How Expectation Affects Interpretation: Evidence from Sell-side Security Analysts*

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October, 2015

* We would like to thank Kalok Chan, Clara Xiaoling Chen, Darwin Choi, Gilles Hilary, Xi Li, Zhihua Li, Wilson Tong, Susheng Wang for helpful comments. We appreciate seminar participants at the Hong Kong University of Science and Technology, City University of Hong Kong, and University of Stavanger, and participants in Singapore Tri-Uni Accounting Research Conference for valuable comments. We also thank Lingwei Li for her able research assistance. The remaining errors are ours.

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Abstract: By examining quarterly earnings forecasts issued by financial analysts, this study explores whether or not individuals' expectations of the public news affect their interpretations of such news. We find that after earnings announcement for quarter *t*, analysts with higher (lower) expectations of quarter *t* earnings on average revise their forecasts higher (lower) for quarter *t*+1 than their peers following the same firm. The results are robust to analysts' strategic incentives, broker fixed effects, and analyst-fixed effects. This evidence suggests that more optimistic (pessimistic) expectations are correlated with more optimistic (pessimistic) interpretations of public information and is consistent with the argument that analysts are subject to confirmatory bias when interpreting earnings announcements. This paper provides insight on how we should model individual behaviors in the financial market.

JEL Classification: G02, G29

Keywords: *analyst forecast, expectation, interpretation, confirmatory bias*

"Agents reading the same morning newspapers with the same stock price lists will interpret the information differently." Ariel Rubinstein (1993)

1. Introduction

Conflicting points of views are unavoidable. People have disagreement over almost everything, from how the universe is formed to how to raise a child. In the financial market, investors take different views about the value of the financial instruments, which is why trading happens. Although existing studies recognize that individuals can interpret the same piece of public information differently (e.g., Hong and Stein 1999; Kandel and Pearson 1995; Kim and Verrecchia 1997), there is little evidence on what affects individuals' different interpretations of public information. This paper makes an attempt to study the determinants of different interpretations with large archival data. In particular, we study whether or not individuals' expectations of public information affect their interpretations of such information by examining earnings forecasts issued by financial analysts.

We use a specific example to explain our research question. Assume that there are two analysts i and j following firm k in quarter t. Analyst i expects firm k's earnings per share (*EPS*) in quarter t to be \$0.80 while analyst j expects it to be \$1.20. In other words, analyst j is more optimistic than analyst i for quarter t's earnings. When firm k announces its actual *EPS* of quarter t to be \$1.00, how will analyst i and j revise their forecasts for firm k's *EPS* in quarter t+1? Will analyst i revise her forecast for quarter t+1 more optimistically or pessimistically comparing to analyst j?

Although the question seems to be intuitive and simple, the answer to this question is not clear. There are three possible answers for the above question in the literature. First, analyst i

may revise her forecast for quarter *t*+1 more optimistically than analyst *j*. By using a similar example, Hong and Stein (2007) argue that because the actual *EPS* ($1.00) is a positive surprise to analyst *i* and a disappointment to analyst *j*, analyst *i* (*j*) will interpret the earnings announcement as good (bad) news. Therefore, analyst *i* will revise her forecast for quarter *t*+1 more optimistically than analyst *j*. We label this conjecture as the *HS* hypothesis.

Second, analyst *i* may revise her forecast for quarter *t*+1 about the same as analyst *j*. This answer is consistent with the assumptions with most models in the different interpretation literature. For example, Kandel and Pearson (1995) propose a different likelihood model in which the different interpretation of the public information is a random noise. Because analyst *i* and *j* have prior expectations of *EPS* in quarter *t*+1 before the earnings announcement of quarter *t*, they will revise their forecasts for quarter *t*+1 based on the earnings announcement only. Their expectations of *EPS* for quarter *t* may not affect their use of actual *EPS* of quarter *t* in revising their forecasts for quarter *t*+1. In such a case, analyst *i* and *j* should revise their forecasts for quarter *t*+1 about the same. We label this conjecture as the *KP* hypothesis.

Lastly, analyst *i* may revise her forecast for quarter *t*+1 more pessimistically than analyst *j*. This answer is consistent with confirmatory bias in behavior economics literature (e.g., Hastorf and Cantril 1954; Rabin and Schrag 1999). Individuals tend to interpret information in a way to justify their own expectations. If analyst *i* (*j*) truly think that firm *k*'s earnings should be bad (good), analyst *i* (*j*) may consider the positive surprise (disappointment) to be temporary and to be reversed in the next quarter. In such a case, it is more likely that analyst *i* revise her forecast for quarter *t*+1 less optimistically than analyst *j*.[1] We label this conjecture as the *RS* hypothesis.

Financial analysts provide an ideal setting to examine this question because they issue

[1] The implicit assumption here is that quarterly earnings are positively correlated in time-series. This assumption has been proven valid in the accounting and finance literature and is validated with our sample. Our results are not affected if we restrict our sample to firms with consecutive quarterly earnings increase or decrease.

earnings for multiple horizons at the same time and all these forecasts are publicly available. Using detailed analyst forecast data from 2001 to 2012, we examine how analysts revise their earnings forecast for quarter t+1 around earnings announcements of quarter t and test whether or not their revisions are correlated with their own earnings forecasts for quarter t. We employ two approaches to conduct our empirical tests.

The first approach is a parameter-free approach. In particular, before the earnings announcement of quarter t, we match each analyst i with another analyst j following the same firm. In addition, we require that before earnings announcements of quarter t, analyst i and j having identical earnings forecasts for quarter t+1, but having different earnings forecast for quarter t. After the matching, each pair of analysts has the same prior forecasts for the earnings of quarter t+1 and will observe the same earnings announcement of quarter t. Therefore, any systematic difference in their revised earnings forecasts of quarter t+1 after the earnings announcement is likely driven by their different expectations of earnings of quarter t. We then examine the association between the rank order of analyst expectations of earnings of quarter t before the earnings announcement and the rank order of their revised earnings forecasts of quarter t+1 after the earnings announcement. The advantage of this approach is that it is free of parameter estimation and the results are clear and easy to interpret.

The second approach is a regression approach. We follow a standard belief update model such as that in Kandel and Pearson (1995) or Kim and Verrecchia (1997) and estimate the impact of analysts' expectations of quarter t's *EPS* on their revised forecasts for quarter $t+1$ after the earnings announcement. The advantage of this approach is that there is no selection problem in the sample construction and that it allows us to control for confounding factors easily.

We find, under both approaches, that analysts with more optimistic forecasts for quarter t on average revise their forecasts for quarter t+1 more optimistically. This result is robust to controlling for analyst strategic incentives, broker fixed effects, and analyst fixed effects. This result is also robust to different revision windows. These findings are consistent with the confirmatory bias explanation (*RS* hypothesis).

We next explore how firm characteristics and analyst characteristics affect the association between expectations and interpretations. We find that the confirmatory bias is stronger in smaller firms, in firms with more growth opportunities, and in firms with more disagreement. In contrast, we do not find analyst characteristics such as firm-specific experience or limited attention affecting their confirmatory bias.

Finally, using the belief update model based on confirmatory bias, we aggregate analyst-level data and develop novel predictions at firm level. We find that the evidence is consistent with the confirmatory bias based model. In particular, the revised forecast consensus of quarter t+1 after the earnings announcement is significantly and positively associated with the forecast consensus of quarter t after controlling for the forecast consensus of quarter t+1 before the earnings announcement. In addition, the variance of the individual analysts' revised forecast consensus of quarter t+1 after the earnings announcement is significantly and positively associated with the covariance between the individual analysts' forecast of quarter t+1 before the earnings announcement and the individual analysts' forecast of quarter t.

There is a broad literature in psychology investigating how people's prior preferences or beliefs influence information processing (e.g., Kunda 1990; Ditto et al. 1998). It is well documented that human beings are strongly impacted by their prior beliefs, and they tend to see what they believe to see (Gilovich 1991). This kind of biased information assimilation is widely explored in many areas using data from experiments, such as political science, decision making, and health care, but it is seldom studied in real financial market because investors' prior beliefs and information process are difficult to measure. According to our knowledge, this is the first paper using large real and professional data in the financial market to study how agents' different expectations influence their information interpretations. We find that analysts' behavior is consistent with the theory of confirmatory bias.

This paper also relates to a broad literature on investor heterogeneous belief and disagreement. Many papers study the consequences of investor heterogeneous belief and disagreement (e.g. Hong and Stein 2007; Scheinkman and Xiong 2003; Xiong and Yan 2010), but few of them explore how the disagreement is generated. This paper directly investigates how expectations generate disagreement and provides insight on the assumptions that we could make in modeling individuals' behavior in financial market.

We organize the remainder of the paper as follows. Research designs and predictions are discussed in Section 2. Our sample is described in Section 3. In Section 4, we present our empirical results using the matching sample approach and we present results using the regression approach in Section 5. We explore the cross-sectional variations in the association between expectation and interpretation and firm level predictions in Section 6 and conclude the paper in Section 7.

2. Research Design

2.1. Predictions

We follow prior literature (e.g., Kandel and Pearson 1995; Kim and Verrecchia 1997) to model how analysts update their forecasts with different interpretations.

$$F_{post,i,t+1} = \alpha \times F_{pre,i,t+1} + (1-\alpha) \times \left(L_t + \varepsilon_{i,t}\right), (1)$$

where $F_{post,i,t+1}$ is the analyst i's revised forecast of *EPS* for quarter t+1 after the earnings announcement of quarter t. $F_{pre,i,t+1}$ is the analyst i's latest forecast of *EPS* for quarter t+1 before the earnings announcement of quarter t. L_t is the common interpretation of the public signal from quarter t's earnings announcement and $\varepsilon_{i,t}$ represents analyst i's individual interpretation of the public signal. α is the weight of analyst i putting on her own prior forecast which is determined by the relative precision of her own forecast and the public signal ($0<\alpha<1$). We omit firm subscript to save space.

In this classic forecast revision model, $\varepsilon_{i,t}$ is usually assumed to be a random noise and analyst i's individual forecast of quarter t's *EPS*, $F_{i,t}$, plays no direct role in the revision process. This study aims to explore whether or not $F_{i,t}$ affects the individual interpretation $\varepsilon_{i,t}$. In other words, we assume that

$$\varepsilon_{i,t} = \beta \times F_{i,t} + \mu_{i,t}, \text{(2)}$$

where $\mu_{i,t}$ is a random noise and β represents the impact of individual expectations (which is proxied by $F_{i,t}$) on individual interpretations of new information. Inserting equation (2) to equation (1), we have our empirical specification as follows:

$$F_{post,i,t+1} = \alpha \times F_{pre,i,t+1} + (1-\alpha) \times (L_t + \beta \times F_{i,t} + \mu_{i,t}). \text{(3)}$$

The *HS* hypothesis suggests that a higher individual expectation leads to a lower individual interpretation. Therefore, the *HS* hypothesis predicts β to be negative (i.e., $\beta < 0$). The *KP* hypothesis assumes $\varepsilon_{i,t}$ to be a random noise. Therefore, the *KP* hypothesis predicts β to be insignificantly different from zero (i.e., $\beta = 0$). Lastly, the *RS* hypothesis argues that higher individual expectation leads to higher individual interpretation. That is, the *RS* hypothesis predicts β to be positive (i.e., $\beta > 0$).

2.2. Research Designs

In order to better establish our arguments, we employ two research designs. In the first part, we employ a parameter-free approach by matching analysts in pairs to conduct a univariate test. In the second part, we include all analyst-firm-quarter observations to use a regression approach. This section explains the two approaches in details.

2.2.1. Parameter-free Approach

In this approach, we match each analyst i with another analyst j who follows the same firm in quarters t and t+1. In addition, we require that analyst i and j have the identical *EPS* forecast for quarter t+1 before the earnings announcement of quarter t, i.e. $F_{pre,i,t+1} = F_{pre,j,t+1}$. Meanwhile, we require that analyst i and j have different forecasts for quarter t's *EPS*, i.e. $F_{i,t} \neq F_{j,t}$.

As we can see from equation (3), L_t is the common interpretation of the public signal and we match on the pre-announcement forecast $F_{pre,t+1}$. Therefore, the systematic difference between analyst i and j's post-announcement forecast $F_{post,t+1}$ is driven by the difference in their expectations of quarter t's *EPS* only ($\beta F_{i,t} - \beta F_{j,t}$).

Without loss of generality, we assume that $F_{i,t} > F_{j,t}$ in all cases. A zero β will lead to a similar likelihood of $F_{post,i,t+1} > F_{post,j,t+1}$ or $F_{post,i,t+1} < F_{post,j,t+1}$ because $E[\beta F_{i,t} - \beta F_{j,t}] = \beta E[F_{i,t} - F_{j,t}] = 0$. In contrast, a positive (negative) β will lead to higher (lower) likelihood of $F_{post,i,t+1} > F_{post,j,t+1}$ than $F_{post,i,t+1} < F_{post,j,t+1}$ because $E[\beta F_{i,t} - \beta F_{j,t}] = \beta E[F_{i,t} - F_{j,t}] > 0$. This approach creates a quasi-experiment setting in which we can infer the sign of β by comparing the frequency of $F_{post,i,t+1} > F_{post,j,t+1}$ and $F_{post,i,t+1} < F_{post,j,t+1}$. Because we simply compare the frequency and do not rely on any parameters and magnitudes, this approach is free of concerns of outliers, scale problems, or estimation methods.

2.2.2. Regression Approach

As discussed above, there are some appealing characteristics with the parameter-free approach. However, the matching process can generate bias from selection, i.e., the analysts in matched pairs may not be representative for all analysts. Therefore, we also conduct regression analysis by including all possible observations. In addition, the flexibility of the regression approach allows us to control for confounding factors easily.

Our empirical model follows equation (3). In addition, we control for the firm-year-quarter effect ($v_{k,t}$) to assure that we are comparing analysts interpreting the same public announcement. L_t drops from the empirical specification because it is absorbed by the firm-year-quarter effect. Our final empirical model is as follows:

$$F_{post,i,t+1} = \alpha_0 + \alpha \times F_{pre,i,t+1} + (1-\alpha) \times \beta \times F_{i,t} + \mu_{i,t} + v_{k,t}. (4)$$

Because $0 < \alpha < 1$ leads to a positive $1 - \alpha$, the sign of coefficient on $F_{i,t}$ is determined by the sign of β. Again, the *HS* (*RS*) hypothesis predicts a negative (positive) β leading to a prediction of negative (positive) coefficient on $F_{i,t}$ and the *KP* hypothesis predicts a zero β leading to a prediction of insignificant coefficient on $F_{i,t}$. We include an intercept (α_0) in our estimation. However, our results are not affected without the intercept.

3. The Sample

I/B/E/S provides comprehensive information about analysts' detailed forecasts and firms' actual earnings over time. Return and trading volume data are obtained from the Center for Research in Security Prices (CRSP). Financial data and dates of earnings announcements are from COPUMSTAT. Our sample covers data from year 2001 through 2012. We start our sample from year 2001 because we want to focus on the interpretation of information available publicly. The passage of Regulation Fair Disclosure (Reg FD) in late 2000 assures that the concern of selective disclosure or private communication is minimized. Kross and Suk (2012) also provide evidence that analysts are more responsive to earnings announcements after Reg FD.

In order to analyze the influence of expectation on interpretation of new information, we need to have analysts' prior and updated forecasts after the same piece of observable information. We require that analysts at least issue one quarterly forecast for both quarter *t* and *t*+1 within 45 days before its earnings announcement of quarter *t* to assure that the forecasts are not outdated (Hilary and Shen 2013).[2] We also require that each sample firm is followed by at least two analysts so that we can control for the same piece of information (firm-year-quarter effect). In addition, we require sample firms that have a price greater than $1 at the end of quarter *t*. When we employ the parameter-free approach, we form matched pair analysts with identical forecasts for the firm's earnings of quarter *t*+1 and require them to have different forecasts for quarter *t*. This leads to a sample of 30,077 pairs of analysts, which consists 5,826 unique analysts covering 3,309 unique firms. When using a general regression approach, we include all analysts-firm-quarter observations after the abovementioned criteria. This leads to a sample of 230,496 firm-quarter-analyst observations, which consists 7,452 unique analysts covering 5,864 unique firms. The actual sample size for each test may vary because of additional sample selection criteria which will be available in later sections.

4. Empirical Results from the Parameter-Free Approach

We focus on two windows of forecast revisions: the 2-day (0, 1) window and the 31-day (0,

[2] We follow Kandel and Pearson (1995) to not impose restrictions on revised forecasts.

30) window. We use the first analyst revisions in the window as our measure of $F_{post,i,t+1}$. We use the 2-day window to examine the immediate responses of analysts. The short window can mostly avoid confounding information during the same time period.[3] The 31-day window allows analysts to react a bit slowly and to assure the robustness of our results. Following Kandel and Pearson (1995), we also consider two types of revisions: explicit and implicit. If analyst *i* revises her forecast within the corresponding window, this forecast is classified as an "explicit" revision. In contrast, if there is no new forecast available for analyst *i* within the corresponding window, we consider it as an "implicit" revision, i.e., the revised forecast is the same as before ($F_{popst,i,t+1}$=$F_{pre,i,t+1}$). We present our results based on both the explicit forecast sample and the all forecast sample including the implicit revisions.

4.1. Summary Statistics

Table 1 presents the summary statistics of the firm and analyst characteristics in our matched sample. In general, the firms are large and covered by many analysts in our matched sample. The average firm possesses more than $29 billion total assets and is covered by more than 16 analysts. This is because matching criteria tends to select large firms in our matched sample. In terms of analyst characteristics, the average analyst works for brokers with more than 53 analysts, follows more than 15 firms at the same time and has followed the particular firm more than three years. These statistics are comparable to other studies studying detail analyst forecasts such as Hilary and Shen (2013).

[Insert Table 1 here]

[3] Kross and Suk (2012) find that majority of analysts revise their forecasts immediately after the earnings announcements during the post Reg FD period.

4.2. Different Expectations and the Likelihood of Different Interpretations

In this part, we first show that the difference in expectations of *EPS* in quarter t is likely to be correlated with the frequency of different interpretations of earnings announcements of quarter t. Table 2 presents the proportions of whether or not $F_{post,i,t+1}$ is the same as $F_{post,j,t+1}$ according to whether or not $F_{i,t}$ is the same as $F_{j,t}$. We label the paired analysts as "identical" if their revised forecasts are the same (i.e. $F_{post,i,t+1} = F_{post,j,t+1}$) and we label them as "disparate" otherwise. The proportion equals the number of pairs of analysts in each type divided by the total number of pairs of analysts. *Diff*_1 equals to the proportion of *identical* minus the proportion of *disparate* in the sample when paired analysts have the same expectations of *EPS* of quarter t ($F_{i,t} = F_{j,t}$). *Diff*_2 equals the proportion of *identical* minus the proportion of *disparate* in the sample when paired analysts have different expectations of *EPS* of quarter t ($F_{i,t} \neq F_{j,t}$).

[Insert Table 2 here]

Panel A of Table 2 shows the results of explicit revisions. In the first row, we include paired analysts who have revised forecasts for quarter t+1 from the day of earnings announcement of quarter t to one day after it. In the same expectation sample ($F_{i,t} = F_{j,t}$), 35.49% of the paired analysts have *identical* revised forecasts for quarter t+1, and 64.51% of the paired analysts have *disparate* revised forecasts for quarter t+1. *Diff*_1 is 29.02%. In the different expectation sample ($F_{i,t} \neq F_{j,t}$), 21.30% of the paired analysts have *identical* revised forecasts for quarter t+1, and 78.70% of the paired analysts have *disparate* revised forecasts for quarter t+1. *Diff*_2 is 57.40%, which is significantly larger than *Diff*_1 (with p-value smaller than 0.001). The results are similar using a 31-day window of revisions.

In Panel B of Table 2, we present the result using all revisions including implicit revisions. In the first row, we include all the paired analysts whether or not they update their forecasts within one day after the earnings announcement. If analysts do not update forecasts in this window, we use their latest forecasts for quarter t+1 before the earnings announcement of quarter t as revised forecasts. We find that *Diff*_2 is consistently larger than *Diff*_1 and the difference is 32.46% with a p-value smaller than 0.001. Taking together, these findings indicate that analysts with heterogeneous expectations tend to have more divergent opinions afterwards.

Although we have documented the impact of prior beliefs on opinion divergence, it is possible that this effect is not driven by new public information. In order to examine whether or not public information release matters, we create a pseudo-event which is 30 days before the actual earnings announcement. We then examine analyst forecast revisions around these pseudo-events. All the differences between *Diff*_2 and *Diff*_1 around pseudo-events are smaller than those around real earnings announcements. In fact, there are very few explicit revisions around the pseudo-events (only 307 observations) which are due to the fact that analysts do not revise their forecasts very frequently without new information. This evidence suggests that our results in Table 1 are indeed driven by public information releases.

4.3. Main Results

The main results are reported in Table 3. Without losing generality, we assume $F_{i,t} > F_{j,t}$ all the time. In Panel A of Table 3, we consider explicit revisions only. In the first row of the 2-day revision window, there are 37.04% of all paired analysts with $F_{post,i,t+1} < F_{post,j,t+1}$ and 41.66% with $F_{post,i,t+1}>F_{post,j,t+1}$. The difference is 4.62% and is highly statistically significant (p-value < 0.001). As discussed in Section 2, the probability of the cases $F_{post,i,t+1}<F_{post,j,t+1}$ ($F_{post,i,t+1}>F_{post,j,t+1}$) depends on the sign of β. When $\beta > 0$ ($\beta < 0$), we should observe higher frequency of the cases with $F_{post,i,t+1}>F_{post,j,t+1}$ than that of the cases with $F_{post,i,t+1}>F_{post,j,t+1}$.

Therefore, the results in Panel A of Table 3 suggest a positive and significant β in equation (3) or (4) and are consistent with the RS hypothesis. The results are similar when we use the 31-day revision window. The difference between the frequency of $F_{post,i,t+1}>F_{post,j,t+1}$ and the frequency of $F_{post,i,t+1}<F_{post,j,t+1}$ is 4.12% and is again highly statistically significant. The results support the RS hypothesis or the confirmatory bias argument.

[Insert Table 3 here]

We next consider all revisions including implicit revisions in Panel B of Table 3. Our results are qualitatively and quantitatively similar to those reported in Panel A of Table 3. We find a higher likelihood of $F_{post,i,t+1}>F_{post,j,t+1}$ than $F_{post,i,t+1}<F_{post,j,t+1}$ in both the 2-day and 31-day windows. The differences in the frequency are 3.65% and 4.00%, respectively. These results are again consistent with the RS hypothesis or the confirmatory bias argument.

We repeat our analyses with the pseudo-events (30 days before earnings announcements). The difference is in the opposite sign with a small magnitude comparing to those for real earnings announcements. The explicit sample is very small in pseudo-events (185 observations) because analysts do not respond to pseudo-events.

4.4. the Effect of Actual Earnings on Analyst Forecast Revisions

Firms' realized earnings may beat or meet analysts' expectation. In Table 4, we study whether or not analysts' information interpretation is influenced by the nature of the news of realized earnings in quarter *t*. When actual *EPS* in quarter *t* is between the paired analysts' forecasts (i.e., $F_{i,t} \geq Actual\ EPS \geq F_{j,t}$), we define this type of actual earnings as "Between." In the same vein, we define actual earnings as "Larger" when actual *EPS* is larger than both of the paired analysts' forecasts (i.e., $Actual\ EPS > F_{i,t} > F_{j,t}$) and define actual earnings as "Smaller" when actual *EPS* is smaller than both of the paired analysts' forecasts (i.e., $F_{i,t} > F_{j,t} > Actual\ EPS$). Paired analysts are categorized in three groups according to the nature of the information about the actual earnings.

In the first half of Panel A, we present the results for explicit revisions in the 2-day windows. In the "Larger" and "Between" groups, the percentages of $F_{post,i,t+1}<F_{post,j,t+1}$ cases are smaller than the percentage of $F_{post,i,t+1}>F_{post,j,t+1}$ cases. The differences in percentage are 5.31% and 6.60%, respectively, and are statistically significant (p-value<0.001). These results are consistent with the RS hypothesis but cannot be explained by the prediction of Kandel and Pearson (1995) or Hong and Stein (2007). However, in the "Smaller" group, the difference between the percentage of $F_{post,i,t+1}<F_{post,j,t+1}$ cases and the percentage of $F_{post,i,t+1}>F_{post,j,t+1}$ cases is small (1.89%) and statistically insignificant (p-value is 0.328).

[Insert Table 4 here]

In the second half of Panel A, we conduct our explicit sample analyses by using the 31-day revision window. The results are similar to those using the 2-day revision window. In the "Larger" and "Between" groups, the frequencies of $F_{post,i,t+1}<F_{post,j,t+1}$ cases are 5.28% and 5.63% less than those of $F_{post,i,t+1}>F_{post,j,t+1}$ cases, respectively. However, in the "Smaller" group the difference between the percentage of $F_{post,i,t+1}<F_{post,j,t+1}$ cases and the percentage of $F_{post,i,t+1}>F_{post,j,t+1}$ cases is small (1.52%) and statistically insignificant (p-value is 0.339). The possible explanation of the insignificant results in the "Smaller" group is that paired analysts less cling to their prior expectations when they face definitely bad news.[4]

In Panel B of Table 4, we repeat our analyses in Panel A of Table 4 by adding implicit analyst revisions. We find that the results are qualitatively and quantitatively the same as those in Panel A of Table 4. For example, based on the 2-day widow, the frequencies of $F_{post,i,t+1}<F_{post,j,t+1}$

[4] Kothar, Shu, and Wysocki (2009) find that investors are more reactive to bad news.

cases are 3.57% and 4.77% less than those of $F_{post,i,t+1}>F_{post,j,t+1}$ cases in the "Larger" and "Between" groups,, respectively. The differences are highly significant. In contrast, in the "Smaller" group the difference between the percentage of $F_{post,i,t+1}<F_{post,j,t+1}$ cases and the percentage of $F_{post,i,t+1}>F_{post,j,t+1}$ cases is small (-0.85%) and insignificant.

In sum, our results are generally consistent with the *RS* hypothesis after considering the nature of the public news suggesting that confirmatory bias plays an important role in public information interpretation.

4.5. Additional Analyses

4.5.1. Analyst Recommendations

It is possible that analysts have strategic incentives when revising their forecasts. For example, analyst who issued "Strong Buy" ("Strong Sell") recommendation for the firm may tend to issue more optimistic forecasts to justify her own recommendations. This incentive can lead to a positive correlation between the expectation of *EPS* of quarter *t* and revised forecast for quarter *t*+1. However, we argue that this case is unlikely for the next quarterly forecast sample for two reasons. First, the valuation is more sensitive to long-term earnings forecasts and long-term growth forecasts than to short-term earnings forecasts. If analysts want to justify their recommendations by inflating forecasts, it is more important to adjust their long-term forecasts instead of short-term forecasts. Second, short-term forecasts will be verified soon and biased forecasts can hurt analysts' reputation. Nevertheless, we provide evidence regarding the strategic incentives.

Instead of examining $F_{i,t}$, we examine analysts' recommendations ($R_{i,t}$) before the earnings announcements. Because analysts do not update recommendations very often (Boulland et al.

2015), we allow for 180 days window to extract the latest recommendations of the analysts. Again, without loss of generality, we assume that analyst *i*'s recommendation is more favorable than analyst *j*'s ($R_{i,t}$ > $R_{j,t}$). The results based on the explicit sample are reported in Panel A of Table 5. The differences between the frequencies of $F_{post,i,t+1}$<$F_{post,j,t+1}$ and $F_{post,i,t+1}$>$F_{post,j,t+1}$ are small and not significant in both 2-day and 31-day revision windows. The differences are 1.21% and 0.78% and the corresponding p-values are 0.845 and 0.410, respectively. The results from all revisions including implicit revisions are similar (reported in Panel B of Table 5). The differences are -0.49% and -0.34% and the corresponding p-values are 0.432 and 0.604, respectively. These results suggest that analyst strategic incentives measured by their recommendations unlikely drive our results in Tables 3 and 4.

[Insert Table 5 here]

4.5.2. Alternative Approaches to Construct Paired Analysts

In the previous setting, we require that paired analysts should have exactly identical forecasts for quarter t+1 before earnings announcements of quarter t (i.e., $F_{pre,i,t+1}$=$F_{pre,j,t+1}$). This restriction is very strict and may filter out too many analysts from our sample. In this part, we loosen this restriction and choose two analysts who have almost identical forecasts, i.e., the difference of their forecasts is within one penny, as paired analysts. Under this new setting, $F_{post,i,t+1}$ < (>) $F_{post,j,t+1}$ means that the difference between $F_{post,i,t+1}$ and $F_{post,j,t+1}$ is greater than one penny and we set $F_{post,i,t+1} = F_{post,j,t+1}$ otherwise.

Table 6 present the proportions of different types of revised forecasts. The observations in Table 6 are larger than those reported in Table 3, in which we use the exact identical restriction. We find that the results in Table 6 are qualitatively and quantitatively similar to those reported in

Table 3 for both the explicit and implicit samples and in both windows. For example, in the explicit sample, the differences in the frequencies between $F_{post,i,t+1}<F_{post,j,t+1}$ and $F_{post,i,t+1}>F_{post,j,t+1}$ are 5.49% and 4.56% for the 2-day and 31-day revision windows, respectively. These differences are highly statistically significant (p-values < 0.001 for both cases). The results are similar for the implicit sample. In sum, our evidence from matched samples provides strong supports to confirmatory bias theory (i.e., the *RS* hypothesis).

[Insert Table 6 here]

5. Empirical Results from the Regression Approach

In this section, we employ a regression approach to explore the correlation between the expectations and interpretations. Similar to the matching sample approach, we focus on the same two windows (2-day and 31-day) of forecast revisions and consider two types of revisions: explicit and implicit. We present our results based on both the explicit forecast sample and the all forecast sample including the implicit revisions. We scale all *EPS* forecasts by the share price at the end of quarter *t*.

5.1. Summary Statistics

Table 7 presents the summary statistics of the firm and analyst characteristics in our regression sample. In general, the firms in our regression sample are smaller and covered by less analysts than those in our matched sample. The average firm possesses around $26 billion total assets and is covered by more than 13 analysts. This is because we impose less criteria in the regression sample. In terms of analyst characteristics, the average analyst works for brokers with more than 52 analysts, follows more than 15 firms at the same time and has followed the particular firm more than three years. These statistics are similar to those in our matched sample and to other studies studying detail analyst forecasts such as Hilary and Shen (2013).

[Insert Table 7 here]

5.2. Main Regression Results

Table 8 reports the main results of our regression analyses. In the first two columns of Panel A, we consider the explicit sample with the 2-day and the 31-day windows of revisions, respectively. We cluster standard errors at the analyst level in all regressions. Taking the 2-day window of the explicit sample as an example, the coefficient on $F_{i,t}$ is positive (0.046) and statistically significant (t-stat = 3.17). A one standard deviation increase in expectation $F_{i,t}$ will lead to 4.1 cents increase in revised forecasts $F_{post,i,t+1}$ or more than 4.5% of the standard deviation of revised forecasts $F_{post,i,t+1}$.[5] The average weight analysts putting on prior forecasts (α) is around 0.401. Using this number, the inferred β is about 0.077.[6] The results from the implicit sample and other windows are qualitatively similar. The coefficients on $F_{i,t}$ are positive and statistically significant across all regressions in Panel A of Table 8 with coefficients ranging from 0.394 to 0.656. The range of inferred β is from 0.077 to 0.104. These results are consistent with those in the previous section and support the *RS* hypothesis.

[Insert Table 8 here]

In Panel B of Table 8, we further control for analysts' strategic incentives by including analyst recommendations before earnings announcements of quarter t. $Rec_{i,t}$ takes value from one to five from "Strong Sell" to "Strong Buy." The higher the value of $Rec_{i,t}$, the more favorable is

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[5] In our sample, the standard deviation of $F_{i,t}$ and $F_{post,i,t+1}$ are 0.0219 and 0.0222, respectively. The average share price is \$40.535.Therefore, the increase in revisions is 0.046× 0.0219×40.535 = 4.1 cents or 0.046×0.0219/0.0222 = 4.54%.

[6] The inferred β is computed as 0.046 / (1-0.401) = 0.077.

the recommendation. The results are reported in Panel B of Table 8. We find that the coefficients on analysts' recommendations are not significant in all samples and all revision windows, which are consistent with our finding in the parameter-free research approach. The result suggests that the incentives of justifying recommendations do not play any important role in short-term information interpretations. More importantly, the coefficients on $F_{pre,i,t+1}$ and $F_{i,t}$ remain almost the same as those in Panel A of Table 8, suggesting that our results are robust.

Besides recommendations, analysts may have other strategic incentives. For example, the brokerage firm of analyst i conducts business with the firm followed by the analyst i. Therefore, analyst i has incentives to issue favorable forecasts for the firm to maintain the good relationship between the firm and her brokerage firm (Michaely and Womack 1999). In order to address this concern, we control for the broker fixed effect. The results are reported in Panel C of Table 6. We find that our results essentially remain unchanged.

It is possible that some analysts are over-optimistic all the time. In this case, we can observe a positive β just because these analysts always issue higher forecasts than others. In order to avoid this potential problem, we include the analyst fixed effect in Panel D of Table 8. We show that our results do not change both qualitatively and quantitatively. Finally, we include recommendations, broker fixed effects, and analyst fixed effects altogether in Panel E of Table, 8. Again, our conclusions are not affected. The coefficients on $F_{i,t}$ range from 0.030 to 0.062 and all are highly significant. The inferred β with all controls ranges from 0.085 to 0.108.

5.3. Analyst Revisions for Longer Horizons

In previous sections, we only examine analyst revisions for quarter t+1. What will happen when analysts interpret public information for *EPS* for longer horizons? In this section, we extend our analyses to explore whether or not the difference in expectations affects interpretations for earnings in longer horizons. In particular, we examine analyst forecast revisions for quarter t+2, t+3 and t+4. We use the following empirical model:

$$F_{post,i,t+s} = \alpha \times F_{pre,i,t+s} + (1-\alpha) \times \beta \times F_{i,t} + \mu_{i,t} + v_{k,t}, \qquad (5)$$

where s=2, 3, and 4. This model is identical to equation (4) except that we use $F_{post,i,t+s}$ and $F_{pre,i,t+s}$ instead of t+1, where s can take a value from 2 to 4. The results are reported in Table 9. From Panel A to Panel E of Table 9, we find that the coefficients on $F_{pre,i,t+s}$ are largely insignificant or even negatively significant some of the times. Using the numbers in Panel E of Table 9 (with all controls) as the example, the inferred βs range from 0.011 to 0.052, -0.015 to 0.064, and -0.086 to -0.015 for quarter t+2, t+3, and t+4, respectively. These results indicate that different expectations likely influence *different* interpretations only for short-term information. These results also suggest that previous results are not likely driven by analysts who maintain consistent forecasting errors for the same firms. Otherwise, we should observe the same pattern in all future quarters. In sum, our results from the regression approach confirm early results and again provide strong support to the RS hypothesis or the confirmatory bias argument.

[Insert Table 9 here]

6. Additional Analyses

6.1. Factors Affecting the Association between Expectation and Interpretation

In previous sections, we have shown that analysts on average exhibit confirmatory bias in interpreting earnings announcements. In this section, we take one step further to examine firm characteristics and analyst characteristics that may affect the confirmatory bias in public information interpretations.

6.1.1. Firm Characteristics

When information acquisition or processing costs are high, individuals may choose to rely on their own prior believes without updating information efficiently (e.g., Sims 2003; Woodford 2009; Coibion and Gorodnichenko 2015). Therefore, we should expect the confirmatory bias is more salient in firms with higher information costs. We use firm size as the measure of firms' information environment because small firms are generally opaque and with limited information available (Hong, Lim, and Stein 2000). Firm size (*Size*) is measured as the market cap of the firm at the end of the fiscal quarter.

When the firm's prospect is clear and stable, analysts can interpret any new information easily and are more likely to reach agreement. In contrast, when the firms' prospect is uncertain, analysts may disagree with each other and are not easily to be convinced by new information or evidence. Therefore, we should expect that the confirmatory bias is more salient when firms' prospects are more uncertain. Because growth firms usually face more uncertainty in the future, we use firms' growth opportunities as proxied by market to book ratio as our first measure for the uncertainty prospects. Market-to-book ratio (*MTB*) is the sum of the market value of equity and the book value of liabilities, divided by the book value of total assets. For the second measure, we use analyst dispersion before earnings announcements because the disagreement among analysts reflects the uncertainty in firms' future (Diether, Malloy and Scherbina 2002; Zhang 2006; Lam and Wei 2011; Cen, Wei, and Yan 2015). Analyst dispersion (*DISP*) is calculated by the standard deviation of analyst *EPS* forecasts before the earnings announcements, scaled by fiscal-quarter-end share price.

We use the regression approach to examine how firm characteristics affect the confirmatory bias because it is very difficult to include additional dimensions in the parameter-free approach. In particular, we use the following empirical model which is an extension of Equation (4):

$$F_{post,i,t+1} = \alpha_0 + \alpha \times F_{pre,i,t+1} + (1-\alpha) \times \beta \times \left(F_{i,t} + \gamma \times Firm\ Char \times F_{i,t}\right)$$
$$+\mu_{i,t} + v_{k,t}, \tag{6}$$

where $Firm\ Char$ is firm characteristics including *Size*, *MTB*, and *DISP*. $F_{post,i,t+1}$, $F_{pre,i,t+1}$, and $F_{i,t}$ are defined previously and all these forecasts are scaled by the share price at the end of quarter t. In each quarter, we put firms into quintiles based on their market cap (*Size rank*), market to book ratio (*MTB rank*) and analyst dispersion (*DISP rank*) and use these quintile ranks as the *Firm Char*. Because we control for firm-year-quarter effects, the *Firm Char* themselves are dropped from the regressions.

The results are reported in Table 10. In Panel A of Table 10, we present results using explicit revisions. The evidence is generally consistent with our conjectures. The coefficients on the interaction terms between $F_{i,t}$ and firm characteristics are negative for *Size rank* and are positive for *MTB rank* and *DISP rank*. The results suggest that the association between expectations and interpretations are stronger for small firms, growth firms, and firms with high disagreement. Panel B of Table 8 reports the results using all revisions including implicit ones. The results are qualitatively similar but a little bit weaker than those using the explicit sample.

[Insert Table 10 here]

6.1.2. Analyst Characteristics

Behavioral bias can be mitigated by experience. In particular analysts can incorporate public information more efficiently by acquiring more firm-specific experience (Mikhail et al. 2003). We measure analyst's firm-specific experience (*Firm Exp*) as the number of years from the first time of analyst issuing an *EPS* forecast for this firm to the current year. We expect that the confirmatory bias should be mitigated by analysts' firm-specific experience. Previous studies suggest that individuals have limited attention (e.g., Hirshleifer et al. 2009). When attention is limited, analysts may fail to interpret public information properly and stick to their own expectations instead. Therefore, the confirmatory bias in information interpretation can be strengthened by limited attention. We use the number of firms followed by the same analysts to measure the scarce of attention. The more firms the analyst follows at the same time, the less attention she can allocate to each firm. The number of firms following (*Num Firms*) is calculated as the number for firms that the analyst has issued at least one quarterly forecast in the fiscal quarter.

We use the following empirical model to examine the effect of analyst characteristics on the confirmatory bias:

$$F_{post,i,t+1} = \alpha_0 + \alpha \times F_{pre,i,t+1} + (1-\alpha) \times \beta \times \left(F_{i,t} + \gamma \times Analyst\ Char \times F_{i,t}\right) + \theta \times Analyst\ Char + \mu_{i,t} + v_{k,t,} \quad (7)$$

where $Firm\ Char$ is firm characteristics including *Firm Exp* and *Num Firms*. Other variables are defined in equation (6). In each quarter, we put analysts into quintiles based on their firm-specific experience (*Firm Exp rank*), and number of firms following (*Num Firms rank*) and use these quintile ranks as the *Analyst Char*.

Panel A of Table 11 presents the results using explicit revisions and Panel B of Table 11 reports the results using all revisions including implicit ones. The coefficients on the interaction term between $F_{i,t}$ and *Firm Exp rank* are negative in all specifications. The results are consistent with our conjecture that the confirmatory bias is mitigated by analysts' firm-specific experience. However, the evidence is weak because the coefficients on these interactions are only significant in 31-day window revisions and not in 2-day window revisions. No evidence is found for the limited attention conjecture. All coefficients on the interaction term between $F_{i,t}$ and *Num Firms rank* are statistically insignificant.

[Insert Table 11 here]

6.2. Firm-level Prediction and Evidence

In previous sections, we conduct tests and provide evidence at individual analyst level. In this section, we examine whether or not our insight at analyst level can be extended to firm level. We start from the belief update model with confirmatory bias, i.e. the Equation (3)

$$F_{post,i,t+1} = \alpha \times F_{pre,i,t+1} + (1-\alpha) \times \left(L_t + \beta \times F_{i,t} + \mu_{i,t}\right).$$

First, we examine the first moment of the aggregation, i.e. the mean of earnings forecasts. By taking average of Equation (3) at firm level, we have

$$\overline{F_{post,t+1}} = \alpha \times \overline{F_{pre,t+1}} + (1-\alpha) \times (L_t + \beta \times \overline{F_t} + \overline{\mu_t}) \quad (8)$$

$\overline{F_{post,t+1}}$ and $\overline{F_{pre,t+1}}$ are the consensus of the revised forecast of quarter t+1 and the forecast of quarter t+1 before the earnings announcement of quarter t, respectively. $\overline{F_t}$ is the consensus forecast of quarter t before the earnings announcement of quarter t. $\overline{\mu_t}$ is the mean of the noise individual interpretation whose expectation is zero. L_t is the common interpretation of the earnings announcement. Because both *(1-α)* and β are positive, we expect to find a positive coefficient of $\overline{F_t}$. This is a novel prediction because in classical belief update model, the consensus of quarter t should not be significant.

We use 3-day market adjusted earnings announcement returns (*CAR3*) as the measure of common interpretation of the earnings announcement. We control for both the level and the square of the return (*CAR3*^{2}) in our regression.

The results are reported in Table 12. Across all specifications, the coefficients of $\overline{F_t}$ are all positive and statistically significant. This firm-level evidence is consistent with a confirmatory bias based belief update model.

[Insert Table 12 here]

We next examine the second moment of the aggregation, i.e. the variance of earnings forecasts. By taking variance of Equation (3) at firm level, we have

$$VAR(F_{post,i,t+1}) = \alpha^2 VAR(F_{pre,i,t+1}) + \alpha(1-\alpha)\beta COV\left(F_{pre,i,t+1}, F_{i,t}\right) + (1-\alpha)^2\beta^2 VAR(F_{i,t}) + VAR(\mu_{i,t}) \ . \quad (9)$$

Based on a confirmatory bias based model (a positive β), the variance of revised forecasts of quarter t+1 will be positively correlated the covariance between individual analysts' forecast of quarter t+1 and quarter t before the earnings announcement of quarter t. This prediction is novel and cannot be generated by other models easily.

The results of testing the second moment prediction are presented in Table 13. We control for *CAR3* and $CAR3^2$ in the regression as well. Again, we consistently find that the coefficients of $COV(F_{pre,i,t+1}, F_{i,t})$ are positive and statistically significant across all specifications. This evidence renders strong support to *RS* hypothesis suggesting β to be positive.

[Insert Table 13 here]

7. Conclusion

In this paper, we study how heterogeneous expectations influence information interpretations. In particular, we use financial analysts to examine whether or not their expectations of *EPS* in quarter *t* affect their use of the actual earnings announcements of quarter *t* in revising their forecasts for quarter *t*+1. With both the matching sample approach and the regression approach, we find consistent results that suggest that analysts with higher (lower) expectations tent to interpret the public information more optimistically (pessimistically), especially for non-bad news. The evidence is consistent with the theory of confirmatory bias and cannot be explained by analyst strategic incentives or analyst constant characteristics. In the cross-sectional analysis, we find that the confirmatory bias is stronger for small firms, growth firms and firms with high disagreement. In contrast, analysts' confirmatory bias is mitigated by their experience.

Overall, this study proposes a novel research design based on analysts' earnings forecasts to test how expectation affects interpretation of public signals. It provides fresh evidence that prior expectations do affect interpretations of public information that are consistent with the predictions of the theory of confirmatory bias. It sheds lights on the assumptions that we can make in modeling individual behaviors in the financial market.

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Table 1 Summary statistics for matched sample

This table presents the summary statistics of firm and analyst characteristics of the matched sample. We require that analysts at least issue one quarterly forecast for both quarter t and t+1 within 45 days before its earnings announcement of quarter t. We also require that each sample firm is followed by at least two analysts so that we can control for the same piece of information (firm-year-quarter effect). In addition, we require sample firms that have a price greater than $1 at the end of quarter t. We form matched pair analysts with identical forecasts for the firm's earnings of quarter t+1 and require them to have different forecasts for quarter t. This leads to a sample of 30,077 pairs of analysts, which consists 5,826 unique analysts covering 3,309 unique firms. *MTB* is market to book ratio calculated as the market value of equity plus book value of debt, divided by book value of total assets in quarter t. *ROA* is income before extraordinary items divided by total assets in quarter t. *Coverage* is the number of analysts issuing earnings forecasts for the firm in quarter t. *Broker Size* is the number of analysts working for the broker in quarter t. *Fol_Firm* is the number of firms for which analyst *i* has issued at least on forecast in quarter t. *Firm_Exp* is the number of years since the first time analyst *i* has issued an earnings forecast for the firm in I/B/E/S.

Variable	Mean	25^{th} percentile	Median	75^{th} percentile	Std.
Total assets	29161.580	1039.797	4007.283	16607.810	93344.950
MTB	2.087	1.172	1.601	2.397	1.454
ROA	0.009	0.002	0.011	0.023	0.034
Coverage	16.090	10.000	15.000	21.000	7.801
Broker Size	53.443	22.000	48.000	82.000	36.397
Fol_Firm	15.742	11.000	15.000	19.000	7.894
Firm_Exp	3.273	1.000	2.000	5.000	3.822

Table 2. Different expectations and the likelihood of different interpretations

This table presents the proportions of paired analysts with the same and the different expectations. The paired revised forecasts are labeled as "identical" if $F_{post,i,t+1} = F_{post,j,t+1}$, and are labeled as "disparate" otherwise. *Diff*_1 equals to the proportion of *identical* minus the proportion of *disparate* in the sample when paired analysts have the same expectations ($F_{i,t} = F_{j,t}$). *Diff*_2 equals the proportion of *identical* minus the proportion of *disparate* in the sample when paired analysts have different expectations ($F_{i,t} \neq F_{j,t}$). The explicit sample only includes paired analysts with explicit revisions and the implicit sample includes paired analysts with both explicit and implicit revisions.

Panel A: The explicit sample

Window	$F_{i,t} = F_{j,t}$				$F_{i,t} \neq F_{j,t}$					
	Identical	Disparate	Diff_1	Obs.	Identical	Disparate	Diff_2	Obs.	Diff_2 – Diff_1	p-value
2 days	35.49%	64.51%	29.02%	5,016	21.30%	78.70%	57.40%	12,000	28.38%	<0.001
30 days	33.32%	66.68%	33.36%	6,612	19.26%	80.74%	61.48%	17,103	28.12%	<0.001

Panel B: The implicit sample

	$F_{i,t} = F_{j,t}$				$F_{i,t} \neq F_{j,t}$					
	Identical	Disparate	Diff_1	Obs.	Identical	Disparate	Diff_2	Obs.	Diff_2 – Diff_1	p-value
2 days	37.84%	62.16%	24.32%	13,892	23.46%	76.54%	53.08%	30,077	28.76%	<0.001
30 days	38.14%	61.86%	23.72%	13,892	23.66%	76.34%	52.68%	30,077	28.96%	<0.001

Table 3. Frequency of the order between $F_{post,i,t+1}$ and $F_{post,j,t+1}$

This table presents the frequencies regarding the order between $F_{post,i,t+1}$ and $F_{post,j,t+1}$. Without loss of generality, we assume that $F_{i,t} > F_{j,t}$. Higher (lower) frequency of $F_{post,i,t+1} < F_{post,j,t+1}$ than $F_{post,i,t+1} < F_{post,j,t+1}$ suggests a negative (positive) β in the following equation.

$$F_{post,i,t+1} = \alpha \times F_{pre,i,t+1} + (1-\alpha) \times (L_t + \beta \times F_{i,t} + \mu_{i,t}).$$

The explicit sample only includes paired analysts with explicit revisions. The implicit sample includes paired analysts with both explicit and implicit revisions.

Panel A: The explicit sample

Window	(1) $F_{post,i,t+1} < F_{post,j,t+1}$	(2) $F_{post,i,t+1} = F_{post,j,t+1}$	(3) $F_{post,i,t=1} > F_{post,j,t+1}$	(1)-(3)	p-value	Obs.
Revised in 2 days	37.04%	21.30%	41.66%	-4.62%	<0.001	12,000
Revised in 30 days	38.31%	19.26%	42.43%	-4.12%	<0.001	17,103

Panel B: The implicit sample

Window	(1) $F_{post,i,t+1} < F_{post,j,t+1}$	(2) $F_{post,i,t+1} = F_{post,j,t+1}$	(3) $F_{post,i,t+1} > F_{post,j,t+1}$	(1)-(3)	p-value	Obs.
Revised in 2 days	32.42%	31.50%	36.07%	-3.65%	<0.001	30,077
Revised in 31 days	36.17%	23.66%	40.17%	-4.00%	<0.001	30,077

Table 4. Actual earnings and analyst revisions

This table presents the frequencies regarding the order between $F_{post,i,t+1}$ and $F_{post,j,t+1}$ in different types of actual earnings. When realized *EPS* in quarter *t* is between the paired analysts' forecasts (including equals one of the paired analysts' forecast), we define this type of actual earnings as "*Between*". In the same vein, we define actual earnings as "*Larger"* when *EPS* is larger than both of the paired analysts' forecasts, and define actual earnings as *"Smaller"* when *EPS* is smaller than both of the paired analysts' forecasts. The explicit sample only includes paired analysts with explicit revisions. The implicit sample includes paired analysts with both explicit and implicit revisions.

Panel A: The explicit sample

Window		(1) $F_{post,i,t+1} < F_{post,j,t+1}$	(2) $F_{post,i,t+1} = F_{post,j,t+1}$	(3) $F_{post,i,t+1} > F_{post,j,t+1}$	(1)-(3)	p-value	Obs.
Revised in 2 days	Between	35.13%	24.43%	40.44%	-5.31%	<0.001	3,823
	Larger	36.21%	20.98%	42.81%	-6.60%	<0.001	5,959
	Smaller	42.56%	16.77%	40.67%	1.89%	0.328	2,218
Revised in 31 days	Between	36.09%	22.55%	41.37%	-5.28%	<0.001	5,451
	Larger	37.79%	18.79%	43.42%	-5.63%	<0.001	8,309
	Smaller	43.22%	15.08%	41.70%	1.52%	0.339	3,343

Panel B: The implicit sample

Window		(1) $F_{post,i,t+1} < F_{post,j,t+1}$	(2) $F_{post,i,t+1} = F_{post,j,t+1}$	(3) $F_{post,i,t+1} > F_{post,j,t+1}$	(1)-(3)	p-value	Obs.
Revised in 2 days	Between	29.93%	36.57%	33.50%	-3.57%	<0.001	10,918
	Larger	33.09%	29.05%	37.86%	-4.77%	<0.001	13,953
	Smaller	35.86%	27.43%	36.71%	-0.85%	0.474	5,206
Revised in 31 days	Between	33.11%	28.95%	37.94%	-4.83%	<0.001	10,918
	Larger	36.69%	21.63%	41.68%	-4.99%	<0.001	13,953
	Smaller	41.16%	18.00%	40.84%	0.32%	0.795	5,206

Table 5. Using recommendations ($R_{i,t}$) instead of earnings expectations ($F_{i,t}$)

This table presents the results based on analyst recommendations ($R_{i,t}$) instead of $F_{i,t}$. Without losing generality, we assume $R_{i,t} > R_{j,t}$ suggesting analyst i issued more favorable recommendation than analyst j before earnings announcements of quarter t. Higher (lower) frequency of $F_{post,i,t+1} < F_{post,j,t+1}$ than $F_{post,i,t+1} > F_{post,j,t+1}$ suggests a negative (positive) β in the following equation.

$$F_{post,i,t+1} = \alpha \times F_{pre,i,t+1} + (1-\alpha) \times (L_t + \beta \times R_{i,t} + \mu_{i,t})$$

The explicit sample only includes paired analysts with explicit revisions. The implicit sample includes paired analysts with both explicit and implicit revisions.

Panel A: The explicit sample

Window	(1) $F_{post,i,t+1} < F_{post,j,t+1}$	(2) $F_{post,i,t+1} = F_{post,j,t+1}$	(3) $F_{post,i,t+1} > F_{post,j,t+1}$	(1)-(3)	p-value	Obs.
Revised in 2 days	35.67%	28.88%	35.46%	1.21%	0.845	6,202
Revised in 31 days	37.30%	26.18%	36.52%	0.78%	0.410	8,411

Panel B: The implicit sample

Window	(1) $F_{post,i,t+1} < F_{post,j,t+1}$	(2) $F_{post,i,t+1} = F_{post,j,t+1}$	(3) $F_{post,i,t+1} > F_{post,j,t+1}$	(1)-(3)	p-value	Obs.
Revised in 2 days	31.09%	37.33%	31.58%	-0.49%	0.432	15,739
Revised in 31 days	34.35%	30.96%	34.69%	-0.34%	0.604	15,739

Table 6. Using alternative criterion to form paired analysts

In this table, we repeat our analyses in Table 2 with a different definition of identical forecasts. In this table, we define two forecasts are identical if the difference between two forecasts are zero or only one penny. Without loss of generality, we assume that $F_{i,t} > F_{j,t}$. $F_{post,i,t+1}$ < (>) $F_{post,j,t+1}$ means the difference between $F_{post,i,t+1}$ and $F_{post,j,t+1}$ is greater than one penny and set $F_{post,i,t+1} = F_{post,j,t+1}$ otherwise. Higher (lower) frequency of $F_{post,i,t+1} < F_{post,j,t+1}$ than $F_{post,i,t+1} > F_{post,j,t+1}$ suggests a negative (positive) β in the following equation.

$$F_{post,i,t+1} = \alpha \times F_{pre,i,t+1} + (1-\alpha) \times (L_t + \beta \times F_{i,t} + \mu_{i,t})$$

The explicit sample only includes paired analysts with explicit revisions. The implicit sample includes paired analysts with both explicit and implicit revisions.

Panel A: the explicit sample

Window	(1) $F_{post,i,t+1} < F_{post,j,t+1}$	(2) $F_{post,i,t+1} = F_{post,j,t+1}$	(3) $F_{post,i,t+1} > F_{post,j,t+1}$	(1)-(3)	p-value	Obs.
Revised in 2 days	38.90%	16.71%	44.39%	-5.49%	<0.001	27,211
Revised in 31 days	40.14%	15.15%	44.70%	-4.56%	<0.001	39,852

Panel B: The implicit sample

Window	(1) $F_{post,i,t+1} < F_{post,j,t+1}$	(2) $F_{post,i,t+1} = F_{post,j,t+1}$	(3) $F_{post,i,t+1} > F_{post,j,t+1}$	(1)-(3)	p-value	Obs.
Revised in 2 days	32.81%	31.00%	36.20%	-3.41%	<0.001	69,652
Revised in 31 days	37.09%	22.21%	40.70%	-3.61%	<0.001	69,652

Table 7 Summary statistics for regression sample

This table presents the summary statistics of firm and analyst characteristics of the matched sample. We require that analysts at least issue one quarterly forecast for both quarter t and t+1 within 45 days before its earnings announcement of quarter t. We also require that each sample firm is followed by at least two analysts so that we can control for the same piece of information (firm-year-quarter effect). In addition, we require sample firms that have a price greater than $1 at the end of quarter t. we include all analysts-firm-quarter observations after the abovementioned criteria. This leads to a sample of 230,496 firm-quarter-analyst observations, which consists 7,452 unique analysts covering 5,864 unique firms. *MTB* is market to book ratio calculated as the market value of equity plus book value of debt, divided by book value of total assets in quarter t. *ROA* is income before extraordinary items divided by total assets in quarter t. *Coverage* is the number of analysts issuing earnings forecasts for the firm in quarter t. *Broker Size* is the number of analysts working for the broker in quarter t. *Fol_Firm* is the number of firms for which analyst *i* has issued at least on forecast in quarter t. *Firm_Exp* is the number of years since the first time analyst *i* has issued an earnings forecast for the firm in I/B/E/S.

Variable	Mean	25^{th} percentile	Median	75^{th} percentile	Std.
Total assets	25867.710	815.688	3021.390	12260.920	90002.330
MTB	1.959	1.128	1.486	2.194	1.377
ROA	0.007	0.001	0.010	0.022	0.036
Coverage	13.706	7.000	13.000	19.000	7.754
Broker Size	52.174	21.000	47.000	79.000	35.352
Fol_Firm	15.610	11.000	15.000	19.000	7.717
Firm_Exp	3.210	1.000	2.000	5.000	3.813

Table 8. Empirical results from the regression approach

We present empirical results for regression approach in this table. The empirical model is as follows.

$$F_{post,i,t+1} = \alpha \times F_{pre,i,t+1} + (1-\alpha) \times \beta \times F_{i,t} + \mu_{i,t} + v_{k,t},$$

where $F_{post,i,t+1}$ is analyst i's *EPS* forecast for quarter t+1 immediate after the earnings announcement of quarter t, scaled by the share price at the end of quarter t. $F_{pre,i,t+1}$ is analyst i's latest *EPS* forecast for quarter t+1 before the earnings announcement of quarter t, scaled by the share price at the end of quarter t. $F_{i,t}$ is analyst i's latest *EPS* forecast for quarter t before the earnings announcement of quarter t, scaled by the share price at the end of quarter t. We present baseline results in Panel A. In Panel B, we include analyst latest recommendation ($Rec_{i,t}$) before the earnings announcement of quarter t as an additional control variable. $Rec_{i,t}$ takes value from one to five from "strong sell" to "strong buy." The higher the value of $Rec_{i,t}$, the more favorable is the recommendation. In Panels C and D, we include broker fixed effects and analyst fixed effects, respectively. We include all controls in Panel E. The explicit sample only includes paired analysts with explicit revisions and the implicit sample includes paired analysts with both explicit and implicit revisions. T-statistics are reported in the parentheses. Standard errors are robust and clustered at analyst level.

Panel A: Baseline results

	Explicit Sample		Implicit sample	
	2-day window	31-day window	2-day window	31-day window
$F_{pre,i,t+1}$	0.401	0.394	0.656	0.519
	(25.77)	(26.03)	(54.92)	(36.27)
$F_{i,t}$	0.046	0.057	0.032	0.050
	(3.17)	(4.46)	(3.97)	(4.96)
Firm-year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	132,994	167,627	230,496	230,496
Adjusted R^2	0.218	0.206	0.422	0.299

Table 8 – continued

Panel B: Controlling for analyst recommendation				
	Explicit Sample		Implicit sample	
	2-day window	31-day window	2-day window	31-day window
$F_{pre,i,t+1}$	0.405	0.394	0.661	0.523
	(19.29)	(19.44)	(45.51)	(28.48)
$F_{i,t}$	0.056	0.070	0.035	0.060
	(3.02)	(4.37)	(3.64)	(4.87)
$Rec_{i,t}$	0.000	0.000	0.000	0.000
	(0.86)	(1.13)	(0.37)	(0.51)
Firm-year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	87,638	109,287	150,510	150,510
Adjusted R^2	0.217	0.208	0.427	0.308

Panel C: Controlling for broker fixed effects				
	Explicit Sample		Implicit sample	
	2-day window	31-day window	2-day window	31-day window
$F_{pre,i,t+1}$	0.398	0.391	0.653	0.513
	(24.57)	(24.98)	(53.27)	(34.55)
$F_{i,t}$	0.042	0.050	0.029	0.045
Firm-year-quarter fixed effects	Yes	Yes	Yes	Yes
Broker fixed effects	Yes	Yes	Yes	Yes
Observations	132,994	167,627	230,496	230,496
Adjusted R^2	0.215	0.208	0.424	0.303

Table 8 – continued

Panel D: Controlling for analyst fixed effects				
	Explicit Sample		Implicit sample	
	2-day window	31-day window	2-day window	31-day window
$F_{pre,i,t+1}$	0.400	0.393	0.655	0.518
	(25.73)	(26.04)	(54.75)	(36.32)
$F_{i,t}$	0.046	0.057	0.032	0.050
	(3.16)	(4.45)	(3.96)	(4.94)
Firm-year-quarter fixed effects	Yes	Yes	Yes	Yes
Analyst fixed effects	Yes	Yes	Yes	Yes
Observations	132,994	167,627	230,496	230,496
Adjusted R^2	0.218	0.206	0.423	0.300

Panel E: Controlling for all effects and analyst recommendations				
	Explicit Sample		Implicit sample	
	2-day window	31-day window	2-day window	31-day window
$F_{pre,i,t+1}$	0.403	0.394	0.658	0.518
	(18.81)	(19.30)	(44.92)	(28.06)
$F_{i,t}$	0.051	0.062	0.030	0.052
	(2.64)	(3.78)	(3.02)	(4.19)
$Rec_{i,t}$	-0.000	0.000	-0.000	-0.000
	(-0.12)	(0.14)	(-0.26)	(-0.76)
Firm-year-quarter fixed effects	Yes	Yes	Yes	Yes
Broker fixed effects	Yes	Yes	Yes	Yes
Analyst fixed effects	Yes	Yes	Yes	Yes
Observations	87,638	109,287	150,510	150,510
Adjusted R^2	0.211	0.205	0.429	0.312

Table 9. Analyst revisions for longer horizons

We present empirical results for analyst revisions for longer horizons in this table. The empirical model is as follows:

$$F_{post,i,t+s} = \alpha \times F_{pre,i,t+s} + (1-\alpha) \times \beta \times F_{i,t} + \mu_{i,t} + v_{k,t},$$

where $F_{post,i,t+s}$ is analyst i's *EPS* forecast for quarter $t+s$ immediate after the earnings announcement of quarter t, scaled by the share price at the end of quarter t. s can take a value from 2 to 4. $F_{pre,i,t+s}$ is analyst i's latest *EPS* forecast for quarter $t+s$ before the earnings announcement of quarter t, scaled by the share price at the end of quarter t. $F_{i,t}$ is analyst i's latest *EPS* forecast for quarter t before the earnings announcement of quarter t, scaled by the share price at the end of quarter t. We present explicit sample in Panel A and implicit sample results in Panel B. We control for analyst latest recommendation ($Rec_{i,t}$) before the earnings announcement of quarter t, broker fixed effects and analyst fixed effects in all regressions. $Rec_{i,t}$ takes value from one to five from "strong sell" to "strong buy". The higher the value of $Rec_{i,t}$, the more favorable the recommendation. The explicit sample only includes paired analysts with explicit revisions and the implicit sample includes paired analysts with both explicit and implicit revisions. T-statistics are reported in the parentheses. Standard errors are robust and clustered at analyst level.

Panel A: Explicit sample results

	2-day window			31-day window		
	s=2	s=3	s=4	s=2	s=3	s=4
$F_{pre,i,t+s}$	0.534	0.599	0.599	0.540	0.606	0.614
	(26.99)	(31.71)	(29.83)	(33.24)	(36.11)	(34.18)
$F_{i,t}$	0.005	-0.006	-0.006	0.011	0.000	-0.027
	(0.32)	(-0.44)	(-0.61)	(0.78)	(0.04)	(-3.14)
$Rec_{i,t}$	0.000	0.000	0.000	0.000	0.000	0.000
	(2.96)	(3.97)	(5.79)	(3.25)	(3.83)	(6.31)
Firm-year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Broker fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Analyst fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,469	47,450	36,428	75,409	60,459	45,690
Adjusted R^2	0.329	0.411	0.436	0.322	0.413	0.437

Table 9 – continued

Panel B: Implicit sample results

	2-day window			31-day window		
	s=2	s=3	s=4	s=2	s=3	s=4
$F_{pre,i,t+s}$	0.731	0.767	0.771	0.646	0.688	0.708
	(49.02)	(60.53)	(61.22)	(46.36)	(51.86)	(53.39)
$F_{i,t}$	0.014	0.015	-0.014	0.010	0.013	-0.025
	(1.69)	(1.74)	(-2.16)	(1.03)	(1.30)	(-3.10)
$Rec_{i,t}$	0.000	0.000	0.000	0.000	0.000	0.000
	(2.83)	(4.22)	(4.96)	(2.64)	(4.78)	(5.95)
Firm-year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Broker fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Analyst fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,120	98,005	72,953	119,120	98,005	72,953
Adjusted R^2	0.539	0.605	0.625	0.432	0.502	0.533

Table 10. Firm characteristics and confirmatory bias

We present empirical results for firm characteristics and confirmatory bias. The empirical model is as follows:

$$F_{post,i,t+1} = \alpha_0 + \alpha \times F_{pre,i,t+1} + (1-\alpha) \times \beta \times (F_{i,t} + \gamma \times Firm\ Char \times F_{i,t}) + \mu_{i,t} + v_{k,t},$$

where $F_{post,i,t+1}$ is analyst *i*'s *EPS* forecast for quarter *t+1* immediate after the earnings announcement of quarter *t*, scaled by the share price at the end of quarter *t*. $F_{pre,i,t+1}$ is analyst *i*'s latest *EPS* forecast for quarter *t+1* before the earnings announcement of quarter *t*, scaled by the share price at the end of quarter *t*. $F_{i,t}$ is analyst *i*'s latest *EPS* forecast for quarter *t* before the earnings announcement of quarter *t*, scaled by the share price at the end of quarter *t*. *Firm Char* includes the quintile rank of *Size*, *MTB*, and *DISP*. *Size* is the market cap of the firm at the end of the fiscal quarter. *MTB* is the market to book ratio of the firm at the end of the fiscal quarter, calculated as the sum of the market value of equity and the book value of liabilities divided by the book value of total assets. *DISP* is the standard deviation of analyst forecasts before the earnings announcement, scaled by fiscal-quarter-end share price. We present explicit sample in Panel A and implicit sample results in Panel B. The explicit sample only includes paired analysts with explicit revisions and the implicit sample includes paired analysts with both explicit and implicit revisions. T-statistics are reported in the parentheses. Standard errors are robust and clustered at analyst level.

Panel A: Explicit sample results

	2-day window			31-day window		
$Firm\ Char =$	Size	MTB	DISP	Size	MTB	DISP
$F_{pre,i,t+s}$	0.399	0.400	0.400	0.392	0.392	0.393
	(25.55)	(25.49)	(25.42)	(26.01)	(25.96)	(26.01)
$F_{i,t}$	0.114	0.013	-0.015	0.077	0.035	-0.021
	(3.15)	(0.73)	(-0.57)	(2.56)	(2.17)	(-0.90)
$F_{i,t} \times Firm\ Char$	-0.026	0.034	0.016	-0.008	0.022	0.021
	(-2.21)	(2.85)	(1.69)	(-0.82)	(2.11)	(2.46)
Firm-year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	133,987	133,856	133,987	168,854	168,680	168,854
Adjusted R^2	0.219	0.219	0.218	0.207	0.207	0.207

Table 10 – continued

Panel B: Implicit sample results

	2-day window			31-day window		
$Firm\ Char =$	Size	MTB	DISP	Size	MTB	DISP
$F_{pre,i,t+s}$	0.654	0.655	0.655	0.517	0.518	0.518
	(55.58)	(55.45)	(55.59)	(36.64)	(36.63)	(36.73)
$F_{i,t}$	0.080	0.026	-0.024	0.063	0.040	-0.007
	(4.82)	(2.58)	(-1.55)	(3.05)	(3.13)	(-0.39)
$F_{i,t} \times Firm\ Char$	-0.019	0.006	0.015	-0.006	0.010	0.015
	(-3.40)	(0.82)	(2.98)	(-0.80)	(1.29)	(2.49)
Firm-year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	232,028	231,759	232,028	232,028	231,759	232,028
Adjusted R^2	0.425	0.424	0.424	0.301	0.300	0.301

Table 11. Analyst characteristics and confirmatory bias

We present empirical results for firm characteristics and confirmatory bias. The empirical model is as follows:

$$F_{post,i,t+1} = \alpha_0 + \alpha \times F_{pre,i,t+1} + (1-\alpha) \times \beta \times \left(F_{i,t} + \gamma \times Analyst\ Char \times F_{i,t}\right) + \theta \times Analyst\ Char + \mu_{i,t} + v_{k,t},$$

where $F_{post,i,t+1}$ is analyst *i*'s *EPS* forecast for quarter *t+1* immediate after the earnings announcement of quarter *t*, scaled by the share price at the end of quarter *t*. $F_{pre,i,t+1}$ is analyst *i*'s latest *EPS* forecast for quarter *t+1* before the earnings announcement of quarter *t*, scaled by the share price at the end of quarter *t*. $F_{i,t}$ is analyst *i*'s latest *EPS* forecast for quarter *t* before the earnings announcement of quarter *t*, scaled by the share price at the end of quarter *t*. *Analyst Char* includes the quintile rank of *Firm Exp* and *Num Firms*. *Firm Exp* is the number of years since the analyst has issued the first *EPS* forecast of the firm. *Num Firms* is the number of firms the analyst has issued at least one *EPS* forecast during the quarter. We present explicit sample in Panel A and implicit sample results in Panel B. The explicit sample only includes paired analysts with explicit revisions and the implicit sample includes paired analysts with both explicit and implicit revisions. T-statistics are reported in the parentheses. Standard errors are robust and clustered at analyst level.

Panel A: Explicit sample results

	2-day window		31-day window	
$Analyst\ Char =$	Firm Exp	Num Firms	Firm Exp	Num Firms
$F_{pre,i,t+s}$	0.400	0.400	0.392	0.393
	(25.46)	(25.38)	(26.03)	(25.99)
$F_{i,t}$	0.065	0.053	0.090	0.071
	(2.77)	(1.98)	(4.16)	(3.02)
$F_{i,t} \times Analyst\ Char$	-0.010	-0.004	-0.017	-0.008
	(-1.15)	(-0.43)	(-2.21)	(-0.84)
$Analyst\ Char$	0.000	-0.000	0.000	0.000
	(0.09)	(-0.34)	(0.40)	(0.18)
Firm-year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	133,987	133,987	168,854	168,854
Adjusted R^2	0.219	0.218	0.207	0.207

Table 11 - continued

Panel B: Implicit sample results

	2-day window		31-day window	
$Analyst\ Char =$	Firm Exp	Num Firms	Firm Exp	Num Firms
$F_{pre,i,t+s}$	0.655	0.655	0.518	0.518
	(55.57)	(55.61)	(36.73)	(36.73)
$F_{i,t}$	0.045	0.036	0.071	0.062
	(3.59)	(2.49)	(4.47)	(3.56)
$F_{i,t} \times Analyst\ Char$	-0.007	-0.002	-0.011	-0.006
	(-1.40)	(-0.41)	(-1.79)	(-0.95)
$Analyst\ Char$	-0.000	-0.000	0.000	-0.000
	(-0.57)	(-0.16)	(0.11)	(-0.87)
Firm-year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	232,028	232,028	232,028	232,028
Adjusted R^2	0.424	0.424	0.301	0.301

Table 12 Firm level evidence – first moment (mean)

We present empirical results for regression approach in this table. The empirical model is as follows.

$$\overline{F_{post,t+1}} = \alpha * \overline{F_{pre,t+1}} + (1-\alpha) * \beta * \overline{F_t} + (1-\alpha) * CAR3 + \theta * CAR3^2 + \overline{\mu_t}$$

$\overline{F_{post,t+1}}$ and $\overline{F_{pre,t+1}}$ are the consensus of the revised forecast of quarter t+1 and the forecast of quarter t+1 before the earnings announcement of quarter t, respectively. $\overline{F_t}$ is the consensus forecast of quarter t before the earnings announcement of quarter t. $\overline{\mu_t}$ is the mean of the noise individual interpretation whose expectation is zero. *CAR3* is the market adjusted 3-day earnings announcement returns. T-statistics are reported in the parentheses. Standard errors are robust and clustered at firm level.

	Explicit Sample		Implicit sample	
	2-day window	31-day window	2-day window	31-day window
$\overline{F_{pre,t+1}}$	0.933	0.940	0.966	0.952
	(78.23)	(98.93)	(180.00)	(132.15)
$\overline{F_t}$	0.108	0.102	0.054	0.076
	(10.00)	(11.10)	(11.09)	(11.03)
CAR3	0.019	0.020	0.013	0.017
	(19.32)	(21.85)	(23.08)	(23.32)
$CAR3^2$	-0.058	-0.059	-0.041	-0.051
	(-8.79)	(-9.89)	(-10.44)	(-10.97)
Observations	16,427	20,600	28,275	28,275
Adjusted R^2	0.9217	0.9164	0.9582	0.9396

Table 13 Firm level evidence – second moment (variance)

We present empirical results for regression approach in this table. The empirical model is as follows:

$$VAR(F_{post,i,t+1}) = \alpha^2 VAR(F_{pre,i,t+1}) + \alpha(1-\alpha)\beta COV\left(F_{pre,i,t+1}, F_{i,t}\right) + (1-\alpha)^2\beta^2 VAR\left(F_{i,t}\right) + \gamma CAR3 + \rho CAR3^2 + VAR(\mu_{i,t})$$

$VAR(F_{post,i,t+1})$, *$VAR(F_{pre,i,t+1})$* and *$VAR(F_{i,t})$* are the variance of the revised forecasts of quarter t+1, the variance of forecasts of quarter t+1 before the earnings announcement of quarter t and the variance of the forecasts of quarter t, respectively. *$COV(F_{pre,i,t+1}, F_{i,t})$* is the covariance between the forecasts of quarter t+1 before the earnings announcement of quarter t and the forecasts of quarter t. *CAR3* is the market adjusted 3-day earnings announcement returns. T-statistics are reported in the parentheses. Standard errors are robust and clustered at firm level.

	Explicit Sample		Implicit sample	
	2-day window	31-day window	2-day window	31-day window
$VAR(F_{pre,i,t+1})$	0.579	0.561	0.882	0.725
	(8.83)	(9.29)	(20.27)	(13.07)
$VAR(F_{i,t})$	0.049	0.062	0.032	0.049
	(1.78)	(2.23)	(2.72)	(2.38)
$COV(F_{pre,i,t+1}, F_{i,t})$	0.290	0.278	0.176	0.232
	(2.37)	(2.47)	(3.05)	(2.43)
CAR3	0.000	-0.000	-0.000	-0.000
	(0.07)	(-0.88)	(-3.92)	(-2.29)
$CAR3^2$	0.000	0.000	0.000	0.000
	(2.86)	(3.16)	(4.97)	(4.34)
Observations	16,427	20,600	28,275	28,275
Adjusted R^2	0.4909	0.5565	0.6986	0.6109