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The role of analyst forecasts in the momentum effect[☆]

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ABSTRACT

We evaluate the extent to which sell-side equity analysts can facilitate market efficiency when there is increasing uncertainty about a stock's future value. The prevalence of the 52-week-high momentum anomaly, that can be largely attributed to information uncertainty, provides a setting for examining the value and timing of analysts' earnings forecast revisions. Our study finds that analysts can provide value-relevant signals to investors by picking up indicators of momentum. The ability to identify under or over-valued stocks suggests that analysts are important information intermediaries in the price-continuation momentum effect. However, we also observe pervasive asymmetric reaction to good and bad news throughout our study that is consistent with incentive-driven reporting and optimistic biases. Nevertheless, analysts' forecast revisions are informative at different stages to re-establish stock prices back to their fundamental valuation.

1. Introduction

Momentum trading profits pose arguably one of the greatest challenges to the semi-strong-form efficient market hypothesis (Fama & French, 2008). Jegadeesh and Titman (1993) demonstrate that individual stock returns exhibit predictable momentum behaviour at intermediate horizons. The simple price-momentum strategy of maintaining a self-funded investment portfolio via simultaneously buying past winners and short-selling past losers, enables momentum traders to earn abnormal profits for the next 12 months (JT strategy).

George and Hwang (2004) investigate the return predictability of the 52-week-high and low price in the US stock market. The 52-week-high momentum strategy is formed based on the current price of stock in relation its' 52-week-high price (GH strategy). When stocks are trade near or far from 52-week-high prices, investors form a psychological "anchor" on the elevated price and subsequently underreact to new information about these stocks. However, as information relating to the true value of stocks continues to persist in the longer term, the correction (adjustment) of investors' prior underreaction behaviour leads to a subsequent price continuation effect. Bhootra and Hur (2013) include a recency measure as an enhancement to the 52-week-high price strategy of George and Hwang (2004). They suggest that the addition of recency bias accentuates anchoring bias. Thus, the 'recency' strategy of Bhootra and Hur (2013) (BH strategy) that conditions recency measure upon the stock's 52-week-high, significantly increases profits to the momentum strategy due to a higher degree of underreaction.[1]

Hao, Chu, Ho, and Ko (2014) find evidence of profitability of the recency strategy in Taiwan. This is an unusual finding as unlike the US, the 52-week-high (and low) prices of individual stocks are not readily reported in the Taiwanese market, therefore the psychological anchor of the 52-week-high price is unavailable. Thus, the evidence of the dissociation of anchoring bias in Hao et al. (2014) leads towards the investigation of other factors that may contemporaneously underpin the profits of the recency strategy. Analysts' forecasts impact stock prices and trading strategies as their recommendations are used by investors to identify under or over-valued stocks. Our paper

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[1] Bhootra and Hur's (2013) recency of the 52-week-high price strategy applies the notion of proximity, i.e., number of days since a stock has attained its 52-week-high price.

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investigates whether analysts' earnings forecasts provide additional explanatory power for future stock returns and profits in the momentum strategy.

Prior studies find that analysts can facilitate market efficiency acting as information intermediaries by collecting and processing information about firms, and their recommendations are important to reconnect stock prices back to their fundamental values (e.g., Barber, Lehavy, McNichols, & Trueman, 2001; Hong & Wu, 2016; Wieland, 2011; Jung, Sun, & Yang, 2012). Womack (1996) suggests that analysts express their opinions of the current price of stocks with earnings forecasts, and this feedback steers investors' investment decisions. Further, Laksanabunsong (2015) suggests that analysts' recent performance affects their credibility, and the magnitude of post-forecast revision drift is greater for stocks associated with positive analysts' performance.

However, several competing studies contend that analysts' forecasts are inefficient as they do not fully incorporate past information into their recommendations. In their forecasts of firm performance, analysts place a greater weight on heuristic valuations than present valuation models known to predict profitability (i.e., residual income models) (Bradshaw, 2004). Jegadeesh, Kim, and Krische (2004) purport that analysts do not take advantage of the various stock characteristics known to predict stock returns and that the implications of their forecasts are in line with economic incentives faced by sell-side brokerage firms. These economic incentives induce analysts to be overly optimistic in their forecasts (Ivković & Jegadeesh, 2004; Chen, Narayanamoorthy, Sougiannis, & Zhou, 2015).

Our study investigates the interaction between analysts' forecast revisions and profits from the recency momentum strategy by using various portfolio-level sorting and regression analyses. We find that the magnitude of analysts' forecast revisions has incremental explanatory power for future stock returns, whereby analysts can facilitate market efficiency by providing earnings forecast revisions that are closely related to price-momentum indicators. Our results show evidence of pervasive asymmetric reaction to good and bad news that is consistent with incentive-driven reporting by analysts. This implies that the direction of analysts' forecast revisions (upwards/downwards) have a significant role at different stages to reconnect stock prices back to their fundamental value. The ability to pick under or overvalued stocks suggests that analysts are an important source of information in the price continuation momentum effect. In addition, our multivariate regressions on stocks in the recency momentum strategy find support for the incremental effects of positive performance for upward revisions.

Our contributions to the literature are two-fold. First, our work is the only study to document the interaction between analysts' forecasts and the 52-week-high momentum trading. We extend the work of Jegadeesh et al.'s (2004) to evaluate analysts' ability to extract value-relevant information from (the 52-week-high) momentum indicators that are closely associated with behavioural factors or information uncertainty. We also incorporate the measure of positive analysts' performance that is relatively new in the literature (Laksanabunsong, 2015), and examine whether analysts' recent performance has an incremental effect on post-forecast revision drift. Second, we evaluate the extent to which sell-side analysts can facilitate market efficiency by picking up indicators of momentum, and translate them into value-relevant information that is incrementally able to predict future stock returns. Burghof and Prothmann (2011) find greater information uncertainty[2] in stocks near and far from the 52-week-high price, thus our results are economically meaningful as they suggest how analysts derive their forecasts when there is ambiguity about stock prospects, and provide valuable signals to investors of the stock's future value. Despite these estimates stemming from heuristic valuations (Bradshaw, 2004), this does not compromise the usefulness of analysts and their ability to provide value-relevant information for investors (Penman, 2010). Furthermore, our research finds evidence in support of the literature documenting evidence of optimistic biases in analysts' forecast revisions that are consistent with the economic incentives faced by sell-side analysts.

The remainder of this paper is structured as follows. Section 2 explores the relevant literature and formally presents the hypotheses. Section 3 describes the data sources, research design and descriptive statistics. Section 4 presents the empirical results and summarizes our findings in relation to our hypotheses. We conclude in Section 5.

2. Literature review and hypothesis development

2.1. Momentum and information uncertainty

George and Hwang (2004) propose a 52-week-high strategy that simultaneously buys stocks near their 52-week-high price and short-sells stocks far from their 52-week-high price. Rather than using past price changes (Jegadeesh & Titman, 1993), they argue that price-levels are more important determinants of momentum returns. Despite the irrelevance of the 52-week-high to the future operating performance of the firm, the 52-week-high strategy (George & Hwang, 2004) exhibits superior returns to the price-momentum strategy (Jegadeesh & Titman, 1993) and has the ability to persist through time without return reversals. In an out-of-sample test, Liu, Liu, and Ma (2011) find that the 52-week-high strategy generates significantly positive momentum returns in 10 out of the 20 international stock markets in their sample.

Based upon a sample period of 1965 to 2008, Bhootra and Hur (2013) find further evidence of significant profits with the 52-week-high momentum strategy, and add a recency measure to refine the broad nearness to the 52-week-high price. This recency strategy of is distinguished by the notion of proximity to the 52-week-high price (i.e., the number of days since a stock has attained its 52-week-high price). By adding this recency measure, they find that stocks that have recently attained the 52-week-high price subsequently outperform those that have attained their 52-week-high price in the distant past by about 0.70% per month. Thus the addition of recency bias enhances the profitability of the 52-week-high price strategy of George and Hwang (2004).

The existence of the 52-week-high price momentum profits can be attributed towards information uncertainty in stocks (Burghof & Prothmann, 2011) that lead to an increase in behavioural biases such as the anchoring and adjustment bias (Tversky & Kahneman, 1974).[3] Burghof and Prothmann (2011) document that stocks nearer to and further from the 52-week-high price have a higher degree of informa-

[2] Information uncertainty refers to the state of scepticism about the impact of new information on a firm's fundamental value. This can surface either due to lack of knowledge, quality of information, or implied riskiness of the firm's fundamentals (Zhang, 2006).

[3] Tversky and Kahneman (1974) document the tendency of humans to orientate strongly on reference points in order to reduce the complexity of making estimates and assessing probabilities.

tion uncertainty,[4] where information uncertainty refers to the state of scepticism about the impact of new information on a firm's fundamental value. This can surface due to lack of knowledge, quality of information, or implied riskiness of the firm's fundamentals (Zhang, 2006). Burghof and Prothmann's (2011) proposition regarding the 52-week-high strategy is consistent with the studies of Daniel and Titman (1999) and Hirshleifer (2001), where psychological biases are greater when there is increasing information uncertainty about a set of stocks, and investors are slow to adjust their initial underreaction or overreaction to firm-specific information (Barberis, Shleifer, & Vishny, 1998, Daniel, Hirshleifer, & Subrahmanyam, 1998, and Hong & Stein, 1999).

In times of greater information uncertainty (embedded in stocks nearer to and further from the 52-week-high price), investors apply the 52-week-high price as a psychological “anchor” to assess the impact of new information about stocks, and are generally reluctant to update their beliefs (Daniel et al., 1998; Burghof & Prothmann, 2011). Similarly, Jiang, Lee, and Zhang (2005) find strong positive correlation between profits from momentum strategies and information uncertainty, and suggest that information uncertainty partly explains the anomalies found in momentum trading profits. The collective findings from Burghof and Prothmann (2011) and Jiang et al. (2005) suggest that information uncertainty offers an important insight into the anomalies found in momentum trading profits. That is, the effect of information uncertainty on stocks, (i.e., volatility in stock prices) explains the rise of behavioural biases behind the 52-week-high strategy.

2.2. Information uncertainty and analysts' forecast revision

The sell-side equity analyst literature finds evidence of the importance of analysts' forecasts in reconnecting stock prices back to their fundamental values. Jegadeesh et al. (2004), and Barber et al. (2001) show that analysts play an instrumental role in the financial market by collecting and processing information about firms. Analysts have a number of informational advantages such as: (1) greater expertise and access to information on companies to make value-relevant recommendations to the public (Jung et al., 2012), (2) skillsets to incorporate salient information, such as firm-specific strategies, industry review, and macroeconomic outlook into their earnings forecasts (Wieland, 2011; Hong & Wu, 2016) and (3) ability to apply earnings forecasts as an avenue to provide their feedback on the relative degree of under- or over-valuation of the current stock price (Womack, 1996). Thus, when analysts disseminate forecast revisions and stock recommendations to the market, there is an empirically observed stock price drift following the release of the earnings estimates.[5]

For example, Stickel (1991) document large-sample evidence of the post-forecast revision drift, where stocks with upward revisions consistently outperform stocks with downward revisions by 13% every 6-months. Similarly, Chan, Jegadeesh, and Lakonishok (1996) confirm the prevalence of the post-forecast revision drift by demonstrating stock price drift to mean forecast consensus of up to 6 months. However, they attribute the post-forecast revision drift phenomenon to a cumulative delayed response to new information by investors as investors inefficiently utilise and underestimate the information embedded in analysts' forecasts (e.g., Mendenhall, 1991; Gleason & Lee, 2003; Abarbanell & Bernard, 1992).

These findings support the theory of conservatism bias (Barberis et al., 1998), where investors do not update their expectations adequately, and consequently adjust their initial under reaction behaviour. Hou, Hung, and Gao (2014) examine the relationship between analysts' earnings forecast revisions and information uncertainty in the Australian stock market returns. They find that investors react slower to analysts' forecast revisions when there is a higher degree of information uncertainty for stocks, and during bear markets. This finding implies that the persistence of stock mispricing is contingent on the degree of uncertainty in firm-specific information (Jiang et al., 2005; Burghof & Prothmann, 2011). Based on this existing literature, we further analyse whether the mean of analysts' earnings forecast revision is a good predictor for future stock returns. The first hypothesis (stated in the alternative form) is:

Hypothesis 1

Stock prices drift in the direction of analysts' earnings forecast revisions.

The pervasiveness of the post-forecast revision drift may not be due to an incomplete reaction by investors alone, but by analysts underreacting to new information and failing to incorporate value-relevant information into their forecasts. A number of studies have find that analysts' forecasts are inefficient as they do not fully incorporate past information available at the time of their forecasts (Klein, 1990; Chen et al., 2015), and subsequently underreact to new information by anchoring onto their previous forecasts (Campbell & Sharpe, 2009). If analysts are efficient information intermediaries, we should expect their forecasts to precede or coincide with public information (Wieland, 2011). However, there are alternative views.

Zhang (2006) and Gu and Xue (2007) examine the effects of information uncertainty and analysts' forecast revisions, and find a positive correlation between information uncertainties and forecast errors, where stocks with greater uncertainty are found to have more subsequent forecast revisions. This evidence supports the pervasiveness of information uncertainty, that causes analysts to delay their incorporation of firm-specific information into their earnings forecasts (Daniel et al., 1998). Intuitively, analysts underreact more to revising their prior forecasts in cases of greater uncertainty. In relation to stocks with lower levels of information uncertainty, however, analysts revise their prior forecasts promptly and almost completely in response to new information.[6] In addition, Bradshaw (2002, 2004) suggests that the value of analysts' recommendations is in fact uninformative. He finds that analysts' recommendations are primarily dominated by stocks with high growth expectations (despite growth rates being reflected in stock prices), and notes that their forecasts are either unrelated or negatively correlated with fundamental analysis models (e.g., residual income valuations) that are known to predict future returns.

Jegadeesh et al. (2004) investigate whether analysts incorporate common information metrics into their earnings forecasts, and show that quarterly changes in analysts' consensus recommendations are positively associated with high-momentum and high-growth stocks.

[4] Burghof and Prothmann (2011) employ six proxies of information uncertainty: (1) firm size (market value), (2) firm's book-to-market ratio, (3) distance between the 52-week-high price of a stock and its 52-week-low price, (4) stock-price volatility, (5) firm age and (6) cash-flow volatility. These proxies quantify uncertainty regarding the impact of news on the stocks' fundamental value.

[5] For example, Barber, Lehavy, and Trueman (2010) empirically document that a trading strategy based on the level and change in stock recommendation yields daily excess returns of 5.2 basis points. This suggests that the predictive power of stock recommendations is not dependent on the shift in investors' demand, but can be attributed to analysts' abilities to collect and process information on a firm's fundamental value.

[6] These findings are consistent with Daniel et al. (1998) and Hong and Stein (1999), who attribute the rise of the momentum effect and behavioural biases to the slow dissemination of information in the market.

That is, stocks that receive more favourable revisions tend to have higher price-momentum signals, although this association is less obvious for contrarian signals. Moreover, Jegadeesh et al. (2004) find that analysts do not take advantage of the various known stock characteristics to predict stock returns (Abarbanell & Bernard, 1992; Finger & Landsman, 2003; Stickel, 2007), and that the implications of analysts' forecasts are in line with economic incentives faced by sell-side brokerage firms.

These "economic incentives" can also be referred to as the "conflicts of interest" faced by analysts, to (1) attract investment banking and brokerage revenue and (2) curry favour with managers. An understanding of the conflicts of interest offers an interesting insight into why analysts are pressured to underweight (overweight) their negative (positive) private information, and why they tend to be overly optimistic in their forecasts (Ivković & Jegadeesh, 2004; Muslu & Xue, 2013; Chen et al., 2015). For example, Ivković and Jegadeesh (2004), and Zhang (2006), find that analysts revise their estimates downward to a greater degree following bad news than upward following good news.[7] Similarly, Chen et al. (2015) demonstrate that the forecast revision momentum and post-forecast revision price drift are more conspicuous for downward forecast revisions than upward revisions. These collective findings suggest that analysts have differential access to good and bad news, and hence a longer price drift is typically observed in downward forecast revisions. In other words, analysts have early access and regular guidance from managers about positive news prior to the earnings announcements, so that firms can meet or beat the consensus recommendations and avoid negative earnings surprise (Bartov, Givoly, & Hayn, 2002; Matsumoto, 2002).

To conclude, analysts can still facilitate market efficiency with their responsive forecast revisions, and can provide value-relevant information for investors (Zhang, 2008). Nevertheless, analysts are susceptible to heuristic behavioural biases.[8] There is an inclination for analysts to be overly optimistic and to underreact to bad news when correcting their forecasts. However, when the earnings announcement period approaches, this optimistic bias diminishes as analysts have more indicators for adjusting their prior forecasts and justifying their downward revisions.[9] This suggests that post-forecast revision drift is associated with a mispricing anomaly and information uncertainty, rather than missing risk factors (Jiang et al., 2005). Furthermore, the asymmetry in post-forecast revision drift suggests that analysts have differential access to good news and bad news in the period before an earnings announcement (Jegadeesh et al., 2004; Ivković & Jegadeesh, 2004). Therefore, as (sell-side) analysts' experiences economic conflict of interest in their analysts' earnings forecasts, we would expect to observe an asymmetric pattern in post-forecast revision drift. The second hypothesis (stated in the alternative form) is therefore:

Hypothesis 2

Post-revision drift following good and bad news is asymmetric.

Laksanabunsong (2015) proposes that stock prices continue to drift in the direction of forecast revisions when the forecasts are made by better performing analysts. That is, even in times of uncertainty, if a stock is covered by analysts whose forecasting performance is improving on aggregate, investors perceive the earnings forecast revisions on that stock to be more credible. Using a sample period of 1985 to 2013, Laksanabunsong (2015) documents significantly positive analysts' forecasting performance that can induce short-run stock price drift following the forecast revisions.

We apply the research design of Laksanabunsong (2015) to incorporate analysts' recent performance into our study. As signals by better performing analysts[10] are more credible and valued by investors (Jackson, 2005), we should expect recently improved analysts' forecasting performance to accentuate stock price drift following these analysts' forecast revisions. Investors are likely to put greater weight on recommendations about stocks from better performing analysts. The third hypothesis (stated in the alternative form) is:

Hypothesis 3

Positive analyst performance accentuates post-forecast revision drift.

In an otherwise semi-strong-form efficient market, analysts can facilitate market efficiency by picking up indicators of 52-week-high momentum, and translate them to relevant and informative news for investors to explain future stock returns. Jegadeesh et al. (2004) find that analysts' consensus recommendations are positively related to the simple price-momentum strategy of Jegadeesh and Titman (1993). In addition, Burghof and Prothmann (2011) show that stocks nearer to and further from the 52-week-high price have higher information uncertainty. If analysts have the ability to scrutinize stocks with information uncertainty as part of their profession (Barber et al., 2010; Wieland, 2011), analysts' forecast revisions should encapsulate information uncertainty (Jiang et al., 2005; Hou et al., 2014). Ultimately, when uncertainty obscures investors' acumen, the guidance of forecast revision reaffirms the direction of the new information and compels investors to update their prior beliefs. Consequently, the fourth hypothesis (stated in the alternative form) is:

Hypothesis 4

Analysts' earnings forecast revisions have incremental explanatory power for future stock returns after momentum and information uncertainties are controlled for.

3. Literature review and hypothesis development

Our sample covers stocks in the U.S. market for the period January 1995 to December 2014 from three primary data sources. First, daily stock prices for all common stocks listed on NYSE, NASDAQ and AMEX with share code 10 and 11 from the CRSP database daily updated stock file. Following Bhootra and Hur (2013), we exclude stocks priced below $5 and stocks in the smallest NYSE size decile at the end of the portfolio formation month to ensure that results are not

[7] Ivković and Jegadeesh (2004) document that as nearing to the earnings announcement date, there is an observed decrease in forecast errors (i.e., improved accuracy) for upward forecast revisions over the weeks.

[8] The three main types of behavioural biases manifested in analysts' earnings forecasts include leniency (optimism), representativeness (overconfidence), and anchoring (underreaction) biases, all of which have been highlighted by Amir and Ganzach (1998) and are evident in the behavioural finance literature.

[9] Amir and Ganzach (1998) and Ivković and Jegadeesh (2004) show that relative forecast errors and stock returns monotonically converge over the months until the earnings announcement date.

[10] Better performing analysts are those with lower updated analysts' forecast errors than the benchmarked analysts' forecast errors.

[11] Bhootra (2011) suggest that the failure to exclude penny stocks from a sample can significantly alter the inferences drawn from empirical tests. Profits found in BH's momentum strategy remain consistent when the smallest NYSE size decile in the sample is included, but stocks priced below $5 have to be excluded.

driven by illiquid and thinly traded stocks[11,12] We include live and dead stocks in our sample to ensure that our data are free of survivorship bias. This process gives us an initial sample size of 829,466 daily stock price observations.

This data is merged with Compustat files to obtain the necessary accounting information (e.g., firms' book-to-market ratios and market capitalization). This reduces the sample to 364,586 observations. Finally, we use quarterly analysts' earnings forecast data from the I/B/E/S Thompson Reuters detailed forecast database. We (1) retain earnings forecasts that are announced before the actual earnings announcement date, (2) select only the latest forecast from the same analysts if there are multiple forecasts in the same month, and (3) ensure that the review date[13] is within 2 months of the actual earnings announcement date. This screening process ensures that our forecast observations are not potentially subjected to irregularities or erroneous data (Zhang, 2008). After we merge the I/B/E/S database with CRSP and Compustat files, and remove duplicates and missing data, our final sample consists of 1410 firm-month observations. For a full description of the variables, please refer to Appendix A.

3.1. Momentum variables

To construct the winner and loser portfolios of 52-week-high strategy (GH) and recency strategy (BH), we first rank stocks based on each strategy's ranking criterion at the end of the portfolio formation period month *t*.

GH's proximity of current price to the 52-week-high price ratio is given by:

$$GH\ 52\ week\ high\ price\ \ (52\ WH) = \frac{Current\ Price_j}{52\ Week\ High\ Price_j} \tag{1}$$

Consistent with GH, stocks are placed into quintiles according to their values from Eq. (1). A higher GH 52-week-high (WH) value indicates that the current price of stock *j* is closer to the 52-week-high price. If the current stock price at the end of the formation period is the 52-week-high price, then the 52WH ratio has the maximum value of 1. In this study, WHH (WHL) is a dummy variable that equals 1 if stocks are in the top (bottom) quintile portfolios based on GH's proximity ratio, and 0 otherwise.

Thereafter, BH's recency ratio measure is as follows:

$$Recency\ Ratio\ \ (RR) = 1 - \frac{Number\ of\ days\ since\ 52\ weeks\ high\ price_j}{364} \tag{2}$$

Consistent with BH, the recency ratio (RR) is inversely proportional to the number of days since the 52-week-high price. For example, if stock *j* has achieved (has not achieved) its 52-week-high price at the end of the formation period month *t*, then the number of days since its 52-week-high price is 0 (364). RR would be the maximum (minimum) possible value of 1 (0). Essentially, stocks that have recently attained the 52-week-high price would take higher values of the RR measure. In this study, RRH (RRL) is a dummy variable that equals 1 if stocks are ranked in the top (bottom) quintile portfolio based on BH's recency ratio, and 0 otherwise.

3.2. Analyst forecast revisions and analyst performance

We classify an analyst as an individual financial professional or department of a research organization that has the expertise to evaluate investments and put together earnings forecasts of securities for I/B/E/S. Motivated by Jegadeesh et al.'s (2004) documentation that the change in analysts' stock recommendations (as opposed to the level) is incrementally useful to predict future stock returns, the main objective of our research is to examine whether the magnitude of forecast revisions plays an important role in facilitating market efficiency. Thus, we follow Chan et al. (1996), Zhang (2008) and Chen et al. (2015) and measure earnings forecast revision[14]

$$Revision_t^j = \frac{Forecast_t^j - Forecast_{t-1mth}^j}{Price_{j,t-1mth}} \tag{3}$$

where:

$Forecast_t^j$ is the monthly mean earnings forecast of stock *j* at month *t*; $Price_{j,\,t-1mth}$ is stock *j*'s prior month's stock price.

A positive (negative) forecast revision would signal good (bad) news about the stock, and represent a favourable (unfavourable) recommendation. The top (bottom) 20% of stocks with the highest analysts' forecast revision variable value are included in the *Buy revision* (*Sell revision)* portfolio. Thereafter, we follow Laksanabunsong (2015) and measure analysts' recent forecasting performance as:

$$Analyst\ Performance_t^i = \frac{1}{N_A}\sum_{j\epsilon A}\frac{Forecast_{jt}^i - Actual_{jt}}{Price_{j,t-1year}} \tag{4}$$

where:

$Forecast_{jt}{}^i$ is analyst *i*'s earnings forecast on stock *j* at month *t; Actual*$_{jt}$ is actual realized earnings of stock *j* released at the next earnings announcement date; Term *A* represents the set of firms that analyst *i* covers that have earnings announcement dates available. Since we are measuring earnings forecast revision at the aggregate level, we compute an overall analyst performance of stock *j* by averaging analyst *i*'s recent forecasting performance at time *t*.[15]

After we have computed analysts' average recent performance, we follow Laksanabunsong (2015) to measure positive analysts' performance in two stages as:

$$ExpectedError_t^j = \frac{1}{12}\sum_t^{12}\left(\frac{1}{N_{Bt}}\sum_{i\epsilon A}Analyst\ Performance_t^i\right) \tag{4}$$

[12] Stock prices are adjusted for stock splits and dividends using the CRSP price adjustment factor. In addition, stocks must not have any missing prices or financial data.

[13] Review date refers to the date when the forecast estimate was confirmed as accurate by I/B/E/S.

[14] We measure forecast consensus revision as the change in monthly consensus mean forecasts so that it can be compatible with the measurement of the momentum variables, which ratios are measured on a monthly basis at portfolio formation month *t*.

[15] In another sense, the analysts' performance measure can also be described as the average analysts' forecast error measure.

$$UpdatedError_t^j = \frac{1}{N_{Bt}} \sum_{i \epsilon Bt} Analyst\ Performance_t^i \tag{5}$$

where:

B_t is the number of analysts that cover stock j in month t.[16] *ExpectedError* is the average analyst performance on stock j at month t over the past year (12 months). This represents the expected intermediate-term performance or benchmark performance of analysts that are covering the stock at month t. *UpdatedError* is the stock's average analyst performance scaled by the number of analysts that cover stock j at month t, which also represents analysts' updated or short-term performance.

The dummy variable *positive performance* ($Perf_j$) equals 1 if *UpdatedError* (average short-term performance of the analysts) is less than *ExpectedError* (intermediate benchmark performance), and 0 otherwise. In other words, stocks that are covered by a better performing analyst have an average short-term forecast error lower than the average expected forecast error.

3.3. Control variables

We use two sets of control variables: (1) standard stock characteristics that are known to predict stock returns (Fama & French, 1993) and (2) additional stock characteristics that proxy for information uncertainty[17] (Zhang, 2006; Burghof & Prothmann, 2011; Hou et al., 2014).

First, as per the momentum literature (Jegadeesh & Titman, 1993; George & Hwang, 2004; Bhootra & Hur, 2013), we include firm size as a control variable. Firm size is a common risk factor and also a salient measure of information uncertainty. We control for prior month's stock returns in the Fama and MacBeth (1973) regression approach as past returns contain information about future stock returns; thus, this controls for short-term price reversals (e.g., Grinblatt & Moskowitz, 2004), bid-ask bounce microstructure problems (Conrad & Kaul, 1998) and behavioural biases (Jegadeesh & Titman, 1993).

Second, we employ three proxies for information uncertainty.[18] The foremost proxy for information uncertainty is book-to-market (BM) ratio. Fama and French (1993) and Daniel and Titman (1997) argue that growth stocks (lower BM ratio) are more volatile because they are heavily dependent on future growth possibilities and on research and development.[19] Another direct measure of information uncertainty is stock price volatility. Intuitively, if stock returns are increasingly unpredictable, they become harder to value, which results in a higher degree of information uncertainty (Daniel et al., 1998). The third proxy for information uncertainty is firm age. As older firms are generally larger, and richer in data and public information, they have a relatively lower degree of information asymmetry and uncertainty than newly listed firms (Barry & Brown, 1985; Bessler & Bittelmeyer, 2008). Moreover, Zhang (2006) suggest that firm age is an indirect measure of industry effects as the age of a firm is closely affiliated with the maturity of the industry.

3.4. Descriptive statistics

Table 1 reports the descriptive statistics. Panel A presents the summary of monthly stock returns, which is the dependent variable used throughout our research. From the descriptive statistics, we observe that stock returns tend to cluster mainly around the mean (median) value of 0.76% (0.70%).

Panel B presents the momentum variables that are consistent with GH and BH. WHH (WHL) is a dummy variable that equals 1 if stocks are in the top (bottom) quintile portfolios based on GH's 52-week-high price ratio, and 0 otherwise. Likewise, RRH (RRL) is a dummy variable that equals 1 if stocks are ranked in the top (bottom) quintile of BH's recency ratio, and 0 otherwise. The mean values of the momentum variables represent the frequency of stocks that are assigned to the winner and loser momentum portfolios respectively in our sample. For example, the mean of WHH is interpreted as 21.1% of the stocks in our sample having a current price that is close to their 52-week-high price. Similarly, 18.63% of the stocks in our sample have recently attained their 52-week-high price, and are therefore ranked in the RHH portfolio.

Panel C presents the summary of analyst-related variables. The average mean forecast revision variable (*Forecast Rev. %*) is − 0.086%.[20] The median forecast revision of 0 also suggests that analysts do not frequently amend their monthly forecast. The mean average analyst performance variable (mean forecast error of the average analysts) implies that, on average, analysts are about 11% wrong in their estimates from the actual realized earnings.

With respect to the positive performance measure, the average *ExpectedError* (intermediate benchmark error) has a mean of 0.0087%, and average *UpdatedError* (short-term error) has a mean of 0.0073%.[21] Positive performance (*Perf*) has a mean value of about 0.573. This indicates that for 57.3% of the stocks in our sample, analysts' short-term performance is better than the benchmark in this period. In other words, more than half the stocks in our sample are covered by better performing analysts who have recently improved the reliability and precision of their earnings forecasts. Overall, our descriptive statistics for analyst-related measures are relatively consistent with Chen et al. (2015) and Laksanabunsong (2015).

Panel D presents the control variables used in our regressions. The mean size of firms in our sample is large, at $3412 million. Book-to-market is evenly distributed around the mean of 0.50. The mean of $Volatility_t$ indicates that monthly stock returns on average fluctuate by 2.52% over the past year. We follow Burghof and Prothmann (2011) and calculate *firm age* as the number of months since Compustat began covering the firm. Consistent with Burghof and Prothmann

[16] Scaling by the number of analysts that cover stock j at month t allows us to compare between *UpdatedError* and *ExpectedError* of individual analysts covering stock j at month t.

[17] Zhang (2006) describes information uncertainty as "the ambiguity about new information and its implications on the stock's fundamental value, which can arise either due to the lack of quality information or stock's volatility."

[18] Burghof and Prothmann (2011) have associated stocks in the 52-week-high strategy with a higher level of information uncertainty and behavioural biases. To ensure that our key variables of interest are not driven by contemporaneous factors in the recency momentum strategy, we control for other explanations that could potentially lead to profits in the recency strategy.

[19] Growth stocks are difficult to value as most of the earnings acquired are likely to be reinvested back into the firm for future development, and are therefore more risky (Daniel & Titman, 1999).

[20] The negative mean forecast revision suggests that there are either generally more downward revisions or the magnitude of change in forecasts is greater for downward revisions than upward revisions (minimum value = − 16.6) at the aggregate level. In our findings, we show that the magnitude of downward revision are larger when more information becomes available, i.e., next earnings announcement period, and the negative mean forecast revision indicates that analysts revise their optimistic biases in the later months to a larger extent.

[21] As *ExpectedError* and *UpdatedError* are the proportioned by the corresponding number of analysts following the stock, thus, it is not surprising that these measures are of a small magnitude.

Table 1
Descriptive statistics

This table reports the descriptive statistics of the key variables in the full sample. Panels A and D present the dependent and control variables in the regression respectively. Panel B presents the momentum variables that are consistent with GH and BH. Panels C and E present the summary of analyst-related variables obtained from I/B/E/S. In each month *t*, stocks are ranked into quintiles on their past 6-months GH's proximity to 52-week-high (WH) ratio and BH's recency ratio (RR). WHH (WHL) is a dummy variable that equals 1 if stocks are ranked in the top (bottom) quintile portfolios based on GH's 52WH ratio, and 0 otherwise. RRH (RRL) is a dummy variable that equals 1 if stocks are ranked in the top (bottom) quintile of BH's RR, and 0 otherwise. Forecast revision is a percentage and is the change in mean earnings forecast between month *t* and the previous month, scaled by previous month's stock price. Analysts' Performance measures the recent forecasting performance of analysts and is computed as the average forecast error of analyst *i*, scaled by beginning year stock price. *ExpectedError* is measured as the average Analysts' Performance on stock *j* at month *t* over the past 12 months and scaled by the number of analysts that cover stock *j*. *UpdatedError* is the short-term forecasting performance of an average analyst as a percentage, computed as the average Analysts' Performance on stock *j* at month *t* scaled by number of analysts that cover stock *j*. Positive Performance (Perf) represents stocks that are covered by better performing analysts, and equals 1 if *UpdatedError* is less than *ExpectedError*, and 0 otherwise. $Returns_{t-1\ month}$ is the prior month's returns. $Size_{t-1\ month}$ is the log of market capitalization (in millions) of stock *j* at the end of previous month. Book to $Market_{t-1\ year}$ is the book-to-market ratio. $Volatility_{t-1\ year}$ is the standard deviation of monthly stock returns over the past year. Firm Age is the firm's age. For full description of the variables, please refer to Appendix A. The sample consists of stocks listed on NYSE, AMEX and NASDAQ for the period January 1995 to December 2014.

Variables	Obs	Mean	SD	Min	p25	Median	p75	Max
Panel A: dependent variable								
$Returns_t$	1410	0.0076	0.1189	− 0.2982	− 0.0596	0.0070	0.0709	0.4057
Panel B: momentum variable								
WHH	1410	0.2110	0.4082	0	0	0	0	1
WHL	1410	0.1672	0.3733	0	0	0	0	1
RRH	1410	0.1863	0.3895	0	0	0	0	1
RRL	1410	0.2166	0.4121	0	0	0	0	1
Panel C: analysts' forecast variable (%)								
Forecast rev. (%)	1410	− 0.0861	1.1676	− 16.6065	− 0.1654	0.0000	0.1171	11.6698
Analyst performance	1410	0.1107	0.1684	0.0000	0.0200	0.0505	0.1298	1.9348
Expected error (%)	1410	0.0087	0.0370	0.0000	0.0006	0.0021	0.0058	1.0323
Updated error (%)	1410	0.0073	0.0456	0.0000	0.0001	0.0006	0.0028	1.5432
Perf	1410	0.5729	0.4947	0	0	1	1	1
Panel D: control variables								
$Returns_{t-1\ month}$	1410	0.0079	0.1079	− 0.3022	− 0.0513	0.0124	0.0655	0.3566
$Size_{t-1month}$	1410	8.1351	1.5879	3.8661	6.8620	8.1441	9.4529	13.1815
Book to $market_{t-1\ year}$	1410	0.5141	0.3480	0	0.2523	0.4520	0.7097	2.4696
$Volatility_{t-1\ year}$	1190	0.0252	0.0116	0.0073	0.0169	0.0227	0.0310	0.1083
Firm age	1410	132.2769	66.8731	14	75	135	189	249

Panel E: Descriptive statistics on analysts

	Number of analysts following each firm						Set of firms that analysts *i* covers					
Year	Mean	Minimum	P25	Median	P75	Maximum	Mean	Minimum	P25	Median	P75	Maximum
1995	51.238	4	7	12	54	288	189.143	12	30	128	218	988
1996	42.964	2	9	18.5	54	172	138.643	3	37	86	163	696
1997	49.971	2	10	33	64	306	205.314	3	30	84	268	1717
1998	52.290	4	17	48	80	132	324.710	13	50	148	458	1688
1999	70.875	2	9.5	26.5	105	640	230.175	11	51	119.5	271	1381
2000	80.781	5	12	28	110	440	215.563	12	45.5	106.5	262.5	1480
2001	63.220	4	14	26	78	352	194.920	4	18	88	286	1072
2002	68.023	4	12	30	74	456	186.442	4	26	84	139	1717
2003	62.702	4	11	22	64	636	154.070	4	58	97	242	664
2004	70.694	2	18	39	78	319	174.016	7	35	90	206	1524
2005	60.025	2	12.5	28	66	341	227.800	5	35	97	277	1524
2006	67.512	3	13	24.5	69	328	195.726	4	50.5	99	279.5	1171
2007	80.696	7	20	36	78	480	192.570	7	56	124	254	1524
2008	55.369	3	11	24	64	450	185.680	4	52	110	202	1171
2009	54.010	3	17	25	78	253	242.381	6	55	115	267	1480
2010	70.149	4	16	25	64	715	256.483	3	57	140	310	1524
2011	78.023	5	16	32	72	539	222.953	6	53	117	226	1171
2012	59.892	3	11	25.5	52	594	177.784	3	48	105	236	1072
2013	52.908	1	13.5	28.5	53	385	162.513	2	24	111.5	194	1078
2014	52.219	3	13	22	38	594	105.578	2	23	52.5	122	590
Average	62.178	3.350	13.125	27.675	69.750	421	199.123	5.75	41.7	105.1	244.050	1261.600

(2011), the average age of the firms in our sample is about 132 months, with the youngest (oldest) firm in our sample at 14 (249) months old.

Panel E presents the descriptive statistics for the number of analysts that are following a particular stock and the number of firms that an analyst typically covers. These figures provide a gauge of the construct of the average positive performance (*Perf*) of analysts. We find that the mean number of analysts' coverage and firms being covered by analysts are relatively stable and evenly distributed across the years. Specifically, we observe that approximately 62 analysts follow an average stock, and an average analyst covers about 199 different types of firms annually (across four quarters). This trend suggests that our mean earnings forecast revisions and recent analysts' performance are not driven by thinly weighted forecasts, i.e., one analyst representing the forecast consensus for the month. We provide the Pearson's correlation matrix of all key variables in Table B.1 of Appendix B. According to Table B.1, the low-levels of correlation across our variables indicate that our study is unlikely to be affected by issues pertaining to multicollinearity.

3.5. Research method

We adopt two empirical approaches in this study: (1) portfolio-level analysis and (2) multivariate panel-data regressions to support the study of the research questions. The portfolio-level analysis is an important analysis that examines the first-order documentation, and captures any potential nonlinear relations in the portfolio aggregation. The panel-data regression (or cross-sectional time-series data) provides second-order confirmation of the relationship documented in the portfolio-level analysis, and addresses any omitted or unknown variable issues that may potentially confound the results established in our study.

3.5.1. Post-forecast revision price drift

We create portfolios similar to George and Hwang (2004) who compare the Jegadeesh and Titman (1993) momentum strategy against the 52-week high strategy to calculate a Winner – Loser strategy. However, our portfolios are based upon the analysis of whether analysts' monthly earnings forecast revision consensus are a good predictor for future stock returns. At the beginning of each month t, stocks are sorted into quintile portfolios based on the magnitude of forecast revision ($Revision_t$).[22] We equally weight stocks in each portfolio, and report the holding-period returns to each forecast revision portfolios and the *Buy-Sell* revision strategy, and the corresponding Fama and French (1993) three-factor alphas to control for standard risk factors that can explain stock returns.

We present analyses up to 5 months ahead, as post-forecast revision drift is a relatively short-term phenomenon with abnormal returns that lasts for at least 6 months (Stickel, 1991; Chan et al., 1996). It is more economically meaningful to analyse short-term price drift, since we are measuring analysts' forecast revision consensus on a quarterly basis. Following our Hypothesis 1 and Hypothesis 2, if indeed investors inefficiently underreact to information in analysts' forecasts, we would expect to find evidence of post-forecast revision drift (Hypothesis 1), consistent with prior studies (e.g., Gleason & Lee, 2003; Chen et al., 2015). Furthermore, we expect to see an asymmetric pattern of stock price drift following upward and downward revisions (Hypothesis 2).

3.5.2. Profitability of the recency momentum strategy

To measure profits from the momentum strategy, we follow JT and BH to implement an overlapping (6-1-6) momentum strategy where stocks are ranked and then placed into quintiles based on their past 6-month returns to BH's RR measure over the months $t-6$ to $t-1$. At the end of portfolio formation month $t-1$, stocks ranked at the top (bottom) 20% of the RR measure are assigned to the winner RRH (loser) RRL portfolio. The stocks are subsequently held in their recency portfolios for the next 6 months (from month t to $t+6$), after imposing a 1-month gap between the portfolio formation period and the holding period (month $t-1$ to t) to alleviate any microstructure issues, such as the bid-ask bounce effect or interaction with other momentum strategies (GH; BH; Hao et al., 2014). We then calculate and report the 6-month equal-weighted returns and corresponding Fama and French (1993)three-factor alphas for stocks in the recency strategy (RRH – RRL), and returns for each of the recency portfolios.

3.5.3. Portfolio formation for two-way portfolio-level analysis and panel regression

To measure the first-order relationship between recency strategy and analysts' forecast revisions, we sort stocks according to BH's recency ratio and analysts' earnings forecast revision. Stocks in BH's recency portfolios are ranked into quintiles based on their past 6-months returns to BH's RR measure over the month $t-6$ to $t-1$.[23] Correspondingly, measurement of stocks in the forecast revision portfolios is based on the magnitude of change in forecast at the beginning of month t. To measure the first-order relationship between recency strategy and analysts' forecast revisions, we sort stocks according to BH's recency ratio and analysts' earnings forecast revision. Fig. 1 presents the timeline to better illustrate the portfolio allocation process of the recency and forecast revision measures respectively.

The staggered configuration for the portfolio-formation arrangement is motivated by Zhang (2008), who finds that both the timing and magnitude of forecast revisions are important aspects of the analysts' forecast that can help facilitate market efficiency. By forming a forecast revision portfolio 1-month ahead of the momentum portfolios, we develop a tractable model to test whether analysts are able to pick up momentum indicators, and make subsequent forecast revisions that contribute to explaining future stock returns (Jegadeesh et al., 2004). This staggered arrangement has the added benefit of preventing endogeneity issues (i.e., analysts' forecast revisions drive the price-momentum effect).

Using a dependent variable of up to 3 months ahead allows for the evaluation of the market's asymmetric reaction to good and bad news. Good (bad) news can be represented by stocks in the recency strategy, where stocks with the most recent (distant) 52-week-high price in the RRH (RRL) portfolio continues to earn positive (negative) excess returns (BH; Hao et al., 2014).

3.5.4. Panel regression

We use panel regressions to assess whether analysts' forecast revisions can predict future stock returns, after controlling for momentum and information uncertainty factors (Hypothesis 4). This multivariate regression approach allows us to conveniently include any variables (e.g., for Hypothesis 3, positive analysts' performance), and compare the source of returns predictability between the portfolios in the momentum strategy and forecast revision portfolios separately. Furthermore, the setup of the regression model allows us to examine the asymmetric pattern of stock price continuation following upward and downward forecast revisions (Hypothesis 2).

3.5.4.1. Baseline momentum model

Consistent with BH and Hao et al. (2014), the baseline momentum model for this study is as follows:

$$\begin{aligned} R_{j,t+p} = {} & \beta_0 + \beta_{1jt}\, WHH_{j,t-1} + \beta_{2jt} WHL_{j,t-1} + \beta_{3jt} RRH_{j,t-1} \\ & + \beta_{4jt} RRL_{j,t-1} + \beta_{5jt} WHH_{j,t-1} \times RRH_{j,t-1} \\ & + \beta_{6jt} WHH_{j,t-1} \times RRL_{j,t-1} + \beta_{7jt} WHL_{j,t-1} \times RRH_{j,t-1} \\ & + \beta_{8jt} WHL_{j,t-1} \times RRL_{j,t-1} + \beta_{9jt}\, Size_{j,t+p-1} + \varepsilon_{jt} \end{aligned} \tag{8}$$

where:

[22] Recall that the top 20% of stocks with the highest forecast revision value is included in *BUY* revision portfolio; the bottom 20% of stocks with the lowest forecast revision value is assigned to *SELL* revision portfolio.

[23] The positioning of momentum variables at month $t-1$ also allows us impose a 1-month gap between the forecast revisions and momentum variables to prevent bid-ask bounce microstructure effects, which is consistent with prior literature (e.g., JT, GH, and BH).

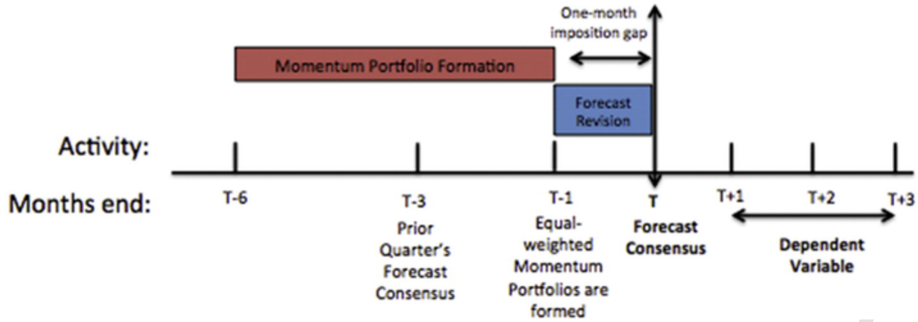

Fig. 1. Timeline for portfolio analysis.

$R_{j,t+p}$ is stock returns in month t; $WHH_{j,t-1}$ ($WHL_{j,t-1}$) is the 52-week-high winner (loser) portfolio; $RRH_{j,t-1}$ ($RRL_{j,t-1}$) is the Recency Ratio winner (loser) portfolio; $Size_{j,t+p-1}$ is firm size. Subscripts *j, t*, and *p* represent stock *j*, time *t* and *p* = month *t + 1 to t + 3* (For a full description of the variables, please refer to Appendix A.).

In the regression approach, future stock returns in month *t + 1*, month *t + 2*, and month *t + 3* are the dependent variables in three different panel-data regressions, each representing the holding period *p* = 1 to 3.The control variables are positioned in relation to the dependent variable at time *t* − *p*, and the momentum variables are taken at month *t* − *1*. A simple illustration follows: If measuring stock returns at month *t + 2* (*p = 2*), size is taken at month *t + 1* and the momentum variables remain at month *t* − *1*. Using this 3-month (one-quarter) ahead analysis, we are able to extend the work of BH and Hao et al. (2014), and examine the explanatory power of the momentum variables at different stages of the future that is consistent with the portfolio-level analysis.

BH suggests that the addition of recency bias causes investors to underreact further, and thus accentuating profits to GH's 52-week-high strategy. Therefore, the coefficients on WHH*RRH and WHH*RRL refer to BH's recency of the 52-week-high price strategy, and WHL*RRH and WHL*RRL refer to recency of the 52-week low strategy (BH; Hao et al., 2014). Consistent with GH and BH, we expect the coefficients of the winner (loser) momentum portfolios to be positively (negatively) related to explain future stock returns.

3.5.4.2. Main regression with forecast revision (without positive performance)

We form the following regression model to examine whether analysts are important information intermediaries in the market that can help explain future stock returns, after we have controlled for momentum and information uncertainty variables (*Hypothesis* 4).

$$R_{j,t+p} = \beta_0 + \beta_{1jt}\, BUY_{j,t} + \beta_{2jt}\, SELL_{j,t} + \beta_{3jt}\, WHH_{j,t-1} + \beta_{4jt}$$

where:

$BUY_{j,t}$.is *Buy* revision; $SELL_{j,t}$ is *Sell* revision.

3.5.4.3. Main Regression with forecast revision (with positive performance)

To examine the incremental effect of positive analysts' performance($Perf_j$), we extend model (9) and incorporate the positive performance variable to forecast revisions into the regression to form model (10).

$$R_{j,t+p} = \beta_0 + \beta_{1jt}\, BUY_{j,t} \times Perf_{j,t} + \beta_{2jt}\, SELL_{j,t} \times Perf_{j,t} + \beta_3$$

where:

$Perf_{j,t}$ is positive performance.

If analysts are able to pick up momentum signals and translate their forecast revisions as news for investors, we would expect forecast revisions to explain future stock returns after controlling for momentum and information uncertainty variables (Hypothesis 4). Thus, β_1(β_2) would be significantly positive (negative) in the regression model (9).

As prior research shows that information on stocks that are covered by better performing analysts are perceived to be more credible (Laksanabunsong, 2015; Jackson, 2005), following Hypothesis 3, we predict that the inclusion of positive performance would improve the coefficient and significance of β_1(β_2) relative to model (10). Motivated by Barber et al. (2001) and Jegadeesh et al.'s (2004) observation that analysts tend to make stock recommendations that are favourably correlated with positive momentum stocks, we also restrict our sample to stocks in the recency strategy (RRH and RRL portfolios) as part of the regression analysis.

In summary, the regressions extend the results from the portfolio-level analysis. The inclusion of information uncertainty variables ensures that our results are not driven by contemporaneous or omitted factors. Moreover, the examination of stock returns at months *t + 1*, *t + 2*, and *t + 3* allows us to conduct a formal statistical analysis of whether the magnitude of analysts' earnings forecast revisions can predict future stock returns at different stages, after controlling for the recency and information uncertainty indicators (*Hypothesis* 4). It also permits us to capture the asymmetric pattern of forecast revision variables (*Hypothesis* 2) and the pervasiveness of sell-side analysts' optimistic bias.

Furthermore, the examination of in-sample quarter-ahead (dependent variable) returns allows us to evaluate the market's asymmetric reaction to good and bad news. Good (bad) news can be represented by stocks in the recency strategy, where stocks with the most recent (distant) 52-week-high price in the RRH (RRL) portfolio continues to earn positive (negative) excess returns (BH; Hao et al., 2014).

4. Results

4.1. Post-forecast revision price drift

We test whether quarterly analysts' forecast revision consensus are a good predictor for future stock returns in the first part of the portfolio-level analysis. Panel A and Panel B of Table 2 report the

Table 2
Stock returns following analysts' forecast revision portfolio
This table presents the 5-months ahead average monthly portfolio returns following analysts' forecast revisions. Panels A and B report the holding-period returns and the corresponding Fama-French three-factor alphas in quintile portfolios respectively. Panel C reports holding-period returns in decile portfolios. *Buy (Sell)* revision is a dummy variable equal to 1 if the change in forecast is ranked in the top (bottom) portfolio at month *t*, and 0 otherwise. For full description of the variable, please refer to Appendix A. The sample consists of stocks listed on NYSE, AMEX and NASDAQ for the period January 1995 to December 2014. The corresponding t-statistics are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels.

Quintile	N	1 month	2 months	3 months	4 months	5 months
Panel A: holding-period returns in quintiles						
1 (Sell)	101	− 0.0013	− 0.0011	− 0.0023	0.0016	− 0.0068
		(− 0.14)	(− 0.09)	(− 0.15)	(0.09)	(− 0.39)
2	91	− 0.0011	− 0.0003	0.0155	0.0169	0.0280
		(− 0.13)	(− 0.03)	(1.05)	(1.07)	(1.59)
3	90	0.0097	0.0279	0.0697***	0.0949***	0.0905**
		(1.19)	(2.46)	(5.10)	(5.55)	(6.08)
4	95	0.0217	0.0473***	0.0767***	0.0887***	0.1076**
		(2.60)	(4.19)	(4.54)	(4.69)	(5.00)
5 (buy)	101	0.0198***	0.0416***	0.0597***	0.0724***	0.0837**
		(3.00)	(3.71)	(4.21)	(4.44)	(4.41)
Buy – sell strategy	101	0.0211***	0.0427***	0.0620***	0.0708***	0.0905**
		(3.02)	(3.35)	(3.91)	(3.70)	(4.34)
Panel B: Fama French 3-factor alpha						
1 (sell)	134	− 0.0152*	− 0.0203**	− 0.0433***	− 0.0373**	− 0.0430
		(− 1.96)	(− 1.98)	(− 2.75)	(− 2.20)	(− 2.56)
2	155	− 0.0136**	− 0.001	0.0165	0.0106	0.0231
		(− 2.15)	(− 0.1)	(1.18)	(0.75)	(1.46)
3	157	0.0025	0.0165*	0.0473***	0.0744***	0.0793**
		(0.46)	(1.68)	(3.64)	(4.43)	(4.83)
4	171	0.0091	0.0263***	0.0501***	0.0666***	0.0909**
		(1.47)	(3.05)	(4.06)	(4.51)	(5.12)
5 (buy)	131	0.0137**	0.0202**	0.0395***	0.0531***	0.0560**
		(0.0287)	(2.04)	(2.90)	(2.88)	(2.82)
Buy – sell strategy	102	0.022***	0.0304**	0.0582***	0.0637***	0.0860**
		(3.09)	(2.53)	(3.46)	(3.98)	(3.93)

Panel C: holding-period returns in deciles

Decile	N	1 month	2 months	3 months	4 months	5 months
1 (sell)	77	0.0015	− 0.0187	− 0.0251	− 0.0302	− 0.0464**
		(0.15)	(− 1.50)	(− 1.46)	(− 1.55)	(− 2.49)
2	70	− 0.0215	− 0.0201	− 0.0274	− 0.0121	− 0.0033
		(− 1.44)	(− 1.47)	(− 1.36)	(− 0.53)	(− 0.12)
3	66	0.0017	0.0105	0.0300	0.0319	0.0398*
		(0.18)	(0.78)	(1.57)	(1.54)	(1.75)
4	68	− 0.0084	0.0089	0.0292	0.0315*	0.0538**
		(− 0.88)	(0.72)	(1.65)	(1.77)	(2.27)
5	70	0.0024	0.0306**	0.0510***	0.0634***	0.0612***
		(0.23)	(2.25)	(2.92)	(3.32)	(3.32)
6	70	0.0086	0.0215*	0.0540***	0.0766***	0.0844***
		(0.99)	(1.72)	(3.36)	(3.82)	(4.39)
7	69	0.0159	0.0260**	0.0765***	0.0749***	0.0712***
		(1.55)	(2.37)	(3.50)	(3.79)	(3.28)
8	66	0.0326***	0.0531***	0.0817***	0.0988***	0.1251***
		(3.30)	(4.97)	(4.82)	(4.67)	(4.44)
9	67	0.0175	0.0305***	0.0555***	0.0769***	0.0970***
		(1.66)	(2.67)	(2.69)	(3.28)	(3.15)
10 (buy)	77	0.0307***	0.0430***	0.0640***	0.0666***	0.0684***
		(3.59)	(3.11)	(3.76)	(3.56)	(3.44)
Buy – sell strategy	77	0.0291***	0.0652***	0.0892***	0.0967***	0.1147***
		(3.25)	(4.50)	(4.90)	(4.22)	(4.72)

holding-period returns and Fama-French three-factor alphas respectively up to 5 months ahead. Consistent with the literature, our findings demonstrate that a self-funded investment strategy (last row of each panel) that simultaneously longs stocks in the *Buy* revision and short-sells stocks in the *Sell* revision portfolios is profitable and highly significant. In addition, the returns are monotonically increasing with time. The corresponding Fama-French three-factor alphas presented in Panel B are consistent with results using raw returns.

For robustness, we disaggregate our sample into decile portfolios as shown in Panel C. From Panel C, we observe that there is greater stock price drift impounded in the *Sell* revision portfolio than the *Buy* revision. For the *Buy* revision, stock returns in the first 3 months are 3.07%, 4.30%, and 6.4% respectively. On the other hand, the decrease in stock returns following the *Sell* earnings forecast revision is gradual, where there is continued stock price drift in the direction of unfavourable news over a period of months.

Table 2 provides support for Hypothesis 1. We observe post-forecast revision drift in the US market in the short and intermediate term, and have established the profitability of the *Buy-Sell* revision strategy that is consistent with prior literature. The findings from Fama-French adjusted alphas indicate that excess returns are not affected by their exposure to risks. Moreover, we find that the pattern of stock price drift is larger following downward revisions than upward revisions. Consistent with Chen et al. (2015), the market reaction to downward revisions tends to be slower.

This finding suggests that investors do not correctly process the implications of analysts' forecast revisions and exhibit a more significant delay in response to bad news than good news.

4.2. Year-by-year analysis of post-forecast revision drift

We evaluate the year-by-year performance of the *Buy-Sell* strategy over the next 3 months based on forecast revisions. We examine for exogenous factors such as the 2003 Regulation Fair Disclosure (Reg FD) and the 2007–2008 Global Financial Crisis (GFC)/Great Recession (GR).

Analysts collect information independently from public or private sources. For example, analysts can collect inside information from managers of the firms that they have a personal connection with. This early information advantage to analysts has drawn considerable regulatory attention. On 23 October 2003, the Securities and Exchange Commission (SEC) adopted Regulation Fair Disclosure (Reg FD) to stamp out “selective disclosure”, in which companies give material information only to a few analysts and institutional investors prior to disclosing it publicly.[24] Gomes, Gorton, and Madureira (2004) show that the adoption of Reg FD has caused a significant shift in analyst attention, resulting in welfare loss and a higher cost of capital for smaller firms. Chen et al. (2015) found that the post-Reg FD period is associated with lower forecast revision momentum. This suggests that we might expect to observe lower stock price drift following analysts' forecast revisions for the period of post-Reg FD.

The next critical event to consider is the GFC/GR. The GFC/GR almost all developed countries into recession, including the U.S. (Claessens, Ayhan Kose, & Terrones, 2010), thus we would expect stock returns to be adversely affected during the post-GFC/GR period.

The findings from Table 8 indicate that the sensitivity of stock returns to forecast revisions has been relatively stable over the years, except for the post-GFC/GR period. The second and third month holding-period returns in the *Buy-Sell* strategy increase to about 8% and > 10% respectively in the year 2007 and 2008. This is largely driven by the decline in stock returns following the *Sell* revision. In contrast to the post-GFC period, it is difficult to make inferences

[24] The Reg FD essentially mandates publicly traded companies to disclose material information to all investors simultaneously, and it would adversely affect the competitive advantage of analysts over investors.

about the enactment of Reg FD as most stock returns during this period are insignificant. This is due to the reduction of the number of consensus forecasts per year when the sample is split into annual observations.

Overall, returns from the *Buy-Sell* strategy for the GFC/GR period are higher, which is mainly driven by returns following the *Sell* revision. We do not find evidence of post-Reg FD affecting our results.

4.3. Profits to the recency strategy

In Section 4.1, we established the existence of post-forecast revision price drift. We now examine stock returns to the recency strategy to validate our RR measure prior to exploring the interaction between the recency strategy and analysts' earnings forecast revisions. In Table 3, We present the 6-month ahead holding-period returns after portfolio formation on month $t-1$ (with a 1-month imposition gap).

The results are statistically significant and consistent with BH. The RRH (RRL) portfolio earns monthly returns of 0.25% (0.08%) on average, and profits to the recency strategy (RRH – RRL) are 0.164% per month at the 1% significance level. Correspondingly, the adjusted Fama-French alpha is 4.27% per month.

Our results continue to be consistent with the outcomes documented by Bhootra and Hur (2013) despite the difference in sample periods. Returns increase almost monotonically from the loser (RRL) to winner (RRH) portfolio. Thus, our results align our methodology with prior literature to exemplify that profits from the recency strategy are indeed predictable and significant.

4.4. Portfolio-level analysis between forecast revision and recency measure

4.4.1. Empirical evidence of analysts' behavioural biases

We investigate the average absolute analysts' performance (mean forecast errors) following good and bad news.[25] Although our findings in Section 4.1 have demonstrated an asymmetric pattern, we need to ascertain whether the results stem from analysts' optimistic bias and differential access to good and bad news. If indeed analysts underreact to new information when revising their forecasts, their adjustment in earnings forecast would be insufficient and this would be captured by positive forecast errors. Subsequently, since analysts underreact to a larger extent to downward revisions, we would expect more forecast errors in the downward revision portfolio (Zhang, 2006).

Table 4 and Fig. 2 report the average absolute analysts' performance (forecast errors) for stocks sorted independently according to the recency ratio (RR) measure and forecast revision ranking. The findings demonstrate that analysts underreact to new information from earnings announcements, and the average forecast errors are significantly higher in the extreme recency portfolios, i.e., stocks in the RRH and RRL portfolios. This indicates that, in cases of information uncertainty, analysts display more noticeable behavioural biases and are slower to revise their forecast revisions (Jiang et al., 2005; Zhang, 2006).

The average absolute performance (forecast errors) for the *Sell* revision portfolio is higher than any of the other revision portfolios (in the first column of Table 5). Of particular interest, the *Sell/RRL* loser

[25] After demonstrating differential monthly returns to stocks in the recency portfolios and established profits from the recency strategy, stocks with the most recent (distant) 52-week-high price in RRH (RRL) portfolio can be related to good (bad) news.

Table 3
Monthly returns to the recency strategy

This table reports the average monthly returns and corresponding Fama-French three-factor alphas in RR quintile portfolios respectively. RRH (RRL) is a dummy variable that equals 1 if stocks are ranked in the top (bottom) quintile of BH's RR, and 0 otherwise. For full description of the variable, please refer to Appendix A. The sample consists of stocks listed on NYSE, AMEX and NASDAQ for the period January 1995 to December 2014. The t-statistics are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels.

Panel A: monthly returns of RR portfolios

Quintiles	N	RR	Fama-French alpha
P1 (RRL)	252	0.0008***	-0.0161
		(3.27)	(− 1.44)
P2	252	0.0014***	0.0082
		(4.78)	(0.73)
P3	252	0.0018***	0.0247**
		(6.00)	(2.22)
P4	252	0.00173***	0.0398***
		(6.15)	(4.56)
P5 (RRH)	252	0.00249***	0.0356***
		(9.17)	(3.48)
RRH – RRL strategy	252	0.00164***	0.0427***
		(14.33)	(3.35)

Table 4
Two-way portfolio level analysis (analysts' performance)

This table reports the average absolute analysts' performance (forecast error) in the two-way portfolio-level analysis. *Buy (Sell)* revision is a dummy variable that equals 1 if the change in forecast is ranked in the top (bottom) portfolio at month *t*, and 0 otherwise. RRH (RRL) is a dummy variable that equals 1 if stocks are ranked in the top (bottom) quintile of BH's RR, and 0 otherwise. For full description of the variables, please refer to Appendix A. The sample consists of stocks listed on NYSE, AMEX, and NASDAQ for the period January 1995 to December 2014. The t-statistics are reported in parentheses. Boldface represents our key variables of interest. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels.

Panel A: average forecast dispersion

Recency portfolio	Forecast revision portfolio				
	Rev 1 (Sell)	Rev2	Rev3	Rev4	Rev 5 (Buy)
P1 (RRL)	**0.0131*****	0.0027***	0.0029***	0.0035***	0.0086***
	(4.56)	(5.35)	(4.09)	(5.69)	(3.81)
P2	0.0075***	0.0038***	0.0032***	0.0030***	0.0040***
	(5.63)	(3.05)	(3.52)	(4.69)	(5.80)
P3	0.0107***	0.0038***	0.0018***	0.0019***	0.0072***
	(4.82)	(5.90)	(3.85)	(6.20)	(4.52)
P4	0.0094***	0.0059***	0.0015***	0.0036***	0.0070***
	(4.28)	(4.40)	(5.89)	(4.62)	(5.07)
P5 (RRH)	0.0072***	0.0048***	0.0020***	0.0031***	**0.0066*****
	(4.84)	(4.43)	(5.41)	(7.69)	**(5.20)**

portfolio displays the highest level of forecast error at 1.31%. This finding indicates that analysts are generally more reluctant to revise their downward forecast revisions and exhibit higher forecast errors following bad news in earnings announcements. Alternatively, the *Buy/RRH* winner portfolio (the last column of Table 5) exhibits an average absolute forecast error of 0.66%, that is half of the *Sell/RRL* loser portfolio.[26]

Overall, the analysis of analysts' performance (forecast errors) allows us to isolate the behavioural biases attributable to analysts rather than investors. The findings support the notion that analysts make timelier upward forecast revisions following good news, and incorpo-

[26] Although the analysts' absolute forecast errors in the *Buy* revision portfolios are systematically lower than its extreme counterpart (*Sell* revision), they are still marginally higher than the other portfolios in Table 5. This suggests that stocks in the RRH and RRL portfolios have high levels of information uncertainty (Zhang, 2006).

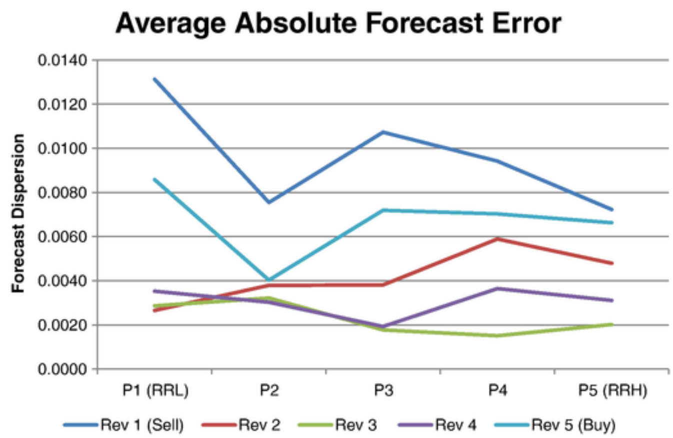

Fig. 2. Average analysts' performance (absolute forecast error).

rate this positive private information into their stock recommendations. However, on average, they are slower to revise their downward revisions following bad earnings announcement news. These findings are consistent with the optimistic bias in Hypothesis 2, and demonstrate that information uncertainty is likely to be greater when firms face bad news (i.e., stocks are ranked in the RRL portfolio).

Furthermore, the findings from the average forecast errors (Table 3) and post-forecast revision drift (Table 2) suggest that the underlying cause of post-forecast revision drift is not entirely caused by investors' underreaction behaviour, but a series of underreactions by analysts. In other words, the failure of analysts to fully incorporate information in earnings announcements has a spillover effect on to investors that explains the post-forecast revision drift anomaly (Chen et al., 2015).

4.4.2. Two-way portfolio-level analysis between recency ratio and forecast revision measures

We conduct the same two-way portfolio-level analysis, by sorting stocks independently according to their recency ratio (RR) measure and forecast revision measure. Table 5 presents the holding-period returns and Fama-French alpha up to 3 months ahead; Fig. C.1 in Appendix C graphically represents Table 5.

We observe that the return to the *Buy/RRH* winner portfolio is positive and statistically significant at the 1% level, suggesting that analysts are able to extract good news from the recency momentum strategy and earn positive holding-period returns for the next 3 months. Specifically, the *Buy/RRH* winner portfolio earns holding-period returns of 10.11%, 13.04% and 17.46% (Panels A, B, and C) in the following 1, 2, and 3 months. The corresponding Fama-French three-factor adjusted alphas to *Buy/RRH* portfolios are consistent.

Conversely to the winner portfolio, the holding-period returns to the *Sell/RRL* loser portfolio are significantly positive at 3.88% in the first month (Panel A), but gradually decline to − 0.97% (Panel B) and − 7.7% (Panel C) in the second and third month, respectively. These findings are interesting and provide additional support to earlier evidence regarding analysts' optimistic bias (e.g., Zhang, 2006; Chen et al., 2015). Thus, analysts tend to underreact to unfavourable news and gradually revise their downward revisions over the months. Consequently, there is a larger stock price drift following downward forecast revisions than upward (Hypothesis 2). With regard to the corresponding Fama-French three-factor alphas, only the coefficient on the *Sell/RRL* portfolio is statistically significant at the 1% level at − 6.90% at the third month.

Table 5
Two-way portfolio level analysis (returns).
This table reports the average monthly portfolio returns in the two-way portfolio-level analysis. Panels A, B, and C present *month t + 1, t + 2* and *t + 3* holding-period returns respectively. The corresponding Fama-French three-factor alphas of the winner and loser portfolios (*Buy/RRH* and *Sell/RRH*) are reported as well. *Buy (Sell)* revision is a dummy variable equal to 1 if the change in forecast is ranked in the top (bottom) portfolio at month *t*, and 0 otherwise. RRH (RRL) is a dummy variable that equals 1 if stocks are ranked in the top (bottom) quintile of BH's RR, and 0 otherwise. For full description of the variables, please refer to Appendix A. The sample consists of stocks listed on NYSE, AMEX, and NASDAQ for the period January 1995 to December 2014. The corresponding t-statistics are reported in parentheses. Boldface represents our key variables of interest. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels.

Recency portfolio	Forecast revision portfolio				
	Rev 1 (Sell)	Rev2	Rev3	Rev4	Rev 5 (Buy)
Panel A: 1-month holding-period returns					
P1 (RRL)	**0.0388****	− 0.0082	− 0.0288***	0.0053	0.0055
	(1.93)	(− 0.74)	(− 2.54)	(0.27)	(0.28)
P2	− 0.0096	− 0.0013	− 0.0226*	− 0.0118	0.0112
	(− 0.61)	(− 0.08)	(− 1.95)	(− 1.04)	(0.76)
P3	− 0.0023	− 0.0084	− 0.0163	− 0.0269**	0.0095
	(− 0.14)	(− 0.60)	(− 1.02)	(− 2.25)	(0.67)
P4	0.0148	− 0.0137	− 0.0082	0.0043	0.0071
	(0.84)	(− 0.66)	(− 0.60)	(0.38)	(0.42)
P5 (RRH)	0.0562**	0.0234	0.0343*	0.0688***	**0.1011*****
	(2.55)	(1.06)	(1.74)	(6.32)	**(2.69)**
1-Month Fama French 3-factor alpha					
Portfolio (*Buy/RRH*)					0.1214**
					(2.61)
Portfolio (*Sell/RRL*)					0.02437
					(0.49)
Panel B: 2-months raw returns					
P1 (RRL)	**− 0.0097**	− 0.0221	− 0.0461***	0.0163	0.0033
	(− 0.39)	(− 1.34)	(− 2.76)	(0.63)	(0.14)
P2	–0.0411*	0.0119	− 0.0155	− 0.0033	0.0136
	(− 1.88)	(0.53)	(− 0.74)	(− 0.21)	(0.71)
P3	− 0.0253	− 0.0161	0.0022	− 0.0076	− 0.0027
	(− 1.49)	(− 0.82)	(0.10)	(− 0.47)	(− 0.19)
P4	0.0082	0.0214	0.0284	0.0230	0.0019
	(0.36)	(0.60)	(1.56)	(1.34)	(0.07)
P5 (RRH)	0.0786**	0.0749***	0.0917***	0.1188***	**0.1304*****
	(2.52)	(2.81)	(2.85)	(8.81)	**(3.48)**
2-Months Fama French 3-factors alpha					
Portfolio (*Buy/RRH*)					0.1119**
					(2.35)
Portfolio (*Sell/RRL*)					− 0.0390
					(− 1.30)
Panel C: 3-months holding-period returns					
P1 (RRL)	**− 0.0770****	− 0.0181	− 0.0532**	0.0129	− 0.0358
	(− 2.34)	(− 0.83)	(− 2.40)	(0.42)	(− 1.03)
P2	− 0.0306	0.0225	− 0.0361	0.0036	0.0068
	(− 0.77)	(0.79)	(− 1.57)	(0.16)	(0.23)
P3	− 0.0224	− 0.0391*	0.0220	0.0213	− 0.0020
	(− 0.86)	(− 1.81)	(0.83)	(0.72)	(− 0.09)
P4	0.0277	0.0497	0.0836***	0.0461**	0.0837**
	(0.81)	(1.41)	(3.08)	(2.15)	(2.04)
P5 (RRH)	0.1477***	0.1054***	0.1905***	0.1730***	**0.1746*****
	(2.94)	(2.88)	(3.38)	(7.56)	**(4.26)**
3-Months Fama French 3-Factors alpha					
Portfolio (*Buy/RRH*)					0.1986***
					(7.37)
Portfolio (*Sell/RRL*)					− 0.0697***
					(− 4.40)

In summary, we find support that analysts are slower to revise their forecast revisions following bad news (stocks in the *RRL* portfolio). Analysts are able to pick up momentum signals throughout the quarter and make forecast revisions that are positively correlated with the positive momentum indicators (Hypothesis 4). Specifically, stocks listed in the winner portfolio (*Buy/RRH* portfolio) earn holding-period returns and Fama-French alphas that are consistently higher than stocks listed in the loser portfolio (*Sell/RRL* portfolio).

4.4.3. Two-way portfolio-level analysis between recency ratio and forecast revision measures with positive performance

In this section, we incorporate analysts' positive performance (*Perf*) into the analysis to test Hypothesis 3. We expect stocks covered by better performing analysts to have higher post-forecast revision drift, as these analysts' forecasts are more accurate, which increases returns to forecast revisions (Laksanabunsong, 2015).

In this analysis, we only include stocks with positive performance, there are 719 observations in the sample. Table 6 presents the holding-period returns and corresponding Fama-French three-factor alphas for the next 3 months ahead.[27] Fig. C.2 in Appendix C graphically represents Table 6. Panels A, B, and C of Table 6 show that the conditioning of stocks covered by better performing analysts has substantially increased holding-period returns for the next 3 months relative to the results shown in Table 5. Specifically, with the addition of the positive performance variable, returns to the *Buy/RRH* (with positive performance) winner portfolio increase by 2.64% for the first month, 0.05% for the second month, and 3.63% for the third month.[28] Similarly, the Fama-French three-factor alphas documented for the winner portfolios are statistically significant across the next 3 months. The *Sell/RRL* (with positive performance) loser portfolio represented in Table 6 exhibits a pattern in the holding-period returns identical to that in Table 5. That is, with or without the inclusion of positive performance, returns in the first month are significantly positive at 4.88% (Panel A), but gradually decline to − 7.94% (Panel C) in the third month.

4.5. Multivariate regressions on stocks in the recency momentum strategy

Our analysis focuses on stocks assigned to the recency strategy portfolio (RRH and RRL portfolio). This tests whether analysts' forecast revisions can pick up indicators of the recency momentum strategy (Hypothesis 4). If analysts base their forecast revisions on evidence of price-momentum, then we would expect upward (downward) forecast revisions to explain future stock returns in the winner (loser) recency portfolio.

Table 7 presents stock returns for month $t + 1$, $t + 2$, and $t + 3$ respectively as the dependent variable. Columns (1), (3) and (5) report results of forecast revision portfolios without positive performance, and Columns (2), (4), and (6) include positive performance. Our sample comprises approximately 578 stocks in the RRH (RRL) portfolios. We control for information uncertainty, GH's 52-week-high momentum variables, firm and time fixed effects, and use robust standard errors to correct for heteroskedasticity.

The results reported in Table 7 are consistent with Hypotheses 2 and 4. First, the coefficient of the *Buy* revision in Column (1) is 1.82% (t-statistic = 2.12), which signifies the ability of upward revision to pick up good news in the recency strategy at month $t + 1$. Within the portfolios covered in our study, the economic significance is that purchasing stocks with a *Buy* revision is an outperformance of 1.82% against a portfolio without a *Buy* revision. This can lead to an annualized outperformance of 24%. In Column (5) we observe that the coefficient of the *Sell* revision is − 3.36% (t-statistic = − 1.92), which denotes the predictability of downward revision at month $t + 3$. Altogether, the asymmetric pattern exhibited in analysts' earnings forecast revisions is pervasive. The forecasting pattern of sell-side analysts remains largely unchanged to support Hypothesis 2. Specifically, analysts make timelier upward revisions (buy stocks in

Table 6
Two-way portfolio level analysis with positive performance (returns)
This table reports the average monthly portfolio returns in the two-way portfolio-level analysis with the inclusion of positive performance (*Perf*). Panels A, B, and C present *month t + 1, t + 2* and *t + 3* holding-period returns respectively. The corresponding Fama-French three-factor alphas of the winner and loser portfolios (*Buy/RRH* and *Sell/RRH*) are reported as well. *Buy (Sell)* revision is a dummy variable that equals 1 if the change in forecast is ranked in the top (bottom) portfolio at month *t*, and 0 otherwise. RRH (RRL) is a dummy variable that equals 1 if stocks are ranked in the top (bottom) quintile of BH's RR, and 0 otherwise. Positive performance (*Perf*) is a dummy variable that equals 1 if *UpdatedError* is less than *ExpectedError*. For full description of the variables, please refer to Appendix A. The sample consists of stocks listed on NYSE, AMEX, and NASDAQ for the period January 1995 to December 2014. The corresponding t-statistics are reported in parentheses. Boldface represents our key variables of interest. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels.

Recency portfolio	Forecast revision portfolio with positive performance				
	Rev 1 (Sell)	Rev2	Rev3	Rev4	Rev 5 (Buy)
Panel A: 1-month raw returns					
P1 (RRL)	**0.0448****	0.0088	− 0.0169	0.0021	0.0275
	(2.09)	(0.61)	(− 1.24)	(0.10)	(0.73)
P2	− 0.0260	− 0.0179	− 0.0278**	− 0.0106	0.0043
	(− 1.33)	(− 0.72)	(− 2.16)	(− 0.71)	(0.30)
P3	− 0.0133	− 0.0163	− 0.0409**	− 0.0240**	0.0189
	(− 0.75)	(− 0.73)	(− 2.09)	(− 2.00)	(0.97)
P4	0.0308	0.0194	0.0069	0.0036	0.0242
	(1.06)	(0.73)	(0.47)	(0.22)	(1.30)
P5 (RRH)	0.0560***	0.0095	0.0438**	0.0504***	**0.1275****
	(3.10)	(0.39)	(2.09)	(4.49)	**(2.07)**
1-Month Fama-French 3-Factors alpha					
Portfolio (RRH, Buy)					0.1193
					(1.39)
Portfolio (RRL, Sell)					0.0268*
					(1.88)
Panel B: 2-months Raw Returns					
P1 (RRL)	**0.0014**	− 0.0001	− 0.0291	0.0270	0.0259
	(0.05)	(− 0.10)	(− 1.32)	(0.73)	(0.65)
P2	-0.0466	-0.0028	-0.0119	0.0037	-0.0188
	(− 1.67)	(− 0.09)	(− 0.43)	(0.17)	(− 1.34)
P3	-0.0158	-0.0279	-0.0298	0.0081	0.0129
	(− 0.76)	(− 0.89)	(− 1.15)	(0.40)	(0.68)
P4	0.0208	0.0663	0.0255	0.0243	0.0444
	(0.61)	(1.63)	(1.15)	(1.09)	(1.13)
P5 (RRH)	0.0913***	0.0396	0.0816***	0.0970***	**0.1390****
	(2.93)	(1.11)	(2.83)	(5.21)	**(2.27)**
2-months Fama-French 3-Factors alpha					
Portfolio (RRH, Buy)					0.1195
					(1.40)
Portfolio (RRL, Sell)					-0.0041
					(− 0.13)
Panel C: 3-months Raw Returns					
P1 (RRL)	**− 0.0794*****	0.0227	− 0.0398	0.0103	− 0.0145
	(− 2.69)	(1.02)	(− 1.42)	(0.24)	(− 0.21)
P2	− 0.0568	0.0190	− 0.0321	0.0294	− 0.0185
	(− 1.30)	(0.44)	(− 1.42)	(0.85)	(− 0.79)
P3	− 0.0206	− 0.0518	0.0229	0.0611	− 0.0011
	(− 0.53)	(− 1.51)	(0.64)	(1.46)	(− 0.04)
P4	0.0478	0.0728	0.0749**	0.0457	0.1368**
	(1.16)	(1.92)	(2.40)	(1.51)	(2.22)
P5 (RRH)	0.1670***	0.0569	0.1922***	0.1221***	**0.2109*****
	(3.05)	(1.42)	(2.74)	(3.85)	**(3.73)**
3-Months Fama French 3-Factors Alpha					
Portfolio (RRH, Buy)					0.1653***
					(3.12)
Portfolio (RRL, Sell)					-0.0901***
					(− 3.02)

[27] With reference to Table 1 (Descriptive Statistics), out of the 1410 observations in our sample, 57.29% of our stocks show positive performance (*Perf* = 1).

[28] In the first month, the incremental effect of positive performance is computed as 12.75% − 10.11% = 2.64%. The second month as 13.09% − 13.04% = 0.05%. The third month as 21.09% − 17.46% = 3.63%.

Table 7
Panel regression with stocks in the recency strategy.
This table reports the regression results for month *t + 1, t + 2*, and *t + 3* stock returns as the dependent variable when we limit our sample to stocks in the recency strategy (RRH and RRL). Columns (1), (3) and (5) report results of forecast revision portfolios without positive performance, and Columns (2), (4), and (6) report results of forecast revision portfolios with positive performance. The full regression model is:

$$
\begin{aligned}
R_{j,t+p} = \beta_0 &+ \beta_{1jt}\, BUY_{j,t} \times Perf_{j,t} + \beta_{2jt}\, SELL_{j,t} \\
&\times Perf_{j,t} + \beta_{3jt}\, Perf_{j,t} + \beta_{4jt}\, WHH_{j,t-1} \\
&+ \beta_{5jt} WHL_{j,t-1} + \beta_{6jt}\, Size_{j,t+p-1} + \beta_{7jt}\, BM_{j,t+p-1yr} \\
&+ \beta_{8jt}\, Vol_{j,t+p-1yr} + \beta_{9jt}\, Age_j + \varepsilon_{jt}..
\end{aligned}
$$

Subscripts *j, t*, and *p* represent stock *j*, time *t* and *p* = month *t + 1 to t + 3*. For full description of the variables, please refer to Appendix A. The sample is stocks listed on NYSE, AMEX, and NASDAQ for the period January 1995 to December 2014. The corresponding t-statistics are in parentheses. Boldface represents our key variables of interest. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels.

	Predicted sign	Stock returns at T + 1 month		Stock returns at T + 2 months		Stock returns at T + 3 months	
Variables		(1) News	(2) With positive performance	(3) News	(4) With positive performance	(5) News	(6) With positive performance
Buy	+	**0.0182****		**− 0.0057**		**− 0.0091**	
		(2.12)		**(− 0.60)**		**(− 0.87)**	
Sell	−	**− 0.0007**		**− 0.0095**		**− 0.0336***	
		(− 0.07)		**(− 0.72)**		**(− 1.92)**	
Buy*Perf	+		**0.0270****		**− 0.0167**		**0.0091**
			(2.10)		**(− 0.93)**		**(0.74)**
Sell *Perf	−		**0.0032**		**− 0.0085**		**− 0.0374****
			(0.19)		**(− 0.49)**		**(− 2.53)**
Perf	±		− 0.0055		− 0.0004		− 0.0018
			(− 0.61)		(− 0.04)		(− 0.17)
WHH	+	0.0420***	0.0414***	0.0409***	0.0406***	0.0352***	0.0335***
		(4.19)	(4.26)	(3.91)	(3.80)	(4.52)	(4.37)
WHL	−	− 0.0565***	− 0.0580***	− 0.0209	− 0.0217	− 0.0612***	− 0.0620***
		(− 3.77)	(− 3.89)	(− 1.37)	(− 1.40)	(− 3.34)	(− 3.35)
$Size_{t-1\ month}$	±	− 0.0293***	− 0.0294***	− 0.0219**	− 0.0218**	− 0.0222***	− 0.0205***
		(− 3.61)	(− 3.75)	(− 2.44)	(− 2.48)	(− 2.96)	(− 2.88)
$BM_{t-1\ year}$	±	− 0.0430	− 0.0463	− 0.0283	− 0.0267	0.0114	0.0106
		(− 1.46)	(− 1.51)	(− 1.35)	(− 1.28)	(0.59)	(0.54)
$Volatility_{t-1\ year}$	±	1.6913**	1.6791**	0.0257	0.0133	1.3818*	1.3915
		(2.10)	(2.03)	(0.03)	(0.02)	(1.75)	(1.67)
Firm age	±	0.0008	0.0008	0.0012	0.0011	− 0.0006	− 0.0007
		(0.60)	(0.60)	(0.96)	(0.85)	(− 0.56)	(− 0.63)
Cons	±	0.2101***	0.2200***	0.1664**	0.1657**	0.1295*	0.1092*
		(2.87)	(3.15)	(2.38)	(2.46)	(1.99)	(1.81)
N		578	578	577	577	592	592
Adj. R^2		0.169	0.165	0.068	0.068	0.129	0.128
F		26.6346	24.0461	9.3275	14.0439	24.66	23.32
Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes

t Statistics in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01

the RRH portfolio), but are generally more reluctant to recommend downward revisions (sell stocks in the *RRL* portfolio).

An interesting finding from Column (5) is that the *Buy* revision is insignificant in the regression at month *t + 3*. As there are greater uncertainties in stocks that form the recency strategy, analysts who subsequently revise their forecasts are likely to be herding upon earlier upward revision consensuses (Chen et al., 2015). Hence, only the foremost upward revision is informative, and the subsequent upward revisions bring less information to the market.

Second, we find that the interaction of positive performance and the *Buy* revision portfolio in Column (2) substantially improves the information content of upward revisions at month *t + 1*. The difference between the *Buy* revision without positive performance in Column (1) and the *Buy*Perf* revision with positive performance in Column (2) is 0.88% (2.70%–1.82%). Within the portfolios covered in our study, the economic significance is that purchasing stocks with a *Buy*Perf* revision with positive performance is an outperformance of 2.70% against a portfolio without a *Buy* revision. This can lead to an annualized outperformance of 38%.

We do not find any significance in the forecast revision variables at month *t + 2*. Since the *Buy* revision in Column (5) is insignificant, we expect not to find the *Buy*Perf* revision in Column (6) predicting returns at month *t + 3*. However, the *Sell* revision of − 3.36% (t-statistic = − 1.92) and the *Sell*Perf* revision of − 3.74% (t-statistic = − 2.53) in Columns (5) and (6) respectively are significant. Surprisingly, the interaction of positive performance and the *Sell* revision generates an incremental effect of − 0.48%.

Generally, the findings confirm the incremental effect of positive performance for upward revisions. However, the same conclusion cannot be drawn for *Sell* revisions. In Table 7, we observe an increase in significance and coefficient magnitude when positive performance is added to the *Sell* revision. We observe a close association between stocks in the 52-week-high strategy and stocks in the recency strategy. Specifically, the 52-week-high momentum variables are mostly statistically significant at the 1% level, except for month *t + 2* where *WHL* is insignificant (in Columns 3 and 4). Furthermore, when we restrict our sample to stocks in the recency strategy, our findings suggest that analysts are able to pick up recency momentum signals at

Table 8
Year by year buy-sell forecast revision strategy.
This table presents the year-by-year analysis of average monthly returns to the Buy-Sell revision strategy up to three-months ahead. *Buy (Sell)* revision is a dummy variable equals to 1 if the change in forecast is ranked in the top (bottom) portfolio at month *t*, and 0 otherwise. The *Buy-Sell* strategy represents a trading strategy that simultaneously buys stocks in Buy revision and short-selling stocks in the Sell revision portfolio. For full description of the variable, please refer to Appendix A. The sample consists of stocks listed on NYSE, AMEX and NASDAQ for the period January 1995 to December 2014. The corresponding t-statistics are reported in parentheses. Boldface represents our key variables of interest. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels.

		Stock returns t			Stock returns t + 1			Stock returns t + 2			Stock returns t + 3		
Year	Obs	Buy mean	Sell mean	Diff (Buy − Sell)	Buy mean	Sell mean	Diff (Buy − Sell)	Buy mean	Sell mean	Diff (Buy – Sell)	Buy mean	Sell mean	Diff (Buy – Sell)
1995	4	0.0273	− 0.0170	0.0442	0.0768	− 0.0325	0.1094**	0.0472*	− 0.0254	0.0726**	0.0571	− 0.0111	0.0682*
		(1.53)	(− 0.38)	(1.18)	(2.00)	(− 1.55)	(4.40)	(2.74)	(− 2.31)	(5.49)	(2.28)	(− 0.54)	(2.52)
1996	4	0.0639	− 0.0155	0.0794	0.0110	− 0.0117	0.0227	0.0738	− 0.0411	0.1148	0.1018	− 0.0511	0.1530
		(0.76)	(− 0.60)	(1.27)	(0.23)	(− 0.23)	(0.54)	(1.23)	(− 0.80)	(2.29)	(1.28)	(− 0.91)	(2.23)
1997	5	0.0367	0.0046	0.0367	0.0445	0.0482	− 0.0037	0.1459	− 0.0232	0.1691	0.1450	− 0.0269	0.1718
		(0.64)	(0.16)	(0.50)	(1.43)	(0.96)	(− 0.14)	(1.38)	(− 0.64)	(1.43)	(1.46)	(− 0.41)	(1.24)
1998	3	0.0753	− 0.0305	0.1059	0.0703	− 0.0242	0.0945	0.0661	0.0442	0.0219	0.0531	0.0372	0.0159
		(0.71)	(− 0.63)	(1.34)	(0.93)	(− 0.39)	(1.90)	(1.79)	(0.61)	(0.54)	(1.02)	(0.39)	(0.28)
1999	7	0.0458	− 0.1043*	0.1501	− 0.0400	− 0.0166	− 0.0234	− 0.0218	− 0.0735	0.0517	− 0.0586	− 0.1014	0.0428
		(0.47)	(− 2.20)	(1.76)	(− 1.00)	(− 0.56)	(− 0.37)	(− 0.82)	(− 1.49)	(1.14)	(− 1.07)	(− 1.45)	(0.54)
2000	**5**	**0.0319**	**0.0889**	**− 0.0570**	**0.0920**	**0.0417**	**0.0502**	**0.0891**	**− 0.0166**	**0.1057**	**0.1479****	**0.0253**	**0.1225**
		(0.43)	**(1.40)**	**(− 0.67)**	**(1.21)**	**(1.09)**	**(1.09)**	**(1.98)**	**(− 0.87)**	**(1.74)**	**(3.28)**	**(0.63)**	**(1.94)**
2001	**6**	**0.0082**	**0.1001**	**− 0.0919**	**− 0.0266**	**− 0.0447**	**0.0182**	**0.0309**	**0.0432**	**− 0.0123**	**0.0813**	**− 0.0221**	**0.1033**
		(0.49)	**(1.32)**	**(− 1.21)**	**(− 0.60)**	**(− 0.61)**	**(0.28)**	**(0.58)**	**(0.47)**	**(− 0.15)**	**(1.18)**	**(− 0.27)**	**(1.30)**
2002	5	− 0.0697	0.0053	− 0.0749	− 0.0118	− 0.0011	− 0.0106	− 0.0169	− 0.1268	0.1099	− 0.0077	− 0.1640	0.1563**
		(− 1.47)	(0.05)	(− 0.83)	(− 0.42)	(− 0.01)	(− 0.17)	(− 0.26)	(− 1.17)	(1.57)	(− 0.09)	(− 1.67)	(2.84)
2003	6	0.0331	− 0.0144	0.0476*	0.0212	0.0102	0.0110	0.0119	0.0137	− 0.0018	0.0824	0.0647	0.0177
		(1.39)	(− 0.41)	(2.29)	(1.46)	(0.60)	(0.57)	(0.42)	(0.32)	(− 0.042)	(1.40)	(0.99)	(0.25)
2004	6	0.0635	0.0033	0.0603	0.0363	0.0024	0.0339**	0.0452	0.0552*	− 0.0100	0.0657	0.0926	− 0.0270
		(1.64)	(0.09)	(1.28)	(1.68)	(0.12)	(5.17)	(1.14)	(2.57)	(− 0.24)	(1.09)	(1.00)	(− 0.24)
2005	6	0.0706**	− 0.0233	0.0939**	0.0101	− 0.0107	0.0209	0.0469*	0.0441	0.0028	0.0296	0.0556	− 0.0259
		(2.65)	(− 2.00)	(4.07)	(0.58)	(− 0.34)	(1.00)	(2.13)	(1.08)	(0.07)	(2.00)	(0.94)	(− 0.48)
2006	4	0.0276*	− 0.0010	0.0286	0.0094	− 0.0036	0.0130	0.0737	0.0152	0.0585	0.1174	0.0085	0.1088
		(2.32)	(− 0.03)	(1.09)	(1.23)	(− 0.23)	(0.61)	(1.30)	(0.40)	(1.54)	(1.70)	(0.27)	(2.09)
2007	**4**	**0.0216**	**− 0.0321**	**0.0537**	**0.0505**	**− 0.0552**	**0.1057***	**0.0492**	**− 0.0358**	**0.0850****	**0.0734**	**− 0.0334**	**0.1069***
		(0.43)	**(− 1.35)**	**(1.37)**	**(1.56)**	**(− 1.23)**	**(2.69)**	**(1.56)**	**(− 1.23)**	**(4.61)**	**(1.57)**	**(− 1.08)**	**(2.85)**
2008	**5**	**− 0.0822***	**− 0.0866*****	**0.0044**	**0.0162**	**− 0.0151**	**0.0313**	**0.0014**	**− 0.0854****	**0.0868*****	**0.0306**	**− 0.1034**	**0.1340****
		(− 2.45)	**(− 4.27)**	**(0.13)**	**(0.36)**	**(− 0.18)**	**(0.69)**	**(0.07)**	**(− 3.16)**	**(6.51)**	**(0.77)**	**(− 1.76)**	**(3.01)**
2009	7	0.0656*	0.0084	0.0571	0.1144*	0.0686	0.0458	0.0216*	0.0704	-0.0488	-0.0005	0.0358	-0.0363
		(2.00)	(0.26)	(1.83)	(2.21)	(1.99)	(1.21)	(0.28)	(1.07)	(− 0.74)	(− 0.01)	(0.38)	(− 0.69)
2010	5	0.0580	0.0152	0.0428*	0.0486	0.0494	− 0.0008	0.0252	− 0.0128	0.0380	0.0796*	0.0126	0.0669*
		(1.91)	(0.36)	(2.47)	(1.56)	(1.06)	(− 0.03)	(0.76)	(− 0.39)	(1.29)	(2.76)	(0.33)	(2.27)
2011	4	− 0.0014	− 0.0119	0.0105	− 0.0077	− 0.0192	0.0115	− 0.0120	− 0.0393	0.0272	0.0397	− 0.0330	0.0726
		(− 0.05)	(− 0.27)	(0.45)	(− 0.29)	(− 0.42)	(0.40)	(− 0.38)	(− 0.88)	(1.97)	(0.54)	(− 0.32)	(2.16)
2012	5	0.0154	− 0.0020	0.0174	0.0435**	0.0124	0.0311	0.1015	0.0287	0.0727	0.1208	0.0472	0.0736
		(0.56)	(− 0.14)	(0.55)	(3.41)	(0.36)	(1.24)	(1.77)	(1.25)	(1.16)	(1.97)	(1.67)	(1.47)
2013	5	0.0625**	0.0231	0.0394	0.0576	0.0395	0.0181	0.1104**	0.0730**	0.0374	0.1388**	0.0656**	0.0732*
		(2.97)	(1.07)	(1.56)	(1.59)	(1.10)	(0.34)	(3.42)	(3.82)	(0.93)	(4.34)	(3.54)	(2.50)
2014	5	− 0.0166	− 0.0147	− 0.0019	0.0222	− 0.0296	0.0518	− 0.0076	0.0323	− 0.0399	− 0.0255	0.0366	− 0.0620
		(− 0.90)	(− 0.59)	(− 0.12)	(0.58)	(− 0.98)	(1.58)	(− 0.28)	(1.46)	(− 0.92)	(− 1.25)	(0.57)	(0.87)
Obs	101												

different stages to make forecast revisions that are instrumental in predicting profits from the recency strategy, even after controlling for information uncertainty. Perhaps analysts do not explicitly make predictions about the profitability of the recency strategy, but Jegadeesh et al. (2004) have shown that analysts generally favour stocks with positive price-momentum. Therefore, the findings from Table 7 suggest that analysts provide forecast revisions that are closely related to price-momentum indicators, and their ability to pick under- or over-valued stocks is an important source of information to reconcile the price-continuation momentum effect. The findings lend support to Hypothesis 4.

Finally, Table 7 validates the incremental effects of positive performance for upward revisions in the short-term. For example, revisions on stocks that are covered by better performing analysts (who have lower short-term forecast errors than expected) are presumed to be generally more credible and precise (Laksanabunsong, 2015). However, we find mixed results for downward revisions. Therefore, we find only partial support for Hypothesis 3 and show that positive performance accentuates stock price drift following upward revisions, but not downward revisions.

4.6. Summary of findings in relation to hypotheses

The summary findings on the four hypotheses of this thesis are as follows:

Hypothesis 1
Stock prices drift in the direction of analysts' earnings forecast revisions.

Our portfolio-level analysis shows that the holding-period returns following analysts' earnings forecast revisions monotonically increase with time, and the *Buy-Sell* strategy is profitable and statistically significant. Results using the corresponding Fama-French three-factor alphas are consistent. As a result, our findings lend support to *Hypothesis* 1.

Hypothesis 2. Post-revision drift following good and bad news is asymmetric.

We find consistent results throughout our empirical analysis that upward (downward) forecast revision is positively (negatively) related to stock returns in the earlier (later) months. For example, the coefficient on *Buy*Perf* is positively significant at the first month across our tests. In contrast, the coefficient on the *Sell* revision does not hold explanatory power for 1-month-ahead stock returns, and is negatively significant at the second month onwards. This collective evidence lends support to the asymmetric pattern observed in post-forecast revision drift following good and bad news, where we observe far more stock price drift in the *Sell* revision portfolio than the *Buy* revision (Ivković & Jegadeesh, 2004; Chen et al., 2015). Overall, these findings lend support to Hypothesis 2.

Hypothesis 3

Positive analyst performance accentuates post-forecast revision drift.

We find that the addition of positive performance can induce short-term post-forecast revision drift only for stocks with upward revisions. However, the same incremental effect is not found for downward revisions: we find mixed results in our analyses. Therefore, Hypothesis 3 is supported for upward revisions but not for downward revisions.

Hypothesis 4

Analysts' earnings forecast revisions have incremental explanatory power for future stock returns after momentum and information uncertainties are controlled for.

We find that upward (downward) forecast revision is persistently statistically significant in the earlier (later) months for stocks in our original sample and stocks in the recency strategy. Therefore, since analysts' forecast revisions have incremental explanatory power for future stock returns after momentum and information uncertainties are controlled for, our findings lend support to Hypothesis 4.

5. Conclusion

We investigate whether sell-side equity analysts can facilitate market efficiency by picking up momentum indicators, thus providing value-relevant information for investors. The prevalence of the 52-week-high momentum anomaly can largely be reconciled with information uncertainty that drives the heuristic biases of investors (Burghof & Prothmann, 2011), and provides a fertile setting for examining the value and timing of forecast revisions (Jiang et al., 2005; Burghof & Prothmann, 2011). Hong and Wu (2016) show that applying past stock returns with different time horizons improves the ability of firm fundamentals to explain stock prices. They also find that firm fundamentals dominate stock price moments of small-sized firms during periods of high market uncertainty.

Sell-side equity analysts' forecast revisions have been found to be inefficient. Amir and Ganzach (1998) show evidence of analysts' underreacting to stocks' fundamental value due to representative biases, and Zhang (2006) report a positive correlation between information uncertainty and analysts' forecast errors. Chen et al. (2015) find that analysts have strong incentives to herd to consensus or to the most recent revisions. Analysts are known for their overly optimistic forecasting behaviour due conflicts of interest, where they are pressured to underweight (overweight) negative (positive) private information initially to improve relationships with management and attract both investment-banking and brokerage revenue (Ivković & Jegadeesh, 2004; Muslu & Xue, 2013).

Despite the prevalence of analysts' biases, we premise that analysts' earnings forecast revisions can still facilitate market efficiency at different stages as analysts have the ability to identify under- or over-valued stocks and provide informed opinions to help reconnect mispriced stocks back to their fundamental value more efficiently (Womack, 1996). The ability to influence investors is more pronounced if a stock with high information uncertainty is covered by better performing analysts. Consistent with prior research, we expect analysts to be slower in their response to stocks with bad news (e.g., a RRL portfolio), and we subsequently observe that analysts revise their estimates downward to a greater degree. Thus, when uncertainty obscures the acumen of investors (i.e., stocks with the most recent or distant 52-week-high price), analysts can play the vital role of an information intermediary by picking up indicators of momentum and therefore provide valuable signals of the stocks' future value.

We find that stock prices drift in the direction of analysts' forecast revisions as the holding-period returns following analysts earnings forecast monotonically increase with time. Our analyses also shows that that upward (downward) forecast revision is positively (negatively) related to stock returns in the earlier (later) months. Thus, there is an asymmetric pattern observed in post-forecast revision drift following good and bad news such that there is greater stock price drift in the *Sell* revision portfolio than the *Buy* revision. In the year-by-year analysis of post-forecast revision drift, our results show that returns from the *Buy-Sell* strategy for the 2007-2008 GFC/GR period are higher, that is mainly driven by returns following the *Sell* revision. We do not find evidence of 2003 post-Reg FD affecting our results. Last, our multivariate regression analysis shows that analysts' forecast revisions have incremental explanatory power for future stock returns after momentum and information uncertainties are controlled for upward revisions.

Finally, for investors, the implications of our study that analysts have the ability to pick up momentum indicators and therefore stocks with potential value. However, the caveat is that analysts are often pressured to balance the costs and benefits in their forecasts, and tend to exhibit a more significant delay in reacting to bad news than good news. (Ivković & Jegadeesh, 2004; Muslu & Xue, 2013; Chen et al., 2015). As a result, it is difficult for investors to discern the timing of a true sell recommendation.

Uncited references

Appendix A. Description of key variables

Table A.1 Description of key variables.

The table presents the definition of variables used in the regression analysis Eqs. (8), (9) and (10). Panel A presents the dependent variable. Panel B presents the momentum and analysts' forecast revision variables. Panel C presents the control variables that are utilized in this analysis. Panel D describes the variables used in the construction of analysts' positive performance.

Variables	Description
Panel A: dependent variable	
Returns	Return of stock *j* in month *t*. (Returns are winsorized at the 1st and 99th percentile)
Panel B: independent variable	

Analysts' forecast buy (sell) revision portfolio	BUY_j ($SELL_j$) is a dummy variable that equals 1 if the change in monthly mean forecast consensus for stocks j is ranked in the top (bottom) 20% portfolio in the end of portfolio formation month t. The change in monthly mean forecast consensus is measured as the difference between mean forecast consensus for month t and the previous month, scaled by previous month's stock price. (Forecast with value of "-999,999" are removed from sample)
Analysts' positive performance	Positive performance ($Perf_j$) refers to the average analysts' recent performance on stock j, and is a dummy variable that equals 1 if $UpdatedError_t^j$ (average short-term performance) is less than $ExpectedError_t^j$ (intermediate benchmark performance), and is 0 otherwise.
52-Week-high (low) portfolio	52WHH (52WHL) is a dummy variable that equals 1 if stock j's $GH\ 52\ week\ high\ price\ measure = \frac{Current\ Price}{52\ Week\ High\ Price}$ .is ranked in the top (bottom) 20% at the end of month $t-1$, and is 0 otherwise.
Recency ratio high (low) portfolio	RRH (RRL) is a dummy variable that equals 1 if stock j's $\boldsymbol{RecencyRatio}\ (\boldsymbol{RR})\ measure = 1 - \frac{\boldsymbol{Numberofdayssince}\ 52\ \boldsymbol{weekshighprice_j}}{364}$ is ranked in the top (bottom) 20% at the end of month $t-1$,and is 0 otherwise.
Panel C: other control variables	
Prior month returns	Return to stock j at the end of the previous month. (prior month's returns are winsorized at the 1st and 99th percentile)
Firm size	The natural logarithm of stock j's market capitalization (Adjusted Price × Shares Outstanding in millions) at the end of previous month.
Book-to-market ratio	Book value of shareholders' equity plus deferred taxes divided by its market value at the end of the last fiscal year. (Negative book-to-market values are removed from sample)
Volatility	Standard deviation of monthly stock returns over the past year
Firm age	The number of months since Compustat began covering the firm
Panel D: Construction of analysts' positive performance	
Analyst performance (forecast error)	Analyst performance is the difference between the average earnings forecasts (at month t) and actual realized earnings (at quarter t) on stock j, scaled by prior year's stock price and set of firms that analyst i covers. (Actual realized earnings of "-999,999" are removed from sample)
$Expected\text{-}Error_t^j$	Expected Error is the average analyst performance on stock j at month t over the past year (12 months), and it represents the intermediate-term or benchmark performance of the average analyst of the stock.
$Updated\text{-}Error_t^j$	Updated Error is the average analyst performance scaled by the number of analysts on stock j at month t, and it represents the short-term or updated performance of the average analyst of the stock.

Appendix B. Pearson's correlation matrix of key information variables

Table B.1 Pearson correlation matrix.

This table reports the Pearson correlation matrix of the key variables in the original sample. In each month *t,* stocks are in quintile-based portfolios based on the past 6-months GH's proximity to 52-week-high (WH) ratio, BH's recency ratio (RR), and the magnitude of forecast revision. WHH (WHL) is a dummy variable that equals 1 if stocks are in the top (bottom)'s portfolios, and 0 otherwise. RRH (RRL) is a dummy variable that equals 1 if stocks are ranked in the top (bottom)'s quintile, and 0 otherwise. Buy (Sell) revision is a dummy variable that equals 1 if the change in forecast is ranked in the top (bottom) quintile portfolios at month t, and 0 otherwise. The change in forecast is the change in mean earnings forecast between month t and the previous month, scaled by previous month's stock price. Analysts' Performance measures the recent forecasting performance of analysts and is computed as the average forecast error of analyst i, scaled by beginning year stock price and the set of firms analyst i covers. Returns $_{t-1\ month}$ is the prior month's returns. $Size_{t-1\ month}$ is the log of market capitalization (in millions) of stock j at the end of previous month. Book to $Market_{t-1\ year}$ is the book-to-market ratio. $Volatility_{t-1\ year}$ is the standard deviation of monthly stock returns over the past year. Firm Age is the firm's age. For full description of the variables, please refer to Appendix A. The sample consists of stocks listed on NYSE, AMEX and NASDAQ for the period January 1995 to December 2014. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels.

	Returns	**WHH**	**WHL**	**RRH**	**RRL**	**Buy**
Returns	1.00					
WHH	0.063	1.00				
WHL	− 0.004	− 0.240***	1.00			
RRH	0.031	0.540***	− 0.144**	1.00		
RRL	− 0.010	− 0.226***	0.156**	− 0.253***	1.00	
Buy	0.062	0.003	− 0.010	0.014	0.027	1.00
Sell	− 0.071	− 0.096	0.140**	0.013	0.055	− 0.2
Perf	− 0.014	− 0.042	0.073	− 0.013	0.083	0.047
$BM_{t-1\ year}$	− 0.021	− 0.096	0.050	− 0.061	0.140**	0.169
$Size_{t-1year}$	− 0.047	0.124*	− 0.138**	0.044	− 0.039	0.015
$Returns_{t-1\ month}$	− 0.114*	0.248***	− 0.230***	0.274***	− 0.083	0.032
$Vol_{t-1\ year}$	0.034	− 0.115*	0.349***	− 0.035	− 0.007	− 0.0
Firm age	− 0.043	0.070	− 0.079	0.034	− 0.149**	0.066

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix C. Graphical representation of two-way portfolio analysis

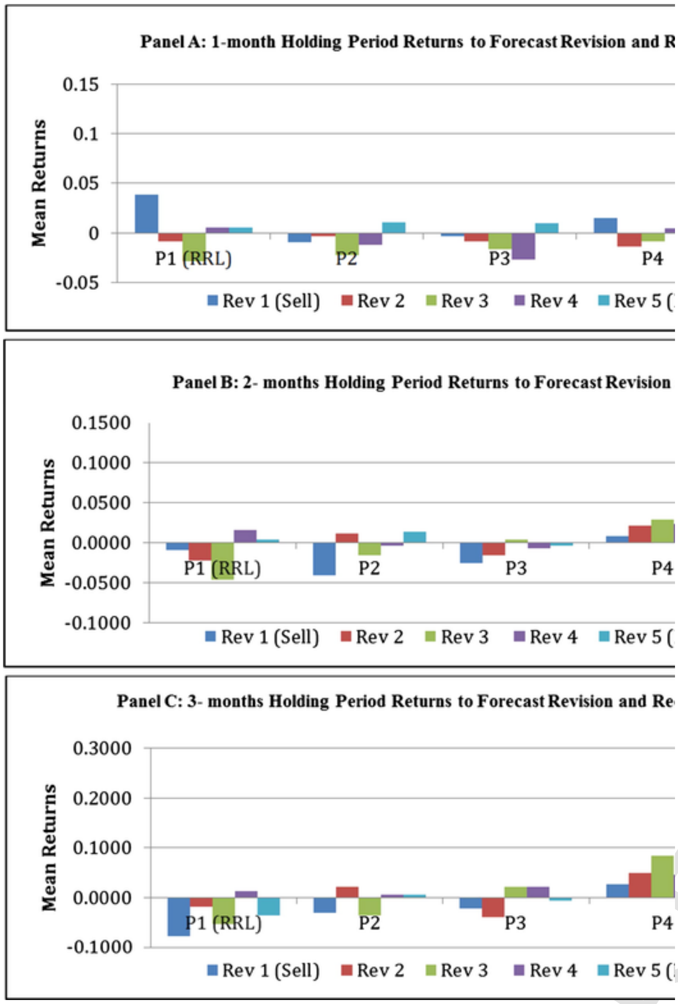

Fig. C.1. Two-way portfolio level analysis.

This figure graphically represents Table 5 and it depicts the two-way portfolio analysis between analysts' forecast revisions and recency portfolios. Panel A, B, and C, presents month $t + 1$, $t + 2$, and $t + 3$ ahead holding-period returns respectively. The vertical-axis represents the corresponding holding-period returns and horizontal-axis represents stocks in the recency portfolio (*P1* to *P5*). The blocks with various colour coding represent stocks in the analysts' forecast revision portfolios (*Rev1* to *Rev5*). Stocks are independently sorted in quintile-portfolios according to their respective criterions. *RRH (RRL)* is a dummy variable that equals 1 if stocks are ranked in the top (bottom) quintile-portfolios based on BH's RR at month $t - 1$, and 0 otherwise. *Buy (Sell)* is a dummy variable that equals 1 if the change in forecast is ranked in the top (bottom) quintile-portfolios at month *t*, and 0 otherwise. For full description of the variables, please refer to Appendix A. The sample consists of stocks listed on NYSE, AMEX and NASDAQ for the period January 1995 to December 2014.

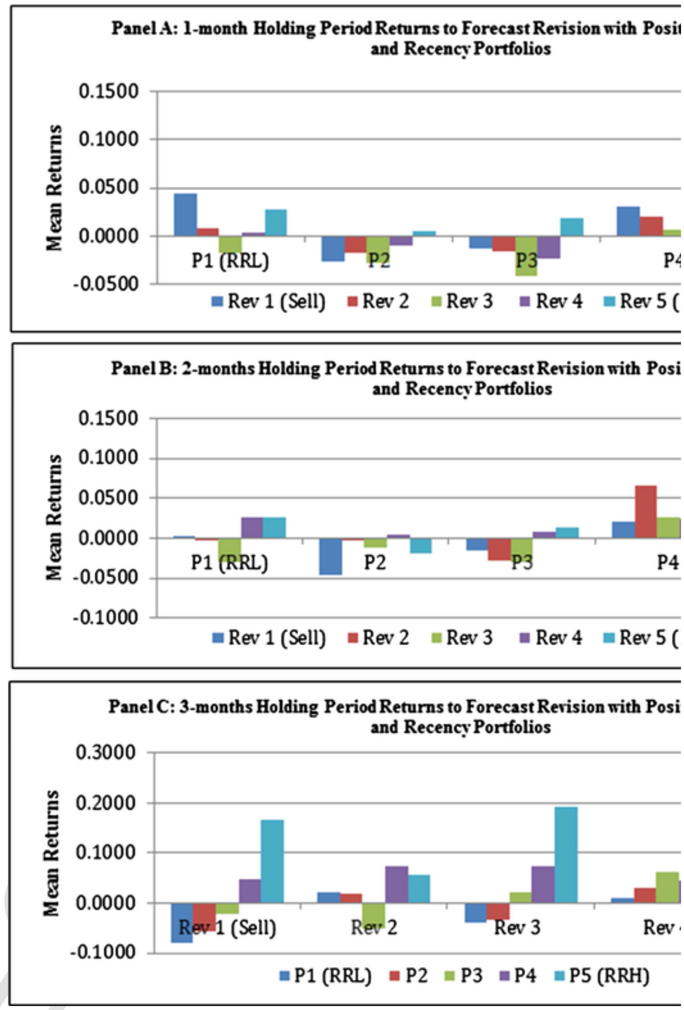

Fig. C.2. Two-way portfolio level analysis with positive performance.

This figure graphically represents Table 6 and it depicts the two-way portfolio analysis between analysts' forecast revisions *with positive performance* and recency portfolios. Panel A, B, and C, presents month $t + 1$, month $t + 2$, and month $t + 3$ ahead holding-period returns respectively. The vertical-axis represents the corresponding holding-period returns and horizontal-axis represents stocks in the recency portfolio (*P1* to *P5*). The blocks with various colour coding represent stocks in the analysts' forecast revision portfolios with positive performance (*Rev1* to *Rev5*). Stocks are independently sorted in quintile-portfolios according to their respective criterions. *RRH (RRL)* is a dummy variable that equals 1 if stocks are ranked in the top (bottom) quintile-portfolios based on BH's RR at month $t - 1$, and 0 otherwise. *Buy (Sell)* is a dummy variable that equals 1 if the change in forecast is ranked in the top (bottom) quintile-portfolios at month *t*, and 0 otherwise. Positive Performance (*Perf*) represents stocks that are covered by better performing analysts, and equals to 1 if their *UpdatedError* is less than *ExpectedError*, and 0 otherwise. For full description of the variables, please refer to Appendix A. The sample consists of stocks listed on NYSE, AMEX and NASDAQ for the period January 1995 to December 2014.

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