Investment Horizon and Price Reaction to Analyst Earnings Forecast Revision

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Aug 22, 2016

ABSTRACT

This paper shows that investment horizon contributes to the stock price reaction associated with analyst earnings forecast revisions. By using share-weighted portfolio turnover levels of mutual fund shareholders of the stock as a measure of investment horizon of the stock's shareholders, we find that investors with short horizon show stronger and more immediate response than for stocks held mainly by long-term investors three days around the three-day window of analyst forecast revision, while those with long-term horizon show slower and gradual reaction and generate more intense post-forecast-revision drift. The results remain robust even after analyst coverage, divergence in opinion, firm size, book-to-market, and momentum are controlled for. Moreover, difference in post-forecast-revision drift between long-term and short-term investors is robust regardless of the information uncertainty level.

Keywords: Analyst forecast revision, Investment horizon, Underreaction, Investor behavior
JEL classification: G10, G11, G14

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1. Introduction

A variety of literature reports that, while analysts' earnings forecast revisions cause an immediate stock price reaction, this price reaction is not complete and drift follows in the subsequent period (Givoly and Lakonishok 1980; Stickel 1991; Engels et al., 2001; Gleason and Lee 2003; Zhang 2006a, 2006b). This phenomenon constitutes evidence against the efficient market hypothesis. Since analysts are generally believed to have superior ability to provide high quality information about firm value, analyst forecast revisions are an important event for investor decision making. Therefore, if the market is efficient and investors actively trade based on this assumption, stock prices should respond to analyst forecast revisions immediately and there should be no price drift after the forecast revision is disclosed to the public.

However, post-forecast revision drift remains a puzzle as to why the information is not perfectly reflected in the stock price. Previous studies of stock price continuation provide behavioral explanations, such as underreaction (Chan et al. 1996), investors' conservatism bias (Barberis et al. 1998), the risk-adjustment explanation (Conrad and Kaul 1998), or market-environment explanations, such as short-sale constraints (Diether, Malloy, and Scherbina 2002). We suggest investors' investment horizon as a potential driver of this phenomenon. Some investors prefer stable profits over a long period. These are known as *long-term investors*. On the other hand, some investors seek high profits in the short-term. We call these investors *short-term investors*. Since short-term investors prefer immediate profits through short-term investment opportunities, they are interested in short-term events, such as analyst forecast revisions, which occur frequently and generate immediate price impacts. However, since long-term investors pursue long-term investment opportunities that offer stable profits over a long horizon, they tend to overlook short-term investment opportunities, such as analyst forecast revisions. Therefore, while investors with short-term investment horizons have a keen interest in the information involved in analyst forecast revisions, investors with long-term horizons are neutral toward this information and respond to it only slowly, so that a drift follows for stocks held mostly by long-term investors.

We hypothesize that investors with different investment horizons exhibit different reactions to information. While short-term investors may respond rapidly to an event or news, long-term investors do not show quick reaction and reflect the event in their actions only gradually. Accordingly, our hypotheses are as follows. First, the magnitude of the event-period reaction of long-term investors to forecast revisions is smaller than that of short-term investors. Second, the magnitude of post-period drift to forecast revision for firms with long-term investors is larger than that for firms with short-term investors.

Investment horizon represents investor time preference, which is one of the important characteristics that affect one's trading frequency. This characteristic is heavily related to investor portfolio turnover level. Short-term investors are likely to pay attention to short-term events and actively trade stocks. Thus, they change their portfolios frequently to exploit short-term profit opportunities. As a result, their portfolio turnover level is high. However, long-term investors are inattentive to short-term events and hardly respond to them. They tend to hold the stock for a long time, which results in a low portfolio turnover level. Theoretical models such as Barberis and Xiong (2012), Ingersoll and Jin (2013), and Kwon and Kim (2015a) argue that short-term investors trade more frequently than long-term investors.

We proxy for investment horizon of a stock's shareholders using share-weighted portfolio turnover levels of mutual fund shareholders for the stock, called the *Sturn* measure, which is adopted from Kwon and Kim (2015a). Specifically, high-*Sturn* implies that the stock is held mostly by investors with short-term investment horizon, and low-*Sturn* implies that shareholders of the stock have long-term investment horizons. Using the *Sturn* measure, we divide stocks into three groups according to investment horizon of their shareholders, and price reactions during the event period and post-event period are estimated for each *Sturn* group. We then compare the price reaction across each horizon group. Consequently, we find evidence that investor reactions to analyst forecast revision differs depending on investment horizon. Stocks covered mostly by short-term investors exhibit an immediate response to analyst forecast revision. On the other hand, stocks covered mainly by long-term investors exhibit a delayed response to analyst forecast revision.

We find that investment horizon plays a significant role in causing post-forecast revision drift. Specifically, stocks held mostly by short-term investors show a stronger and more immediate response than stocks held mainly by long-term investors over the three days around the analyst forecast revision, while the drift following the analyst forecast revision for stocks held mostly by long-term investors is larger than that for stocks held mainly by short-term investors. These results are robust even after controlling for variables that could be related to post-forecast-revision drift, such as analyst coverage, stock liquidity, forecast dispersion, firm size, book-to-market ratio, and past 12-month return.

We find that investors are able to profit from post-forecast-revision drift through exploiting the market's underreaction by constructing a strategy based on forecast revision and investment horizon of a stock's shareholders. Abnormal returns from such a strategy are consistent with stocks held mostly by long-term investors showing delayed reaction to analyst forecast revisions.

According to Barberis and Xiong (2012), Ingersoll and Jin (2013), and Lan, Moneta, and Wermers (2014), investment horizon can also be related to other firm characteristics, such as size, book-to-market ratio, past return, turnover, illiquidity, and return volatility. To resolve this issue and extract only the effect of investment horizon of shareholders, we measure the stocks' *Residual Sturn* from a cross-sectional regression for all stocks with *Sturn* against the above variables. With this delicate measure of investment horizon, I find that stocks with long-horizon investors have more intense post-forecast-revision-drifts than those short-horizon investors again.

Zhang (2006a) investigates the role of information uncertainty in price continuation and finds that greater information uncertainty produce relatively higher future stock price drift following good news and relatively lower price drift following bad news, suggesting that uncertainty delays the reflection of information into stock prices. Using six proxies following Zhang (2006), we check and reconfirm that price drifts are stronger for stocks with greater information uncertainty. However, we find that post-forecast-revision-drifts of long-term investors exist regardless of the information uncertainty level. Moreover, price reaction in the event-period of the short-term investor is stronger than those of long-term investor. Therefore, we confirm that stock price reaction to analyst forecast revisions differs according to investment horizon after controlling the information uncertainty.

A substantial literature examines how price response to analyst forecast revision varies according to analyst-related characteristics of the revision: analyst celebrity (Bonner et al. 2007), analyst ranking (Stickel 1992), analyst accuracy (Sinha et al. 1997, Brown 2001), analyst experience (Mikhail et al. 1997), analyst aptitude and brokerage house characteristics (Jacob et al. 1999), and analyst industry specialization and firm experience (Barniv and Cao 2006). Also, several papers document that firm-specific informative characteristics affect price reaction to forecast revision, including analyst coverage (Brennan et al. 1993, Elgers et al. 2001) and information uncertainty of a firm (Hou et al. 2014, Zhang 2006b). However, there are no studies that suggest whether investor characteristics contribute to stock price reaction to analyst forecast revisions. The present paper is the first to generate evidence that investment horizon can affect price reaction to analyst forecast revisions. A similar recent paper that addresses price reaction based on investment horizon is Kwon and Kim (2015b), that find that post-earnings-announcement-drift, PEAD, is stronger for stocks held by long-term investors. The fact that analyst forecast revisions occur fairly continuously and frequently throughout the year, unlike earnings announcements, gives us an empirical advantage to investigate investor reaction associated with firm-specific news according to investment horizon.

The remainder of this paper proceeds as follows. Section 2 describes the sample data, construction of variable measures, and empirical methodology. Section 3 shows the empirical results and Section 4 reports robustness checks and additional tests. Finally, Section 5 describes our conclusions.

2. Data and Methodology

A. Analyst forecast revision data

Our sample of individual analyst earnings per share, EPS, forecast data is obtained from the I/B/E/S unadjusted detail file. We address forecasts of annual earnings (FY1). Our sample period covers U.S. stocks from January 1993 to December 2012. We exclude stocks with less than two analyst forecasts in that fiscal year so as to create a consensus forecast. We also exclude the forecast revision if there is no return data at the announcement date of the revision. Since our purpose is to examine the analyst forecast revision drift and not the PEAD, we remove analyst forecast revisions whose event period includes I/B/E/S quarterly earnings announcement date. Our final sample consists of 938,930 forecast revisions on 9631 firms from 12,959 analysts.

Using the I/B/E/S analyst forecast database, we classify forecast revisions into four levels based on prior consensus forecast and analysts' prior own forecasts. Previous studies of analyst earnings forecasts use various methods of dividing the levels of analyst forecast revisions. Typically, there are two representative standards, prior consensus forecast and analyst's prior own forecast. First, prior consensus forecast of analysts covering that firm–year is an important criterion as a yardstick to judge the new analyst forecast, since the consensus represents the commonality of the view on a firm's future earnings. Elgers et al. (2001) use market consensus as a criterion. Second, analyst prior own forecast is also a significant and appropriate measure to assess the new forecast revision of the analyst, because the fact that prior own forecast and the new forecast revision stem from the same analyst gives this criterion consistency.

We adopt the method of dividing the level of analyst forecast revision suggested by Gleason and Lee (2003). These authors combine the prior consensus forecast with the analyst's own prior forecast; this serves as the criterion for dividing analyst forecast revisions. Labeling revisions using these criteria reflects both the commonality of analyst beliefs and the consistency of analysts' own time-series forecasts, yielding greater confidence in their quality. An analyst's own prior forecast is the preceding forecast of that analyst before the current forecast. Prior consensus forecast is estimated each day by taking the average of all analysts' most recent forecasts as of the end of the day preceding the revision.

In this methodology, we define the level of analyst forecast revision as follows. If forecast revision is higher than both the analyst's own prior forecast and the prior consensus, it is labeled as high-innovation good-news. Similarly, a revision that is lower than both analyst's own prior forecast and the prior consensus is labeled as high-innovation bad-news. If a forecast is between the analyst's own prior forecast and the prior consensus, this is called low-innovation revisions—low-innovation good news for forecasts higher than the own prior forecast and lower than the prior consensus, and low-innovation bad news for forecasts lower than the own prior forecast and higher than the prior consensus.

As robustness tests for our methodology of labeling the forecast revision, we require alternative measures of forecast revision, *Revise*. Revise is the forecast revision relative to the analyst's own prior forecast, as a percentage of price two days before the announcement date of the revision. We winsorize at the 0.5% level to avoid outliers. While our main methodology focuses on quality of the revision, the alternative measure, *Revise*, focuses on magnitude degree of the revision.

B. Construction of measure

We adopt the *Sturn* measure as a proxy for investment horizon of shareholders of a stock. Kwon and Kim (2014) measure the overall portfolio turnover level of mutual fund shareholders of the stock. Specifically, at the end of every quarter, we first calculate a cross-sectional percentile ranking of the Carhart (1997) portfolio turnover measure for each mutual fund during that quarter by using its stock holdings. Since this portfolio turnover measure is highly skewed, we then assign each stock the share-weighted average of the cross-sectional percentile rankings of mutual funds that are shareholders of the stock, or *Sturn*. Then, we consider that the stock with high (low) *Sturn* is held mostly by short-term (long-term) investors, that is, *High (low) Sturn* means that shareholders of the stock have short-term (long-term) investment horizon.

To construct a measure for investment horizon of shareholders of the stock, we obtain the quarterly equity holdings snapshot data of mutual funds and institutions from Thompson Reuters Mutual Fund Common Stock Holding Database (S12) and Thompson Reuters Institutional (13f) Holdings, respectively. Also, the data for mutual fund characteristics are from the Center for Research in Security Prices (CRSP) Mutual Fund Database. The mutual fund databases are merged following the method suggested by Wermers (2000).

We exclude stocks whose number of actively managed mutual fund shareholders is less than 10. We exclude mutual funds whose S12 investment objective codes denote *international*, *municipal bonds*, *bond & preferred or balanced*, those whose CRSP objective codes are not in the domestic equity category, and those that denote *sector*, *large cap*, *hedged*, or *short*. This exclusion process leads to a focus on actively managed mutual fund shareholders. If a fund has no CRSP objective code, then the most recent one is used. We also exclude funds whose CRSP or S12 name includes *Index*, *S&P*, *DOW*, *Wilshire*, *Russell*, or *NASDAQ*, those whose proportion of common stock is less than 80%, and those whose previous quarter's assets are less than $5 million.[2] Computing investment horizon of shareholders of these stocks from mutual fund holding data is not appropriate to our study.

We consider additional characteristics of the stock held by a fund in our sample, which could affect the price drift, for the robustness checks. We measure a stock's liquidity using the Amihud (2002) illiquidity measure, which is average daily absolute return divided by daily dollar trading volume (in millions) over the prior quarter, which is the same horizon over which *Sturn* is measured. We also measure analyst coverage of a firm annually as the number of analysts following the firm in the previous year, who issued FY1 earnings forecasts for a given firm. Divergence of opinion about

[2] Those mutual funds are ruled out when we calculate the stock's share-weighted average of the percentile rankings of mutual funds' portfolio turnover, because the stocks might be little affected by those mutual fund shareholders.

the firm also contributes to the stock price drift. It is measured by dispersion in analyst forecasts. It is calculated as the most recent standard deviation of analyst forecasts scaled by the absolute value of the mean estimate.

C. Abnormal stock return during event- and post-event periods

We obtain the daily returns of U.S. stocks from the CRSP. Market capitalization, book-to-market ratio, and momentum are used to assign a stock into Daniel, Grinblatt, Titman, and Wermers (1997) (hereafter DGTW) characteristic portfolios, by using CRSP and Compustat. The Fama–French three factors (excess market returns (MKT), returns on the size and value factor mimicking portfolios, SMB and HML, respectively) and the Carhart momentum factor (UMD) are acquired from Wharton Research Data Services' Fama–French Portfolios and Factors. We calculate DGTW characteristic-adjusted return as abnormal return around forecast revision, following Daniel, Grinblatt, Titman, and Wermers (1997).

The revision date is set to day 0, the date that analyst announces the new earnings forecast. The event period is defined as day -1 to day 1 surrounding day 0, the revision date. We define the price reaction for this three-day period as investors' short-term reaction to forecast revision. The post-event period is the period beginning from day 2, the day right after the event period. Price discovery for this post-event period is the long-term stock price drift for the forecast revision. We mainly use periods of 10, 20 and 30 days after the event-period as post-event periods.

D. Summary statistics

< Table I >

Table I presents the descriptive statistics. Panel A shows the summary statistics of analyst forecast revision. In Panel B, characteristics of three *Sturn* groups (High, Medium, and Low) are reported.

Panel A is separated into three categories. The first category shows statistics about analysts. The average time period between revisions of each firm is 19.24 days, about 3 weeks. Each analyst issues a new forecast revision for a specific firm about once every 2 months (61.65 days). Average number of analysts per firm in a given year is 6.51. Each analyst covers 6.74 firms in each year on average. In the second category, the number of revisions in each direction is reported. The number of upward and downward revisions is similar. The total number of upward revisions is 435,062 and the total number of downward revisions is 498,613. There are few no-change revisions compared with upward and downward revisions. We divide each revision into four levels, as specified in section 2.A. The number of each level of revision is reported in the third category. In both good and bad news, the number of high-innovation level is much greater than that of the low-innovation level.

We divide stocks into three groups based on their *Sturn* measure. The estimates are the time-series average of cross-sectional median value at the end of each quarter. Panel B shows the characteristics of each *Sturn* group. Median *Sturn* measure of high-, medium-, and low-*Sturn* groups are 0.611, 0.446, and 0.308, respectively. The size of stocks in the high-*Sturn* group are much smaller than other groups. They have lower prices and lower coverage than stocks in other *Sturn* groups. Shares outstanding are increasing, in order, for high-, medium-, and low-*Sturn* groups; this is consistent with the increasing order of stocks' market capitalization for each *Sturn* group. However, trading volume is not consistent with market capitalization. Since *Sturn* is a proxy for shareholder investment horizon or portfolio turnover, the trading volume and stock turnover of a high-*Sturn* group are higher than those of a low-*Sturn* group. Amihud illiquidity and bid–ask spread of a low-*Sturn* group are higher than those of other groups. Forecast dispersion of a high-*Sturn* group are larger than other groups. The mean dispersion are in order of increasing, high-, medium-, and low-*Sturn* groups, the order is the complete opposite to size and coverage. It is rational because forecast dispersion and the reciprocals of size and coverage are widely used to proxy for the information uncertainty of the firm together. The median number of

Institute shareholders of low, medium, and high-*Sturn* groups are 203, 182, and 138, respectively; also, the percentages of shares that institutions hold are 62.5%, 64.5%, and 64.8%, respectively.

3. Results

A. Stock price reaction in each *Sturn* group

The revision sample is categorized into four groups according to their revision level, independently of *Sturn* groups. At each quarter, all stocks are sorted into three *Sturn* groups.

Using this method does not give the same number of revisions for each revision group. However, it allows us to determine the level of forecast revision immediately after the forecast revision is announced such that it allows formation of an investment strategy that exploits post-forecast-revision drift.

We calculate cumulative abnormal return during the event period and the post-event period. Abnormal return is adjusted to Daniel, Grinblatt, Titman, and Wermers (1997) characteristics. Event date is set to the announcement date, day 0. The event period spans three days from day -1 to day +1. Post-event periods are set to the period up to 10, 20, and 30 days after the event period, respectively.[3]

Stickel (1991) and Gleason and Lee (2003) report that stock price drift following the analyst forecast revision continues for as little as six months or as long as one year. We examine the drift pattern for one year and confirm that the tendency remains consistent with our hypothesis. We do not report the result since it is not our main topic. However, the later period's reaction likely shows that it is diluted or mixed with another forecast revision, since analyst forecast revisions are too frequent and repetitive.

[3] Each post-event period represent the period during 10 days, 20 days, and 30 days, respectively. We drop the events which has at least one day of return omitted during the period.

Also, our purpose is to examine the slower reaction of long-term investors to analyst forecast revisions compared to short-term investors. Therefore, the post-event periods should not be too long, to avoid being affected by too many follow-on revisions. Further, 30 trading days of the post-revision period are enough to observe market reaction to the forecast revision.

< Figure I >

Figure I shows the cumulative abnormal returns (CAR) around the analyst forecast revision for each revision level.[4] The figure shows that the price movements of each revision level are well-ordered according to their revision level and that a substantial amount of the stock price movement occurs during the event period. However, there are also price drifts following the favorable levels of forecast revision.

< Figure II >

CAR during the post-event period of each *Sturn* group is illustrated in Figure II. For each quarter, the sample stocks are divided into three groups based on *Sturn*. Also, all revisions are divided into four groups based on their revision level, independently of *Sturn*.

The upper-left graph shows the CAR for low-*Sturn* groups. In this graph, there is a more clearly defined drift. However, the medium-*Sturn* group and the high-*Sturn* group, whose graph is in the upper-right and lower-left, respectively, do not show clear drifts. The CAR differences between good news and bad news are decreasing in *Sturn*. In the lower-right graph, we illustrate CAR of both the low-*Sturn* group and high-*Sturn* group together on the same plane. Note the distinct spread difference between the two groups. The results suggest that post-forecast-revision drift appears severe among stocks held mostly by long-term investors.

[4] The number denote the revision level of the groups. The horizontal axis shows the date relative to the forecast revision date.

The tabular evidence is reported in Table 2. All estimates are standardized and t-statistics based on Huber–White standard error estimator clustered by calendar date are in parentheses below the estimates.[5]

< Table II >

Table II shows that average *Revise* value, the forecast revision relative to the analysts' own prior forecast scaled by the price two days before the revision date, within each revision level, is not variable across the *Sturn* groups.[6] The entire H–L, high minus low *Sturn* difference in revision level is not statistically significant. The difference in H–L difference between high-innovation good and bad revision is also not significantly different from zero (0.03 with t-statistics 0.32). In Panels B, C, D, and E, the average cumulative abnormal returns (CAR) of each *Sturn*-revision level are reported.[7] Within the same *Sturn* groups, the highest level of revision shows larger price reaction than the lowest level of revision in all cases. Panel B shows the return during the event period. Within the same revision level, the cumulative abnormal returns of the high-*Sturn* group are larger than those of the low-*Sturn* group. The difference between the high- and low-*Sturn* group is significantly positive in high-innovation good news (0.26 with t-statistic 4.10) and significantly negative in high-innovation bad news (-1.17 with t-statistic -13.03). The difference-in-difference is the most important point that we note. The difference-in-difference is substantially positively significant, with *p*-value less than 0.001. The mean spread is 1.43% during only 3 days. Therefore, short-term investors react more quickly and heavily than long-term investors in the event period, which is consistent with our hypothesis.

However, in Panels C, D, and E, we report the results of the post-event period for 10, 20, and 30 days, respectively. The difference-in-difference is negative and statistically significant. For 10 days

[5] Huber–White estimator is described in Huber (1967), White (1980), and Diggle et al. (1994).
[6] We winsorized the extreme 0.5 percent of the Revise value in order to avoid the effect of outliers.
[7] We execute all tests by using buy-and-hold return instead of cumulative return as abnormal return. The results show greatly similar pattern to the results with CAR.

after the forecast revision is announced, the return spread between high-innovation good news and high-innovation bad news is 0.62% in the low-*Sturn* group, and 0.22% in the high-*Sturn* group, with t-statistics of 10.63 and 2.38, respectively. The H-L difference between them is -0.52% with t-statistic -3.70. The low-*Sturn* group exhibits strong post-drift, while the high-*Sturn* group exhibits weaker post-drift. The 20 days and 30 days H–L return spread is -0.48% and -0.61%, with t-statistic -3.48 and -3.61, respectively. During the post-event periods, investor reaction incorporated in the price drift is positively related to investment horizon. The investor with longer horizon shows the larger drift. This means that underreaction to analyst forecast revision is long-lasting only among stocks held mostly by long-term investors. This result implies that long-term investors respond slowly and gradually to forecast revision news, whereas short-term investors' reaction is quick and occurs mostly in the short-term.

Overall, Table II supports our hypotheses. Low-*Sturn* stocks generate less immediate reaction and larger post-drifts in response to analyst forecast revision than high-*Sturn* stocks. This is consistent with an investment horizon explanation for the analyst forecast revision.

B. Cross-sectional determinants of stock price reaction to forecast revision

Prior literature holds that firm-specific characteristics such as firm size, book-to-market ratio, momentum, and analyst coverage might affect the immediate stock price reaction and post-forecast-revision drift. In this section, we run panel regressions to investigate whether the effect of investment horizon is robust after controlling for other factors that may be related to analyst forecast revision drift. We conduct a two-way sort regression to resolve the sample dependency problem. The regression specification is

$$DGTW_{i,t+1} = \alpha_t + \beta_t Revise_{i,t} + \gamma_t Signal_{i,t} + \delta_t Revise_{i,t} \cdot Sturn_{i,t} + \mu_t Revise_{i,t} \cdot X_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable "abnormal return" is DGTW characteristic-adjusted returns during the event period and post-event period. *Sturn* is our main variable, which measures the investment horizon of investors in the stock in the quarter to which the date of revision belongs. *Revise* measures revision quantity, that is, the size and direction of the analyst forecast revision. *Revise* is the forecast revision relative to the analyst's own prior forecast, as a percentage of the price two days before the revision date, with the extreme 1% of observations winsorized. *Signal* measures revision quality, that is, the effect of the level of innovation in the revision *Signal* is a categorical variable that takes the value +1 for high-innovation good news, 0 for low-innovation news, and -1 for high-innovation bad news. *X* are control variables that may be related to post-forecast-revision-drift, such as analyst coverage, Amihud illiquidity of the firm, log of firm size (ME), log of book-to-market ratio (B/M), and log of past 12-month return (Momentum). In particular, *Coverage* implies the amount of informative attention a firm receives. The dummy variable of analyst coverage takes the value 1 if the firm is followed by more than the median number of analysts, and 0 otherwise. Also, we add *Amihud illiquidity* as a control variable that could be related to the market reaction to analyst forecast revision. Amihud illiquidity measure implies the daily price response associated with one dollar of trading volume; it is able to affect the speed of price discovery in the market for the information. Less liquid stocks might show slower reaction than liquid stocks due to their high transaction costs. This is measured as average daily absolute return divided by daily dollar trading volume over the quarter over which the *Sturn* variable is measured. Divergence of opinion about the firm is the proxy for the information uncertainty, which also contributes to the stock price drift. It is measured by dispersion in analyst forecasts. It is calculated as the most recent standard deviation of analyst forecasts scaled by the absolute value of the mean estimate. Since market reaction to fully incorporating the effect of high- versus low-innovation revisions might depend on firm-specific characteristics, we include these control variables in the regression equation as interaction terms with *Revise*, the quantitative degree of the revision.[8] Our main focus is the coefficient of *Revise·Sturn*. If stock price reaction is related to investment horizon in a coincident direction with our hypothesis, the coefficient δ should be negative.

[8] The extreme top and bottom 1 percent of the *Revise* is winsorized to attenuate the effect of the outliers.

< Table III >

In Table III, the results of the panel regression are reported. All estimates are standardized and t-statistics are estimated based on two-way clustered robust standard errors for the firm and date. Event-period return from day -1 to day +1 (Panel A) and 30 days post-event period return from day +2 to day +31 (Panel B) are used as dependent variables in each cross-sectional regression. Model 1 incorporates independent variables of only revision attributes and *Sturn*, *Signal*, *Revise*, and *Revise·Sturn*. We add model 2 control variables for analyst coverage, firm Amihud illiquidity, forecast dispersion, firm size, book-to-market ratio, and momentum.

In Panel A, in which the regression result of event period return is reported, the coefficient of *Revise·Sturn* is significantly positive in both models 1 and 2. This implies that investors' immediate reaction to forecast revision is stronger in the same direction of the revision as *Sturn* if the stock is higher and Revise is larger, while it is weaker if *Sturn* of the stock is lower and Revise is smaller. This result is consistent with our hypothesis that stocks held mostly by short-term investors show larger price movement during the event period.

For 30 days post-event period drift (Panel B) in model 1 when there are no control variables, the coefficient δ is -0.460 with t-statistics -2.23. Since β, the coefficient of *Revise*, is 0.179, a one-standard-deviation increase in *Sturn* attenuates post-forecast-revision-drift dramatically. This indicates that price drift in the post-event period is larger (smaller) when investment horizon of the stock's shareholder is longer (shorter).

The t-statistics on *Signal* confirm the importance of the innovation in forecast revision in explaining post-forecast-revision drift. *Signal* has the high t-statistics in almost every regression (39.69, 40.92, 3.93, and 3.88). *Revise*, which is the quantitative measure for forecast revision, is not as important as *Signal* in terms of its ability to account for immediate stock price reaction, however, it has strong explanatory power to explain future price drift. This result suggests that *Signal* captures qualitative effects of a forecast revision, and our classification method of revision ranking is reasonable. We add the interaction terms of *Revise* and control variables in model 2. The coefficients of control variables have signs consistent with the expected signs according to the prior literature. Some coefficients are not statistically significant, However, the direction of the effect of the control variables is as expected. The coefficient for *Revise·Coverage* is negative, which means that price drift to *Revise* is smaller for firms with high analyst coverage. The estimated coefficient for *Revise·Amihud* is positive, implying that price drift to *Revise* is larger for less liquid firms. *Revise·Dispersion* shows the same result. The coefficient of it is not statistically significant, however, it is negative, which indicates that greater divergence in opinion produce relatively higher price drift following good news and lower price drift following bad news, the result is consistent with Zhang (2006a, 2006b). Other variables, such as *ME*, *B/M*, and *Momentum*, also affect price drift by undermining or aggravating the market reaction to incorporating the information in forecast revision.

In summary, Table III shows that investment horizon for the firm, i.e., *Sturn*, is an important and robust factor in accounting for the cross-sectional variations in post-forecast-revision drift. Specifically, price drift following the analyst forecast revision is more pronounced for low-*Sturn* stocks, and less pronounced for high-*Sturn* stocks.

C. Time-series regression of post-forecast-revision-drift strategy portfolio returns

To determine the differences in price drift between short- and long-horizon stocks, we conduct a time-series regression on the daily rebalanced portfolio strategy. For each *Sturn* group, we form a daily calendar time portfolio based on the forecast revision. The strategy is buying stocks with high-innovation good news and selling stocks with high-innovation bad news two trading days after the date of revision. If more than one analyst revise their earnings forecast and generate the high-innovation news for a particular stock, then that stock can appear multiple times in the portfolio. We keep the stock position for 30 trading days until the next revision for the stock is announced. Specifically, if the new forecast revision is issued 11 days after the last revision day, we liquidate the stock position and reconsider the new position of the stock based on the new revision level. If there is no forecast revision of the stock for 30 days after the last revision day, the stock's position is maintained for 30 days. Return days with stock's lagged price is less than $1 are excluded from the portfolio. Since announcement of a new revision dilutes the price effect of the original revision, we exclude the stock whose next revision is issued one day after the revision date, which is not included in the post-event period. Long and short portfolios are rebalanced every trading day based on the forecast revisions and give equal weight to each stock. Stocks' return day with the price of the end of previous trading day is less than $1 are excluded from the portfolio. If there is no strategy return in the day for the portfolio, I assume that the portfolio invests in the market portfolio. The weight of stock is the cumulative value of $1 invested in the forecast revision drift strategy from the day of the stock enters the portfolio. Note that if a stock experiences the same news in a day multiple times, each revision is treated as separate event.

We calculate abnormal portfolio return from the strategy using four models: excess return, CAPM, Fama–French three-factor model, and Carhart four-factor model. Specifically, for the four-factor model, daily excess returns of the portfolio are regressed on the Fama and French (1993) three factors and Carhart (1997) momentum factor.[9]

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \varepsilon_{i,t}$$

where $R_{i,t}$ is the rate of return of fund i; $R_{f,t}$ is the one-month T-bill rate; MKT_t is the excess return on the value-weighted (VW) market portfolio; and SMB_t, HML_t, and UMD_t are the size, value, and momentum factor portfolios, respectively.

< Table IV >

Table IV shows the results of the time-series regressions. The revision strategy in the low-*Sturn* group earns positive abnormal return whichever model we use. For brevity, we mention the four-factor results only. Monthly four-factor alpha of the low-*Sturn* group through the strategy is 0.919% (with t-

[9] We obtain those factors from Kenneth French's website, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

statistic 4.12), whose annualized value is 11.028%. Meanwhile, the strategy in the high-*Sturn* group does not exhibit a statistically significant abnormal return. The return difference of the strategy in low- and high-*Sturn* groups is 0.564% per month, which is statistically significant at the 5% level (with t-statistic 2.12). The return difference is converted to 6.768% per year. The results show that return differences for this strategy, which exploits post-forecast revision drift, is significantly positive for all four models.

The results of the time-series regression of the strategy still supports our hypothesis that post-forecast revision drift is strong for stocks held mostly by investors with long-term investment horizons.

4. Additional Tests

A. Results with *Residual Sturn*

Sturn could capture variables other than shareholders' investment horizon since it is calculated from mutual fund shareholders' portfolio turnover, which could be related by shareholders' portfolio construction style or investing strategy. For this reason, *Sturn* is somewhat correlated to variables related to stock's characteristics (such as size, book-to-market ratio, past 12-month returns, turnover, illiquidity, or the volatility).

Based on realization utility models, Barberis and Xiong (2012) and Ingersoll and Jin (2013) claim that short-term investors are more favorable to volatile stocks than long-term investors are. Portfolio turnover (investment horizon) can also be associated with their holding stocks' characteristics, such as size, book-to-market, and momentum, illiquidity (Lan, Moneta, and Wermers, 2014). The authors find that relative to short-term investors, funds with long-term investment horizons tilt toward large stocks, growth stocks, less popular (low turnover) stocks, and more liquid stock, while short-term funds prefer past winners.

< Table V >

Table V reports the Pearson (Spearman) correlation between those variables and *Sturn*. . The Pearson correlations are shown above the diagonal and the Spearman correlations are shown below the diagonal. *Sturn* has innegligible correlation with those firm characteristic variables. The Pearson (Spearman) correlation between *Sturn* and size is -0.090 (-0.071). The B/M-*Sturn* correlation is also negative in both Pearson and Spearman measure. Past 12-month returns, turnover, and return volatility are positively correlated with *Sturn*, while Amihud illiquidity has negative correlation with *Sturn*. These results supports the previous papers' argument that investment horizon are correlated to those firm-specific variables, which means that *Sturn* might capture variables other than investment horizon.

To resolve this issue and extract only the effect of investment horizon of shareholders, we measure the stocks' *Residual Sturn* and divide stocks into three groups based on the *Residual Sturn*. For all stocks, we conduct a cross-sectional regression of *Sturn* on turnover, return volatility, Amihud (2002) illiquidity, during the prior quarter over which *Sturn* is measured, and Size, Book-to-Market Ratio, and Prior 12-month returns at the end of the prior quarter. The residual of the regression is *Residual Sturn*, which is stocks' shareholders' average portfolio turnover proxy orthogonal to size, book-to-market, past 12-month returns, turnover, illiquidity, and volatility.

< Table VI >

Table VI conduct the same analysis in Table II except that stocks are sorted based on their *Residual Sturn* instead of raw *Sturn*. The results in Table VI are consistent with the results of Table II and support our hypothesis.

B. Alternative ways to estimate revision ranking

We use alternative ways to estimate forecast revision level and conduct a robustness check. Since it is hard to say that our dividing method is a quantitative measure, we adopt the measure of quantifying forecast revision level, which is broadly used in empirical studies of information shock as Standardized unexpected earnings (SUE). As I mentioned above, we calculate another revision measure, *Revise*. At the end of each quarter, revisions that have arisen during the quarter are divided into five groups according to the value of *Revise*, independent of *Sturn* group. Table VII presents the results.

< Table VII >

Using the alternative method of division, the results show a similar pattern to those of previous results. The abnormal return difference between High-Good news and High-Bad news during the event period for stocks with short-term investors is 6.44%, which is much larger than the 4.65% of long-term investors. The difference-in-difference of the two *Sturn* groups is 1.80% with t-statistics 11.66, which is statistically significant at the 0.001% level.

However, during the post-event period, the difference in these returns becomes negative, -0.44% for 10 days, -0.45% for 20 days, and -0.55% for 30 days with t-statistics of -3.42, -2.66, and -2.59, respectively. The results argue that short-term investors tend to have more critical return shocks when the news is announced than do long-term investors. Moreover, post-forecast-revision drift is more concentrated among stocks with long-term investment horizons.

C. Subsample tests controlling for Information uncertainty variables

Zhang (2006a) investigates the role of information uncertainty in price continuation and finds that greater information uncertainty produce relatively higher future stock price drift following good news and relatively lower price drift following bad news, suggesting that uncertainty delays the reflection of information into stock prices. The author uses several proxies for information uncertainty such as firm size, firm age, analyst coverage, dispersion in analyst forecasts, stock return volatility, and cash flow volatility. Although the effect of *Sturn* on the price reaction survives after controlling the other variables that might affect the stock price continuation or drift in Table III, we reexamine price reaction according to investment horizon by grouping stocks based on their level of information uncertainty variables that could be related to post-forecast revision drift..

The first proxy is firm size (*ME*). We measure firm size as the market capitalization at the end of the prior quarter. It is reasonable that small firms are less diversified and have less information available for the market than large firms. Therefore, small firms are regarded more uncertain and are likely to be suffered more severe information asymmetry than large firms.

The second proxy is firm age (*AGE*). We measure age as the number of years since the firm was first covered by CRSP. Firms with longer history implies that more information is available to the market than those with shorter history. Hence, age inversely proxies for information uncertainty, which means that younger firms are subject to more severe information uncertainty.

The third proxy is analyst coverage (*COV*), Analyst coverage is used to proxy information uncertainty and investors' opinion. It is widely used to proxy for the information uncertainty about future earnings or consensus among analysts about the firm, it is an indicator of less information asymmetry (Hong, Lim, and Stein 2000). Also, it is obvious that stocks followed by more analysts will have more visibility and more frequent announcements of forecast revision, such stocks will receive more attention, and this leads to rapid incorporation of the information in the stock price. Several papers document that analyst coverage affects price reaction to the analyst forecast revision (Brennan et al., 1993; Elgers et al., 2001; Gleason and Lee 2003; Zhang 2006a, and 2006b). Loh (2010) confirms that delayed price response is more pronounced for low-coverage firms by using the analyst coverage measure as an alternative measure for investor inattention.

The fourth proxy is dispersion in analyst earnings forecasts (*DISP*), proxy for the divergence of opinion. It is widely used to proxy for the information uncertainty about firms' future earnings or consensus among analysts in the prior literature (Diether, Malloy, and Scherbina, 2002; Zhang, 2006a, 2006b). Zhang (2006a, 2006b) shows that investors underreact to public information even more in cases of greater information uncertainty. Consequently, firms with greater forecast dispersion could generate more price drift in the direction indicated by the forecast revision.

The fifth proxy is stock return volatility (*SIGMA*), which could also affect the firms' information uncertainty. We measure stock volatility as the standard deviation of daily excess returns over the prior quarter, while Zhang (2006) measure it as the standard deviation of weekly excess returns over the year ending the portfolio formation date. Predicting future returns of a stock with more volatile returns in the past would be more difficult. Therefore, the more volatile the stock return, the more uncertain its future return, and the more likely it is to be mispriced. Hence, stock return volatility could proxy for the information uncertainty of the firm.

The Sixth proxy is cash flow volatility (*CVOL*). We measure cash flow volatility as the standard deviation of cash flow from operations in the past five years with a minimum of three years of data. Cash flow from operations is measured as earnings before extraordinary items (Compustat annual item IB) minus total accruals, scaled by average total assets (item AT). Here, total accruals equal changes in current assets (item ACT) minus changes in depreciation expense (item DP), cash (item CHE), and changes in current liabilities (item LCT), plus changes in short-term debt (item DLC). The more volatile the past cash flow, the more uncertain the underlying business.

If *Sturn* of the stock could significantly affect the price reaction irrespective of the level of information uncertainty, it suggests that investment horizon of shareholders play an important role in producing the stock price drift.

The stocks are grouped into two groups, low information uncertainty group and high information uncertainty group, based on the firm size, firm age, analyst coverage, forecast dispersion, stock volatility, and cash flow volatility. Following Zhang (2006), we use reciprocals of some proxies (i.e., size, age, and analyst coverage) to confirm that high-ranked stocks are stocks with more information uncertainty. For each quarter, we sort all stocks into two groups based on their information uncertainty proxy level, independent of *Sturn* groups. In each group of stocks according to their information uncertainty level, we conduct the same analysis shown in Table II again.

The results are reported in Table VIII. Panel A shows the cumulative abnormal return during the event period of each *Sturn*-revision group. Panel B shows the post-drift after the analyst forecast revision. Panel C shows the cumulative abnormal return of each *Sturn*-revision group during the post-event period for 30 trading days. In all panels, the results of each information uncertainty level are reported separately.

< Table VIII >

The results are consistent with our hypothesis regardless of the level of information uncertainty.

Price reactions in event period are stronger in high-*Sturn* group then low-*Sturn* group in both high and low information uncertainty level. For example, for the firm size (*ME*) proxy, the differences-in-differences of the event period are 1.52% and 0.52%, which are statistically significant at the 1% and 5%, in the high and low information uncertainty groups, respectively.

The important thing is, as Zhang (2006) argued, that analyst forecast revision drift significantly exists only in the low information uncertainty group or is stronger in low information uncertainty group than high information uncertainty group. However, we can see that analyst forecast revision drifts in low-*Sturn* group are significantly positive in both high and low information uncertainty groups for all proxies except for firm size. Moreover, the differences in post-event period drift of low-*Sturn* group are much stronger than those of high-*Sturn* group in all information uncertainty level regardless of the proxy.

For example, for the analyst coverage (*COV*) proxy, the differences-in-difference of the 30 days post-event period are -0.55% and -0.61%, which are statistically significant at the 5% and 1%, respectively.

Overall, our results support Zhang (2006). However, post-event drift of the long-term investor still significantly exists regardless of the level of the information uncertainty. In addition, price reaction in the event-period of the short-term investor is stronger than those of long-term investor. Therefore, we confirm that stock price reaction to analyst forecast revisions differs according to investment horizon after controlling the information uncertainty. These results are consistent with our hypothesis. This suggests evidence that investment horizon may be a source of post-forecast revision drift.

5. Conclusion

Using share-weighted portfolio turnover levels of mutual fund shareholders for a stock as a measure of investment horizon of the stocks' shareholders, we examine whether investment horizon contributes to post-forecast revision drift.

Stocks held mostly by long-term investors exhibit stronger post-revision drift than stocks held mostly by short-term investors, since long-term investors do not pay much attention to short-term events; they have a tendency toward underreaction and delayed reaction. On the other hand, short-term investors show immediate large price reactions, because they are eager to seek short-term profits. The results are robust even after controlling for variables that could be related to post-forecast-revision drift, such as analyst coverage, stock liquidity, forecast dispersion, firm size, book-to-market ratio, and past 12-month return. Additionally, the effect of investment horizon to the price reaction survives regardless of stocks' information uncertainty. Our findings indicate that investors are able to profit from post-forecast-revision drift by exploiting the market's underreaction by constructing a strategy based on forecast revision and investment horizon of a stocks' shareholders. Moreover, the results still support our hypothesis when we adopt delicate measure of investment horizon, *Residual*

Sturn, which purge other stock characteristics which might affect investment horizon. In addition, we still confirm that stock price reaction to analyst forecast revisions differs according to investment horizon after controlling the information uncertainty. The evidences support investors' investment horizon as a source of the analyst forecast revision drift. In sum, we find that short-term investors contribute to market efficiency and long-term investors contribute to post-event drift.

This paper is the first study to show evidence that investor characteristics contribute to the price reaction to analyst forecast revision. Also, we show that investors' investment horizon can affect the price reaction to analyst forecast revision. It would be worthwhile to further examine the role of investment horizon of shareholders on other stock price anomalies.

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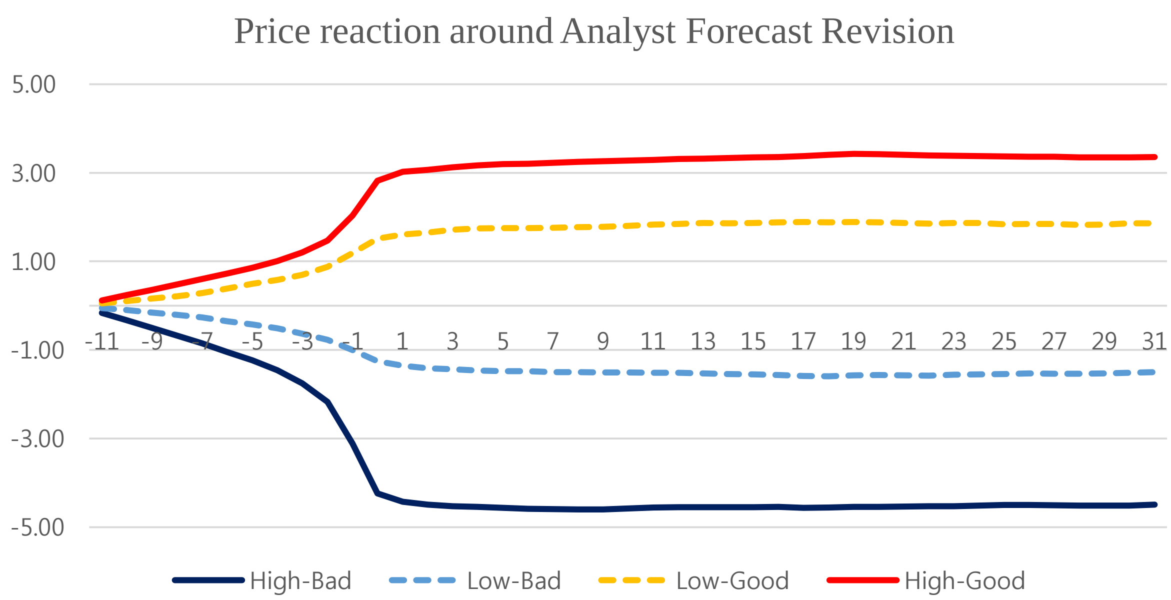
Figure I. Cumulative Abnormal Returns around Analyst Forecast Revision

This figure shows the cumulative abnormal returns (CAR) around analyst forecast revision of each revision level group. The letter denotes the revision level of the groups. The horizontal axis shows the date relative to the forecast revision date. The vertical axis means the DGTW characteristics-adjusted returns. All revisions are grouped into four levels based on their revision level. A revision level is defined as follows. If forecast revision is higher than both the analyst's own prior forecast and the prior consensus, it is labeled as high-innovation good-news (denoted as *High-Good*). Similarly, revision that is lower than both analyst's own prior forecast and the prior consensus are labeled as high-innovation bad-news (denoted as *High-Bad*). If forecasts are higher than the own prior forecast but lower than the consensus is labeled as low-innovation good-news (denoted as *Low-Good*). If forecasts are lower than the own prior forecast but higher than the consensus is labeled as low-innovation bad-news (denoted as *Low-Bad*). Analyst forecast data are obtained from I/B/E/S and the sample period is from 1993 to 2012.



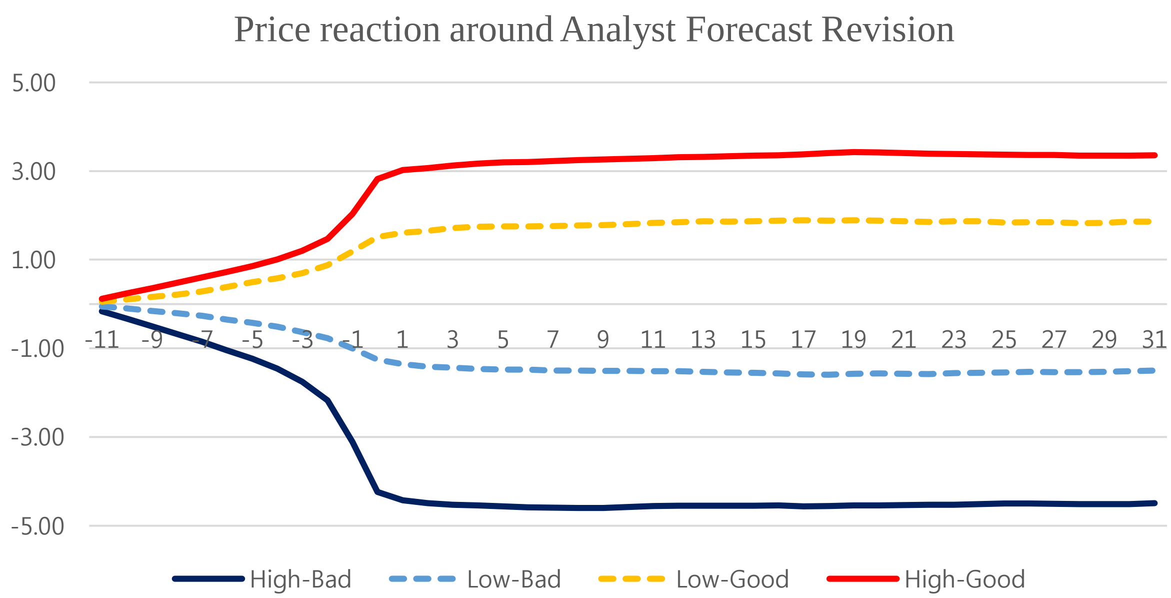


Figure II. Post Forecast Revision Drift and Investment Horizon

The figures illustrate the cumulative abnormal returns (CAR) during the post-event period of each *Sturn* group. For each quarter, samples stocks are divided into 3 groups based on their *Sturn* measure. Also, all the revision is divided into 4 groups based on their revision level, independently of *Sturn*. The horizontal axis shows the date relative to the forecast revision date. The vertical axis means the DGTW characteristics-adjusted returns. The upper-left, upper-right, and lower-left graphs show the cumulative abnormal returns for low-, medium-, and high-*Sturn* groups. In the lower-right graph, cumulative abnormal returns graphs of both low-*Sturn* group and high-*Sturn* group are illustrated together on the same plane.

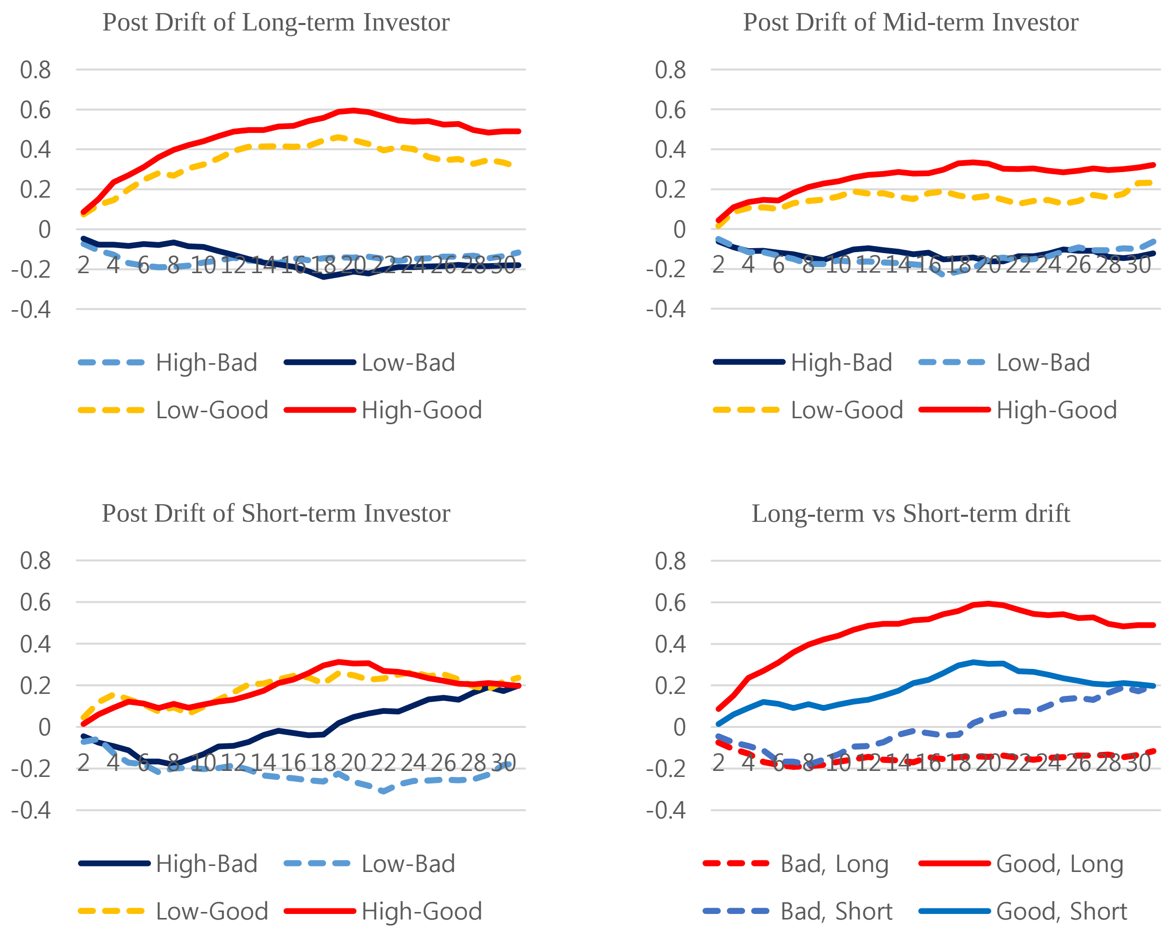


Table I. Descriptive Statistics

This table shows the descriptive statistics. Panel A shows the summary statistics of analyst forecast revision data and Panel B reports the characteristics of the three *Sturn* groups (High, Medium, and Low). Analyst forecast data are obtained from I/B/E/S for the period 1993–2012. Panel A is separated into three categories. The first category shows the statistics on analysts. The second category shows number of revisions in each direction. The number of each level of revision is reported in the third category. The estimates in Panel B are the time-series average of cross-sectional median value at the end of each quarter. *Sturn* is our main variable, which is a proxy for investment horizon of shareholders of the stock. Specifically, at the end of each quarter, we first calculate the cross-sectional percentile ranking of the Carhart (1997) portfolio turnover measure for each mutual fund during that quarter by using its stock holdings. We then assigned each stock the share-weighted average of the cross-sectional percentile rankings of mutual funds that are shareholders of the stock, which is called *Sturn*. *Size* is market capitalization. *BM* is book-to-market ratio. *MOM* is past 12-month cumulative stock return skipping the most recent one month. *Amihud illiquidity* is measured as average daily absolute return divided by daily dollar trading volume over the quarter over which the *Sturn* variable is measured. *Coverage* is the number of analysts, calculated annually, who issued a one-year-ahead forecast for a given firm in a given year. *Forecast dispersion* is calculated as the most recent standard deviation of analyst forecasts scaled by the absolute value of the mean estimate. *Institute Shareholders* is the number of Institutional shareholders during the quarter. *Institutional Ownership* is the percentage of shares held by institution at the end of the quarter.

Panel A. Analyst forecast revision

Total Number of Firms	9631
Total Number of Analysts	12959

Analyst	**25th**	Mean	Median	**75th**	Std
Revision term (days)	3	19.24	8	25	25.35
Revision term of each analyst (days)	28	61.65	56	91	41.93
Number of Analysts per Firm (fiscal year)	3	6.51	5	9	5.07
Number of Firms covered by an analyst (fiscal year)	2	6.74	5	10	5.78

Revision	N	**25th**	Mean	Median	**75th**	Std
Total Forecast revision	938930	6	16.00	11	20	16.75
Upward revision	435062	2	8.24	5	10	9.84
Downward revision	498613	3	9.51	6	12	11.72
No change	5255	1	1.14	1	1	0.48

News	N	**25th**	Mean	Median	**75th**	Std
High-innovation bad news	336747	2	7.92	4	10	10.81
Low-innovation bad news	86997	1	2.99	2	4	3.35
Low-innovation good news	95196	1	3.01	2	4	3.37
High-innovation good news	269481	2	6.55	3	8	8.76

(Continued)

(Continued)

Panel B. Three *Sturn* Groups

Characteristics	Low Sturn	Medium Sturn	High Sturn
Sturn	0.308	0.446	0.611
Transaction characteristics			
Size ($\times 10^6$)	3165.8	2398.5	1450.4
BM	0.507	0.452	0.414
MOM	0.072	0.125	0.242
Price	23.76	22.40	20.89
Shrout ($\times 10^7$)	13.503	11.316	7.233
Volume ($\times 10^5$)	3.661	4.075	3.952
Turnover ($\times 10^{-3}$)	2.968	3.980	5.141
Amihud illiquidity	0.023	0.018	0.022
Bid-Ask spread	5.925	5.766	5.566
Other characteristics			
Number of analysts	8.090	7.506	6.564
Forecast dispersion	0.051	0.052	0.061
Institute Shareholders	203	182	138
Institute Ownership (%)	0.625	0.645	0.648

Table II. Abnormal Returns around Analyst Forecast Revision

This table reports the *Revise* measure and average percentage cumulative abnormal return of analyst forecast revision of each *Sturn* group and each revision level. For each revision level, firms with forecast revisions are classified into high-, medium-, and low-*Sturn* group. *Revise* is calculated as forecast revision less analysts' own prior forecast, as a percentage of stock price as of two days before the revision date, with the extreme 1% winsorized. The abnormal return each day is raw return less the DGTW characteristics-adjusted return. Panel A shows *Revise* of the analyst forecast revision of each *Sturn*-revision group. Panel B shows the cumulative abnormal return during the event period of each *Sturn*-revision group. Panels C, D, and E show the cumulative abnormal return of each *Sturn*-revision group during the post-event period for 10, 20, and 30 days, respectively. Analyst forecast data are obtained from I/B/E/S from 1993 to 2012. All estimates are expressed in percentages. Statistical significance is based on Huber–White standard error estimator clustered by calendar date with the associated *t*-statistics in parentheses below the estimates.

Panel A. Revise value

Sturn	High-Bad	Low-Bad	Low-Good	High-Good	HG-HB
Low	-1.53	-0.72	0.58	0.81	2.34***
	(-41.45)	(-14.67)	(29.34)	(34.09)	(44.92)
Medium	-1.39	-0.61	0.53	0.73	2.13***
	(-45.07)	(-22.67)	(33.25)	(39.06)	(50.57)
High	-1.62	-0.65	0.56	0.75	2.37***
	(-43.18)	(-29.68)	(32.58)	(38.80)	(46.36)
H-L	-0.09	0.07	-0.02	-0.06	0.03
	(-1.29)	(1.12)	(-0.72)	(-1.31)	(0.32)

Panel B. Day -1 to Day +1

Sturn	High-Bad	Low-Bad	Low-Good	High-Good	HG-HB
Low	-1.76	-0.31	0.74	1.47	3.22***
	(-40.48)	(-7.99)	(13.72)	(34.34)	(50.69)
Medium	-2.29	-0.53	0.68	1.48	3.77***
	(-41.75)	(-11.16)	(13.29)	(34.54)	(52.38)
High	-2.93	-0.98	0.84	1.73	4.66***
	(-37.81)	(-14.18)	(11.60)	(32.15)	(47.18)
H-L	-1.17***	-0.67***	0.11	0.26***	1.43***
	(-13.03)	(-8.45)	(1.23)	(4.10)	(12.93)

(Continued)

(Continued)

Panel C. Day +2 to Day +11

Sturn		High-Bad	Low-Bad	Low-Good	High-Good	HG-HB
Low		-0.16	-0.11	0.36	0.47	0.62***
		(-3.53)	(-1.92)	(6.35)	(11.40)	(10.63)
Medium		-0.10	-0.16	0.19	0.26	0.36***
		(-1.81)	(-2.72)	(3.30)	(6.21)	(5.13)
High		-0.09	-0.20	0.13	0.12	0.22**
		(-1.29)	(-2.53)	(1.67)	(2.28)	(2.38)
H-L		0.06	-0.09	-0.22**	-0.35***	-0.52***
		(0.78)	(-0.94)	(-2.41)	(-5.41)	(-3.70)

Panel D. Day +2 to Day +21

Sturn		High-Bad	Low-Bad	Low-Good	High-Good	HG-HB
Low		-0.14	-0.22	0.43	0.59	0.72***
		(-2.29)	(-2.78)	(5.40)	(10.70)	(8.96)
Medium		-0.16	-0.14	0.15	0.30	0.46***
		(-2.14)	(-1.76)	(1.78)	(5.25)	(4.96)
High		0.06	-0.28	0.23	0.31	0.24*
		(0.63)	(-2.55)	(2.11)	(4.05)	(1.95)
H-L		0.20*	-0.06	-0.20	-0.28***	-0.48***
		(1.87)	(-0.47)	(-1.55)	(-3.11)	(-3.48)

Panel E. Day +2 to Day +31

Sturn		High-Bad	Low-Bad	Low-Good	High-Good	HG-HB
Low		-0.12	-0.18	0.31	0.49	0.61***
		(-1.59)	(-1.90)	(3.15)	(7.18)	(6.14)
Medium		-0.12	-0.06	0.23	0.32	0.44***
		(-1.31)	(-0.63)	(2.30)	(4.53)	(3.89)
High		0.20	-0.18	0.24	0.20	0.00
		(1.61)	(-1.35)	(1.77)	(2.12)	(-0.01)
H-L		0.31**	0.01	-0.08	-0.29**	-0.61***
		(2.40)	(0.03)	(-0.47)	(-2.60)	(-3.61)

Table III. Cross-Sectional Determinants of Price Reaction to Analyst Forecast Revision

This table shows the result of two-way sort panel regression to investigate whether the effect of investment horizon is robust after controlling for other factors that may be related to analyst forecast revision drift. The regression specification is

$$DGTW_{i,t+1} = \alpha_t + \beta_t Revise_{i,t} + \gamma_t Signal_{i,t} + \delta_t Revise_{i,t} \cdot STurn_{i,t} + \mu_t Revise_{i,t} \cdot X_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is DGTW characteristic-adjusted returns during the post-event period. *Signal* is a categorical variable that has +1 for high-innovation good news, 0 for low-innovation news, and -1 for high-innovation bad news. X are control variables such as analyst coverage, Amihud illiquidity, forecast dispersion of the firm, log of firm size (*ME*), log of book-to-market ratio (*B/M*), and log of past 12-month return (*Mom*). *Coverage* is a dummy variable of analyst coverage, which has the value of 1 if the firm is followed by more than the median number of analysts, and 0 otherwise. Also, *Amihud illiquidity* is measured as average daily absolute return divided by daily dollar trading volume over the quarter over which the *Sturn* variable is measured. *Forecast dispersion* is calculated as the most recent standard deviation of analyst forecasts scaled by the absolute value of the mean estimate. Event period is defined as day -1 to day +1 relative to forecast revision date. Post-event periods is from day +2 to day +31. All estimates are standardized and *t*-statistics are estimated based on two-way clustered robust standard errors for the firm and date.

	Panel A. Event Period		Panel B. Post Period	
Variables	Model 1	Model 2	Model 1	Model 2
Intercept	-0.002***	-0.002***	-0.001	-0.002***
	(-5.46)	(-5.17)	(-1.62)	(-2.61)
Revise	0.043	0.715***	0.179**	1.289***
	(0.95)	(8.29)	(2.15)	(7.14)
Signal	0.019***	0.019***	0.003***	0.003***
	(39.69)	(40.92)	(3.93)	(3.88)
Revise · Sturn	0.445***	0.248***	-0.460**	-0.607***
	(4.73)	(2.73)	(-2.23)	(-3.08)
Revise · Coverage		0.083*		-0.058
		(1.88)		(-0.53)
Revise · Amihud		-0.046***		0.014
		(-2.66)		(0.48)
Revise · Dispersion		-0.038**		-0.057
		(-2.45)		(-1.32)
Revise · ME		-0.112***		-0.130***
		(-8.95)		(-3.56)
Revise · B/M		-0.156***		0.112**
		(-7.44)		(2.35)
Revise · Mom		0.111***		0.450***
		(3.69)		(7.69)
R-Squared	0.0628	0.0665	0.0004	0.0029

Table IV. Time-series Regression of Post-Forecast-Revision-Drift Strategy Returns

This table reports the time-series regression results of the daily rebalanced portfolio strategy based on analyst forecast revision. For each *Sturn* group, daily calendar time portfolio is formed based on the forecast revision. The strategy is buying stocks with high-innovation good news and selling stocks with high-innovation bad news two trading days after the date of revision. The position of the stocks is kept for 30 trading days until the next revision for the stock is announced. Long and short portfolios are rebalanced every trading day based on the forecast revisions and give equal-weight to each stock. The abnormal return of portfolio from the strategy using 4 models, Excess return, CAPM, Fama-Freanch three-factor model, and Carhart four-factor model. Daily raw return of the portfolio in excess of the risk-free rate is regressed on the factors according to the model. The reported alpha is monthly risk-adjusted return. All estimates are expressed in percentage. The t-statistics are corrected for autocorrelation based on the Newey-West (1987) standard errors.

Sturn	Excess Return	CAPM		FF 3 Factors		Carhart 4 Factors	
	alpha	alpha	Adj_R2	alpha	Adj_R2	alpha	Adj_R2
Low	0.993	1.074	0.042	1.160	0.076	0.919	0.287
	(5.10)	(5.22)		(5.87)		(4.12)	
Medium	0.494	0.579	0.038	0.670	0.066	0.345	0.385
	(1.68)	(1.98)		(2.39)		(1.63)	
High	0.470	0.619	0.076	0.713	0.093	0.355	0.334
	(1.60)	(2.02)		(2.34)		(1.11)	
L-H	0.523**	0.455*	0.016	0.447*	0.008	0.564**	0.036
	(2.11)	(1.77)		(1.69)		(2.12)	

Table V. Correlation Matrix (Pearson Correlations Are Shown above the Diagonal with Spearman Correlations Below)

This table reports the Pearson (Spearman) correlation between those variables and Sturn. The Pearson correlations are shown above the diagonal and the Spearman correlations are shown below the diagonal. Sturn proxy investment horizon which is measured as the share-weighted average of the cross-sectional percentile rankings of portfolio turnover of mutual funds that are shareholders of the stock. Firm size (*ME*) is the market capitalization (in millions of dollars) at the end of month t. Book-to market (*B/M*) is the book value of equity divided by its market value at the end of the last fiscal year. *Momentum* is accumulated returns from months $t-11$ to $t-1$. Stock turnover (*Turnover*) is the average daily turnover over the prior quarter. Amihud illiquidity (*Amihud*) is the average daily absolute return divided by daily dollar trading volume (in millions) over the prior quarter. Stock volatility (*Volatility*) is the standard deviation of daily excess returns over the prior quarter. Stocks with a price less than $5 are excluded from the sample. The sample period is from 1993 to 2012.

	Sturn	ME	B/M	Momentum	Turnover	Amihud	Volatility
Sturn	1	-0.090	-0.049	0.202	0.176	-0.052	0.070
ME	-0.071	1	-0.064	0.012	-0.036	-0.029	-0.076
B/M	-0.115	-0.140	1	0.077	-0.051	0.047	-0.034
Momentum	0.216	0.198	0.080	1	0.186	-0.045	-0.021
Turnover	0.251	0.097	-0.193	0.023	1	-0.064	0.331
Amihud	0.023	-0.916	0.159	-0.173	-0.393	1	0.082
Volatility	0.172	-0.424	-0.171	-0.212	0.440	0.343	1

Table VI. Results with *Residual Sturn*

This table shows the correlation matrix. Firm size (ME) is the market capitalization at the end of prior quarter. Book-to market (B/M) is the book value of equity divided by its market value at the end of the last fiscal year. Past 12-month return (Momentum) is accumulated returns from months t − 11 to t − 1. Turnover (Turnover) is measured as average daily turnover over the prior quarter. Daily turnover is the shares traded divided by the total number of shares outstanding. Amihud illiquidity (Amihud) is measured as the average daily absolute return divided by daily dollar trading volume (in millions) over the prior quarter. Return volatility (Volatility) is the standard deviation of daily stock return over the prior quarter. The Pearson correlations are shown above the diagonal and the Spearman correlations are shown below the diagonal. The sample period is from 1993 to 2012.

Panel A. Day -1 to Day +1

Residual Sturn	High-Bad	Low-Bad	Low-Good	High-Good	HG-HB
Low	-1.94	-0.35	0.74	1.57	3.51***
	(-39.92)	(-7.96)	(13.15)	(34.08)	(50.08)
Medium	-2.21	-0.54	0.66	1.46	3.67***
	(-40.75)	(-10.68)	(12.86)	(32.01)	(50.15)
High	-2.70	-0.89	0.83	1.65	4.35***
	(-38.14)	(-14.75)	(12.60)	(33.48)	(48.13)
H-L	-0.76***	-0.54***	0.09	0.08	0.84***
	(-9.25)	(-7.40)	(1.03)	(1.23)	(8.07)

Panel B. Day +2 to Day +11

Residual Sturn	High-Bad	Low-Bad	Low-Good	High-Good	HG-HB
Low	-0.10	-0.08	0.36	0.42	0.53***
	(-2.11)	(-1.21)	(5.88)	(9.14)	(7.96)
Medium	-0.09	-0.21	0.15	0.24	0.33***
	(-1.51)	(-3.54)	(2.57)	(5.42)	(4.47)
High	-0.07	-0.18	0.20	0.16	0.22***
	(-1.01)	(-2.48)	(2.63)	(3.20)	(2.72)
H-L	0.04	-0.10	-0.16*	-0.27***	-0.30***
	(0.51)	(-1.08)	(-1.71)	(-4.25)	(-3.19)

(Continued)

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Panel C. Day +2 to Day +21

Residual Sturn	High-Bad	Low-Bad	Low-Good	High-Good	HG-Hb
Low	-0.04	-0.15	0.51	0.54	0.57***
	(-0.55)	(-1.63)	(5.73)	(8.88)	(6.40)
Medium	-0.12	-0.24	0.07	0.29	0.42***
	(-1.57)	(-2.93)	(0.79)	(4.69)	(4.19)
High	0.06	-0.25	0.28	0.31	0.25**
	(0.70)	(-2.50)	(2.71)	(4.38)	(2.15)
H-L	0.10	-0.10	-0.23*	-0.23***	-0.33**
	(1.02)	(-0.79)	(-1.72)	(-2.64)	(-2.50)

Panel D. Day +2 to Day +31

HG-HB	High-Bad	Low-Bad	Low-Good	High-Good	HG-HB
Low	0.05	-0.11	0.46	0.53	0.48***
	(0.63)	(-1.05)	(4.18)	(6.98)	(4.36)
Medium	-0.08	-0.11	0.08	0.24	0.32***
	(-0.86)	(-1.02)	(0.74)	(3.16)	(2.72)
High	0.17	-0.24	0.33	0.19	0.01
	(1.55)	(-2.09)	(2.57)	(2.15)	(0.09)
H-L	0.12	-0.13	-0.13	-0.35***	-0.47***
	(1.01)	(-0.85)	(-0.83)	(-3.15)	(-2.85)

Table VI. Abnormal Returns around Analyst Forecast Revision using Quintile *Revise* Ranking

This table reports the average percentage cumulative abnormal return of analyst forecast revision for each *Sturn* group and each revision ranking based on *Revise* value. For each revision ranking, firms with forecast revisions are classified into high-, medium-, and low-*Sturn* group. At the end of each quarter, forecast revisions during the quarter are ranked into Quintile groups according to the value of *Revise* independent of *Sturn* group. *Revise* is calculated as forecast revision less analysts' own prior forecast, as a percentage of stock price two days before the revision date, with the extreme 1% of values winsorized. The abnormal return each day is raw return less the DGTW characteristics-adjusted return. All estimates are expressed in percentages. Statistical significance is based on Huber–White standard error estimator clustered by calendar date, with the associated *t*-statistics in parentheses below the estimates.

Panel A. Revise Value

Sturn	1	2	3	4	5	HG-HB
Low	-3.08	-0.42	-0.06	0.19	1.49	4.57***
	(-56.33)	(-139.67)	(-43.35)	(138.98)	(47.04)	(59.22)
Medium	-2.84	-0.42	-0.05	0.18	1.38	4.22***
	(-61.73)	(-147.58)	(-40.74)	(129.09)	(54.53)	(67.79)
High	-3.02	-0.42	-0.05	0.18	1.42	4.44***
	(-56.79)	(-139.24)	(-32.44)	(136.94)	(52.57)	(60.17)
H-L	0.06	0.00	0.02***	0.00	-0.07	-0.13
	(0.48)	(0.14)	(7.15)	(-0.40)	(-0.86)	(-0.68)

Panel B. Day -1 to Day +1

Sturn	1	2	3	4	5	HG-HB
Low	-2.57	-1.32	-0.34	0.95	2.08	4.65***
	(-37.36)	(-31.64)	(-11.25)	(25.58)	(35.22)	(50.06)
Medium	-3.27	-1.89	-0.44	1.11	2.06	5.34***
	(-37.77)	(-34.61)	(-12.21)	(27.41)	(34.19)	(50.11)
High	-3.95	-2.45	-0.68	1.12	2.49	6.44***
	(-36.27)	(-33.64)	(-11.19)	(21.76)	(35.48)	(48.33)
H-L	-1.39***	-1.13***	-0.33***	0.17**	0.41***	1.80***
	(-10.79)	(-12.96)	(-4.92)	(2.66)	(5.00)	(11.66)

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Panel C. Day +2 to Day +11

Sturn	1	2	3	4	5	HG-HB
Low	-0.25	-0.14	-0.05	0.24	0.80	1.05***
	(-3.77)	(-3.31)	(-1.48)	(6.09)	(14.52)	(12.66)
Medium	-0.14	-0.12	-0.12	0.10	0.62	0.76***
	(-1.89)	(-2.28)	(-2.91)	(2.27)	(11.27)	(8.36)
High	-0.11	-0.25	-0.26	-0.08	0.50	0.61***
	(-1.26)	(-3.52)	(-4.42)	(-1.44)	(7.70)	(5.60)
H-L	0.14	-0.11	-0.20***	-0.32***	-0.30***	-0.44***
	(1.35)	(-1.39)	(-3.05)	(-4.87)	(-3.81)	(-3.42)

Panel D. Day +2 to Day +21

Sturn	1	2	3	4	5	HG-HB
Low	-0.20	-0.21	-0.15	0.29	1.11	1.31***
	(-2.23)	(-3.63)	(-2.96)	(5.23)	(15.16)	(11.58)
Medium	-0.04	-0.18	-0.25	0.02	0.90	0.94***
	(-0.40)	(-2.41)	(-4.29)	(0.33)	(12.05)	(7.99)
High	0.03	-0.15	-0.34	-0.04	0.89	0.86***
	(0.28)	(-1.56)	(-4.36)	(-0.56)	(10.06)	(5.93)
H-L	0.24*	0.07	-0.20**	-0.33***	-0.21**	-0.45***
	(1.77)	(0.61)	(-2.19)	(-3.55)	(-1.98)	(-2.66)

Panel E. Day +2 to Day +31

Sturn	1	2	3	4	5	HG-HB
Low	-0.04	-0.26	-0.26	0.09	1.23	1.27***
	(-0.37)	(-3.54)	(-4.46)	(1.29)	(13.62)	(9.46)
Medium	0.15	-0.13	-0.28	-0.05	1.08	0.93***
	(1.31)	(-1.56)	(-3.97)	(-0.61)	(11.86)	(6.64)
High	0.15	0.03	-0.37	-0.15	0.87	0.72***
	(1.00)	(0.23)	(-4.04)	(-1.49)	(8.07)	(4.06)
H-L	0.19	0.28**	-0.11	-0.23*	-0.36***	-0.55***
	(1.11)	(2.20)	(-1.01)	(-1.96)	(-2.71)	(-2.59)

Table VIII. Abnormal Returns around Analyst Forecast Revision and Information Uncertainty Proxy

This table reports the average percentage cumulative abnormal return of analyst forecast revision for each *Sturn*-revision group by dividing stocks into two groups based on their information uncertainty level. We use six proxy for information uncertainty, such as 1/ME, 1/AGE, 1/COV, DISP, SIGMA, and CVOL. Firm size (ME) is the market capitalization at the end of prior quarter. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts following the firm in the prior year. Forecast dispersion (DISP) is the standard deviation of analyst forecasts in month t scaled by the absolute mean forecast. Stock return volatility (SIGMA) is the standard deviation of daily market excess return over the prior quarter. Cash flow volatility (CVOL) is the standard deviation of cash flow from operations in the past five years (with a minimum of three years), where cash flow from operations is earnings before extraordinary items minus total accruals, scaled by average total assets. 1/ME, 1/AGE, and 1/COV are the reciprocals of ME, AGE, and COV, respectively. The abnormal return each day is raw return less the DGTW characteristics-adjusted return. All estimates are expressed in percentages. Statistical significance is based on Huber–White standard error estimator clustered by calendar date, with the associated *t*-statistics in parentheses below the estimates.

Information Uncertainty Proxy	Low Information Uncertainty Firms				High Information Uncertainty Firms			
	Panel A. Day -1 to Day +1							
	Sturn	Bad	Good	G-B	Sturn	Bad	Good	G-B
1/ME	Low	-1.26	0.79	2.05***	Low	-2.25	2.71	4.96***
		(-27.63)	(23.02)	(36.64)		(-23.39)	(24.51)	(35.30)
	Medium	-1.59	0.94	2.52***	Medium	-2.69	2.17	4.86***
		(-27.50)	(22.51)	(37.61)		(-26.74)	(23.99)	(36.29)
	High	-2.29	1.27	3.56***	High	-3.20	2.27	5.48***
		(-22.41)	(19.50)	(30.09)		(-25.92)	(24.67)	(36.33)
	H-L	-1.03***	0.48***	1.52***	H-L	-0.96***	-0.44***	0.52**
		(-8.92)	(6.32)	(11.10)		(-5.93)	(-2.99)	(2.47)

	Sturn	Bad	Good	G-B	Sturn	Bad	Good	G-B
1/AGE	Low	-1.28	1.00	2.28***	Low	-2.05	1.91	3.96***
		(-35.36)	(29.98)	(46.64)		(-23.10)	(23.19)	(33.69)
	Medium	-1.51	1.04	2.55***	Medium	-2.67	1.64	4.31***
		(-31.92)	(29.14)	(43.62)		(-30.33)	(23.12)	(40.02)
	High	-1.97	1.25	3.23***	High	-3.01	1.77	4.77***
		(-26.80)	(24.21)	(35.73)		(-31.22)	(25.14)	(40.88)
	H-L	-0.69***	0.25***	0.94***	H-L	-0.96***	-0.14	0.81***
		(-8.37)	(4.14)	(9.32)		(-7.07)	(-1.32)	(4.82)
	Sturn	Bad	Good	G-B	Sturn	Bad	Good	G-B
1/COV	Low	-1.25	0.98	2.23***	Low	-1.76	1.69	3.45***
		(-26.04)	(21.98)	(35.10)		(-24.33)	(23.40)	(34.51)
	Medium	-1.74	1.07	2.81***	Medium	-2.37	1.51	3.87***
		(-29.08)	(23.19)	(38.75)		(-25.98)	(20.90)	(34.70)
	High	-2.37	1.39	3.76***	High	-2.64	1.73	4.37***
		(-25.46)	(20.76)	(33.54)		(-22.68)	(20.79)	(31.68)
	H-L	-1.12***	0.41***	1.52***	H-L	-0.89***	0.04	0.92***
		(-10.28)	(5.15)	(11.40)		(-6.25)	(0.32)	(5.36)
	Sturn	Bad	Good	G-B	Sturn	Bad	Good	G-B
DISP	Low	-1.14	1.12	2.26***	Low	-1.72	1.37	3.09***
		(-27.18)	(25.99)	(38.22)		(-31.99)	(24.05)	(41.04)
	Medium	-1.47	1.28	2.76***	Medium	-2.31	1.23	3.54***
		(-27.06)	(29.43)	(40.79)		(-33.45)	(21.57)	(40.98)
	High	-2.11	1.45	3.55***	High	-2.78	1.62	4.39***
		(-25.77)	(24.91)	(34.70)		(-31.22)	(22.88)	(40.21)
	H-L	-0.97***	0.32***	1.29***	H-L	-1.06***	0.25***	1.30***
		(-10.19)	(4.45)	(10.77)		(-10.17)	(2.85)	(10.06)

	Sturn	Bad	Good	G-B	Sturn	Bad	Good	G-B
SIGMA	Low	-1.09	0.83	1.92***	Low	-2.17	2.07	4.25***
		(-31.93)	(26.31)	(41.34)		(-23.16)	(20.90)	(33.34)
	Medium	-1.36	0.94	2.30***	Medium	-2.59	1.69	4.28***
		(-31.21)	(26.52)	(42.04)		(-28.15)	(21.44)	(37.55)
	High	-1.85	1.19	3.03***	High	-2.87	1.68	4.55***
		(-25.21)	(21.23)	(32.51)		(-27.53)	(22.22)	(36.54)
	H-L	-0.75***	0.36***	1.11***	H-L	-0.70***	-0.40***	0.30*
		(-8.90)	(5.74)	(10.57)		(-5.16)	(-3.32)	(1.72)

	Sturn	Bad	Good	G-B	Sturn	Bad	Good	G-B
CVOL	Low	-2.15	2.24	4.39***	Low	-1.26	0.86	2.12***
		(-27.52)	(25.71)	(39.40)		(-27.68)	(21.77)	(37.09)
	Medium	-2.74	2.12	4.86***	Medium	-1.62	0.94	2.56***
		(-27.77)	(25.45)	(38.36)		(-29.05)	(22.67)	(39.02)
	High	-3.21	1.88	5.09***	High	-2.05	1.37	3.42***
		(-26.18)	(23.07)	(34.60)		(-23.94)	(21.86)	(33.32)
	H-L	-1.06***	-0.36***	0.71***	H-L	-0.79***	0.51***	1.30***
		(-6.97)	(-3.05)	(3.83)		(-8.02)	(6.84)	(10.64)

(Continued)

Panel B. Post Analyst Forecast Drift

	News	Bad	Good	G-B	Bad	Good	G-B	Difference in Drifts
1/ME	CAR	-0.04	0.05	0.08	0.03	0.90	0.87***	0.79***
		(-0.54)	(0.99)	(1.09)	(0.31)	(9.18)	(6.80)	(5.69)
1/AGE	CAR	-0.10	0.19	0.28***	-0.05	0.49	0.54***	0.26**
		(-1.73)	(3.91)	(4.07)	(-0.51)	(6.59)	(4.91)	(2.25)
1/COV	CAR	0.05	0.11	0.06	-0.22	0.38	0.60***	0.55***
		(0.71)	(1.81)	(0.65)	(-2.49)	(4.81)	(5.34)	(4.28)
DISP	CAR	-0.23	-0.05	0.18**	0.03	0.68	0.65***	0.47***
		(-3.79)	(-0.88)	(2.34)	(0.34)	(10.18)	(6.98)	(4.30)
SIGMA	CAR	0.34	0.47	0.13	-0.29	0.12	0.41***	0.28**
		(2.94)	(5.14)	(1.05)	(-6.19)	(2.46)	(6.61)	(2.23)
CVOL	CAR	-0.07	0.26	0.33***	-0.04	0.27	0.31***	-0.02
		(-0.82)	(3.10)	(2.89)	(-0.53)	(4.67)	(3.80)	(-0.12)

Panel C. Day +2 to Day +31

	Sturn	Bad	Good	G-B	Sturn	Bad	Good	G-B
1/ME	Low	0.14	0.22	0.08	Low	0.37	0.68	0.31
		(1.91)	(3.31)	(0.79)		(2.37)	(4.19)	(1.48)
	Medium	-0.04	0.09	0.13	Medium	0.30	0.27	-0.04
		(-0.36)	(1.26)	(1.11)		(1.92)	(2.07)	(-0.18)
	High	0.18	-0.43	-0.61***	High	0.79	0.23	-0.56**
		(1.13)	(-3.46)	(-3.29)		(4.16)	(1.56)	(-2.49)
	H-L	0.04	-0.65***	-0.69***	H-L	0.42*	-0.45**	-0.86***
		(0.23)	(-4.69)	(-3.41)		(1.78)	(-2.09)	(-2.87)

	Sturn	Bad	Good	G-B	Sturn	Bad	Good	G-B
1/AGE	Low	-0.12	0.31	0.43***	Low	-0.16	0.77	0.93***
		(-1.79)	(5.24)	(5.17)		(-1.16)	(5.57)	(5.11)
	Medium	-0.06	0.21	0.28***	Medium	-0.19	0.44	0.63***
		(-0.80)	(3.21)	(2.85)		(-1.24)	(3.90)	(3.56)
	High	-0.06	0.00	0.06	High	0.28	0.38	0.10
		(-0.49)	(0.01)	(0.41)		(1.82)	(3.22)	(0.57)
	H-L	0.06	-0.31***	-0.37**	H-L	0.44**	-0.39**	-0.82***
		(0.46)	(-2.68)	(-2.32)		(2.25)	(-2.16)	(-3.27)

	Sturn	Bad	Good	G-B	Sturn	Bad	Good	G-B
1/COV	Low	0.08	0.31	0.22**	Low	-0.36	0.50	0.86***
		(1.01)	(3.97)	(2.07)		(-3.07)	(4.04)	(5.56)
	Medium	-0.13	0.06	0.18	Medium	-0.23	0.43	0.66***
		(-1.18)	(0.70)	(1.49)		(-1.67)	(3.68)	(3.76)
	High	0.31	-0.01	-0.32*	High	0.03	0.28	0.25
		(2.12)	(-0.09)	(-1.85)		(0.14)	(1.79)	(1.10)
	H-L	0.23	-0.32**	-0.55***	H-L	0.39*	-0.22	-0.61**
		(1.45)	(-2.35)	(-2.81)		(1.84)	(-1.12)	(-2.22)

	Sturn	Bad	Good	G-B	Sturn	Bad	Good	G-B
DISP	Low	0.06	0.29	0.23**	Low	-0.28	0.57	0.85***
		(0.78)	(4.25)	(2.56)		(-2.95)	(5.71)	(6.68)
	Medium	-0.06	0.17	0.23**	Medium	-0.14	0.49	0.63***
		(-0.61)	(2.42)	(2.06)		(-1.23)	(4.48)	(4.36)
	High	0.20	-0.10	-0.30**	High	0.06	0.55	0.48***
		(1.70)	(-0.93)	(-2.00)		(0.41)	(4.32)	(2.67)
	H-L	0.15	-0.39***	-0.54***	H-L	0.35**	-0.02	-0.37*
		(1.09)	(-3.15)	(-3.10)		(2.11)	(-0.15)	(-1.75)

(Continued)

	Sturn	Bad	Good	G-B	Sturn	Bad	Good	G-B
SIGMA	Low	-0.27	0.25	0.52***	Low	0.26	0.80	0.54***
		(-4.76)	(4.19)	(6.75)		(1.62)	(4.83)	(2.61)
	Medium	-0.29	0.11	0.40***	Medium	0.32	0.46	0.15
		(-3.92)	(1.68)	(4.28)		(1.97)	(3.44)	(0.79)
	High	-0.32	-0.05	0.26*	High	0.57	0.33	-0.24
		(-2.95)	(-0.55)	(1.95)		(3.37)	(2.40)	(-1.23)
	H-L	-0.05	-0.31***	-0.26*	H-L	0.31	-0.47**	-0.78***
		(-0.43)	(-2.80)	(-1.70)		(1.48)	(-2.30)	(-2.85)

	Sturn	Bad	Good	G-B	Sturn	Bad	Good	G-B
CVOL	Low	-0.26	0.29	0.54***	Low	-0.12	0.35	0.47***
		(-2.02)	(2.28)	(3.15)		(-1.42)	(4.50)	(4.48)
	Medium	0.07	0.50	0.43**	Medium	-0.08	0.24	0.32***
		(0.45)	(3.82)	(2.29)		(-0.87)	(3.03)	(2.87)
	High	0.11	-0.01	-0.12	High	0.18	0.26	0.08
		(0.69)	(-0.06)	(-0.58)		(1.29)	(2.33)	(0.49)
	H-L	0.36*	-0.29	-0.66**	H-L	0.30**	-0.09	-0.39**
		(1.87)	(-1.60)	(-2.55)		(2.00)	(-0.65)	(-2.10)