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The Value of Analyst Forecast Revisions: Evidence from Earnings Announcements

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The Value of Analyst Forecast Revisions: Evidence from Earnings Announcements

A dissertation submitted in partial satisfaction
of the requirements for the degree
Doctor of Philosophy in Management

by

Kanyuan Huang

2022

ABSTRACT OF THE DISSERTATION

The Value of Analyst Forecast Revisions: Evidence from Earnings Announcements

by

Kanyuan Huang
Doctor of Philosophy in Management
University of California, Los Angeles, 2022
Professor Judson Andrew Caskey, Co-Chair
Professor Brett Michael Trueman, Co-Chair

This paper examines the information contained in analyst forecast revisions following earnings announcements. I find that sorting firms on aggregated forecast revisions generates a much stronger post-earnings-announcement drift than sorting on measures of earnings surprises. The strong association between aggregated forecast revisions and post-earnings-announcement returns is driven by the subsample of firms with large-magnitude earnings surprises. This result is consistent with analysts' roles in interpreting corporate earnings. Further, the mispricing is the strongest when forecast revisions contradict earnings surprises, suggesting investors have difficulties in processing contradictory signals. Lastly, I document aggregated forecast revisions are more informative when the information environment around earnings announcements is more opaque, when firms have high accruals and when investors do not pay attention to the firm. They are less informative when analysts disagree with each other. Overall, these results point to the value of analyst forecast revisions following earnings announcements.

The dissertation of Kanyuan Huang is approved.

Henry L. Friedman

Daniel Andres Saavedra Lux

Judson Andrew Caskey, Committee Co-Chair

Brett Michael Trueman, Committee Co-Chair

University of California, Los Angeles

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CHAPTER 1

The Value of Analyst Forecast Revisions: Evidence from Earnings Announcements

1.1 Introduction

Do analyst forecast revisions provide incremental information to investors? Early studies document strong market reactions following analyst forecast revisions (Givoly and Lakonishok 1979, Stickel 1991, Park and Stice 2000 and Gleason and Lee 2003), providing evidence consistent with the informational role of equity analysts. However, a few recent studies cast doubt on this conclusion. Altınkılıc and Hansen (2009) and Altınkılıc et al. (2013) find that stock returns immediately following forecast revisions and recommendation changes are economically unimportant. Further, they document significant stock returns before forecast revisions. They conclude that post-forecast-revision returns are likely to be triggered by economic events before analyst forecast revisions/recommendations. In other words, forecast revisions do not provide incremental value as analysts appear to be piggybacking on events that happened before revisions (Kim and Song 2015).

However, there are two limitations to these studies. First, Altınkılıc and Hansen (2009) and Altınkılıc et al. (2013) argue that analyst forecast revisions are piggybacking on the information before the revisions, but they do not observe that information in their studies. As a result, the returns before forecast revisions could be driven by information leakage from forecast revisions (Irvine et al. 2007). Second, these studies only examine the immediate market reaction following forecast revisions. They find that the immediate market reaction following forecast revisions is not economically significant and conclude that forecast revisions contain little information. However, the market may be slow to incorporate the information in forecast revisions due to limited attention (Hirshleifer and Teoh 2003). Thus, it is also important to examine longer-term stock returns following analyst forecast revisions.

In this paper, I revisit this empirical debate on the informational value of analyst forecast revisions by examining forecast revisions issued immediately following earnings announcements. Focusing on earnings announcements as the setting allows me to precisely control for the information shock (i.e., earnings surprises) before forecast revisions. Further, I examine longer-term stock returns following forecast revisions as the information in forecast revisions may be slow to be incorporated into the price. If analysts are piggybacking on earnings surprises, one should expect no statistically significant association between forecast revisions and post-earnings-announcement returns after controlling for earnings surprises. On the other hand, a positive and statistically significant association between the two would imply that these revisions contain incremental information.

I find that the aggregated forecast revision, measured as the average of all analysts' forecast revisions following an earnings announcement, contains information that is incremental to earnings surprises, and the market underreacts to this information. Specifically, a simple strategy that buys firms with the highest aggregated forecast revisions and shorts firms with the lowest aggregated forecast revisions yields a 90-day abnormal return of 3.4%, higher than abnormal returns on strategies that are based on earnings surprises (1.8% to 2.2%, Figure 1). The strong association between aggregated forecast revisions and post-earnings-announcement returns is mainly observed in the subsample of firms with large-magnitude earnings surprises.

(Insert Figure 1 about here)

To statistically compare the information contained in aggregated forecast revisions and earnings surprises, I regress post-earnings-announcement returns on aggregated forecast revisions and measures of earnings surprises simultaneously. Following Livnat and Mendenhall (2006), I measure earnings surprises using both the IBES-based definition and the time-series definition based on Compustat earnings. The magnitude of the coefficient on aggregated forecast revisions is statistically and economically larger than that of the coefficient on earnings surprises, suggesting aggregated forecast revisions are better signals in predicting post-earnings-announcement returns. In Appendix B, I develop a conceptual framework to formalize the economic interpretation of these regression coefficients.

Further, I find that aggregated forecast revisions completely subsume the IBES-based earnings surprise in predicting post-earnings-announcement returns, but not the Compustat-based earnings surprise, suggesting analyst forecast revisions fully incorporate the information contained in the IBES-based earnings surprise. This result also echoes Livnat and Mendenhall's (2006) and Doyle et al.'s (2006) finding that these two measures of earnings surprises may capture somewhat different forms of mispricing. Additional analysis shows that the incremental power of the Compustat-based earnings surprise in predicting future returns is driven by extreme positive earnings surprises (Koester et al. 2016). To put it differently, analysts are not able to fully understand the implication of extreme positive earnings surprises, measured using the time-series method, to firms' future performances.

Next, I examine the interaction between earnings surprises and aggregated forecast revisions. I find analysts' forecast revisions reinforce earnings surprises when these two signals are consistent with each other. This result is similar to Lobo et al. (2017)'s findings on earnings announcement returns. However, I find strong mispricing when these two signals contradict each other. Specifically, post-earnings-announcement returns are highest when earnings surprises are in the lowest decile but aggregated forecast revisions are in the highest decile, suggesting that the market underreacts to positive forecast revisions when firms have extremely negative earnings surprises.

To further understand the role of analysts in helping investors interpret earnings, I study conditions under which aggregated forecast revisions are more (or less) valuable to market participants. I find that aggregated forecast revisions are more informative to future returns when there the earnings contain high accruals and when investors pay less attention to the firm. They are less informative when analysts disagree with each other. These results are consistent with the informational value of analyst forecast revisions.

One alternative hypothesis for my main results is that aggregated forecast revisions might be capturing the information contained in management guidance, which is an omitted variable in my main analysis (Kim and Song 2015). To rule out this alternative argument, I partition my sample into earnings announcements with/without management guidance. If analysts are piggybacking on management guidance, one should expect a higher association between post-earnings-announcement returns and aggregated forecast revisions in the subsample of earnings announcements with management guidance. However, in robustness tests, I show that the positive association between post-earnings-announcement returns and aggregated forecast revisions is primarily driven by earnings announcements with no management guidance. This result is consistent with the view that analyst forecast revisions are more valuable when information environments around earnings announcements are more opaque.

This paper contributes to the literature on equity analysts by reconciling the seemingly contradictory results on the information value of analyst forecasts: on the one hand, there is no immediate price movement following analyst forecast revisions, suggesting that analysts may simply piggyback on events before forecasts (Altınkılıç et al. 2013). On the other hand, studies using textual analysis find that analyst reports following earnings announcements contain topics that are beyond what the manager discusses during the conference call, and this information can facilitate the interpretation of earnings results (Huang et al. 2018). By explicitly controlling for the economic event before forecast revisions (i.e., earnings announcements), I show that analyst forecast revisions provide incremental information to investors, and the market is slow to incorporate this information. These results also complement Li et al.'s (2015) findings on analyst recommendations.[1]

This paper also contributes to the literature on the post-earnings-announcement drift by providing novel insights on the interaction between the post-earnings-announcement drift and analyst forecast revisions. I document that aggregated forecasts revisions are better predictors of post-earnings-announcement returns than measures of earnings surprises, and the post-earnings-announcement drift is completely explained away by aggregated forecast revisions when using the IBES-based measure of earnings surprises. These results suggest that the post-earnings-announcement drift appears to stem from investors' underreactions to a broader set of information released during earnings announcements. This information is better captured by analyst forecast revisions as opposed to measures of earnings surprises. Lastly, these results are useful to practitioners who implement trading strategies to exploit the mispricing following earnings announcements.

The structure of the paper is as follows: section 1.2 discusses the related literature. Section 1.3 discusses the sample and variable construction. Sections 1.4 and 1.5 present the main results. Section 1.6 provides robustness tests. Section 1.7 concludes.

[1] Li et al. (2015) match analyst recommendations to preceding news. They find only a small minority (i.e., around 30%) of these returns directionally confirms the information in the preceding events. Li et al. (2015) argue that the pre-recommendation return documented by Altınkılıç and Hansen (2009) are partially due to information leakage. Li et al.'s (2015) results are also consistent with the informational role of analysts.

1.2 Related Literature

This paper is related to the literature on the information content of analyst forecasts. Givoly and Lakonishok (1979), Stickel (1991), and Gleason and Lee (2003) show that the market underreacts to analyst forecasts. This paper differs from these papers in two major ways: (1) prior literature focuses on market reactions to an individual analyst's forecast revisions. For instance, Gleason and Lee (2003) show that the analyst's characteristics affect the magnitude of the post-revision drift. This paper examines the aggregated forecast revision by taking the average of all analysts' revisions issued within 2-days following the earnings announcement. (2) Prior studies on analyst forecast revisions do not control for the information from events before revisions, and as a result, they are subject to the alternative argument of the piggybacking hypothesis (Altınkılıc and Hansen 2009 and Altınkılıç et al. 2013). In this paper, by explicitly controlling for the informational event immediately before revisions (i.e., earnings announcement), I provide clear evidence that analyst forecast revisions contain incremental information.

A few studies also examine the information content of analysts' forecast revisions during earnings announcements (Cornell and Landsman 1989, Beaver et al. 2008, Lobo et al. 2017). These studies find announcement returns are positively correlated with changes in consensus forecasts, consistent with Kormendi and Lipe (1987)'s model that announcement returns reflect changes in investors' expectations for future earnings. However, these studies focus on stock returns during earnings announcements as opposed to post-earnings-announcement returns, and they do not compare the information content of earnings surprises to forecast revisions.[2] Zhang

[2] In addition, one technical difference between Cornell and Landsman's (1989) and Beaver et al.'s (2008) studies and this paper is that prior papers measure forecast revisions using the change in IBES consensus forecasts after the quarterly earnings announcement. One disadvantage of using the consensus forecast, as discussed by Cornell and Landsman (1989), is reporting lags. IBES does not update consensus forecast immediately following the

(2008) documents that the post-earnings-announcement drift is weaker when analysts are more responsive, but she focuses on the timeliness of the forecast revisions.[3]

This paper is also related to the literature on the post-earnings-announcement drift. Ball and Brown (1968) and Bernard and Thomas (1989) document that stock returns drift in the direction of earnings surprises following earnings announcements, suggesting that the market underreacts to the information contained in earnings surprises. Bernard and Thomas (1990) and Rangan and Sloan (1998) provide evidence consistent with the underreaction hypothesis, as they show that quarterly earnings surprises in the same fiscal year exhibit strong first-order autocorrelation. Kothari (2001) and Livnat and Mendenhall (2006) provide detailed reviews of prior literature on the post-earnings-announcement drift. This paper contributes to the literature by documenting novel interactions between earnings surprises, forecast revisions, and post-earnings-announcement returns.

1.3 Data and sample construction

1.3.1 Sample construction

My initial sample consists of over 290,000 quarterly earnings announcements in IBES that can be matched to Compustat. My sample starts from 1995 as DellaVigna and Pollet (2009) document that announcement dates in IBES are sometimes inconsistent with Compustat dates before 1995. My sample ends in the fourth quarter of 2019.

I measure each analyst's annual EPS forecast revision around a quarterly earnings announcement as the following:

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announcement, and as a result, change in consensus may incorporate information that is not in the earnings announcement.

[3] Similar to Zhang (2008), Li et al. (2020) examine the timeliness of information and underreaction to earnings news. They document that delayed disclosures of financial statement items in earnings announcements lead to a stronger post-earnings-announcement drift.

$$[E(X_{yr+1}|X_q) - E(X_{yr+1})]/P_q$$

Where $E(X_{yr+1}|X_q)$ is the analyst's first annual EPS forecast issued after the announcement of quarterly earning X_q. I restrict my sample to the first forecast issued within two days (from day 0 to day 2) following the quarterly announcement to ensure that it only incorporates information from the earnings announcement. $E(X_{yr+1})$ is the analyst's last annual EPS forecast issued before the quarterly announcement but after the previous quarter's announcement. If the previous quarter's announcement date is missing in Compustat, I assume the prior quarter's earnings are announced 90 days before the current quarter's announcement date for fiscal quarters 1, 2 and 3. For the fourth fiscal quarter, I assume the prior quarter's earnings are announced 120 days before the current announcement date, as the filing deadlines for 10-Ks are twenty to forty-five days longer than 10-Qs. P_q is the quarter end per-share stock price. I then aggregate all analysts' forecast revisions during a quarterly earnings announcement by taking the average of them.

Following Livnat and Mendenhall (2006), I use two measures of earnings surprises: one based on the IBES consensus forecast and the other one based on the time-series model using Compustat earnings. Prior studies find statistically significant drift using both measures of earnings surprises (see Livnat and Mendenhall 2006's section 2 for a review). Livnat and Mendenhall (2006) and Doyle et al. (2006) compare the magnitude of the post-earnings-announcement drift using these two measures and find that the drift is larger when using earnings surprises measured from the IBES consensus forecast. As in Livnat and Mendenhall (2006), I define the IBES-based earnings surprises as:

$$SUE\ (IBES)_q = (X_q - X_f)/P_q$$

Where X_q is the quarterly EPS from IBES and X_f is the most recent median consensus forecast before earnings announcements in the IBES summary file. P_q is the quarter end per-share price. Similarly, Compustat-based earnings surprises are defined as:

$$SUE\ (Compustat)_q = (X'_q - X'_{q-4})/P_q$$

Where X'_q is the EPS before extraordinary items. X'_{q-4} is the four-quarter lagged EPS in Compustat. To alleviate the effects of outliers and non-linearity in earnings surprises-return relation, I follow the prior literature by sorting my measures of forecast revisions and earnings surprises into 10 deciles for each year-quarter (Bernard and Thomas 1989, Bartov et al. 2000, Livnat and Mendenhall 2006).

Lastly, I match each earnings announcement to CRSP daily return. I compute post-earnings-announcement returns as cumulative abnormal returns (CAR) from day 3 to day 90 following earnings announcements. I define the abnormal return as the size/book-to-market adjusted return using 10 ×10 matched portfolios. I exclude firms with per-share stock price less than one dollar. Table 1 reports the sample construction.

(Insert Table 1 about here)

1.3.2 Summary Statistics

Table 2 reports the summary statistics.[4] The average of aggregated forecast revisions is -0.24% of the share price (p<1%), suggesting that on average, analysts lower their expectations for future earnings after the earnings announcements. The median revision is 0. A closer look at the distribution reveals that a larger number of observations fall into the extreme negative tail of the distribution than the extreme positive end of the distribution. For instance, the cutoff point

[4] Following prior literature (i.e., Abarbanell and Lehavy 2003), all continuous variables are winsorized at 1-99% except for stock returns. Extreme stock returns are discussed in the robustness test.

for the lowest 5% aggregated forecast revisions is -2.7%, while the cutoff point for the highest 5% is only 1.4%. In other words, analysts are more likely to issue large and negative revisions following the earnings announcement than large and positive revisions. This asymmetry in forecast revisions complements Abarbanell and Lehavy's (2003) finding that incidences of large and negative earnings surprises are more frequent than that of large and positive earnings surprises. Figure 2 plots the time-series of aggregated forecast revisions from 1995 to 2019. While the aggregated forecast revision is slightly negative for most years, there is a noticeable dip in 2008, reflecting the impacts of the financial crisis.

(Insert Table 2 and Figure 2 about here)

Next, I examine correlations between variables (Table 2, Panel B). As documented in Imhoff and Lobo (1984), analysts' forecast revisions during earnings announcements are highly correlated with earnings surprises. However, the correlation is higher between forecast revisions and IBES-based earnings surprises (0.57) than between forecast revisions and Compustat-based earnings surprises (0.29). Further, under the IBES-based method, 72% of earnings announcements with positive earnings surprises are followed by positive aggregated forecast revisions, and 83% of negative earnings surprises are followed by negative revisions. Under the Compustat-based method, these numbers are 62% for both positive and negative earnings surprises. These results are different from Li et al. (2015), where the authors find only less than half of analyst recommendation changes directionally confirm the preceding news. Lastly, forecast revisions are also positively correlated with firms' market capitalizations. The correlations between forecast revisions and book-to-market ratio, momentum, and analyst coverage are relatively small.

1.4 Results

1.4.1 Main results

In Panel A, I sort all firms into deciles by forecast revisions and earnings surprises for each year-quarter. The 90-day CAR spread between firms with the highest forecast revisions and firms with the lowest forecast revision is 3.43%, while the spread between firms with the highest earnings surprises and the lowest earnings surprises is 2.18% when using the IBES-based definition, and 1.78% when using the Compustat-based definition. In Panels B and C, I double sort firms into portfolios based on forecast revisions and earnings surprises. Aggregated forecast revisions exhibit stronger associations with post-earnings-announcement returns in the subsample of firms with larger magnitudes of earnings surprises. In particular, the mispricing appears to be the strongest for earnings announcements with extreme positive/negative earnings surprises. These preliminary results suggest that forecast revisions provide information that is incremental to earnings surprises. Later I examine the interaction between forecast revisions and earnings surprises in Section 4.2.

(Insert Table 3 about here)

To statistically test whether forecast revisions are better signals for post-earnings-announcement returns than earnings surprises, I run the following regression:

$$CAR_{i,t} = b_1 * SUE\ Decile_{i,t} + b_2 * Forecast\ Revision\ Decile_{i,t} + Year\ FE + Quarter\ FE$$

Where each observation is a quarterly earnings announcement. The independent variable $Forecast\ Revision\ Decile$ is the decile of average forecast revision, aggregated at the earnings announcement level. $SUE\ Decile$ is the decile of earnings surprise, measured using either the IBES-based definition or the Compustat-based definition. This empirical specification is similar to Livnat and Mendenhall (2006), where the authors compare the information content of different measures of earnings surprises. In Appendix B1, I use a simple model to formalize economic interpretations of these regression coefficients.

Table 4 reports the regression results. As a benchmark, column 1 first regresses post-earnings-announcement returns only on IBES-based earnings surprises ($SUE\ Decile$) without controlling for aggregated forecast revisions ($Forecast\ Revision\ Decile$). The coefficient on *SUE Decile (IBES-based)* is 0.017 (p<1%), consistent with the prior literature on the post-earnings-announcement drift. In the second column, I add $Forecast\ Revision\ Decile$. The coefficient on $Forecast\ Revision\ Decile$ is 0.027 (p<1%). The coefficient on *SUE Decile (IBES-based)* becomes 0.001 and statistically insignificant. An F test comparing the magnitude of these two coefficients (i.e. 0.001 vs. 0.027) suggests that the magnitude on $Forecast\ Revision\ Decile$ is statistically larger than that on *SUE Decile (IBES-based)*. These results imply that aggregated forecast revisions incorporate the information in IBES-based earnings surprises. In the third column, I include all firm-level control variables, and the results are similar to the second column.

(Insert Table 4 about here)

Columns 4 to 6 repeat the exercise in columns 1 to 3 but use Compustat-based earnings surprises. Specifically, in column 4, where I only include *SUE Decile (Compustat-based)* without controlling for $Forecast\ Revision\ Decile$, the coefficient on *SUE Decile (Compustat-based)* is 0.017 (p<1%).[5] In column 5, I add $Forecast\ Revision\ Decile$. The coefficient on *SUE*

[5] The coefficients on Compustat-based SUE Decile and IBES-based SUE Decile are similar in my sample. Livnat and Mendenhall (2006) document that the drift is larger when using IBES-based SUE Decile than Compustat-based SUE Decile. The difference is mainly driven by my sample selection, as my sample only includes earnings announcements with at least 1 analyst forecast revision during the announcement. This requirement filters out small firms with lower analyst coverage and less timely forecast revisions. To reconcile my result with Livnat and Mendenhall (2006)'s, I replicate Livnat and Mendenhall (2006)'s tests using the full sample of IBES earnings announcements, and find consistent results with the Livnat and Mendenhall (2006) (i.e. drift is larger for IBES-based SUE).

Decile (Compustat-based) is still significantly different from 0 but the magnitude decreases from 0.017 to 0.010. The coefficient on $Forecast\ Revision\ Decile$ is 0.025. An F test comparing the magnitude of these two coefficients (i.e., 0.010 vs. 0.025) suggests that the magnitude on $Forecast\ Revision\ Decile$ is statistically larger than that on *SUE Decile (Compustat-based)*. Column 6 includes firm-level controls. Results remain unchanged. These results suggests that aggregated forecast revisions are better predictors of post-earnings-announcement returns than Compustat-based earnings surprises.

To the extent that aggregated forecast revisions completely subsume the predictive power of the IBES-based SUE in explaining post-earnings-announcement returns but not the Compustat-based SUE (Table 4), I next examine the differences between these two measures of surprises. In particular, I attempt to understand why analyst forecast revisions do not fully capture the information contained in Compustat-based SUE.

Koester et al. (2016) show that managers sometimes use extreme positive earnings surprises to signal strong future performance, and analysts often miss these signals. I posit that analysts are slow to incorporate these signals into their forecasts immediately following the earnings announcement. Table 5 reports results consistent with my conjecture. In column 1, I created an indicator variable *Extreme Positive SUE* that equals one if Compustat-based earnings surprises are in the top two deciles. The dependent variable is post-earnings-announcement returns. After controlling for forecast revisions, the coefficient on *Extreme Positive SUE* is still positive and statistically significant (p<1%), and the coefficient on *SUE Decile (Compustat-based)* become insignificant from zero. This result suggests that the positive correlation between *SUE Decile (Compustat-based)* and post-earnings-announcement returns reported in table 4 column 6 is mainly driven by extreme positive earnings surprises, and analyst forecast revisions fail to incorporate the information contained in extreme positive surprises.

(Insert Table 5 about here)

Column 2 of Table 5 provides further evidence of analysts' underreactions to extremely positive earnings surprises by documenting a negative correlation between *Extreme Positive SUE* and forecast revisions, suggesting analysts are reluctant to give large and positive forecast revisions to firms experiencing extreme positive earnings surprises.[6] Columns 3 and 4 repeat the first two columns using IBES-based earnings surprises. The results are directionally consistent with columns 1 and 2 but with much weaker statistical significance. These results are consistent with my conjecture that forecast revisions fail to capture all information contained in extreme positive surprises, and this underreaction is stronger when using Compustat-based earnings surprises.

Overall, results in tables 3 and 4 suggest: (1) aggregated forecast revisions are more precise signals for post-earnings-announcement returns than measures of earnings surprises; (2) aggregated forecast revisions completely subsume the predictive power of the IBES-based SUE but not the Compustat-based SUE, highlighting the difference between these two measures (Livnat and Mendenhall 2006). Additional analyses show that the incremental predictive power of the Compustat-based earnings surprise for future returns is driven by extreme positive surprises, suggesting that analyst forecast revisions fail to incorporate all information contained in extreme positive earnings surprises (Koester et al. 2016).

[6] In column 2 of Table 4, the dependent variable is *forecast revision decile*. The coefficient on *Extreme Positive SUE* is negative, and the coefficient on *SUE Decile* is still positive. This points to an increasing and concave relationship between *SUE Decile* and *forecast revision decile,* suggesting that analysts are reluctant to give large and positive forecast revisions to firms experiencing extreme positive earnings surprises.

It is important to point out that these results do not necessary imply that analyst forecast revisions provide new information after earnings announcements. Forecast revisions can also reflect analysts' efforts in summarizing and aggregating information from existing information. These revisions are still valuable to the market in that they reduce investors' information processing cost (Blankespoor et al. 2019).

1.4.2 Confirmatory/Contradictory Signals

This subsection examines interactions between forecast revisions and earnings surprises. Lobo et al. (2017) study the announcement returns when forecast revisions provide consistent/contradictory signals to earnings surprises. They find that earnings response coefficients are larger when the two signals are consistent with each other, and smaller when these two signals are inconsistent. I extend their results by examining the interactions of forecast revisions and earnings surprises in post-earnings-announcement periods.

Table 6 presents the results. In panel A, I double sort firms by earnings surprises and aggregated forecast revisions. In earnings announcements where earnings surprises are consistent with aggregated forecast revisions, that is, when both earnings surprises and aggregated forecast revisions are in the highest (lowest) decile, the portfolio returns are positive (negative). Further, the magnitudes of these returns are large. For instance, a strategy that buys firms where both earnings surprises and aggregated forecast revisions are in the highest decile and short firms when both variables are in the lowest decile earns 90-day CARs from 4% to 4.75%. These returns are higher than returns achieved by sorting on either aggregated forecast revisions or earnings surprises alone. This is consistent with Lobo et al. (2017)'s finding that forecast revisions reinforce earnings surprises when these two signals are consistent with each other.

(Insert Table 6 about here)

However, results are more nuanced when earnings surprises are inconsistent with forecast revisions. Specifically, I find that abnormal returns are large and positive ($p<1\%$) when forecast revisions are high but earnings surprises are low. For instance, when using the IBES-based SUE measure, the abnormal return on firms with the highest forecast revisions but lowest earnings surprises is 4.35%, suggesting delayed reactions to analysts' bullish revisions when firms experience large and negative earnings surprises. On the other hand, the abnormal return on firms with the lowest forecast revisions and highest earnings surprises is close to 0.[7]

Panel B reports regression results of post-earnings-announcement returns on the interactions between forecast revisions and earnings surprises. Specifically, I create four indicator variables representing four categories of the earnings announcements. For instance, the indicator variable *High Revision Low SUE* equals one if the announcement is in the highest decile of forecast revisions but the lowest decile of earnings surprises. The other three indicator variables are constructed analogously. In columns 1 and 2 where earnings surprises are defined using the IBES-based definition, the coefficient on *High Revision Low SUE* is positive and statistically significant, suggesting positive post-earnings-announcement drift for announcements with the highest forecast revisions but lowest SUE. Columns 3 and 4 use Compustat-based earnings surprises. The coefficient on *High Revision Low SUE* is still positive and statistically significant, but its economic significance and statistical significance are much smaller when

[7] One may wonder why post-announcement returns differ in these two cases. In untabulated results, I find that the [0,2] day announcement return is 0 for firms with high forecast revision but low SUE, suggesting delayed reactions to forecast revisions during the announcement window. This mispricing is slowly corrected in post-announcement periods. For firms with low forecast revision but high SUE, announcement returns are -1.7% ($p<1\%$), suggesting the market correctly priced in the forecast revision information during the announcement window.

compared to columns 1 and 2. This result suggests that the mispricing is smaller when analyst forecast revisions are contradictory to the Compustat-based earnings surprises.[8]

The larger mispricing on the *High Revision Low SUE* portfolio using the IBES-based SUE (i.e., 4.35%) over the Compustat-based SUE (i.e., 1.75%) could be driven by differences in earnings (i.e., street vs. GAAP) or expectations (analyst vs. seasonal random walk). To distinguish these two potential drivers, I partition the sample by the difference between IBES earnings (i.e., street) and Compustat earnings (i.e., GAAP). If the difference in post-announcement returns is driven by different earnings definitions used by IBES and Compustat, one should expect that the mispricing mainly exists in the subsample of firms where IBES earnings are different from GAAP earnings. In Panel C of Table 6, I find that the mispricing does not differ much by the difference between IBES earnings and GAAP earnings. Specifically, the mispricing is 3.9% when IBES earnings are similar to GAAP earnings. It is 4.8% when these two earnings are different. The difference (i.e., 0.9%) is not statistically significant (t=-0.4). These results suggest that the larger mispricing using the IBES-based SUE over the Compustat-based SUE is mainly attributable to the expectation difference, instead of the differences in earnings definitions (Livnat and Mendenhall 2006).

Overall, these results suggest that forecast revisions reinforce earnings surprises when these two types of signals are consistent with each other. However, the results are more nuanced when forecast revisions contradict earnings surprises. Specifically, firms have higher abnormal returns when earnings surprises are most negative, but analysts are most bullish for future earnings. This result suggests that the market underreacts to the information contained in forecast

[8] This is also consistent with Panel A, which shows that the return on the *High Revision Low SUE* portfolio is 4.35% using the IBES definition and 1.75% using the Compustat definition. The difference between these two numbers is statistically significant at the 5% level.

revisions when firms experience negative earnings surprises. In addition, one practical implication of this result is that when implementing a trading strategy to exploit the post-earnings-announcement drift, one may want to exclude firms with the most negative earnings surprises but most positive forecast revisions from the short side.

1.5 Additional Tests

1.5.1. Analyst Disagreement

In the prior section, I show aggregated forecast revisions information that is incremental to earnings surprises. This subsection investigates how the information contained in aggregated forecast revisions varies by the information environment around earnings announcements and earnings characteristics. The first factor I examine is analyst disagreement. I conjecture that aggregated forecast revisions are less informative when analysts disagree with each other.[9] I measure analyst disagreement using the standard deviation of all forecast revisions around an earnings announcement, scaled by the mean of these revisions. I then create an indicator variable *Analyst Disagreement* equal to one if the scaled standard deviation of forecast revisions during an earnings announcement is greater than the median standard deviation around all earnings announcements in the same year. I exclude earnings announcements with only one analyst.

Table 7 reports the results. The coefficient on *Forecast Revision Decile* is positive and statistically significant as in the main results (Table 4). The coefficient on the interaction term between *Forecast Revision Decile* and *Analyst Disagreement* is negative and statistically significant, suggesting the association between aggregated forecast revisions and post-earnings-

[9] Appendix B1 formally derives this prediction. The intuition is that the informational value of aggregated forecast revisions is decreasing in the noisiness of the signal. In extreme cases where forecast revisions are sufficiently noisy, aggregated forecast revisions may provide little information to investors and the regression coefficient will be close to 0.

announcement returns is weaker in the subsample of earnings announcements with high dispersion of forecast revisions. This result is consistent with my conjecture that aggregated forecast revisions are less information when analysts disagree with each other. Lastly, the coefficient on *Analyst Disagreement* is positive but not statistically significant.

(Insert Table 7 about here)

1.5.2. Accruals

The second factor I consider is accounting accruals. Sloan (1996) documents that investors overprice firms with high accruals, suggesting the manager's opportunistic use of accruals in managing earnings. On the other hand, accruals are also positively associated with growth potential (Allen et al. 2013). I conjecture that forecast revisions help investors distinguish good accruals that are correlated with growth potential from bad accruals that are driven by earnings management (Barth and Hutton 2004). In other words, I expect returns to be higher for firms with high accruals and high forecast revisions, as high forecast revisions following earnings announcements generally reflect analysts' expectation for greater future growth.

To test this argument, I regress post-earnings-announcement returns on the interaction between aggregated forecast revisions and accruals, where the level of accruals is measured as the difference between net income and operating cash flow divided by total assets for each firm-quarter (Hribar and Collins 2002). I expect the coefficient on the interaction term to be positive.

Table 7 reports the regression results. The variable of interest is *High Accrual*× *Forecast Revision Decile*, where *High Accrual* is an indicator variable that equals 1 if the level of accruals is greater than the median accrual for all firms in the same year. The coefficient on *High Accrual* is negative and statistically significant, consistent with prior studies documenting that high accruals predict lower future returns (Sloan 1996, Collins and Hribar 2000). The coefficient on the interaction term is positive and statistically significant across all specifications, suggesting that high accrual firms with high forecast revisions perform better than high accrual firms with low forecast revisions. This result is consistent with my conjecture that analysts help investors better understand the implications of accruals for future earnings (Barth and Hutton 2004).

(Insert Table 8 about here)

1.5.3. Investor Attention

Prior studies document that investor attention increases the speed of price formation and reduces mispricing (Blankespoor et al. 2020). With respect to the post-earnings-announcement drift, Hirshleifer et al. (2009), DellaVigna and Pollet (2009) and Drake et al. (2016) show that the drift is larger when investors are distracted. These studies provide indirect evidence of the effect of the attention on the post-earnings-announcement drift. Lawrence et al. (2016) and Li et al. (2019) measure investors' attention using Yahoo finance search volume and EDGAR downloads, and find that the drift is larger when investors' attention is low.

Given the prior literature, I conjecture that the correlation between aggregated forecast revisions and post-earnings-announcement returns is stronger in the subsample of announcements that receive low investor attention. In the context of my conceptual framework (Appendix B1), it would imply that the underreaction coefficient b is larger when the investors' attention is low. Following Drake et al. (2012) and Drake et al. (2015), I use the number of EDGAR downloads within five-days following the earnings announcement as a proxy for investors' attention. In addition, I exclude the robot IP addresses in the EDGAR log data using Ryans' 2017 method. Since the EDGAR log data is only available from 2003 to mid-2017, all analyses in this subsection are conducted using the subsample where the EDGAR data is available.[10]

Table 8 reports the results. In Panel A, I sort announcements by aggregated forecast revisions in subsamples of high and low investor attention. In the subsample of announcements where investor attention is lower than the median attention of all firms in the same year, the magnitude of the drift is much larger. Specifically, the spread between the announcements in the highest forecast revision deciles and the lowest forecast revision deciles is 4.3% in the low-attention subsample. This spread is only 1.4% in the high-attention subsample.

(Insert Table 9 about here)

To statistically test whether investors' attention reduces post-earnings-announcement drift, Panel B regresses post-earnings-announcement returns on the interaction between aggregated forecast revisions and investors' attention. I create an indicator variable *High Attention* equal to 1 if the number of EDGAR downloads for the announcement is greater than the median number of downloads received by all firms in that year. Across all specifications, the coefficient on *High Attention* × *Forecast Revision Decile* is negative and statistically significant ($p<1\%$), suggesting that the correlation between aggregated forecast revisions and post-earnings-announcement returns are much weaker when investors' attention is high. These results suggest that the underreaction to aggregated forecast revisions is more severe when the earnings announcement receives little or no investors' attention.

Overall, the results on analyst disagreement, accruals and investor attention provide additional evidence on the informational value of aggregated forecast revisions following earnings announcements, and the market underreacts to this information.

[10] The average (median) number of EDGAR downloads is 139 (77) times.

1.6 Alternative Mechanisms and Robustness Tests

This subsection discusses the robustness of my main results in Table 4.

1.6.1. Management guidance. One alternative explanation to my main results is that forecast revisions are simply piggybacking on management guidance, which is an omitted variable in my main analyses. Kim and Song (2015) find that analyst forecasts are more accurate when the management issues guidance, consistent with analysts piggybacking on management guidance.

To address this concern, I match each quarterly earnings announcement to management EPS guidance in IBES. If the incremental information in forecast revisions is mainly driven by management guidance, one should expect that the positive association between forecast revisions and post-earnings-announcement returns is stronger in the subsample of announcements with management guidance.

To test this alternative hypothesis, I create an indicator variable *Have Guidance* equal to 1 if the manager issues EPS guidance during the earnings announcement. Approximately 22.4% of earnings announcements have management guidance. This ratio is similar to what Lee et al. (2012) find in their sample.[11] In columns 1 and 2 of Table 10 Panel A, the coefficient on the interaction term *Have Guidance* × *Forecast Revision* is negative and statistically significant ($p<1\%$), suggesting that the correlation between forecast revisions and post-earnings-announcement returns is weaker when the manager provides guidance. One the other hand, the coefficient on the *Forecast Revision* remains statistically significant at the 1% level. These results are inconsistent with the alternative argument. Moreover, they suggest that analyst forecast revisions are more valuable in more opaque information environments (i.e., no

[11] A small number of firms reports guidance in one to two days after earnings announcements. Including delayed guidance does not change the results. In addition, while I only focus on management guidance on EPS in Table 9, I also include non-EPS guidance in unreported tests, and the results are similar.

management guidance), providing further evidence on the incremental value of forecast revisions following earnings announcements.

In columns 3 and 4 of Table 10 Panel A, I further control for management optimism. Specifically, I create an indicator variable *High Management EPS* equal to one if the management EPS guidance is greater than her prior EPS guidance for the same fiscal end, and an indicator variable *High Management Other* equal to one if the management guidance on revenue, EBITDA or operating profit is greater than her prior guidance. The coefficients on *High Management Other* are statistically significant, suggesting that the market underreacts to non-EPS information in management guidance.[12] The coefficients on *Forecast Revision* remain statistically significant at the 1% level.

(Insert Table 10 about here)

1.6.2. Analyst recommendation changes. Li et al. (2015) show that analyst recommendation changes contain incremental information to recent corporate news. To rule out the possibility that the results in this paper are driven by recommendation changes, I control for analyst recommendation changes in Table 10 Panel B. Specifically, for each earnings announcement, I compute the average of analysts' recommendation changes.[13] Approximately 25% of the earnings announcements in my sample are accompanied by at least one analyst recommendation change. In columns 1 and 2, I find that the coefficients on recommendation changes are positive and statistically significant, suggesting that recommendation changes contain incremental information. This is consistent with Li et al.'s (2015) findings. However, the

[12] In unreported tests, I find that these two variables are positively correlated with announcement returns.
[13] IBES assigns each analyst recommendation with a number, i.e., strong buy=1, buy=2, hold=3, sell=4, strong sell=5. I compute each analyst's recommendation change as – (new rating – old rating). For example, if an analyst upgrades a company from hold to strong buy, the recommendation change would be – (1-3) =2.

coefficients on *Forecast Revision* are still positive and statistically significant, suggesting that the results I document in this paper are not driven by analyst recommendation changes.

1.6.3. Extreme returns. To alleviate the effect of extreme returns on my results, I delete observations in the lowest 1% and the highest 1% of the post-earnings-announcement returns distribution as in Livnat and Mendenhall (2006). Columns 1 and 2 of Table 10 Panel C report the results. The coefficient estimates are similar to those in Table 4, but with larger t statistics.

1.6.4. Firm Fixed Effects. Another concern is that aggregated forecast revisions may be correlated with firm-level characteristics, and these characteristics are also systematically correlated with post-earnings-announcement returns. While I control for commonly used firm-level characteristics that are correlated with returns, and adjust post-earnings-announcement returns by size and book-to-market matched portfolios, it is still possible certain unobservable firm characteristics are correlated with both my dependent variable and independent variable. To alleviate this concern, columns 3 and 4 of Table 10 Panel C present my main results with firm fixed effects, which draw the inferences from within-firm variations. These results are qualitatively similar to the results in Table 4, suggesting that unobservable firm-level characteristics are not driving my results.

1.7 Conclusion

To conclude, this paper presents novel results on the interactions between the post-earnings-announcement drift and the analyst forecast revisions. I find that aggregated forecast revisions are better predictors of post-earnings-announcement returns than measures of earnings surprises. Further, the post-earnings-announcement returns are more positive when the firm experience extremely negative earnings surprises, but analyst forecasts are more bullish. These results suggest that forecast revisions contain information that is incremental to earnings surprises, and the market underreacts to this information.

In addition, aggregated forecast revisions completely subsume the predictive power of the IBES-based measure of earnings surprises but not the time-series measure based on Compustat earnings, highlighting the difference between these two measures in predicting post-earnings-announcement returns (Livnat and Mendenhall 2006). Further analyses show that the incremental predictive power of Compustat-based earnings surprises on post-earnings-announcement returns is driven by extreme positive earnings surprises. Lastly, I show that aggregated forecast revisions are more informative when investor attention is low, when the accrual component in earnings is high and when there is no management guidance. They are less informative when analysts disagree with each other.

Overall, this paper resolves the seemingly contradictory results on the value of analyst forecast revisions in prior studies. The results in this paper provide evidence supporting the view that analysts play an important role in interpreting earnings news. In addition, these results suggest that the post-earnings-announcement drift is an underreaction to a broader set of information around earnings surprises, and aggregated analyst forecasts are better signals to capture this underreaction. These results have implications for practitioners who exploit the mispricing following earnings announcements. Lastly, it is important to point out that the strong correlation between forecast revisions and post-announcement returns could be driven by analysts generating new information or by analysts processing public information faster than the market. This paper does not necessarily distinguish these two potential mechanisms. Future studies should explore settings to better understand analysts' roles as information creators or as information processors.

Figure 1. Cumulative abnormal returns on portfolios sorting on forecast revisions and measures of earnings surprises

This figure plots the cumulative abnormal return on portfolios that sort on aggregated forecast revisions and measures of earnings surprises in post-earnings-announcements periods. The Y-Axis is the cumulative abnormal return, calculated as the cumulative sum of size and book-to-market adjusted returns. The X-Axis is the number of trading days following earnings announcements. The blue line is the cumulative abnormal returns on a portfolio that buys firms in the top 10% of the distribution of aggregated forecast revisions in a given year and shorts firms in the bottom 10% of the distribution. Analogously, the orange line and the grey line are cumulative abnormal returns on portfolios that sort on IBES-based earnings surprises and Compustat-based earnings surprises.

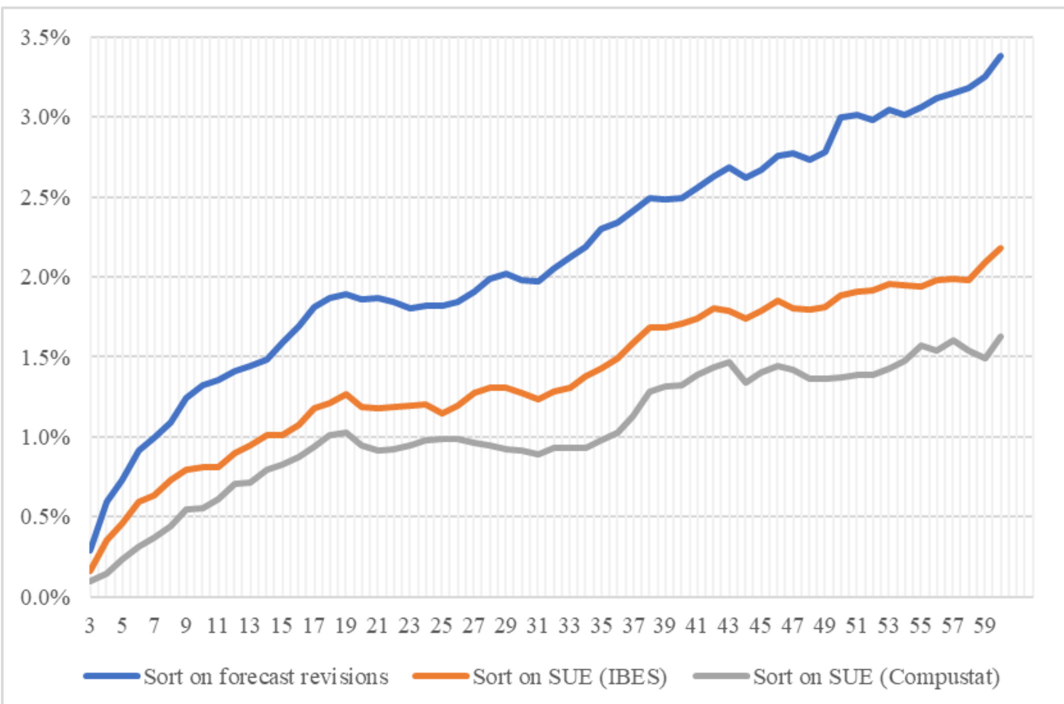

Figure 2. Aggregated forecast revisions by year

This figure reports the aggregated forecast revisions by the earnings announcement year. The Y Axis is the aggregated forecast revisions, measured as the average of analysts' forecast revisions issued within two days followings the earnings announcement as a percentage of the per share price at the quarter end. The X Axis is the earnings announcement year. The error bars represent the standard errors of the mean forecast revisions for a given year.

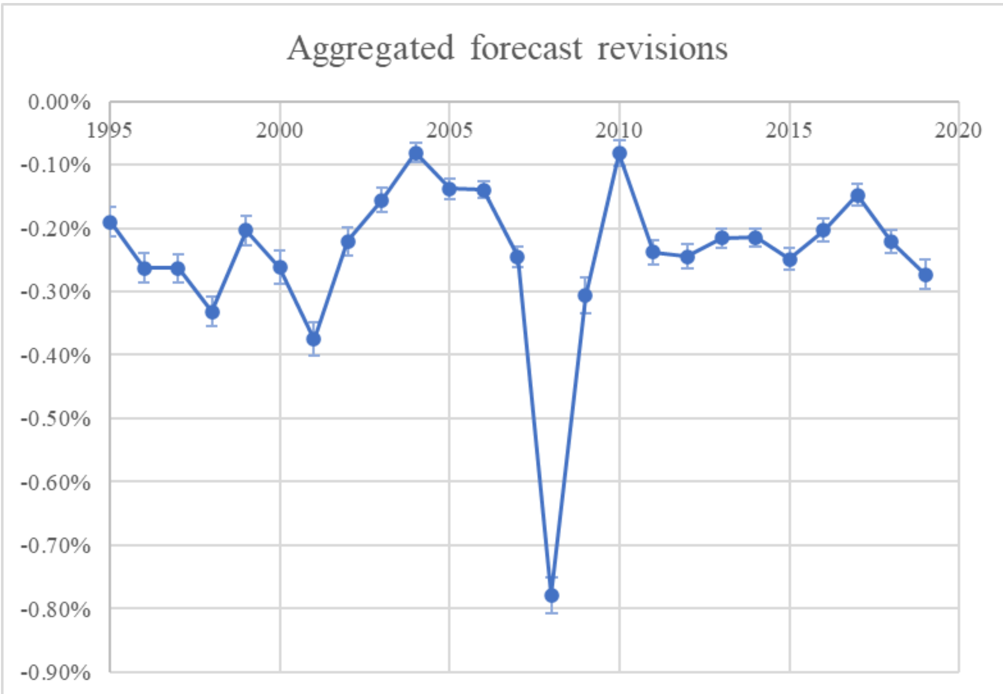

Table 1. Sample Construction

This table provides details on the construction of my samples of quarterly earnings announcements.

	Observations
# Quarterly announcements in IBES matched to Compustat	297,754
Less	
Missing analyst forecast revisions	-117,472
Missing earnings surprises	-1,639
Missing CRSP returns	-8,469
Share price less than $1	-520
# Observations in sample	168,306

Table 2. Summary Statistics

Panel A. reports summary statistics variables in my sample. All variables are defined in the Appendix A. Panel B reports the pairwise correlation between variables.

Panel A.

Variables	N	mean	sd	p1	p25	p50	p75	p99
Aggregated Forecast Revision	168,306	-0.0024	0.0168	-0.0977	-0.0035	0.0001	0.0021	0.0514
SUE (IBES)	168,306	0.0000	0.0095	-0.0541	-0.0006	0.0004	0.0019	0.0344
SUE (Compustat)	168,306	-0.0017	0.0430	-0.2377	-0.0060	0.0009	0.0058	0.1829
Forecast Revision Decile	168,306	0.5497	0.2872	0.1	0.3	0.5	0.8	1
SUE Decile (IBES)	168,306	0.5451	0.2897	0.1	0.3	0.5	0.8	1
SUE Decile (Compustat)	168,306	0.5498	0.2872	0.1	0.3	0.5	0.8	1
Log Mkt Cap	168,306	14.028	1.7056	10.516	12.799	13.917	15.128	18.457
Book/Mkt	168,306	0.5744	0.4391	0.0329	0.2692	0.4697	0.7549	2.5141
Past 12-Month Return	168,306	0.1007	0.1647	-0.3861	0.0232	0.1300	0.1930	0.4700
Num Analysts	168,306	11.581	8.3037	1	5	9	16	40

Panel B.

	(a)	(b)	(c)	(d)	(e)	(f)
(a) Forecast Revision Decile	1					
(b) SUE Decile (IBES)	0.5746	1				
(c) SUE Decile (Compustat)	0.2852	0.2962	1			
(d) Log Mkt Cap	0.0782	0.0021	0.0323	1		
(e) Book/Mkt	-0.0338	0.008	-0.0404	-0.2195	1	
(f) Past 12-Month Return	0.0006	0.0009	-0.0003	0.0513	-0.0905	1
(g) Num Analysts	0.0344	0.0064	-0.0014	0.7061	-0.149	0.016

Table 3. Portfolios Sort

This table reports the size/book-to-market adjusted cumulative abnormal returns (CAR) in [3,90] following earnings announcements by portfolio sorts. In panel A, the first three columns (i.e. Revision Decile) sort firms by aggregated forecast revisions for each year. The next three columns sort firms by IBES-based earnings surprises. The last three columns sort firms by Compustat-based earnings surprises. Panel B and Panel C report the CAR in portfolios double sorted by aggregated forecast revisions and earnings surprises. The first row reports the portfolio return. The second row reports the return standard deviation. The third row reports the number of observations.

Panel A.

	Revision Decile			SUE (IBES)			SUE (Compustat)		
Decile Rank	CAR	SD	Obs	CAR	SD	Obs	CAR	SD	Obs
1	-0.892%	0.287	16,873	-0.230%	0.284	16,875	-0.139%	0.275	16,872
2	-0.020%	0.207	16,835	0.017%	0.200	16,837	0.073%	0.212	16,835
3	-0.269%	0.196	16,838	-0.086%	0.174	21,300	0.148%	0.192	16,837
4	-0.082%	0.165	16,852	0.368%	0.167	15,597	0.091%	0.175	16,825
5	0.433%	0.151	16,838	0.831%	0.143	13,640	0.240%	0.161	16,811
6	0.835%	0.148	16,792	0.573%	0.157	16,781	0.251%	0.152	16,849
7	0.561%	0.157	16,830	0.344%	0.168	16,827	0.825%	0.156	16,826
8	0.658%	0.172	16,828	0.613%	0.176	16,829	0.497%	0.173	16,831
9	1.023%	0.190	16,844	0.605%	0.202	16,844	1.150%	0.195	16,841
10	2.538%	0.261	16,776	1.954%	0.261	16,776	1.643%	0.256	16,779
Decile 10 - 1	3.430%***			2.183%***			1.783%***		

Panel B. Double Sort on Forecast Revisions and IBES-Based SUE

IBES-Based Earnings Surprises		Aggregated Forecast Revisions P1 (Low)	2	3	4	P5 (High)	P5-P1
	P1	-0.61%	0.13%	0.00%	0.69%	2.63%	3.24% ***
	(Low)	*0.2621*	*0.2038*	*0.1897*	*0.2063*	*0.2731*	
		20,480	7,591	1,614	1,375	2,652	
	2	-0.38%	-0.32%	0.57%	0.43%	1.12%	1.50% ***
		0.2168	*0.1619*	*0.1461*	*0.1662*	*0.2174*	
		5,328	14,275	10,819	4,234	2,241	
	3	0.11%	0.01%	1.14%	0.50%	0.19%	0.08%
		0.2013	*0.1591*	*0.1404*	*0.1491*	*0.1785*	
		1,213	4,985	14,190	8,575	1,458	
	4	-0.21%	-0.60%	0.02%	0.82%	1.06%	1.28%***
		0.2078	*0.1825*	*0.1541*	*0.1603*	*0.1885*	
		2,495	4,286	5,487	14,588	6,800	
	P5	-0.11%	0.06%	-0.71%	0.31%	2.09%	2.20% ***
	(High)	*0.2680*	*0.2369*	*0.1898*	*0.1877*	*0.2380*	
		4,192	2,553	1,520	4,886	20,469	

Panel C. Double Sort on Forecast Revisions and Compustat-Based SUE

Compsutat-Based Earnings Surprises		Aggregated Forecast Revisions P1 (Low)	2	3	4	P5 (High)	P5-P1
	P1	-0.70%	-0.02%	0.63%	0.19%	1.15%	1.84%***
	(Low)	*0.2724*	*0.2111*	*0.1709*	*0.1870*	*0.2665*	
		15,124	5,948	3,119	3,533	5,983	
	2	-0.73%	-0.11%	0.53%	0.60%	0.59%	1.32%***
		0.2137	*0.1827*	*0.1519*	*0.1620*	*0.2122*	
		6,558	9,791	7,401	5,827	4,085	
	3	-0.27%	-0.32%	0.43%	0.42%	0.94%	1.21%**
		0.1998	*0.1548*	*0.1378*	*0.1484*	*0.1953*	
		2,711	7,948	11,633	7,986	3,382	
	4	-0.09%	-0.01%	0.88%	0.59%	1.38%	1.47%***
		0.1972	*0.1669*	*0.1455*	*0.1522*	*0.1875*	
		2,850	5,429	8,128	10,590	6,660	
	P5	0.14%	-0.46%	0.99%	1.17%	2.82%	2.68%***
	(High)	*0.2709*	*0.1916*	*0.1725*	*0.1940*	*0.2399*	
		6,465	4,574	3,349	5,722	13,510	

Table 4. Regression Results

This table reports regression results of return on aggregated analyst forecast revisions and earnings surprises. The dependent variable is size/book-to-market adjusted cumulative abnormal returns in [3,90] following earnings announcements. The independent variable *Forecast Revision Decile* is the decile of aggregated analyst forecast revisions. In column 1 to 3, *SUE Decile* is the earnings surprise based on IBES definition. In column 4 and 6, *SUE Decile* is the earnings surprise based on Compustat definition. All control variables are defined in the Appendix A. Each coefficient's t-statistic appears directly below the coefficient estimate. Robust standard errors are clustered at firm level. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	[3, 90] Day CAR					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	IBES-Based SUE			Compustat-Based SUE		
SUE Decile	0.017***	0.001	-0.000	0.017***	0.010***	0.008***
	(8.14)	(0.51)	(-0.01)	(8.17)	(4.61)	(3.95)
Forecast Revision Decile		0.027***	0.026***		0.025***	0.024***
		(10.84)	(9.71)		(11.73)	(9.75)
Log Mkt Cap			-0.003***			-0.003***
			(-7.30)			(-7.37)
Book/Mkt			-0.002			-0.002
			(-1.26)			(-1.20)
Past 12-Month Return			0.005***			0.005***
			(4.41)			(3.97)
Num Analysts			0.000***			0.000***
			(5.15)			(5.22)
[0,2] Day CAR			0.011			0.010
			(1.06)			(0.98)
Constant	0.038*	0.032	0.075***	0.038*	0.028	0.071***
	(1.86)	(1.55)	(3.47)	(1.83)	(1.38)	(3.33)
Observations	168,306	168,306	168,306	168,306	168,306	168,306
R-squared	0.001	0.002	0.003	0.001	0.002	0.003
Year FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES

Table 5. Extreme Positive Earnings Surprises

This table reports regression results of return on aggregated analyst forecast revisions and extreme positive earnings surprises. In columns 1 and 3, the dependent variable is size/book-to-market adjusted cumulative abnormal returns in [3,90] following earnings announcements. In columns 2 and 4, the dependent variable is the decile of aggregated forecast revisions. The independent variable *Extreme Positive SUE* an indicator variable equals to 1 if the earnings surprises are in the top two deciles of earnings surprises. Columns 1 and 2 use Compustat-based earnings surprises and columns 3 and 4 uses IBES-based earnings surprises. All control variables are defined in the Appendix A. Each coefficient's t-statistic appears directly below the coefficient estimate. Robust standard errors are clustered at firm level. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	[3, 90] Day CAR	Forecast Revision Decile	[3, 90] Day CAR	Forecast Revision Decile
	(1)	(2)	(3)	(4)
VARIABLES	Compustat-Based SUE		IBES-Based SUE	
Extreme Positive SUE	0.006***	-0.024***	0.003*	-0.004
	(3.54)	(-9.30)	(1.67)	(-1.60)
SUE Decile	0.002	0.256***	-0.003	0.516***
	(0.95)	(64.22)	(-0.99)	(144.15)
Forecast Revision Decile	0.024***		0.026***	
	(9.81)		(9.71)	
Log Mkt Cap	-0.003***	0.012***	-0.003***	0.016***
	(-6.94)	(15.12)	(-7.10)	(24.60)
Book/Mkt	-0.003	-0.000	-0.002	-0.010***
	(-1.59)	(-0.05)	(-1.42)	(-5.13)
Past 12-Month Return	0.005***	0.033***	0.005***	0.034***
	(4.02)	(16.42)	(4.46)	(17.82)
Num Analysts	0.000***	-0.001***	0.000***	-0.001***
	(4.98)	(-4.10)	(5.13)	(-10.23)
[0,2] Day CAR	0.010	0.969***	0.011	0.617***
	(0.99)	(94.66)	(1.08)	(71.72)
Constant	0.071***	0.246***	0.074***	0.066***
	(3.31)	(8.67)	(3.45)	(2.59)
Observations	168,306	168,306	168,306	168,306
R-squared	0.003	0.187	0.003	0.381
Year FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES

Table 6. Confirmatory/Contradictory Signals

Panel A. tabulates the CAR in [3,90] days following earnings announcements for announcements in the highest/lowest deciles of SUE and forecast revisions. In Panel B, the dependent variable is size/book-to-market adjusted cumulative abnormal returns in [3,90] following earnings announcements. The independent variable *High Revision Low SUE* is an indicator variable equal to 1 if the announcement is in the highest decile of forecast revisions and lowest decile of SUE. The other three independent variables are defined analogously. All control variables are defined in the Appendix A. Panel C reports the differences in returns for the *High Revision Low SUE* partition by whether IBES earnings are similar to GAAP earnings. *Street earnings close to GAAP* are company-quarters where *High Revision Low SUE (IBES)* equals one and IBES earnings are within 10% of GAAP earnings. *Street earnings not close to GAAP* are company-quarters where *High Revision Low SUE (IBES)* equals one and IBES earnings differ from GAAP earnings by more than 10%. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Panel A.

	IBES-Based SUE		Compustat-Based SUE	
	Highest SUE Decile	Lowest SUE Decile	Highest SUE Decile	Lowest SUE Decile
Highest Revision Decile	2.82%	4.35%	3.54%	1.75%
t-stat	*9.95****	*4.29****	*9.02****	*2.67****
Lowest Revision Decile	0.49%	-1.18%	0.41%	-1.21%
t-stat	*0.63*	*-3.74****	*0.65*	*-3.03****

Panel B.

	[3, 90] Day CAR			
	(1)	(2)	(3)	(4)
VARIABLES	IBES-Based SUE		Compustat-Based SUE	
High Revision Low SUE	0.039***	0.038***	0.013**	0.012*
	(3.73)	(3.67)	(2.01)	(1.86)
High Revision High SUE	0.024***	0.022***	0.031***	0.028***
	(8.29)	(7.25)	(7.76)	(6.82)
Low Revision Low SUE	-0.016***	-0.014***	-0.016***	-0.014***
	(-4.75)	(-4.23)	(-3.90)	(-3.40)
Low Revision High SUE	0.000	0.000	-0.000	-0.000
	(0.03)	(0.02)	(-0.06)	(-0.08)
Log Mkt Cap		-0.003***		-0.003***
		(-6.21)		(-6.35)
Book/Mkt		-0.003*		-0.002
		(-1.67)		(-1.57)
Past 12-Month Return		0.006***		0.006***
		(5.32)		(5.08)
Num Analysts		0.000***		0.000***
		(4.70)		(4.75)
[0,2] Day CAR		0.025**		0.029***
		(2.48)		(2.99)
Constant	0.047**	0.081***	0.046**	0.081***

	(2.27)	(3.76)	(2.26)	(3.80)
Observations	168,306	168,306	168,306	168,306
R-squared	0.002	0.003	0.001	0.002
Year FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES

Panel C.

High Revision and Low SUE (IBES)	Obs	Post- Announcement Returns	SD
Street earnings close to GAAP	553	3.93%	0.33
Street earnings not close to GAAP	496	4.82%	0.33
Difference		-0.88%	
t-value		-0.43	

Table 7. Analyst Disagreement

This table reports regression results of return on the interaction term between aggregated analyst forecast revisions and accruals. the dependent variable is the [3,90] day CAR. The independent variable *Analyst Disagreement* is an indicator variable equal to one if the standard deviation of analyst forecast revisions around an earnings announcement, scaled by the mean of these revisions, is greater than the median standard errors of all earnings announcements in the same year. Each coefficient's t-statistic appears directly below the coefficient estimate. Robust standard errors are clustered at firm level. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	[3, 90] Day CAR			
	(1)	(2)	(3)	(4)
	IBES-Based SUE		Compustat-Based SUE	
Forecast Revision Decile * Analyst Disagreement	-0.015***	-0.015***	-0.013***	-0.014***
	(-3.01)	(-3.07)	(-2.74)	(-2.79)
Forecast Revision Decile	0.024***	0.025***	0.020***	0.021***
	(6.87)	(6.71)	(6.80)	(6.33)
Analyst Disagreement	0.004	0.004	0.003	0.004
	(1.30)	(1.44)	(1.06)	(1.19)
SUE Decile	-0.003	-0.004	0.006**	0.005**
	(-0.92)	(-1.27)	(2.45)	(2.02)
Log Mkt Cap		-0.004***		-0.004***
		(-6.90)		(-6.86)
Book/Mkt		0.001		0.001
		(0.42)		(0.43)
Past 12-Month Return		0.005***		0.005***
		(3.74)		(3.54)
Num Analysts		0.000***		0.000***
		(4.72)		(4.70)
[0,2] Day CAR		-0.004		-0.005
		(-0.43)		(-0.53)
Constant	0.040	0.084***	0.038	0.081**
	(1.29)	(2.64)	(1.22)	(2.56)
Observations	124,354	124,354	124,354	124,354
R-squared	0.002	0.002	0.002	0.002
Year FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES

Table 8. Accounting Accruals

This table reports regression results of return on the interaction term between aggregated analyst forecast revisions and accruals. the dependent variable is the [3,90] day CAR. The independent variable *High Accrual* is an indicator variable equal to one if the announcement receives above median accrual of all firms in the same year. Each coefficient's t-statistic appears directly below the coefficient estimate. Robust standard errors are clustered at firm level. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	[3, 90] Day CAR			
	(1)	(2)	(3)	(4)
	IBES-Based SUE		Compustat-Based SUE	
High Accrual × Forecast Revision Decile	0.011***	0.011***	0.011***	0.011***
	(2.66)	(2.61)	(2.68)	(2.61)
High Accrual	-0.018***	-0.017***	-0.019***	-0.018***
	(-7.24)	(-6.99)	(-7.55)	(-7.26)
Forecast Revision Decile	0.021***	0.021***	0.019***	0.019***
	(6.57)	(6.00)	(6.34)	(5.61)
SUE Decile	0.002	0.001	0.012***	0.010***
	(0.69)	(0.28)	(5.49)	(4.83)
Log Mkt Cap		-0.003***		-0.003***
		(-6.06)		(-6.08)
Book/Mkt		-0.002		-0.002
		(-1.38)		(-1.27)
Past 12-Month Return		0.005***		0.004***
		(3.84)		(3.33)
Num Analysts		0.000***		0.000***
		(3.28)		(3.29)
[0,2] Day CAR		0.008		0.007
		(0.71)		(0.62)
Constant	0.037*	0.073***	0.033	0.070***
	(1.77)	(3.38)	(1.60)	(3.22)
Observations	162,444	162,444	162,444	162,444
R-squared	0.003	0.003	0.003	0.004
Year FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES

Table 9. Investor Attention

Panel A. tabulates the CAR in [3,90] days following earnings announcements by subsamples of high (low) investor attention, where high (low) attention subsample consists of earnings announcements that receive above (below) median number of EDGAR downloads for all earnings announcements in the same year. In Panel B, the dependent variable is the [3,90] day CAR. The independent variable *High Attention* is an indicator variable equals 1 if the announcement receives above median attention. Each coefficient's t-statistic appears directly below the coefficient estimate. Robust standard errors are clustered at firm level. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Panel A.

Forecast Revisions Decile Rank	Low Attention			High Attention		
	CAR	SD	Obs	CAR	SD	Obs
1	-0.880%	0.269	6,335	0.785%	0.262	5,026
2	-0.370%	0.200	6,274	0.681%	0.184	5,069
3	-0.062%	0.198	6,088	0.121%	0.163	5,251
4	0.117%	0.159	5,538	-0.235%	0.145	5,827
5	0.466%	0.151	4,934	-0.292%	0.128	6,406
6	0.736%	0.139	4,769	0.139%	0.127	6,532
7	0.932%	0.148	5,233	-0.082%	0.130	6,103
8	1.119%	0.163	5,502	0.171%	0.146	5,832
9	1.767%	0.175	6,021	0.555%	0.164	5,323
10	3.394%	0.245	6,443	2.201%	0.231	4,868
Decile 10 - 1	4.274%***			1.415%***		

Panel B.

	[3, 90] Day CAR			
	(1)	(2)	(3)	(4)
	IBES-Based SUE		Compustat-Based SUE	
High Attention × Forecast Revision Decile	-0.031***	-0.030***	-0.031***	-0.030***
	(-6.98)	(-6.79)	(-7.03)	(-6.82)
Forecast Revision Decile	0.034***	0.036***	0.036***	0.037***
	(9.39)	(9.77)	(10.90)	(10.85)
High Attention	0.013***	0.015***	0.013***	0.015***
	(4.74)	(5.35)	(4.79)	(5.42)
SUE Decile	0.008***	0.007**	0.009***	0.010***
	(2.91)	(2.53)	(3.91)	(4.41)
Constant	-0.005	0.032***	-0.007	0.030***
	(-0.83)	(3.34)	(-1.13)	(3.18)
Observations	113,374	113,374	113,374	113,374
R-squared	0.003	0.003	0.003	0.003
Firm Level Controls	NO	YES	NO	YES
Year FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES

Table 10. Robustness Tests

This table reports the robustness results. In Panel A columns 1 and 2, I report the results interacting forecast revision with management guidance, where *Have Guidance* is an indicator variable equals 1 if the manager issues a guidance during the announcement. In columns 3 and 4, I include variables *high management EPS* and *high management other*, where *high management EPS (other)* equals one if the management EPS (Sales, EBITDA or profit margin) guidance is greater than her prior guidance for the same fiscal end. Panel B controls for analyst recommendation changes. Panel C columns 1 and 2 exclude CARs in 1% lowest and highest of the distribution. Columns 3 and 4 report results with firm fixed effects. Each coefficient's t-statistic appears directly below the coefficient estimate. Robust standard errors are clustered at firm level. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Panel A. Management Guidance

	(1)	(2)	(3)	(4)
Dependent Variable	[3, 90] Day CAR			
Forecast Revision Decile	0.028***	0.026***	0.026***	0.023***
	(10.03)	(9.98)	(9.55)	(9.50)
Forecast Revision Decile × Have Guidance	-0.018***	-0.018***		
	(-3.79)	(-3.75)		
Have Guidance	0.013***	0.013***		
	(4.47)	(4.44)		
High Management EPS			0.001	0.001
			(0.56)	(0.48)
High Management Other			0.009***	0.009***
			(4.94)	(4.94)
SUE Decile (IBES)	-0.000		-0.000	
	(-0.13)		(-0.13)	
SUE Decile (Compustat)		0.008***		0.008***
		(3.93)		(3.94)
Observations	168,306	168,306	168,306	168,306
R-squared	0.003	0.003	0.003	0.003
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES

Panel B. Recommendation Changes

Dependent Variable	(1) [3, 90] Day CAR	(2)
Forecast Revision Decile	0.026***	0.023***
	(9.60)	(9.64)
Avg. Recommendation Changes	0.002***	0.002***
	(2.79)	(2.85)
SUE Decile (IBES)	0.000	
	(0.01)	
SUE Decile (Compustat)		0.008***
		(3.98)
Observations	168,306	168,306
R-squared	0.003	0.003
Controls	YES	YES
Year FE	YES	YES
Quarter FE	YES	YES

Panel C. Extreme values and firm fixed effects

	[3, 90] Day CAR			
	(1)	(2)	(3)	(4)
VARIABLES	Exclude Extreme Returns		Firm FE	
Forecast Revision Decile	0.021***	0.021***	0.023***	0.020***
	(10.49)	(11.73)	(8.35)	(7.97)
SUE Decile (IBES)	0.002		-0.003	
	(1.02)		(-1.24)	
SUE Decile (Compustat)		0.006***		0.006**
		(3.65)		(2.57)
Have Guidance				
Observations	164,940	164,940	168,306	168,306
R-squared	0.003	0.003	0.120	0.120
Control Variables	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Firm FE	NO	NO	YES	YES

Appendix A. Variable Definitions

Variables	Definitions
Aggregated Forecast Revision	The average of analysts' forecast revisions within two days following the earnings announcement
SUE (IBES)	Actual EPS in IBES minus the latest IBES median consensus forecast denominated by quarter end stock price
SUE (Compustat)	EPS before extraordinary items (Compustat item No. 19) minus the four-quarter lagged EPS denominated by quarter end stock price
Forecast Revision Decile	Decile of *Aggregated Forecast Revision*
SUE Decile (IBES)	Decile of *SUE (IBES)*
SUE Decile (Compustat)	Decile of *SUE (Compustat)*
Log Mkt Cap	Log market capitalization, measured at the quarter end before the earnings announcement
Book/Mkt	Book-to-market ratio as of the prior fiscal year end
Past 12-Month Return	Past 12-month buy-and-hold return
Num Analysts	Number of analysts covering the firm for the current fiscal year
Have Guidance	An indicator variable equals 1 if the manager issues an EPS guidance during the earnings announcement
High Management EPS	An indicator variable equals 1 if the management EPS guidance is greater than her prior EPS guidance for the same fiscal end
High Management Other	An indicator variable equals 1 if the management Sales, EBITDA or profit margin guidance is greater than her prior guidance for the same fiscal end
Analyst Disagreement	An indicator variable equal to one if the standard deviation of analyst forecast revisions around the earnings announcement, scaled by the mean of these revisions, is greater than the median standard errors of all earnings announcements in the same year
High Accrual	An indicator variable equal to one if accounting accruals of the earnings announcement is greater than the median accruals for all earnings announcements in the same year. Accounting accruals are calculated as the difference between the net income and the operating cash flow denominated by the total asset
High Attention	An indicator variable equal to one if the number of EDGAR downloads with five days following the earnings announcement is greater than the median downloads all earnings announcements in the same year
Avg. Recommendation Changes	The average of analyst recommendation changes in the 2-day window following the earnings announcement.

Appendix B. Conceptual Framework

This appendix provides a simple conceptual framework to facilitate the interpretation of the regression coefficients in main results. It will attempt to achieve two goals: (1) it formally derives regression coefficients on earnings surprises and aggregated forecast revisions, providing insights on factors that may affect these coefficients; (2) it provides directional predictions with respect to the magnitudes of the coefficients on earnings surprises and aggregated forecast revisions. To begin, suppose the post-earnings-announcement return follows the following random process:

$$y_i = b * s_i + \epsilon_i$$

where y_i is the post-announcement return for the quarterly earnings announcement i.[14] s_i is a signal to future earnings derived from all publicly available information during the earnings announcement. Specifically, it incorporates all information in earnings, conference calls and EDGAR filings. There is no assumption being made on the distribution of s. ϵ_i is an independent random variable following $N\left(0, \sigma_y^2\right)$. b is a constant that measures the extent to which the market underreacts to the information during the earnings announcement. If the market incorporates all the information into the price immediately following the earnings announcement, b would be zero as there is no underreaction. On the other hand, if the market is slow to incorporate the information revealed during the earnings announcement, b would be positive.

In the setting of post-earnings-announcement drift documented by Bernard and Thomas (1989) and Livnat and Mendenhall (2006), measures of earnings surprises (SUE) can be viewed as noisy proxies of s. Specifically, $SUE = s + \epsilon_{sue}$, where ϵ_{sue} follows $N(0, \sigma_{sue}^2)$ and is

[14] Empirically, I define post-earnings-announcement return as cumulative abnormal returns in the [3,90] day period following the earnings announcement. The announcement return, on the other hand, is defined as the [0,2] day CAR following the announcement.

independent to other random variables. If one regresses y on SUE using OLS, the regression coefficient on SUE will converge to $\frac{cov(y,SUE)}{var(SUE)} = \frac{b\sigma_y^2}{\sigma_y^2+\sigma_{sue}^2}$.[15] Intuitively, this coefficient is larger when earnings surprises are more informative to future returns (low σ_{sue}^2) and when the underreaction coefficient (i.e., b) is larger. Note that in this simple model, the underreaction coefficient b is treated as an exogenous variable.[16]

Now consider running the following regression:

$$y = b_1 * SUE + b_2 * Revision + \epsilon'_y$$

Where $Revision$ is the forecast revision, and it is also a noisy signal of s. Specifically, $Revision = s + \epsilon_{rev}$, where ϵ_{rev} follows $N(0, \sigma_{rev}^2)$ and is independent to other variables. σ_{rev}^2 measures the noisiness of the forecast revision as a signal to post-announcement returns, and it is inversely correlated with the analyst's ability to aggregate and interpret the information around the earnings announcement.

There are three cases to consider. The first case is when $\sigma_{rev}^2 > \sigma_{sue}^2$. In this case, the forecast revision is a nosier signal than SUE. For instance, analysts may not be able to grasp the full implication of earnings surprises on future earnings, or even misinterpret information in earnings surprises due to biases or conflict of interests (De Bondt and Thaler 1990, Easterwood and Nutt 1999, So 2013, Corwin et al. 2017, Engelberg et al. 2020). In these cases, the OLS estimators $\widehat{b_2} < \widehat{b_1}$.[17]

[15] This result does not reply on the distributional assumptions on s, ϵ_y or ϵ_{sue}. Instead, it is from the asymptotic properties of the least square estimator. For a sufficiently large sample, the least square estimator will converge to linear projection coefficient by the law of large numbers. See Hansen (2021)'s textbook Chapter 6.2.
[16] Empirical literature has documented various factors that may affect the underreaction to earnings news, such as analyst coverage, investor attention, institutional holdings, etc. I do not attempt to model these factors in this simple framework.
[17] $\widehat{b_1}$ and $\widehat{b_2}$ denote least square estimators for b_1 and b_2. Appendix B2 provides simulation results to illustrate how $\widehat{b_1}$ and $\widehat{b_2}$ change with respect to σ_{rev}^2 and σ_{sue}^2. Appendix B3 provides a more rigorous derivation of least square estimators $\widehat{b_1}$ and $\widehat{b_2}$.

The second case is when $\sigma^2_{rev} < \sigma^2_{sue}$. In this case, the forecast revision is a more precise signal to future returns than earnings surprises. For instance, analysts may incorporate their knowledge of the industry when making the forecast and thus be able to produce a more precise interpretation of the earnings (Hui and Yeung 2013). In this case, $\widehat{b_2}$> $\widehat{b_1}$.

A special scenario in the second case is when $SUE = Revision + \epsilon$. That is when the forecast revision incorporates all information contained in earnings surprises SUE. In other words, upon observing the forecast revision, earnings surprises do not provide any incremental information. In this case, the coefficient on SUE will be zero (i.e. $\widehat{b_2}$> $\widehat{b_1} = 0$).

The third case is when $\sigma^2_{rev} = \sigma^2_{sue}$. In this case, the forecast revision is equally informative to earnings surprises and $\widehat{b_2}$= $\widehat{b_1}$.

Simulation results

This section simulates results for my conceptual framework. To recap, the data generating process is the following:

$$y = b * s + \epsilon_y$$

For this simulation exercise, I set b=2, $s \sim N(0,1)$, $\epsilon_y \sim N(0,1)$. In addition, $SUE = s + \epsilon_{sue}$, $Rev = s + \epsilon_{rev}$, $\epsilon_{sue} \sim N(0, \sigma^2_{sue})$, $\epsilon_{rev} \sim N(0, \sigma^2_{rev})$.

There are three cases:

Case 1: SUE is a more precise signal than forecast revisions. I set $\sigma^2_{sue} = 1$, $\sigma^2_{rev} = 4$.

Case 2: SUE is a less precise signal than forecast revisions. I set $\sigma^2_{sue} = 4$, $\sigma^2_{rev} = 1$.

Case 3: SUE is equally precise as forecast revisions. I set $\sigma^2_{sue} = 1$, $\sigma^2_{rev} = 1$.

I estimate the following specification using OLS:

$$y = b_1 * SUE + b_2 * Revision + \epsilon'_y$$

For each case, I set observation level in each iteration to 1000 and simulate 200 times. Below I report the results. $\widehat{b_1}$ and $\widehat{b_2}$ are the averages of simulated OLS estimators of $b_1$and b_2. The simulated standard errors are reported in the parentheses below the coefficient estimate.

	y		
	1	2	3
	Case 1	Case 2	Case 3
$\widehat{b_1}$	0.888	0.221	0.669
	(0.039)	(0.025)	(0.040)
$\widehat{b_2}$	0.221	0.888	0.668
	(0.025)	(0.040)	(0.040)

Discussions: the simulated results are consistent with my arguments in the conceptual framework. The magnitude of the OLS coefficients is inversely correlated with the nosiness (i.e. variance) of the signals. In fact, given the above parameters, one can derive the asymptotic limits of $\widehat{b_1}$ and $\widehat{b_2}$ are 8/9 and 2/9 in case 1; 2/9 and 8/9 in case 2; 2/3 and 2/3 in case 3. Appendix B3 derives the general form of OLS estimators when there are two regressors.

Proof

Consider estimating the following model using ordinary least squares (OLS) regression:

$$y = b_1 * x_1 + b_2 * x_2 + b_0 + \epsilon_1$$

Where $y, x_1$and x_2 are demeaned data (demeaning data does not affect regression coefficients but will simplify the derivation of the least square estimators later). The least square estimators $\widehat{b_1}$, $\widehat{b_2}$ and $\widehat{b_0}$ are estimated by minimizing the sum of squared residuals:

$$\left(\widehat{b_1}, \widehat{b_2}, \widehat{b_0}\right) = \arg\min \sum_{i=1}^{n} \left(y_i - b_1 * x_{1,i} - b_2 * x_{2,i} - b_0\right)^2$$

By setting the partial derivatives equal to 0, one will have a system of 3 linear equations with 3 unknows.

$$\frac{\partial y}{\partial b_1} = \sum_{i=1}^{n} \left(y_i - \widehat{b_1} * x_{1,i} - \widehat{b_2} * x_{2,i} - \widehat{b_0} \right) * x_{1,i} = 0$$

$$\frac{\partial y}{\partial b_2} = \sum_{i=1}^{n} \left(y_i - \widehat{b_1} * x_{1,i} - \widehat{b_2} * x_{2,i} - \widehat{b_0} \right) * x_{2,i} = 0$$

$$\frac{\partial y}{\partial b_0} = \sum_{i=1}^{n} \left(y_i - \widehat{b_1} * x_{1,i} - \widehat{b_2} * x_{2,i} - \widehat{b_0} \right) = 0$$

Solving for $\widehat{b_1}, \widehat{b_2}, \widehat{b_0}$ yields:

$$\widehat{b_1} = \frac{(\sum_{i=1}^{n} x_{i,2}^2)\,(\sum_{i=1}^{n} x_{i,1} y_i) - (\sum_{i=1}^{n} x_{i,1} x_{i,2})(\sum_{i=1}^{n} x_{i,2} y_i)}{(\sum_{i=1}^{n} x_{i,1}^2)\,(\sum_{i=1}^{n} x_{i,2}^2) - \left(\sum_{i=1}^{n} x_{i,1} x_{i,2}\right)^2}$$

$$\widehat{b_2} = \frac{(\sum_{i=1}^{n} x_{i,1}^2)\,(\sum_{i=1}^{n} x_{i,2} y_i) - (\sum_{i=1}^{n} x_{i,1} x_{i,2})(\sum_{i=1}^{n} x_{i,1} y_i)}{(\sum_{i=1}^{n} x_{i,1}^2)\,(\sum_{i=1}^{n} x_{i,2}^2) - \left(\sum_{i=1}^{n} x_{i,1} x_{i,2}\right)^2}$$

$$\widehat{b_0} = \bar{y} - \widehat{b_1} * \overline{x_1} - \widehat{b_2} * \overline{x_2}$$

For sufficiently large n, we can apply the law of large number, and we have the asymptotic limits of $\widehat{b_1}, \widehat{b_2}, \widehat{b_0}$:

$$\widehat{b_1} \to \frac{var(x_2)cov(x_1, y) - cov(x_1, x_2)cov(x_2, y)}{var(x_1)var(x_2) - cov(x_1, x_x)^2}$$

$$\widehat{b_2} \to \frac{var(x_1)cov(x_2, y) - cov(x_1, x_2)cov(x_1, y)}{var(x_1)var(x_2) - cov(x_1, x_x)^2}$$

In my conceptual framework, $x_1 = s + \epsilon_1$, $x_2 = s + \epsilon_2$ and $y = b * s + \epsilon_y$. Thus,

$$var(x_1) = \sigma_s^2 + \sigma_1^2$$

$$var(x_2) = \sigma_s^2 + \sigma_2^2$$

$$cov(x_1, x_2) = \sigma_s^2$$

$$cov(x_j, y) = b\sigma_s^2 \ for\ j = 1,2$$

Plug these expressions into $\widehat{b_1}, \widehat{b_2}$:

$$\widehat{b_1} \to \frac{(\sigma_s^2 + \sigma_2^2)b\sigma_s^2 - b\sigma_s^4}{(\sigma_s^2 + \sigma_1^2)(\sigma_s^2 + \sigma_2^2) - \sigma_s^4}$$

$$\widehat{b_2} \to \frac{(\sigma_s^2 + \sigma_1^2)b\sigma_s^2 - b\sigma_s^4}{(\sigma_s^2 + \sigma_1^2)(\sigma_s^2 + \sigma_2^2) - \sigma_s^4}$$

In other words, $\widehat{b_1}$>$\widehat{b_2}$ if x_1 is a more precise signal than x_2 (i.e. σ_2^2>σ_1^2);

$\widehat{b_1}$<$\widehat{b_2}$ if x_1 is a less precise signal than x_2 (i.e. σ_2^2<σ_1^2);

$\widehat{b_1}$=$\widehat{b_2}$ if x_1 and x_2 are equally precise (i.e. σ_2^2=σ_1^2).

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