistically significant, yielding corresponding t-statistics of 2.22, 3.12, and 4.1.

To sum up this section, analyst coverage apparently does not constitute a clean test for the "information asymmetry" hypothesis because it might proxy for other factors, but it certainly possesses some power to predict future drift. While my results are consistent with HLS (2000) in the short-run, the results for longer horizons are more supportive for a hypothesis that analyst coverage predicts the firm's future performance. There also is the possibility that these inconsistencies emerge because of the data used in my analysis. Unlike HLS (2000), I exclude firms with no analyst coverage owing to the SUE measure that requires at least one analyst per firm. Thus, I lose observations in the lowest size deciles, where the mispricing is expected to be most severe. On the top of this, HLS (2000) show that the relation between analyst coverage and the momentum is highlighted when one compares the no-coverage stocks with the at-least-some-coverage stocks. In the next section, I further disaggregate the analysis presented in Table 4 and 5 by size.

B. Cuts on Size and Residual Coverage

In this section, I test if, and how the results change when I look at four separate size subsamples. As noted before, one might conjecture that the marginal importance of analysts declines with size because it seems plausible that one extra analyst should matter much more if a firm has few analysts than if it has many. Moreover, I have to be aware of possible nonlinearities in firm size within residual coverage subsamples, as discussed above (Table 3). To address these concerns, I rerun all the tests from previous section except that I further disaggregate the analysis by size. Particularly, I run the analyst coverage regressions separately for each size-cut subsample. I split stocks into four groups based on their market capitalization. Group 1 consists of firms below the 40^{th} percentile NYSE/AMEX breakpoint, group 2, 3, 4 consists of firms between the 40^{th}-60^{th} percentile, 60^{th}-80^{th} percentile and above the 80^{th} percentile, respectively. I decided for the sort of wider range in group 1 due to very few observations in the lowest 20^{th} percentile. Since I need to form nine portfolios (3 SUE portfolios * 3

[12] As I show later, the returns on the monthly strategy become exploitable for the smallest stocks

RC portfolios) for each size group, I would end up with too few firms in each of the portfolios below the 20th percentile breakpoint thereby increasing the standard errors in my tests. Applying the 4-group structure to my data yields approximately the same number of observations in each group (see Table 6).

Cutting the universe of all stocks based on size, results in better size matches across residual coverage classes, thereby allowing the relationship between size and analyst coverage to be somewhat more linear. In this spirit, I hope to remedy deficiencies that arise from implementing a simple linear regression analysis on the entire sample. Consider Table 6 which displays the mean and median size analysis across different size and residual coverage classes. One can see that the imperfect size matching from Table 3 has improved tremendously. Mean and median size differences across three residual coverage classes have almost dissipated (except for the stocks above the 80th percentile).

Table 6
Mean and Medium Size, Cuts on Size

This table reports mean (median) firm size in thousands of dollars in market capitalization across the three residual coverage portfolios disaggregated by size. I classify firms into 4 size sub-portfolios. Group 1 consists of firms below the 40th percentile NYSE/AMEX breakpoint, group 2, 3, 4 consists of firms between the 40th-60th percentile, 60th-80th percentile and above the 80th percentile, respectively. I decided for the relatively wider range in group 1 due to very few observations in the lowest 20th percentile. The mean (median) numbers and the number of observations in any given portfolio/group are aggregated for the 40 quarters examined in the paper and are stacked on the top of each other.

Mean		Size Rank				
Median		Group 1	Group 2	Group 3	Group 4	
Obs.		<40th	40th-60th	60th-80th	>80th	All
	Low: RC1	182560.2	709753.7	2111899.	26299517	8495765.
		172045.3	693083.2	1969987.	8130395.	1478458.
		2439	3183	3506	3788	12916
	Medium: RC2	170498.2	707540.5	2126338.	23084281	7652034.
		161577.8	683378.8	1998672.	10399742	1507677.
Residual		3390	4185	4743	5225	17543
Coverage Class	Large: RC3	181379.3	711971.2	2110194.	17267224	5868922.
		176351.2	689325.3	1974558.	9874004.	1451549.
		2643	3164	3538	3917	13262
	All	177365.3	709540.5	2117198.	22264010	7360412.
		169429.3	688216.9	1983192.	9590441.	1486225.
		8472	10532	11787	12930	43721

Furthermore, it is very important to check whether higher desegregation of stocks, with fewer stocks in each portfolio, still possesses a sufficient variation in coverage. Table 7 illustrates the mean and median statistics of analyst coverage for the size disaggregated sample. Indeed, even in group 1 there is a healthy variation in analyst coverage with 1 analyst (median) in the low-coverage portfolio and 5 analysts (median) in the high-coverage portfolio.

Table 7
Mean and Median Analyst Coverage, Cuts on Size

Table reports the mean (median) of I/B/E/S analysts per firm who provide fiscal year 1earnings estimates, across the three residual coverage portfolios disaggregated by size. I classify firms into 4 size sub-portfolios. Group 1 consists of firms below the 40th percentile NYSE/AMEX breakpoint, group 2, 3, 4 consists of firms between the 40th-60th percentile, 60th-80th percentile and above the 80th percentile, respectively. I decided for the relatively wider range in group 1 due to very few observations in the lowest 20th percentile. The mean (median) numbers and the number of observations in any given portfolio/group are aggregated for the 40 quarters and are stacked on the top of each other.

Mean Median Obs.		Size Rank Group 1 <40th	 Group 2 40th-60th	 Group 3 60th-80th	 Group 4 >80th	 All
	Low: RC1	1.64	2.82	5.20	10.70	5.56
		1.00	3.00	5.00	10.00	4.00
		2399	3160	3481	3766	12806
	Medium: RC2	2.72	5.23	8.72	15.76	8.83
		2.00	5.00	8.00	15.00	7.00
Residual		3352	4156	4710	5188	17406
Coverage						
Class	High: RC3	5.06	9.30	14.09	21.67	13.38
		5.00	9.00	13.00	21.00	12.00
		2631	3154	3515	3900	13200
	All	3.14	5.73	9.28	16.07	9.25
		3.00	5.00	9.00	15.00	8.00
		8382	10470	11706	12854	43412

The main goal is to look for whether the interesting patterns, documented in the previous section, still continue to appear after controlling for firm size. Two key findings emerge from my results presented in Table 8 (on the next page). First, when moving to subsamples with the larger firms, the momentum loses its strength. Consider rows "all stocks" for "SUE3 – SUE1" strategy in Table 8. The drift is significant across all size classes for any of the displayed holding periods, but the magnitude of drift decreases with size. While the strategy earns 7.1 % (t-statistic=9) for the smallest stocks, it generates only 2.9 % for the large stocks, both within 60 trading days following the earnings release. The momentum in the smallest stocks continues to build up after 60 days, yielding 9.3% after 120 days and peaking at 12.1% another 120 days later. The earnings momentum runs out of steam after a year subsequent to the earnings announcements. Turning to the monthly method (Table 8 in the Appendix), the returns to the SUE3-SUE1 strategy for small stocks also are of an exploitable magnitude, with an abnormal return of 3.9% (t-statistic=5.3), 5.7% (t-statistic=5.6) and 7.7% (t-statistic=5.3) when holding a portfolio of small stocks for three, six and twelve months, respectively. The arbitrage portfolio SUE3 – SUE1 is insignificant for stocks above the 40th percentile for the monthly method.

The researchers are well aware that firm size has an effect on stock prices. It is not clear, however, why the momentum should be strongest in small firms. Risk or liquidity differences between small and large firms might account for one possibility. Another EMH consistent explanation is that some (small) stocks react with a lag to common (market) factors. In this regard, Lo and MacKinlay (1990)

Table 8
Earnings Momentum Strategies, Q1/1998-Q4/2007, Sorting By Firm Size and Equation 5 Analyst Residuals

This table reports the average cumulative abnormal returns on portfolios based on the SUE measure and portfolios formed by sorts on size and equation 5 analyst residuals of log size over different holding periods. Portfolio SUE1 consists of stocks in the 30 percent most negative unexpected earnings changes, portfolio SUE2 includes the middle 40 percent, and portfolio SUE3 contains stocks in the 30 percent most positive unexpected earnings changes. The least-covered stocks are in RC1 portfolio, the medium covered stocks in RC2 portfolio, and the most covered stocks in RC3 portfolio. The numbers in "SUE3-SUE1" panels are α coefficients of regressions of the form of equations 7 and 8. The numbers in "RC1-RC3" panels are α coefficients of regressions of the form of equations 9 and 10. T-statistics are in parentheses.

			60 days: Size Classes				240 days: Size Classes			
			<40th	40th-60th	60th-80th	>80th	<40th	40th-60th	60th-80th	>80th
60 days / 240 days	SUE3 - SUE1	RC1	0.06149	0.05111	0.04324	0.00919	0.10215	0.07068	0.02941	0.00953
			(5.07)	(5.30)	(4.58)	(1.02)	(3.33)	(3.70)	(1.06)	(0.47)
		RC2	0.08308	0.04369	0.02774	0.04038	0.15405	0.04654	0.02383	0.03042
			(6.95)	(5.28)	(3.93)	(5.07)	(4.63)	(2.10)	(2.20)	(1.23)
		RC3	0.05137	0.04564	0.02965	0.02894	0.09614	0.04547	-0.0153	0.06410
			(3.19)	(4.28)	(3.60)	(2.91)	(2.44)	(1.54)	(-0.59)	(2.35)
		all stocks	0.07059	0.04636	0.03082	0.02900	0.12099	0.05313	0.01339	0.04064
			(8.96)	(8.44)	(5.37)	(5.41)	(4.98)	(3.15)	(0.82)	(2.39)
	RC1 - RC3	SUE1	-0.00617	-0.00334	-0.02631	-0.01336	-0.0279	-0.03813	-0.08981	-0.03314
			(-0.32)	(-0.25)	(-2.75)*	(-1.70)***	(-0.71)	(-1.14)	(-3.85)*	(-1.55)
		SUE3	0.00395	0.00213	-0.01272	-0.03311	-0.02189	-0.01292	-0.04507	-0.08771
			(0.32)	(0.22)	(-1.06)	(-2.98)*	(-0.64)	(-0.58)	(-2.13)**	(-3.73)*
		all stocks	0.01012	0.00546	0.01358	-0.01975	0.00601	0.02521	0.04473	-0.05457
			(0.55)	(0.37)	(1.29)	(-1.65)	(0.17)	(0.69)	(1.33)	(-1.94)***

			120 days: <40th	40th-60th	60th-80th	>80th	360 days: <40th	40th-60th	60th-80th	>80th
120 days / 360 days	SUE3 - SUE1	RC1	0.08646	0.05148	0.04469	0.00172	0.06999	0.05454	-0.0035	0.00580
			(5.43)	(3.47)	(2.23)	(0.11)	(2.28)	(2.80)	(-0.10)	(0.19)
		RC2	0.11621	0.03358	0.02467	0.04007	0.11553	0.02421	0.01882	0.02264
			(6.83)	(2.63)	(2.15)	(2.64)	(3.06)	(0.95)	(1.21)	(0.96)
		RC3	0.06245	0.04077	0.01096	0.03593	0.10197	0.04030	-0.0093	0.06987
			(2.10)	(2.43)	(0.69)	(1.96)	(1.98)	(1.15)	(-0.31)	(2.72)
		all stocks	0.09309	0.03948	0.02359	0.02749	0.09893	0.03535	0.00090	0.04153
			(6.55)	(4.03)	(1.87)	(2.42)	(4.22)	(1.78)	(0.04)	(2.54)
	RC1 - RC3	SUE1	-0.01951	-0.02011	-0.06116	-0.02155	-0.01629	-0.01253	-0.09476	-0.08072
			(-0.59)	(-1.02)	(-4.43)*	(-1.43)	(-0.37)	(-0.27)	(-4.04)*	(-3.11)*
		SUE3	0.00450	-0.0094	-0.02743	-0.05577	-0.04827	0.00170	-0.08893	-0.14479
			(0.26)	(-0.71)	(-1.67)	(-3.38)*	(-1.56)	(0.05)	(-3.49)*	(-4.01)*
		all stocks	0.02401	0.01070	0.03373	-0.03421	-0.03198	0.01424	0.00583	-0.06407
			(0.86)	(0.47)	(1.48)	(-1.78)***	(-0.77)	(0.40)	(0.16)	(-1.58)

* Significant at the 1% level (reported only for RC1-RC3 differential)
** Significant at the 5% level (reported only for RC1-RC3 differential)
*** Significant at the 10% level (reported only for RC1-RC3 differential)

pointed out a lead-lag relationship in stock prices. In their model, the returns of large stock lead those of smaller stocks. Behavioral economists propose different stories. A model of Daniel et al. (1998) sees the profits of momentum strategies arising from overreaction to a private signal. Since smaller stocks are more difficult to value, more private information is required to judge the correct value, hence leading to more severe overreaction. Hong and Stein (1999) support the underreaction story.

They show that stock prices of smaller stocks will underreact more because “information asymmetry” is greater among small stocks, assuming that information gradually diffuses among investors.

Second, the effect of analyst coverage, as examined by HLS (2000), recedes, once I look at separate size classes. The bottom rows in Table 8 for each size class and each holding period (RC1 – RC3/all stocks) show no significant relationship between low- and high- coverage stocks. The only significant results are for the large stock portfolios after 120 trading days, which even go the opposite way as the Hong and Stein model would predict. Note, that using the monthly method, the only significant result for “RC1 – RC3/all stocks” combination is for stocks in the smallest size group and the 3-month holding period. The abnormal return in the low-coverage portfolio is 5.5% (t-statistic=5.9), while it is only 2.4% (t-statistic=2.1) in the high coverage portfolio. The difference of 3.1% is significant with t-statistic 2.53. The result is in line with HLS (2000) who conjecture that the marginal effect of analyst coverage should decline with size. Nonetheless, the return difference between low- and high-coverage stocks with small market capitalization dissipates after 3 months.

The essential finding in Table 8 is that the potential return-predictive feature of analyst coverage continues to hold, although mostly in larger stocks. Row SUE1/RC1-RC3 (SUE3/RC1-RC3) in Table 8 shows how stock prices react to bad news (good news) when firm has few analysts compared to when it has many analysts. Vast majority of coefficients (all of them if I consider only stocks above the 60^{th} percentile) are negative and mostly significant as size increases. For good-news firms, it implies that the high-coverage winner stocks earn more than the low-coverage winner stocks. For instance, dealing only with large stocks (size group 4), buying high-coverage winners and shorting low-coverage winners – the winner analyst spread – results in an abnormal return of 14.5 % (t-statistic=-4) over the 360-day holding period. This strategy is not only size neutral but also momentum neutral, since it only deals with good news firms. Furthermore, the strategy only involves buying or selling large stocks that are presumably more liquid and easier to short-sell. Taken together, an abnormal return of 14.5 % over the 360-day period is intriguing.

Turning to bad-news firms, negative coefficients in SUE1 row in Table 8 signals that the low-coverage loser stocks underperform the high coverage loser stocks. As discussed above, HLS (2000) call it LAST strategy. For example, considering only stocks in size group 3, buying high-coverage losers and selling low-coverage losers generates an abnormal return of 6.1 % over 120 trading days. Again, the strategy is size and momentum neutral. Of course, in examples above, I have chosen the best results that emerge from Table 8. Many other coefficients, although negative, are not highly significant. However, larger standard errors are expected because by forming another four size sub-portfolios I ended up with 36 (4*3*3) less diversified portfolios. Thus, solving the problem with size matching is at the expense of losing some statistical power. In addition, HLS (2000) suspect that holding size fixed, the effect of information asymmetry cannot be fully captured owing to both size and analyst coverage being a proxy for information asymmetry to some extent.

Table 9
Simple Earnings Momentum Strategies and Earnings Momentum Strategies Based on Equation 5 Analyst Residuals, Using Abnormal Returns, Sorting by Size

The first row of this table reports the mean cumulative abnormal returns on strategies sorted by size that buy stocks with the most positive unexpected earnings changes and sell stocks with the most negative unexpected earnings changes over different holding periods. The numbers are α coefficients of regressions of the form of equation 7 sorted by size. The second row reports the cumulative abnormal returns on strategies sorted by size that buy high-coverage stocks with the most positive unexpected earnings changes and sell low-coverage stocks with the most negative unexpected earnings changes over different holding periods. The numbers are α coefficients of regressions of the form of equation 11 sorted by size. The last row (difference) reports the average difference in the mean cumulative abnormal returns between the two strategies. The numbers are α coefficients of regressions of the form of equation 12 sorted by size. T-statistics are in parentheses.

	Size classes			
Strategy	$<40^{th}$	40^{th}-60^{th}	60^{th}-80^{th}	$>80^{th}$
	60 trading days			
"Simple Earnings momentum strategy"	0.07059	0.04636	0.03082	0.02900
SUE3-SUE1	(8.96)	(8.43)	(5.37)	(5.41)
"Analyst Earnings Momentum"	0.05754	0.04897	0.05596	0.04230
RC3SUE3-RC1SUE1	(3.94)	(4.34)	(4.86)	(4.20)
Difference				
(P3RC3-P1RC1)-(P3-P1)	-0.01305	0.00261	0.02513	0.01330
	(-0.98)	(0.26)	(2.42)**	(1.82)***
	120 trading days			
"Simple Earnings momentum strategy"	0.09309	0.03948	0.02359	0.02749
SUE3-SUE1	(6.55)	(4.03)	(1.87)	(2.42)
"Analyst Earnings Momentum"	0.08196	0.06088	0.07212	0.05748
RC3SUE3-RC1SUE1	(4.01)	(3.59)	(4.55)	(4.15)
Difference				
(P3RC3-P1RC1)-(P3-P1)	-0.01113	0.02139	0.04852	0.02999
	(-0.53)	(1.57)	(4.05)*	(2.30)**
	240 trading days			
"Simple Earnings momentum strategy"	0.12099	0.05313	0.01339	0.04064
SUE3-SUE1	(4.98)	(3.15)	(0.82)	(2.39)
"Analyst Earnings Momentum"	0.12404	0.08360	0.07448	0.09724
RC3SUE3-RC1SUE1	(3.52)	(3.89)	(3.34)	(4.67)
Difference				
(P3RC3-P1RC1)-(P3-P1)	0.00304	0.03047	0.06108	0.05659
	(0.08)	(1.23)	(3.62)*	(3.12)*
	360 trading days			
"Simple Earnings momentum strategy"	0.09893	0.03535	0.00090	0.04153
SUE3-SUE1	(4.22)	(1.78)	(0.04)	(2.54)
"Analyst Earnings Momentum"	0.11826	0.05283	0.08542	0.15059
RC3SUE3-RC1SUE1	(3.06)	(1.42)	(2.84)	(5.09)
Difference				
(P3RC3-P1RC1)-(P3-P1)	0.01933	0.01748	0.08452	0.10905
	(0.56)	(0.48)	(4.38)*	(4.42)*

* Significant at the 1% level (reported only for the difference of the two strategies)
** Significant at the 5% level (reported only for the difference of the two strategies)
*** Significant at the 10% level (reported only for the difference of the two strategies)

Clearly, relatively lower analyst coverage appears to predict negative future returns and relatively high analyst coverage tends to predict positive future performance. If this is true, the strategy of buying high-coverage winners and selling low-coverage losers (Analyst-Earnings Momentum Strategy) should, on average, surpass the Simple Earnings Momentum Strategy. To see that, I replicate results from Table 5 for each size decile. Results are reported in Table 9 (above). These results give credence to my previous results. As I move to higher size classes, the difference between the two strategies is wider and statistically significant. Analyst coverage seems to predict future drift already after 60 days. To be more specific, the simple earnings momentum strategy produces drift of 3.1% (t-statistic=5.4), 2.9% (t-statistic=5.4) in large stocks, which is 2.5% (t-statistic=2.4), 1.3% (t-statistic=1.8) less than if I construct the analyst earnings momentum strategy. When holding stocks for 360 trading days, the simple strategy achieves an abnormal return of 0% and 4.2% for the large stock portfolios, while the magnitude of my strategy is 8.5% and 15.1%, respectively. The difference of 8.5%, 10.9% is highly significant, yielding t-statistic of 4.4. This evidence raises the question of why analyst coverage can only predict drift in larger stocks. One possibility is that analyst coverage has different impact on stocks when these are small than if they are large. For example, HLS (2000) showed that analyst coverage, as a proxy for information diffusion, seems to work better among small stocks.[13] Another possibility is that my approach excludes stocks with zero analyst coverage. Excluding these stocks, I have lost many observations, the majority of them among the smallest stocks. This might have potentially affected my results for smaller stocks.

C. *Robustness Tests*

This section examines the possibility that the salient patterns documented in the previous section might emerge due to other factors. Thus far, I assumed that analyst coverage may proxy for investor interest and expectations to give a support to my results. However, in this section I allow analyst coverage to be a proxy for other factors such as beta risk, the book-to-market ratio, constraints on short-selling or trading volume.

Returns Adjusted For Market-Wide Factors

One possibility why the results discussed above might not be a sufficient condition for the analyst coverage effect to be confirmed is because it could be due to higher returns being required on high-coverage stocks owing to high-coverage stocks being more risky. Thus, there is a plausible reason to redo previous tests using returns adjusted for market factors, rather than simple size-adjusted returns. Furthermore, H&S (2000) find evidence that analyst coverage is correlated with beta. They rerun regressions of form of equation 5, adding firm's beta on the right hand side of equation 5. As it turns out, the coefficient on beta is positive and significant. Thus, in this sensitivity analysis, all the abnormal returns are adjusted for beta, as obtained from the CRSP database. In the CRSP data

[13] Note, that HLS (2000) examined the price momentum. I showed that analyst coverage has different effect on post-earnings announcement drift.

description guide, the beta excess return (BER) denotes the excess return of a stock less the average return of all stocks in its beta portfolio. Betas are estimated using the Scholes-Williams method (1977) for no synchronous data by regressing the individual stock return against market returns from the previous, current and subsequent periods divided by one plus twice the estimated autocorrelation coefficient for the market index. Such extracted returns are then cumulated over the 60-, 120-, 240- and 360-holding period after earnings announcement q for firm j:

(13) $$CBER_{jq} = \sum_{t=q}^{q+\pi} BER_{jt}$$

In equation (13) $CBER_{jq}$ denotes the firm j's cumulative beta excess return after earnings announcement q. Greek letter *Π* represents a period over which I sum the excess returns.

In Table 10, I replicate the results reported in Table 4 except that I use CBERs instead of CARs when I run regressions 6-10. As it turns out, using beta risk adjusted abnormal returns does not alter the overall magnitude of the post-earnings announcement phenomenon. Most of it occurs over the 20-day horizon subsequent to the earnings announcements (3.4% with t-statistic=19.5), but it is only slightly boosting afterwards.

The results in Table 10 display the evidence suggested by HLS (2000) that high- coverage stocks are riskier than low-coverage stocks. To show that, consider how the results for RC1-RC3 in Table 10 have changed compared to Table 4. The LAST strategy (RC1-RC3/SUE1) is still significant after 120 days even after adjusting for risk differences, though achieving smaller magnitude.[14] On the other hand, the return differences between low- and high-coverage winners (the winner analyst spread – RC1-RC3/SUE3) are not significantly different from zero (except for the 360-day horizon) compared to Table 4 when they were negative and mostly significant. In Table 4, the results indicated that prices of low-coverage winners initially drift and then strongly rebound. When using CBERs in Table 10, the story is that the abnormal returns to both low- and high-coverage winners are positive at the beginning and then both slightly retreat, although the returns to low-coverage winners still retreat more. This implies that the risk differences between low- and high-coverage stocks are more severe and alter my results more among the winner stock portfolios. This evidence, however, might not be that surprising given the implications of the "Earnings Expectation Life Cycle" framework explained above. Recall that when a stock has bottomed out, analyst coverage rises and analysts' earnings expectations might be becoming higher. At this point, the earnings momentum strategy becomes more risky. The risk is that an earnings disappointment might occur in a very short time. Hence, the framework suggests good-news stocks with relatively higher coverage to be more risky.

[14] This evidence lends further credence to the hypothesis of bad news travelling more slowly.

Table 10
Earnings Momentum Strategies, Q1/1998-Q4/2007, Using Beta Excess Returns, Sorting By Equation 5 Analyst Residuals

This table reports the mean cumulative beta excess returns (CBERs) on portfolios based on the SUE measure and portfolios formed using an independent sort on equation 5 analyst residuals of log size over different holding periods. Portfolio SUE1 consists of stocks in the 30 percent most negative unexpected earnings changes, portfolio SUE2 includes the middle 40 percent, and portfolio SUE3 contains stocks in the 30 percent most positive unexpected earnings changes. The least-covered stocks are in RC1 portfolio, the medium covered stocks in RC2 portfolio, and the most covered stocks in RC3 portfolio. The numbers are α coefficients of regressions of the form of equations 6-10, using CBERs. T-statistics are in parentheses.

		Residual Coverage Class			
Past	all stocks	Low: RC1	Medium: RC2	High: RC3	RC1-RC3
		20 trading days			
SUE1	-0.01454	-0.01675	-0.0136	-0.01027	-0.00648
	(-7.49)	(-6.16)	(-5.25)	(-2.58)	(-1.27)
SUE2	0.003168	0.000482	0.004300	0.003926	-0.00344
	(1.38)	(0.21)	(1.50)	(1.56)	(-1.44)
SUE3	0.019211	0.021016	0.020948	0.018166	0.002850
	(10.80)	(10.42)	(8.78)	(6.24)	(0.88)
SUE3 - SUE1	0.033754	0.037761	0.034547	0.028433	0.009327
	(19.48)*	(11.31)*	(16.54)*	(8.29)*	(2.14)**
		60 trading days			
SUE1	-0.02675	-0.02771	-0.02895	-0.01823	-0.00949
	(-5.95)	(-5.91)	(-5.41)	(-2.51)	(-1.26)
SUE2	-0.00655	-0.01098	-0.00648	-0.00414	-0.00683
	(-1.68)	(-2.75)	(-1.56)	(-0.75)	(-1.45)
SUE3	0.017300	0.020949	0.016364	0.018042	0.002907
	(5.46)	(4.74)	(4.38)	(3.79)	(0.51)
SUE3 - SUE1	0.044049	0.048661	0.045309	0.036267	0.012395
	(9.72)*	(7.20)*	(8.87)*	(5.32)*	(1.60)
		120 trading days			
SUE1	-0.03619	-0.03835	-0.04398	-0.01701	-0.02135
	(-4.94)	(-5.39)	(-5.18)	(-1.41)	(-1.75)***
SUE2	-0.01025	-0.01632	-0.01194	-0.00447	-0.01186
	(-1.32)	(-2.17)	(-1.38)	(-0.45)	(-1.32)
SUE3	0.010030	0.012607	0.009395	0.015646	-0.00304
	(1.49)	(1.78)	(1.24)	(1.96)	(-0.59)
SUE3 - SUE1	0.046216	0.050961	0.053379	0.032653	0.018308
	(5.63)*	(5.05)*	(5.95)*	(2.73)*	(1.41)
		240 trading days			
SUE1	-0.04705	-0.0569	-0.05716	-0.01939	-0.03752
	(-4.38)	(-4.79)	(-5.16)	(-1.09)	(-2.05)**
SUE2	-0.02203	-0.0353	-0.0217	-0.01425	-0.02106
	(-1.62)	(-2.54)	(-1.43)	(-0.90)	(-1.45)
SUE3	0.004871	0.005875	-0.00125	0.016132	-0.01026
	(0.42)	(0.51)	(-0.08)	(1.30)	(-0.90)
SUE3 - SUE1	0.051917	0.062778	0.055913	0.035520	0.027258
	(4.03)*	(5.14)*	(4.09)*	(2.04)**	(1.67)***
		360 trading days			
SUE1	-0.04607	-0.05023	-0.0623	-0.01516	-0.03507
	(-3.63)	(-3.64)	(-4.74)	(-0.65)	(-1.60)
SUE2	-0.03454	-0.05263	-0.03664	-0.02154	-0.03109
	(-1.95)	(-2.85)	(-1.89)	(-1.07)	(-1.67)
SUE3	-0.0075	-0.01179	-0.01463	0.012741	-0.02453
	(-0.60)	(-1.06)	(-0.98)	(0.84)	(-1.95)***
SUE3 - SUE1	0.038563	0.038448	0.047663	0.027902	0.010545
	(2.85)*	(3.38)*	(3.61)*	(1.30)	(0.56)

* Significant at the 1% level (reported only for SUE3-SUE1 differential and RC1-RC3 differential)

** Significant at the 5% level (reported only for SUE3-SUE1 differential and RC1-RC3 differential)

*** Significant at the 10% level (reported only for SUE3-SUE1 differential and RC1-RC3 differential)

The overall effect of analyst coverage on post-earnings announcement drift stays positive across all holding periods, but is only significant for the shortest holding period and marginally significant for the 360-day holding period. In line with HLS (2000), the beta excess return on a portfolio with long (short) positions in low coverage firms within the highest (lowest) decile of unexpected earnings is 3.8% over the 20-day horizon, while it is only 2.8% in high coverage firms (the difference of almost 1% has t-statistic 2.1).

The evidence from Table 10 apparently casts doubts on the profitability of the “Analyst-Earnings Momentum” strategy, derived in the previous section. While relatively low analyst coverage still seems to predict lower future returns even when controlling for beta risk, relatively higher analyst coverage might predict higher returns, but these can be materialized only at the expense of taking more risk. Table 11, which replicates the results from Table 9 except that I use CBERs, demonstrates three noteworthy findings.

First, the very right column of Table 11 shows that the analyst earnings momentum strategy, on average, modestly beats the simple earnings momentum strategy, but the return differential between the strategies is not significant.

Second, disaggregating the analysis by size, one can see that dealing with larger stock, the analyst-earnings momentum strategy earns a significantly (after 120 trading days) higher beta excess return than the simple earnings momentum strategy. For example, consider the coefficients for the 120-day holding period. A zero-investment portfolio with short (long) positions within low-coverage (high-coverage) bad-news firms (good-news firms) in the largest stocks produces a beta excess return of 4.8% (t-statistic=3.3), 5.1% (t-statistic=4), whereas a simple zero-investment portfolio with short (long) positions within bad-news (good-news) firms yields tiny 2% (t-statistic=1.7), 2.4% (t-statistic=1.9). Unreported in Table 11, high- (low-) coverage winners (losers) tend to outperform (underperform) low- (high-) coverage winners (losers). Note that this only applies to larger stocks. For instance, dealing only with large stocks, buying high-coverage winners and shorting low-coverage winners results in a beta excess return of 11.6 % (t-statistic=-4.8) over the 360-day holding period. This strategy is size neutral, beta risk neutral and momentum neutral. Furthermore, one cannot argue that liquidity or short-sale restrictions account for the excess return since the strategy only involves buying or selling large stocks.

Third, closer examination of my results for the smallest stocks (below the 40th percentile NYSE/AMEX size breakpoint) confirms the evidence that the market is typically more inefficient for smaller companies. The magnitude of drift within small stocks is 8.6% (t-statistic=9.2), 11.2% (t-statistic=6.3), and 14.4% (t-statistic=4.5) over the 60-, 120- and 240-day horizon, respectively, measured in excess of the return to the portfolio consisting of stocks of approximately the same beta risk.

Table 11
Simple Earnings Momentum Strategies and Earnings Momentum Strategies Based on Equation 5 Analyst Residuals, Using Beta Excess Returns, Sorting by Size

The first row of this table reports the mean cumulative beta excess returns (CBERs) on strategies sorted by size that buy stocks with the most positive unexpected earnings changes and sell stocks with the most negative unexpected earnings changes over different holding periods. The numbers are α coefficients of regressions of the form of equation 7, using CBERs. The second row reports the CBERs on strategies sorted by size that buy high-coverage stocks with the most positive unexpected earnings changes and sell low-coverage stocks with the most negative unexpected earnings changes over different holding periods. The numbers are α coefficients of regressions of the form of equation 11 sorted by size and using CBERs. The last row (difference) reports the average difference in the CBERs between the two strategies. The numbers are α coefficients of regressions of the form of equation 12 sorted by size and using CBERs. T-statistics are in parentheses.

	Size classes				
Strategy	$<40^{th}$	40^{th}-60^{th}	60^{th}-80^{th}	$>80^{th}$	all stocks
60 trading days					
"Simple Earnings momentum strategy" SUE3-SUE1	0.08625	0.04904	0.02963	0.02672	0.04404
	(9.20)	(8.00)	(5.17)	(4.87)	(9.72)
"Analyst Earnings Momentum" RC3SUE3-RC1SUE1	0.06779	0.04455	0.04366	0.03710	0.04575
	(3.50)	(4.76)	(4.10)	(4.04)	(7.35)
Difference					
(P3RC3-P1RC1)-(P3-P1)	-0.01847	-0.00449	0.01403	0.01038	0.00170
	(-1.05)	(-0.56)	(1.56)	(1.38)	(0.32)
120 trading days					
"Simple Earnings momentum strategy" SUE3-SUE1	0.11207	0.04960	0.02026	0.02387	0.04621
	(6.29)	(5.17)	(1.66)	(1.92)	(5.62)
"Analyst Earnings Momentum" RC3SUE3-RC1SUE1	0.11460	0.04601	0.04796	0.05119	0.054
	(4.22)	(2.96)	(3.25)	(4.00)	(4.91)
Difference					
(P3RC3-P1RC1)-(P3-P1)	0.00253	-0.00358	0.0277	0.02731	0.00778
	(0.08)	(-0.30)	(2.65)*	(2.81)*	(0.87)
240 trading days					
"Simple Earnings momentum strategy" SUE3-SUE1	0.14388	0.05706	0.00715	0.03033	0.05191
	(4.45)	(3.59)	(0.46)	(1.72)	(4.02)
"Analyst Earnings Momentum" RC3SUE3-RC1SUE1	0.14842	0.06187	0.04527	0.08331	0.07303
	(3.37)	(2.32)	(2.26)	(3.79)	(4.32)
Difference					
(P3RC3-P1RC1)-(P3-P1)	0.00453	0.00481	0.03811	0.05298	0.02111
	(0.09)	(0.19)	(2.39)**	(3.51)*	(1.40)
360 trading days					
"Simple Earnings momentum strategy" SUE3-SUE1	0.11726	0.04059	-0.00798	0.03351	0.03856
	(3.87)	(1.98)	(-0.36)	(1.93)	(2.84)
"Analyst Earnings Momentum" RC3SUE3-RC1SUE1	0.09300	0.03911	0.04392	0.12866	0.06297
	(1.67)	(0.96)	(1.53)	(4.25)	(3.05)
Difference					
(P3RC3-P1RC1)-(P3-P1)	-0.02426	-0.00149	0.05190	0.09514	0.02441
	(-0.43)	(-0.04)	(2.71)*	(4.71)*	(1.56)

* Significant at the 1% level (reported only for the difference of the two strategies)
** Significant at the 5% level (reported only for the difference of the two strategies)
*** Significant at the 10% level (reported only for the difference of the two strategies)

All in all, the bottom line of this diagnostic test is that market-wide factors partially account for abnormal returns presented in previous sections. Some investment strategies are riskier than they initially appear. Nevertheless, the salient features of my analysis continue to hold.

Book-to-Market Ratio Analysis

This subsection examines whether results presented thus far cannot be attributed to different loadings on book-to-market factors across analyst-coverage portfolios. Fama and French (1995) document that book-to-market ratio signals future returns and future earnings, which could be consistent with rational pricing. Moreover, the "Earnings Expectation Life Cycle" framework suggested by Bernstein (1993), which I adopt in my analysis, also suggests a stock closer to the bottom of the cycle to have higher loadings on book-to-market factors (value stock) and a stock at the top of the cycle to have low book-to-market ratio (glamour stock). In this sense, one might suspect that relatively high-coverage stocks will also have a higher book-to-market ratio and vice versa. If this was the case, then the documented return-predictive power of analyst coverage would be driven by book-to-market factors.

To asses this possibility, I add a book-to-market variable on the right-hand side of equation 5:

$$\text{(14)} \qquad Log\left(1 + Analysts_{jq}\right) = b_0 + b_1 \log(Size_{jq}) + b_2 \frac{Book}{Mkt} + \varepsilon$$

In equation 14, $Analysts_{jq}$ denotes the number of analysts for firm j in quarter q. $Size_{jq}$ is measured as market capitalization (shares outstanding * closing price) for firm j on its last trading day in current quarter q. Book/Mkt is the ratio of a firm's year-end book-to-market value, only available until 2006. The Greek letter ε denotes an error term. I run separate regressions for each quarter to test whether analyst coverage is related to book-to-market factors. Results for coefficient b_2 are reported in panel A of Table 12. Coefficients do not change in each quarter, thus I only display the coefficients for the first quarter of each year. As can be seen, coefficients are positive across years, but they are significant only for the first few years of the examined sample period. Note that adjusted R^2 almost does not change compared to what is reported in Table 1.

Table 13 displays mean and median statistics for book-to-market across the nine portfolios, as they were formed for the purpose of analysis in section IV.A (using regression 5 residuals). The mean value of book-to-market is 0.53, 0.61 for a portfolio of the low- and high-coverage stocks, respectively. The difference is larger for the bad-news firms (0.63 versus 0.78) than for the good-news firms (0.57 versus 0.65). HLS (2000) found similar spreads. They argue that this book-to market spread can only justify a very small fraction of the returns on their LAST strategy. In my analysis, however, a strategy of buying high-coverage winners and selling low-coverage losers is of higher magnitude among larger stocks. In this regard, when I tried to further disaggregate Table 13 by size (unreported), the book-to-market spread between low- and high-coverage stocks shrink even more as firm's size increases.

Table 12
Determinants of Analyst Coverage

Panel A, B, C of this table illustrate the results of regressions of the form of equation 14, 15 and 16, respectively. I rerun these regressions for each quarter starting in 1998Q1 and ending in 2007Q4 (except for the book-to-market analysis due to the missing data after 2006). Outcomes of the regressions do not change in each quarter, thus I only display the results for the first quarter of each year. Table includes the numbers for coefficient b_2 estimation (coefficient b_3 in panel C), its t-statistic, R^2, adjustedR^2 and the number of observations included in each regression.

Year	Coefficient	T-statistic	R2	Adjusted R2	No.obs
		Panel A: Book-to-market Ratio			
1998	0.09	2.88	0.63	0.63	994
1999	0.07	2.92	0.63	0.63	1009
2000	0.01	1.88	0.59	0.59	961
2001	0.03	1.67	0.65	0.65	910
2002	0.00	0.21	0.58	0.58	956
2003	0.05	1.18	0.57	0.56	1024
2004	0.06	1.38	0.57	0.57	1035
2005	0.01	0.25	0.59	0.59	1098
2006	0.05	1.05	0.61	0.61	1104
		Panel B: Turnover			
1998	0.31	10.29	0.67	0.67	1091
1999	0.41	12.47	0.68	0.68	1176
2000	0.29	8.27	0.62	0.62	1111
2001	0.23	7.99	0.67	0.67	995
2002	0.30	13.05	0.65	0.65	1002
2003	0.28	12.98	0.63	0.63	1053
2004	0.23	10.46	0.61	0.61	1061
2005	0.21	10.37	0.62	0.62	1111
2006	0.16	8.87	0.64	0.64	1127
2007	0.1	9.41	0.62	0.62	1146
		Panel C: Options Listing			
1998	0.28	9.09	0.67	0.67	1091
1999	0.37	10.84	0.68	0.68	1176
2000	0.26	7.26	0.62	0.62	1111
2001	0.22	7.39	0.67	0.67	995
2002	0.28	12.16	0.65	0.65	1002
2003	0.26	11.74	0.63	0.63	1053
2004	0.21	9.11	0.61	0.61	1061
2005	0.18	8.63	0.63	0.63	1111
2006	0.14	7.47	0.64	0.64	1127
2007	0.11	7.61	0.63	0.63	1146

Table 13
Book-to-Market across Residual Coverage Portfolios

This table reports the mean (median) of a firm's year-end book-to-market value across the nine portfolios. Portfolios are formed by sorts on the SUE measure and equation 5 estimation residuals. Portfolio SUE1 consists of stocks in the 30 percent most negative unexpected earnings changes, portfolio SUE2 includes the middle 40 percent, and portfolio SUE3 contains stocks in the 30 percent most positive unexpected earnings changes. The least-covered stocks are in RC1 portfolio, the medium covered stocks in RC2 portfolio, and the most covered stocks in RC3 portfolio. The mean (median) numbers are averaged for the 1998 to 2006 period.

Mean		SUE Portfolios			
Median		SUE1	SUE2	SUE3	All
	Low: RC1	0.63	0.40	0.57	0.53
		0.54	0.35	0.51	0.46
	Medium: RC2	0.71	0.42	0.59	0.54
Residual Coverage Portfolios		0.52	0.37	0.51	0.45
	High: RC3	0.78	0.47	0.65	0.61
		0.54	0.40	0.52	0.47
	All	0.70	0.43	0.60	0.56
		0.53	0.38	0.51	0.46

Transactions costs analysis

There might be another alternative explanation of my results. As mentioned above, I conjecture that the results are primarily driven by analyst coverage being a proxy for investor interest in a stock. However, HLS (2000) point out that analyst coverage may double as a proxy for differences in transactions costs. Although one can say that differences in transaction costs should be captured by the size factor, this is not necessarily true. Think of two companies A and B of equal size; firm A is more difficult to short-sell or harder to trade than firm B. It is conceivable that firm A will attract fewer analysts than firm B. This could seriously confound my results. The finding that bad news travels slowly (low-coverage losers significantly underperform high-coverage losers) might stem from short-sale restrictions or other trading constraints on low-coverage stocks so that the drift occur simply because profits from mispricing cannot be materialized.

To address this possibility, I follow HLS (2000) and examine two proxies for transactions costs: share turnover and a dummy variable for the existence of listed options on a given stock. First, a share turnover variable is added to the right-hand side of equation 5, yielding:

$$(15) \qquad Log\left(1 + Analysts_{jq}\right) = b_0 + b_1 \log(Size_{jq}) + b_2\, Turnover_{jq} + \varepsilon$$

In equation 15, $Analysts_{jq}$ and $Size_{jq}$ are defined as before. The turnover measure is defined as the prior six months' trading volume divided by shares outstanding. Similarly to prior analysis, I run quarter-by-quarter regressions and then I classify stocks into three sub-portfolios based on firms' standings relative to the residuals of these regressions. Panel B in Table 12 illustrates some results obtained from these regressions (displayed only for the first quarter of each year). Positive and highly significant coefficients (b_2) across year quarters signal a positive relation between analyst coverage and trading volume, as suggested above. Adjusted R^2 slightly rises compared to R^2 in regressions with a size variable as the only independent variable (equation 5).

To see whether using regression 15's residuals alter my findings, I rerun all tests needed to replicate Table 4 and Table 5. The turnover numbers are presented in panel A of Table 14 and panel A of Table 15. Before turning to the brief discussion of the results, I have to address a concern about the turnover measure, pointed out by HLS (2000). They show that there might be a two-way causality in a relation between analyst coverage and trading volume. The causality from former to latter suggests that stocks with higher analyst coverage enjoy lower adverse-selection costs thus attract more trading.[15] If this was the case, then adding a variable for turnover could introduce some noise into my results and could

[15] For more details, see Brennan and Subrahmanyam (1995)

Table 14
Earnings Momentum Strategies, Q1/1998-Q4/2007, Using Abnormal Returns, Sorting By Equation 15 and 16 Analyst Residuals

Panel A of this table reports the mean cumulative abnormal returns on portfolios based on the SUE measure and portfolios formed using an independent sort on equation 15 analyst residuals of log size and turnover over different holding periods. Panel B of this table reports the mean cumulative abnormal returns on portfolios based on the SUE measure and portfolios formed using an independent sort on equation 16 analyst residuals of log size, turnover and options listing dummy variable over different holding periods. Portfolio SUE1 consists of stocks in the 30 percent most negative unexpected earnings changes, portfolio SUE2 includes the middle 40 percent, and portfolio SUE3 contains stocks in the 30 percent most positive unexpected earnings changes. The least-covered stocks are in RC1 portfolio, the medium covered stocks in RC2 portfolio, and the most covered stocks in RC3 portfolio. The numbers are α coefficients of regressions of the form of equations 6-10. T-statistics are in parentheses.

Residual Coverage Class							
	Low: RC1	High: RC3	RC1-RC3		Low: RC1	High: RC3	RC1-RC3
Panel A: Turnover Analysis (equation 15)				Panel B: Options Listing Analysis (equation 16)			
60 trading days				60 trading days			
SUE1	-0.03209	-0.01340	-0.01869	SUE1	-0.02989	-0.01467	-0.01522
	(-7.68)	(-2.13)	(-2.44)**		(-7.03)	(-2.34)	(-2.07)**
SUE2	-0.01950	-0.00518	-0.01432	SUE2	-0.01922	-0.00569	-0.01352
	(-5.40)	(-1.35)	(-2.25)**		(-5.47)	(-1.50)	(-2.16)**
SUE3	0.01835	0.02274	-0.00438	SUE3	0.01759	0.02278	-0.00519
	(4.72)	(4.74)	(-0.76)		(4.61)	(4.61)	(-0.87)
SUE3 - SUE1	0.05045	0.03615	0.01430	SUE3 - SUE1	0.04748	0.03745	0.01002
	(8.11)*	(5.81)*	(2.00)***		(7.40)*	(6.03)*	(1.35)
120 trading days				120 trading days			
SUE1	-0.05034	-0.00974	-0.04059	SUE1	-0.04901	-0.01410	-0.03491
	(-7.91)	(-0.85)	(-3.27)*		(-7.86)	(-1.13)	(-2.74)*
SUE2	-0.03070	-0.01017	-0.02053	SUE2	-0.03074	-0.01161	-0.01912
	(-4.15)	(-1.73)	(-1.67)		(-4.76)	(-1.94)	(-1.66)
SUE3	0.00728	0.02770	-0.02041	SUE3	0.00635	0.02633	-0.01997
	(1.23)	(4.49)	(-2.29)**		(1.09)	(4.44)	(-2.35)**
SUE3 - SUE1	0.05762	0.03744	0.02018	SUE3 - SUE1	0.05537	0.04043	0.01494
	(6.15)*	(3.90)*	(1.70)***		(5.69)*	(3.87)*	(1.15)
240 trading days				240 trading days			
SUE1	-0.07890	-0.00860	-0.07029	SUE1	-0.07371	-0.01501	-0.05870
	(-7.66)	(-0.46)	(-3.58)*		(-7.07)	(-0.79)	(-3.05)*
SUE2	-0.05969	-0.02026	-0.03942	SUE2	-0.06106	-0.02263	-0.03842
	(-5.60)	(-2.04)	(-2.10)**		(-6.42)	(-2.35)	(-2.18)**
SUE3	-0.01045	0.03161	-0.04207	SUE3	-0.00793	0.03004	-0.03797
	(-1.30)	(2.93)	(-2.86)*		(-1.13)	(2.91)	(-2.93)*
SUE3 - SUE1	0.06845	0.04022	0.02822	SUE3 - SUE1	0.06578	0.04505	0.02073
	(6.06)*	(2.48)**	(1.66)		(5.37)*	(2.68)**	(1.18)

* Significant at the 1% level (reported only for SUE3-SUE1 differential and RC1-RC3 differential)
** Significant at the 5% level (reported only for SUE3-SUE1 differential and RC1-RC3 differential)
*** Significant at the 10% level (reported only for SUE3-SUE1 differential and RC1-RC3 differential)

Table 15
Simple Earnings Momentum Strategies and Earnings Momentum Strategies Based on Equation 15 and 16 Analyst Residuals, Using Abnormal Returns

The first row of this table reports the mean cumulative abnormal returns on strategies that buy stocks with the most positive unexpected earnings changes and sell stocks with the most negative unexpected earnings changes over different holding periods. The numbers are α coefficients of regressions of the form of equation 7. The second row reports the cumulative abnormal returns on strategies that buy high-coverage stocks with the most positive unexpected earnings changes and sell low-coverage stocks with the most negative unexpected earnings changes over different holding periods. The numbers are α coefficients of regressions of the form of equation 11. The last row (difference) reports the average difference in the mean cumulative abnormal returns between the two strategies. The numbers are α coefficients of regressions of the form of equation 12. For the purpose of analysis in the second and third row, residual coverage for panel A analysis is set by using a sort on equation 15 analyst residuals of log size and turnover. In panel B, residual coverage is set by using a sort on equation 16 analyst residuals of log size, turnover and options listing dummy variable. T-statistics are in parentheses.

	Holding Period					
Strategy	60 days	120 days	240 days	60 days	120 days	240 days
	Panel A: Turnover			Panel B: Options Listing		
"Simple Earnings momentum strategy" SUE3-SUE1	0.04590	0.05099	0.06077	0.04590	0.05099	0.06077
	(11.07)	(6.78)	(4.65)	(11.07)	(6.78)	(4.65)
"Analyst Earnings Momentum" RC3SUE3-RC1SUE1	0.05484	0.07804	0.11052	0.05268	0.07534	0.10375
	(8.04)	(8.00)	(7.15)	(7.65)	(8.36)	(6.69)
Difference						
(P3RC3-P1RC1)-(P3-P1)	0.00893	0.02705	0.04975	0.00677	0.02435	0.04298
	(1.34)	(2.74)*	(3.12)*	(1.04)	(2.78)*	(3.17)*

* Significant at the 1% level (reported only for the difference of the two strategies)
** Significant at the 5% level (reported only for the difference of the two strategies)
*** Significant at the 10% level (reported only for the difference of the two strategies)

lead to a loss of the power of my tests. Conversely, one might argue that it is not the firm's market capitalization that mainly drives analyst coverage but rather the firm's trading volume. For instance, Lee and Swaminathan (2000) suggest that trading volume might be a proxy for investor interest in a firm. If higher trading volume arises from rising investor interest, then the higher volume stock will also gain more analyst coverage. In this spirit, it is warranted to check the turnover effect on analyst coverage. Since the turnover measure requires stocks to be recorded on the CRSP tapes for at least six months, I further lose some observations, typically among the smaller stocks. Nevertheless, the findings (as reported in panel A of Table 14 and Table 15) still carry over and are even more significant. In addition, I also rerun the tests (unreported) disaggregated by size and obtained similar results as in section IV.B (Table 8).

The second transactions costs diagnostic test is to rerun my tests using the residuals from a model, when a dummy variable for the availability of listed options on a given stocks is added to the right-hand side of equation 15. This variable proxies for differences in ease of shorting because if it is hard to short a stock for any reason, to compensate, one can still take a position in a stock's option. About 18% of my sample firms did not have listed options in 1998, with this small fraction falling to 14% in 2007. Not surprisingly, mostly smaller stocks lack options listing. Thus, I run quarter-by-quarter regressions of the following form:

$$(16) \qquad Log\left(1 + Analysts_{jq}\right) = b_0 + b_1 \log(Size_{jq}) + b_2\, Turnover_{jq} + b_3\, OptDum_{jq} + \varepsilon$$

In equation 16, $Analysts_{jq}$, $Size_{jq}$, $Turnover_{jq}$ are defined as before. The option dummy variable takes value 1 if firm j has a listed option as of quarter q and 0 otherwise. Panel B of Table 12 shows the results of these regressions. As expected, coefficient b_3 is positive and highly significant in each year. This demonstrates that firms that are easier to short-sell have higher analyst coverage. Note that adjusted R^2 increases only slightly relative to adjusted R^2 in Table 1.

Panel B in Table 14 replicates the analysis from section IV.A (Table 4) except that stocks are ranked based on residuals of estimation of equation 16. Similar to the turnover numbers, the results confirm my prior findings. Panel B in Table 15 shows that the return differential between the Earnings Momentum Strategy and the Simple Earnings Momentum is not driven by cross-sectional differences in ease of shorting. Thus, I can conclude that neither difference in trading volume nor short-sale constraints can undermine the potential return-predictive power of analyst coverage.

V. Conclusions

The empirical evidence in my thesis gives credence to previous studies on post-earnings announcement drift. Using a contemporaneous sample period, I have shown that post-earnings announcement stock prices drift in the direction of the initial surprise. The abnormal returns generated within 20 trading days following the earnings announcement account for more than half of the drift. The drift does not last for long and there is little evidence of statistically significant drift beyond 240 trading days. My work gives evidence that the magnitude of the drift is particularly large among small-sized firms on the NYSE/AMEX. I have further ruled out the possibility that beta risk might undermine this evidence.

In my thesis, I have extended the prior research on the prediction of intermediate horizon returns following the earnings announcement by examining the relation between earnings momentum and recent analyst coverage. I have showed that high-coverage stocks outperform low-coverage stocks following the earnings news announcement. The analyst-spread is wider among firms with bad earnings news, implying that bad news travels more slowly. The evidence points to a strategy of buying good-news firms with high analyst coverage and selling bad-news firms with low analyst coverage. This strategy yields higher abnormal results than the simple earnings momentum strategy of buying good-news firms and selling bad-news firms without conditioning on analyst coverage. Existing theories of investor behaviour can only partially explain the findings and do not fully account for all of the evidence. To motivate the salient conclusions of my results, I adopt a framework of the "Earnings Expectation Life Cycle".

My results suggest that analyst coverage plays an important role in determining where a given firm is in its expectation cycle – relatively low analyst coverage sends out a signal that a firm is expected to perform badly in the near future, while relatively high analyst coverage indicates that analysts expect a firm to deliver good earnings in the near future. This implies that analyst coverage helps momentum investors make their strategies more time-dependent. They should buy a stock of a relatively high-coverage firm that has enjoyed better-than-expected earnings and short a stock of a relatively low-coverage firm that has delivered disappointing earnings. I stress that these results are only valid at the portfolio level because my analysis reflects mean behavior of stocks in constructed portfolios. For stock-picking, analyst coverage is far less predictable because, as Bernstein suggests, each stock travels through the cycle at its own speed and does not necessarily follow the full path of the expectation cycle.

Another noteworthy result of my analysis is that high-coverage stocks are riskier than their low-coverage counterparts. Specifically, it seems that stocks covered by more analysts require higher abnormal returns as they tend to be more risky. This is especially true for high-coverage stocks announcing better-than-expected earnings, thereby weakening the analyst-spread among good news firms. Nevertheless, the analyst-spread among bad news firms continues to hold. This evidence is consistent with the "Earnings Expectation Life Cycle" framework. The framework suggests that when a stock approaches the top of the cycle, analyst coverage together with earnings expectations rises. The stock becomes riskier because the chance that earnings disappointment occurs any time soon increases. I have conducted additional robustness tests and ruled out the possibility that the results are driven by analyst coverage being a proxy for differences in transactions costs or book-to-market factors.

My results also raise at least two interesting questions for future research. First, the timing difference in the analyst coverage effect between winners and losers remains unexplained. I show that high-coverage losers stop losing quickly and strongly outperform low-coverage losers within a few days after the earnings announcement. However, it takes high-coverage winners longer (more than 120 trading days) to significantly outperform low-coverage winners. In other words, the loser-analyst spread reveals itself faster than the winner-analyst spread. Perhaps, a more complex theoretical framework could help to explain this difference. Second, questions remain why the patterns documented in this paper are mostly present among larger-size firms. One possible explanation is that in my analysis I mostly deal with larger companies and leave out firms with no-analyst coverage. Another possibility is that analyst coverage has different impact on large and small stocks.

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Appendix

Table A1
Size as a Determinant of Analyst Coverage

This table replicates Table 1 in the main text for the monthly method. It illustrates the results of regressions of the form of equation 5. I rerun the regression for each month starting in January 1998 and ending in December 2007. Table includes the numbers for coefficient b_1 estimation, its t-statistic, R^2, adjusted R^2 and the number of observations included in each regression. The number of observations represents all stocks that are suitable for inclusion in my earnings momentum portfolios in each given month.

Period	Coefficient	T-stat	R^2	Adjusted R^2	No.obs
1998/Jan	0.35	48.03	0.64	0.63	1299
1998/Feb	0.35	43.40	0.65	0.65	975
1998/Mar	0.35	47.61	0.64	0.64	1264
1998/Apr	0.35	48.71	0.64	0.64	1334
1998/May	0.35	49.04	0.64	0.67	1346
1998/Jun	0.35	50.38	0.64	0.64	1371
1998/Jul	0.34	49.62	0.64	0.64	1355
1998/Aug	0.34	47.08	0.62	0.62	1339
1998/Sep	0.33	47.03	0.60	0.60	1417
1998/Oct	0.33	46.83	0.62	0.61	1369
1998/Nov	0.33	48.19	0.64	0.64	1301
1998/Dec	0.32	48.89	0.62	0.62	1425
1999/Jan	0.31	45.18	0.60	0.60	1357
1999/Feb	0.31	41.24	0.63	0.62	1000
1999/Mar	0.32	47.80	0.63	0.63	1303
1999/Apr	0.32	50.01	0.64	0.66	1367
1999/May	0.32	51.49	0.65	0.65	1381
1999/Jun	0.33	50.97	0.64	0.64	1403
1999/Jul	0.32	49.84	0.64	0.64	1352
1999/Aug	0.33	48.58	0.64	0.64	1309
1999/Sep	0.33	50.39	0.64	0.64	1400
1999/Oct	0.32	48.36	0.63	0.63	1341
1999/Nov	0.32	47.47	0.63	0.63	1294
1999/Dec	0.32	49.29	0.63	0.63	1381
2000/Jan	0.31	45.30	0.61	0.61	1289
2000/Feb	0.32	41.59	0.64	0.64	948
2000/Mar	0.32	43.39	0.59	0.59	1260
2000/Apr	0.31	45.24	0.61	0.61	1287
2000/May	0.31	45.55	0.61	0.61	1281
2000/Jun	0.31	46.17	0.62	0.62	1297
2000/Jul	0.30	41.73	0.61	0.61	1113
2000/Aug	0.31	41.63	0.61	0.61	1082
2000/Sep	0.31	44.58	0.63	0.63	1131
2000/Oct	0.31	45.10	0.62	0.62	1215
2000/Nov	0.31	41.66	0.62	0.62	1036
2000/Dec	0.30	42.54	0.62	0.62	1079
2001/Jan	0.31	42.48	0.64	0.63	1024
2001/Feb	0.32	41.56	0.66	0.66	890
2001/Mar	0.33	44.65	0.64	0.64	1117
2001/Apr	0.33	43.69	0.61	0.61	1177
2001/May	0.32	44.61	0.62	0.62	1192
2001/Jun	0.33	45.06	0.62	0.62	1195
2001/Jul	0.32	43.58	0.62	0.62	1147
2001/Aug	0.32	41.55	0.61	0.61	1081
2001/Sep	0.32	41.45	0.59	0.59	1190
2001/Oct	0.32	40.46	0.58	0.58	1153
2001/Nov	0.32	40.96	0.60	0.60	1097
2001/Dec	0.32	41.62	0.59	0.59	1164
2002/Jan	0.32	39.89	0.58	0.58	1125
2002/Feb	0.32	37.06	0.61	0.61	860
2002/Mar	0.33	40.66	0.60	0.60	1091
2002/Apr	0.33	40.55	0.59	0.59	1138
2002/May	0.34	40.63	0.58	0.58	1153
2002/Jun	0.33	41.32	0.59	0.59	1175
2002/Jul	0.33	39.36	0.57	0.57	1165

2002/Aug	0.32	39.17	0.57	0.57	1137
2002/Sep	0.32	39.91	0.57	0.56	1203
2002/Oct	0.34	38.74	0.55	0.57	1198
2002/Nov	0.32	39.63	0.57	0.57	1143
2002/Dec	0.33	42.26	0.59	0.59	1223
2003/Jan	0.32	39.58	0.56	0.56	1205
2003/Feb	0.31	36.39	0.59	0.59	889
2003/Mar	0.32	40.21	0.58	0.58	1159
2003/Apr	0.32	40.34	0.57	0.57	1217
2003/May	0.32	40.68	0.57	0.57	1225
2003/Jun	0.34	43.49	0.60	0.60	1239
2003/Jul	0.34	42.28	0.58	0.59	1223
2003/Aug	0.34	41.55	0.59	0.59	1187
2003/Sep	0.35	43.98	0.60	0.60	1240
2003/Oct	0.35	43.01	0.59	0.59	1241
2003/Nov	0.36	42.53	0.60	0.60	1176
2003/Dec	0.36	42.95	0.59	0.59	1245
2004/Jan	0.36	41.34	0.58	0.58	1214
2004/Feb	0.35	35.86	0.59	0.59	869
2004/Mar	0.36	41.68	0.59	0.59	1162
2004/Apr	0.35	41.30	0.58	0.58	1230
2004/May	0.35	41.60	0.58	0.58	1237
2004/Jun	0.36	41.77	0.58	0.58	1241
2004/Jul	0.36	41.62	0.58	0.58	1238
2004/Aug	0.35	40.65	0.58	0.58	1170
2004/Sep	0.35	42.18	0.58	0.58	1278
2004/Oct	0.35	41.65	0.57	0.57	1270
2004/Nov	0.34	38.11	0.55	0.55	1173
2004/Dec	0.35	41.22	0.56	0.56	1287
2005/Jan	0.35	39.06	0.54	0.54	1263
2005/Feb	0.34	34.02	0.58	0.58	826
2005/Mar	0.35	37.15	0.54	0.54	1142
2005/Apr	0.35	41.35	0.57	0.57	1253
2005/May	0.34	41.34	0.57	0.57	1248
2005/Jun	0.34	41.72	0.57	0.57	1292
2005/Jul	0.34	42.00	0.57	0.57	1290
2005/Aug	0.34	41.25	0.59	0.58	1184
2005/Sep	0.34	43.24	0.58	0.58	1304
2005/Oct	0.34	43.37	0.59	0.59	1271
2005/Nov	0.34	41.45	0.60	0.60	1128
2005/Dec	0.34	44.39	0.60	0.60	1291
2006/Jan	0.34	43.83	0.60	0.60	1271
2006/Feb	0.34	38.15	0.64	0.64	812
2006/Mar	0.34	42.31	0.60	0.60	1152
2006/Apr	0.33	44.21	0.60	0.60	1267
2006/May	0.34	44.31	0.61	0.60	1257
2006/Jun	0.32	42.92	0.58	0.58	1304
2006/Jul	0.32	41.91	0.57	0.57	1298
2006/Aug	0.32	39.86	0.57	0.57	1168
2006/Sep	0.31	42.15	0.57	0.57	1340
2006/Oct	0.31	40.93	0.56	0.56	1304
2006/Nov	0.32	40.00	0.58	0.58	1149
2006/Dec	0.31	41.58	0.56	0.56	1327
2007/Jan	0.31	39.08	0.54	0.54	1292
2007/Feb	0.32	36.87	0.61	0.61	842
2007/Mar	0.31	37.99	0.55	0.55	1176
2007/Apr	0.31	41.10	0.57	0.57	1232
2007/May	0.30	40.18	0.57	0.57	1199
2007/Jun	0.30	39.94	0.56	0.56	1212
2007/Jul	0.29	37.97	0.55	0.55	1159
2007/Aug	0.28	35.46	0.55	0.55	992
2007/Sep	0.29	36.67	0.54	0.54	1123
2007/Oct	0.27	32.78	0.50	0.50	1032
2007/Nov	0.27	30.43	0.50	0.50	921
2007/Dec	0.27	29.73	0.47	0.47	975

Table A4
Earnings Momentum Strategies, January/1998-December/2007, Using Abnormal Returns, Sorting By Equation 5 Analyst Residuals

This table replicates Table 4 in the main text for the monthly method. It reports the average cumulative abnormal returns on portfolios based on the SUE measure and portfolios formed using an independent sort on equation 5 analyst residuals of log size over different holding periods. Portfolio SUE1 consists of stocks in the 30 percent most negative unexpected earnings changes, portfolio SUE2 includes the middle 40 percent, and portfolio SUE3 contains stocks in the 30 percent most positive unexpected earnings changes. The least-covered stocks are in RC1 portfolio, the medium covered stocks in RC2 portfolio, and the most covered stocks in RC3 portfolio. The numbers are α coefficients of regressions of the form of equations 6-10. T-statistics are in parentheses.

		Residual Coverage Class			
Past	all stocks	Low: RC1	Medium: RC2	High: RC3	RC1-RC3
		1 month			
SUE1	-0,00522	-0,00640	-0,00503	-0,00277	-0,00362
	(-5,15)	(-5,02)	(-3,83)	(-1,21)	(-1,34)
SUE2	-0,00407	-0,00490	-0,00436	-0,0028	-0,00208
	(-6,87)	(-4,08)	(-4,96)	(-2,59)	(-1,19)
SUE3	0.00114	0.00128	-4,11E-05	0.00211	-0,00083
	(1.50)	(0.85)	(-0,04)	(1.26)	(-0,33)
SUE3 - SUE1	0.00637	0.00768	0.00499	0.00489	0.00278
	(5.35)*	(3.83)*	(3.24)*	(2.23)**	(0.88)
		3 months			
SUE1	-0,01172	-0,01533	-0,01287	-0,00415	-0,01118
	(-4,03)	(-5,23)	(-3,85)	(-0,64)	(-1,52)
SUE2	-0,01081	-0,01474	-0,01194	-0,00699	-0,00774
	(-8,18)	(-4,29)	(-5,04)	(-3,18)	(-1,54)
SUE3	-0,00185	-0,00367	-0,00471	0.00288	-0,00655
	(-1,08)	(-1,41)	(-2,25)	(0.66)	(-1,30)
SUE3 - SUE1	0.00986	0.01166	0.00815	0.00703	0.00462
	(3.44)*	(2.71)*	(2.30)**	(1.27)	(0.64)
		6 months			
SUE1	-0,02120	-0,0252	-0,02558	-0,00808	-0,01719
	(-4,39)	(-5,41)	(-4,47)	(-0,83)	(-1,62)
SUE2	-0,01914	-0,02873	-0,02136	-0,00964	-0,01909
	(-8,37)	(-5,22)	(-5,58)	(-2,60)	(-2,36)**
SUE3	-0,00615	-0,01492	-0,0118	0.00942	-0,02434
	(-2,31)	(-4,36)	(-3,18)	(1.33)	(-2,97)*
SUE3 - SUE1	0.01504	0.01034	0.01376	0.01750	-0,00715
	(3.27)*	(1.77)***	(2.35)**	(1.97)***	(-0,69)
		12 months			
SUE1	-0,03570	-0,04864	-0,03830	-0,01009	-0,03854
	(-5,13)	(-7,14)	(-4,48)	(-0,74)	(-2,51)**
SUE2	-0,03771	-0,05685	-0,03839	-0,02020	-0,03664
	(-10,94)	(-7,25)	(-6,45)	(-3,53)	(-3,30)*
SUE3	-0,01568	-0,02766	-0,02551	0.01261	-0,04028
	(-3,71)	(-6,55)	(-4,67)	(1.18)	(-3,37)*
SUE3 - SUE1	0.02002	0.02098	0.01279	0.02271	-0,00173
	(2.69)*	(2.64)*	(1.24)	(1.78)***	(-0,11)
		18 months			
SUE1	-0,0439	-0,06108	-0,04942	-0,00698	-0,05410
	(-5,11)	(-8,44)	(-5,34)	(-0,38)	(-2,94)*
SUE2	-0,05685	-0,08302	-0,05778	-0,03239	-0,05063
	(-12,05)	(-9,98)	(-7,59)	(-3,61)	(-3,55)*
SUE3	-0,02754	-0,04571	-0,03957	0.01268	-0,05840
	(-5,38)	(-8,84)	(-5,92)	(1.25)	(-5,38)*
SUE3 - SUE1	0.01636	0.01537	0.00985	0.01967	-0,00430
	(1.72)***	(1.86)***	(0.80)	(1.23)	(-0,24)

* Significant at the 1% level (reported only for SUE3-SUE1 differential and RC1-RC3 differential)
** Significant at the 5% level (reported only for SUE3-SUE1 differential and RC1-RC3 differential)
*** Significant at the 10% level (reported only for SUE3-SUE1 differential and RC1-RC3 differential)

Table A5
Simple Earnings Momentum Strategies and Earnings Momentum Strategies Based on Equation 5 Analyst Residuals, Using Abnormal Returns

This table replicates Table 5 in the main text for the monthly method. The first row of this table reports the mean cumulative abnormal returns on strategies that buy stocks with the most positive unexpected earnings changes and sell stocks with the most negative unexpected earnings changes over different holding periods. The numbers are α coefficients of regressions of the form of equation 7. The second row reports the cumulative abnormal returns on strategies that buy high-coverage stocks with the most positive unexpected earnings changes and sell low-coverage stocks with the most negative unexpected earnings changes over different holding periods. The numbers are α coefficients of regressions of the form of equation 11. The last row (difference) reports the average difference in the mean cumulative abnormal returns between the two strategies. The numbers are α coefficients of regressions of the form of equation 12. T-statistics are in parentheses.

	Holding Period			
Strategy	3 months	6 months	12 months	18 monhs
"Simple Earnings momentum strategy" SUE3-SUE1	0.00986	0.01504	0.02002	0.01636
	(3.44)	(3.27)	(2.69)	(1.72)
"Analyst Earnings Momentum" RC3SUE3-RC1SUE1	0.01821	0.03469	0.06126	0.07377
	(3.20)	(3.86)	(4.81)	(5.39)
Difference				
(P3RC3-P1RC1)-(P3-P1)	0.00835	0.01964	0.04123	0.05741
	(1.47)	(2.22)*	(3.12)*	(4.10)*

* Significant at the 1% level (reported only for the difference of the two strategies)
** Significant at the 5% level (reported only for the difference of the two strategies)
*** Significant at the 10% level (reported only for the difference of the two strategies)

Table A8
Earnings Momentum Strategies, January/1998-December/2007, Sorting By Firm Size and Equation 5 Analyst Residuals

This table replicates Table 8 in the main text for the monthly method. It reports the average cumulative abnormal returns on portfolios based on the SUE measure and portfolios formed by sorts on size and equation 5 analyst residuals of log size over different holding periods. Portfolio SUE1 consists of stocks in the 30 percent most negative unexpected earnings changes, portfolio SUE2 includes the middle 40 percent, and portfolio SUE3 contains stocks in the 30 percent most positive unexpected earnings changes. The least-covered stocks are in RC1 portfolio, the medium covered stocks in RC2 portfolio, and the most covered stocks in RC3 portfolio. The numbers in "SUE3-SUE1" panels are α coefficients of regressions of the form of equations 7 and 8. The numbers in "RC1-RC3" panels are α coefficients of regressions of the form of equations 9 and 10. T-statistics are in parentheses.

			Size Classes					Size Classes			
			<40th	40th-60th	60th-80th	>80th		<40th	40th-60th	60th-80th	>80th
3 months	SUE3 - SUE1	RC1	0.05499	0.00367	-4.70E-05	-0.01172	12 months	0.09258	0.01557	-0.03232	0.00401
			(5.87)	(0.50)	(-0.01)	(-1.68)		(4.60)	(1.21)	(-1.63)	(0.24)
		RC2	0.03187	-0.00575	-0.00070	0.00398		0.06198	-0.02537	0.00055	0.00166
			(3.80)	(-1.03)	(-0.10)	(0.52)		(3.75)	(-2.57)	(0.04)	(0.09)
		RC3	0.02412	0.00955	-0.00981	5.48E-05		0.07911	0.00390	-0.01165	0.02247
			(2.14)	(1.07)	(-1.14)	(0.01)		(2.98)	(0.20)	(-0.62)	(1.36)
		all stocks	0.03859	0.00077	-0.00455	-0.00115		0.07727	-0.00349	-0.00981	0.01191
			(5.30)	(0.15)	(-0.87)	(-0.24)		(5.28)	(-0.32)	(-0.71)	(1.15)
	RC1 - RC3	SUE1	-0.01689	0.00251	-0.01929	-0.00653		-0.01473	-0.02109	-0.05617	-0.03675
			(-1.31)	(0.24)	(-2.62)*	(-0.98)		(-0.58)	(-1.08)	(-3.63)*	(-2.46)**
		SUE3	0.01397	-0.00336	-0.00952	-0.01831		-0.00126	-0.00942	-0.07684	-0.05521
			(1.37)	(-0.49)	(-1.19)	(-2.32)**		(-0.06)	(-0.57)	(-3.72)*	(-3.11)*
		all stocks	0.03086	-0.00587	0.00976	-0.01177		0.01347	0.01167	-0.02067	-0.01846
			(2.53)**	(-0.51)	(1.07)	(-1.09)		(0.49)	(0.59)	(-1.00)	(-0.75)
6 months	SUE3 - SUE1	RC1	0.05916	0.00655	-0.01679	-0.01426	18 months	0.09231	0.02569	-0.05041	0.00404
			(4.37)	(0.65)	(-1.31)	(-1.35)		(3.84)	(1.69)	(-2.29)	(0.19)
		RC2	0.05390	-0.00955	0.00198	0.00214		0.06273	-0.03416	0.00357	-0.00784
			(4.18)	(-1.19)	(0.19)	(0.18)		(3.01)	(-1.98)	(0.19)	(-0.42)
		RC3	0.05429	0.00842	-0.01361	0.00613		0.09147	0.00869	-0.02093	0.01397
			(3.36)	(0.64)	(-1.02)	(0.51)		(2.58)	(0.35)	(-0.79)	(0.84)
		all stocks	0.05739	0.00053	-0.00759	0.00080		0.07810	-0.00154	-0.01992	0.00944
			(5.60)	(0.06)	(-0.86)	(0.10)		(4.13)	(-0.10)	(-1.14)	(0.93)
	RC1 - RC3	SUE1	-0.00864	-0.00947	-0.03544	-0.01548		-0.02815	-0.03515	-0.06992	-0.06495
			(-0.45)	(-0.64)	(-2.96)*	(-1.40)		(-0.89)	(-1.37)	(-3.42)*	(-3.40)*
		SUE3	-0.00376	-0.01133	-0.03862	-0.03587		-0.02731	-0.01824	-0.09943	-0.07488
			(-0.28)	(-1.05)	(-2.60)*	(-3.30)*		(-1.40)	(-0.94)	(-4.87)*	(-3.43)*
		all stocks	0.00487	-0.00186	-0.00318	-0.02039		0.00084	0.01691	-0.02951	-0.00993
			(0.29)	(-0.13)	(-0.20)	(-1.31)		(0.02)	(0.69)	(-1.12)	(-0.34)

* Significant at the 1% level (reported only for RC1-RC3 differential)
** Significant at the 5% level (reported only for RC1-RC3 differential)
*** Significant at the 10% level (reported only for RC1-RC3 differential)

Table A9
Simple Earnings Momentum Strategies and Earnings Momentum Strategies Based on Equation 5 Analyst Residuals, Using Abnormal Returns, Sorting by Size

This table replicates Table 9 in the main text for the monthly method. The first row of this table reports the mean cumulative abnormal returns on strategies sorted by size that buy stocks with the most positive unexpected earnings changes and sell stocks with the most negative unexpected earnings changes over different holding periods. The numbers are α coefficients of regressions of the form of equation 7 sorted by size. The second row reports the cumulative abnormal returns on strategies sorted by size that buy high-coverage stocks with the most positive unexpected earnings changes and sell low-coverage stocks with the most negative unexpected earnings changes over different holding periods. The numbers are α coefficients of regressions of the form of equation 11 sorted by size. The last row (difference) reports the average difference in the mean cumulative abnormal returns between the two strategies. The numbers are α coefficients of regressions of the form of equation 12 sorted by size. T-statistics are in parentheses.

	Size classes			
Strategy	$<40^{th}$	40^{th}-60^{th}	60^{th}-80^{th}	$>80^{th}$
3 months				
"Simple Earnings momentum strategy" SUE3-SUE1	0.03859	0.00077	-0,00455	-0,00115
	(5.30)	(0.15)	(-0,87)	(-0,24)
"Analyst Earnings Momentum" RC3SUE3-RC1SUE1	0.04101	0.00704	0.00948	0.00658
	(3.23)	(0.88)	(1.09)	(1.05)
Difference				
(P3RC3-P1RC1)-(P3-P1)	0.00242	0.00627	0.01403	0.00773
	(0.20)	(0.96)	(1.86)***	(1.23)
6 months				
"Simple Earnings momentum strategy" SUE3-SUE1	0.05739	0.00053	-0,00759	0.00080
	(5.60)	(0.06)	(-0,86)	(0.10)
"Analyst Earnings Momentum" RC3SUE3-RC1SUE1	0.06293	0.01789	0.02183	0.02161
	(3.43)	(1.31)	(1.54)	(2.20)
Difference				
(P3RC3-P1RC1)-(P3-P1)	0.00553	0.01735	0.02942	0.02080
	(0.32)	(1.56)	(2.21)**	(2.20)**
12 months				
"Simple Earnings momentum strategy" SUE3-SUE1	0.07727	-0,00349	-0,00981	0.01191
	(5.28)	(-0,32)	(-0,71)	(1.15)
"Analyst Earnings Momentum" RC3SUE3-RC1SUE1	0.09384	0.02500	0.04451	0.05923
	(4.01)	(1.25)	(2.05)**	(3.98)*
Difference				
(P3RC3-P1RC1)-(P3-P1)	0.01657	0.02850	0.05433	0.04732
	(0.70)	(1.67)***	(3.07)*	(3.48)*
18 months				
"Simple Earnings momentum strategy" SUE3-SUE1	0.07810	-0,00154	-0,01992	0.00944
	(4.13)	(-0,10)	(-1,14)	(0.93)
"Analyst Earnings Momentum" RC3SUE3-RC1SUE1	0.11963	0.04385	0.04899	0.07892
	(5.05)	(1.86)	(2.03)	(4.68)
Difference				
(P3RC3-P1RC1)-(P3-P1)	0.04152	0.04539	0.06891	0.06948
	(1.85)***	(2.03)**	(3.49)*	(4.13)*

* Significant at the 1% level (reported only for the difference of the two strategies)
** Significant at the 5% level (reported only for the difference of the two strategies)
*** Significant at the 10% level (reported only for the difference of the two strategies)