Is News Informative or Sentimental to Analysts*

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Keywords: Media news; tone; sentiment; information; forecast accuracy

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Abstract

We examine how news affects financial analysts' expectations, and find that news tones improve analysts' information set, thus helping analysts achive a better forecast accuracy. Analysts' forecast bias, on the contrary, seems to be insensitive to news tones. In particular, positive tones are not informative as negative tones in predicting actual earnings, but analysts are able to differentiate valuable information from both tones and incorporate new information into their forecasts in a correct way. Among the analysts, bold and overconfident analysts seem to overweight their private information so their forecast behavior is not affected by news tones. Meanwhile, experienced and good ranking analysts have better information set so news provides little contribution in improving their forecasts. Overall, media news improves information environment and reduce information asymmetry among the analysts.

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1 Introduction

Media news has strong power in predicting future stock returns as it plays an important role in affecting investors' expectations. On the one hand, news may contain soft information about firms' fundamental values, and so it has incremental explanatory power on firms' future performance, especially when hard information is incomplete or is biased. For example, Tetlock (2008) finds that negative words predict future earnings and Bushee et al. (2010) show that the media serves as an information intermediary which incrementally contribute to firms information environment. On the other hand, media news may contain the authors' sentiment that may bias investors' expectation from the fundamental stock price, which can also generate return predictability. Importantly, Tetlock, Saar-Tsechansky, and Macskassy (2008), Loughran and McDonald (2011), and Lerman and Livnat (2010) find that stocks with positive (negative) news over one day have subsequent predictably high (low) returns for 1-2 days that are largely reversed, which suggests that investors overreact to positive news due to sentiment bias.

In this paper, we argue that previous evidence of news sentiment effects on stock returns do not differentiate news effects between rational investors and irrational investors. In particular, news effects also depends on how investors interpret news. For those rational investors, they have better ability to analyze news information. In this case, news is not sentimental to rational investors. To have this argument, we explore news effects on financial analysts who are regarded as sophisticated investors. Different from general investors, financial analysts may not rely on media news to make their decisions. First, analysts have better access to information through their relationship with management and other firm insiders. Private meetings between management and analysts are quite common in practice (Koch, Lefanowicz, and Robinson, 2013) and remain a significant information source to analysts (Green, Jame, Markov, and Subasi, 2012, 2014; Soltes, 2014). Second, analysts may be less motivated to exploit information in media news, because they focus on specific types of corporate events, such as earnings surprises (e.g., Abarbanell and Bernard, 1992), stock price changes (e.g., Abarbanell, 1991; Conrad et al., 2006; Clement et al., 2011), dividend policy changes (e.g., Denis et al., 1994; Ely and Mande, 1996). Therefore, analysts may think of media news less salient and quantifiable, and do not necessarily process it for earnings forecasts.

On top of that, since analysts are regarded as sophisticated investors (Hirabar, 2012), they may interpret it differently from general investors. Analysts are supposed to have better ability to generate assessments about the quality of a firm's fundamentals based on public information than general investors (Kim and Verrecchia 1994, 1997).

Overall, the real effect of news on analysts' forecast behavior are not straightforward and there is no research that examines how analysts process news to benefit their forecasts. However, understanding news effects on analyst forecast behavior helps us understand how analysts assemble and process the numerous types of value relevant information available to them. Moreover, it sheds light on how rational investors react to public news, which helps us understand the sophisticated investors' behavior.

In this paper, we ask the question whether news is informative to analysts. To answer the question, we first study news prediction power on Standard Unexpected Earnings (SUE). If news is informative to analysts, it must contain incremental information on firm fundamentals. We use Thomson Reuters' firm-specific news tone as proxy for news content. Each news has a positive tone and a negative tone, ranging from 0 to 1. Both tones can be proxy for informativeness of news - a high negative (positive) tone indicate the the firm's decaying (prosperous) future fundamentals. Consistent with Tetlock et al (2008), we find negative news tones show significantly negative effect in predicting actual earnings while positive tones seem to be less informative than the negative.

We then analyze the news tone effects on forecast bias and forecast accuracy. If media news reflects new information to analysts, news tones should improve their forecast accuracy. In contrast, if news is sentimental to analysts, positive tones should induce optimism into analysts' forecasts whereas negative tones induce pessimism. Our results reveal that both positive and negative tones have no effects on analysts' forecast bias while both of them significantly improve analyst forecast accuracy, suggesting media news reflects new information to analysts. Indeed, positive tones' effect seems to be a contradiction to the emprical results in terms of actual earnings. In this case, we expect that positive tones mixed valuable information with noise information and analysts are able to figure out valuable information from positive tones.

We further explore which type of analysts rely on public news to make forecasts, and which one is more capable of exploiting qualitative information from news. Indeed, we find good ranking, experienced, large firm coverage, less hard-working, boldness and overconfident analysts are not sensitive to news tone effects - their forecast accuracy are not significantly affected by news tones. While other type of analysts seem to benefit from interpreting news information. Meanwhile, we find overconfident and bold analysts tend to overweight their private information, which makes them underreact to news information. While experienced and good ranking analysts are more capable in balancing public and private information than others so their insensitivity to news tones may indicate their superior information set.

We also discuss other possibilities that drive our empirical results. One of channels is that news information may overlap with private information which analysts collect from other resources. It is diffcult for us to identify the private information but we argue that news information is different from private information by proposing two evidence - a. news significantly reduces information asymmetry among the analysts [1]; b. analysts with better private information are not sensitive to news tones. Both evidence suggest that news serves as public information that improves information environment.

Our paper contributes to the literature in three ways. First, it contributes to the literature on analysts' behavior. Easterwood and Nutt (1999) show that analysts underreact

[1] according to Barry and Jennings (1992) and Barron et al. (1998), public information reduces forecast dispersion, while privately observed information is the only factor that drives information asymmetry among analysts.

to unfavorable information but overreact to favorable information. In this paper, we find that analysts make their decision based on their understanding about news. Both their information set and information processing are important to affect the analysts' forecast behavior. Second, we suggest an alternative way to distinguish the information in media news from sentiment by studying the relation between news tones and analysts' forecast bias and accuracy. By focusing on earnings forecast bias and accuracy, we can clearly know whether analyst forecast approaches firm's fundamentals, which suggests whether the change of expectation is due to information improvement or sentiment bias. Third and most importantly, this paper contributes to the research on the effect of social media. By documenting a significant impact of news tone on analysts' earnings forecasts, this paper provides strong evidence that firm-specific news contain incremental information and contribute to the firm information environment. In fact, as analysts can be regarded as sophisticated investors, our study also serves as a strong test of the role of public news.

2 News Tone and Analysts' Forecast Behavior

Our objective is to examine how financial analysts use media news. The effect of the news media on the forecast behavior of analysts is twofold. First of all, the effect is highly dependent on how influential or informative of the media news is. Recent studies on social media provide ways to measure the impact of the news. Tetlock (2007) documents that negative words have strong prediction power when it comes to firm fundamentals and stock returns. Moreover, the prediction power of negative words is much stronger than that of positive words. Therefore, the effects of the news on analyst forecasting behavior is initially influenced by the news content itself. To test this, we use both positive and negative scores in regards to Thomson Reuters to measure the impact of each piece of news. For an information story, both positive and negative scores are proxy of informativeness of news - a high positive or negative score indicate analysts express more altitude about a firm hence providing more information to the public. For a sentiment story, a positive (negative) score means the news contains overall optimistic (pessimistic) sentiments about the firm.

The second effect relies on how analysts interpret the news. According to Hong and Stein (2007), Harris and Raviv (1993), as well as Kandel and Pearson (1995), investors have different economic models that cause them to interpret news in different ways. Peress et. al (2008) examine this effect by looking at news coverage of specific stories. Their empirical results show a positive correlation between media coverage and analysts' forecast dispersion, suggesting that media coverage does not lead to a convergence of opinions. Other studies also document different market reactions from analysts and investors towards the news arrivals. For example, Zhang (2006) shows under-reactions from analysts when new information arrives, whereas Peress (2008) documents overreactions from investors after abnormal media coverage of a specific event. Therefore, we expect that analysts perform differently when presented with the same news in comparison to participants from other markets or even other analysts within the same market.

2.1 Information Effect

Ovearall, for a news to be informative to analysts, it must satisfiy two conditions. First, it contains valuable information about actual earnings. Second, analysts are able to incorporate news information into their forecasts in a correct way. Violation of either condition makes news tone not informative to analysts.

In terms of our first argument, if news reflects aspects of firms' fundamentals that have not been impounded in current information available to analysts, we would expect news tone will predict actual earnings. According to Tetlock et al (2007), news is a potentially important source of information in regard to a firms fundamental values. As very few stock market investors can directly observe firms' production activities, they get most of their information secondhand. In this case, if the hard information (such as accounting variables) is incomplete or biased measures of the firms fundamentals, linguistic variables may provide incremental explanatory power for the firm's future earnings. In fact, Tetlock et al (2008) found that negative words have a strong prediction power on overall firm earnings, measured as SUE, by controllilng related public information. Thus, it can be deduced that the news provides extra information about firm fundamentals. However, this finding is a preliminary requirement for news being informative to analysts because analysts may also collect information from other resources, such as firm insiders. If news tone information is reflected by private information or they are not informative as private information, news is not useful to analysts. More details have been discussed in the next section.

In term of second argument, analysts increase forecast accuracy by correctly processing news information. Specifically, if an analyst's prior expectations about firm earnings are different from the actual earnings, he can adjust his expectations according to news information, and therefore, improving his forecast accuracy. Important notion is that, news tone serves as new resource that expands the information set of analysts and analysts adjust their expectation based on their own beliefs. Since different analysts may have different information set, a positive tone could increase or decrease an analysts' forecast depending on how different between analysts' prior expectation and actual earnings. Meanwhile, while the tone of the news drives analysts' forecasts approaching to actual earnings, it cannot predict forecast bias, given the fact that actual earnings are fixed. To sum up, if news is informative to analysts, it systematically increases analysts' forecast accuracy.

2.2 Weakness of Information Effect

We must emphasize that in our previous analyses, detection on informativeness of news is quite strict in terms of two important requirements mentioned in previous section. Indeed, it is more likely the case either of conditions is not satisfied. To start with, there are several reasons to suggest a general supply of news may not provide a credible source to incrementally drive analysts decision making (Huang and Mamo 2015). First, analysts may have private access to firm insiders, making public news less relevant. Second, analysts may focus on specific events and ignore other less influential and less quantifiable events. Third, the general information in the public news may already be incorporated by other general measures taken by the firm information environment and information arrival shocks. Fourth, news information in regards to actual earnings may be biased or inaccurate, which distorts forecasts. For example, Kothari et. al, 2009 show that managers have a tendency to withhold bad news, thus information reflected by bad news can be biased or less accurate. Overall, news may contain noise information, which adds no value to analysts' forecasts and can even damage analysts' forecast accuracy.

On top of this, it is also possible that news contains valuable information, but analysts may not be always to interpret news information correctly. In fact, existing studies provide evidence that analysts (1) make biased forecasts and (2) misinterpret the impact of new information. Related studies include Fried and Givoly (1982), O'Brien (1988), Butler and Lang (1991), Brous (1992), Brous and Kini (1993), Francis and Philbrick (1993), Kang, O'Brien, and Sivaramakrishnan (1994), as well as Dreman and Berry (1995), which all provide evidence that analysts normally produce upwardly biased forecasts. Several other studies document analysts' tendency to misinterpret new information. In particular, Lys and Sohn (1990), Abarbanell (1991), Abarbanell and Bernard (1992), Ali, Klein, and Rosenfeld (1992), Elliot, Philbrick, and Wiedman (1995), as well as Teoh and Wong (1997) suggest that analysts systematically underreact to new information, while DeBondt and Thaler (1990) found that analysts systematically overreact to new information. Regardless, both under-reactions and overreactions can affect analysts' existing forecast error, though we cannot necessarily conclude that such reactions will increase forecast bias. For example, Analyst A may have a prior belief about earnings which is lower than the actual earnings. Although Analyst A overreacts to a good information, as long as they adjust their forecast close to the actual earnings, Analyst A can still benefit from news information.

The above analysis suggests that if news is not informative to analysts, it could be deduced that either media news does not include valuable information beyond the analysts' information set or it contains valuable information but analysts are unable to interpret the information correctly.

2.3 Sentiment Effect

On the other hand, certain news stories may contain a specific news writers' personal sentiments in addition to fundamental information. If analysts cannot separate information from sentiment, their forecasts or expectations will be distorted. For example, Hribar and McInnis (2012) found that during a high sentiment period, analysts forecasts are more optimistic than other periods. Walther and Willis (2013) decomposed the index of consumer expectations into fundamental components and sentimental" components, then found analysts were more optimistic when the sentimental components were high. Bergman, et. al (2008) and Corredor, et. al (2012) found similar results showing that sentimental news induces optimism in forecasts. As a result, if a news story reflects sentiment to analysts, a positive (negative) tone induces an optimistic (pessimistic) forecast, thus resulting in a lower (higher) forecast bias. Accordingly, we expect that a positive (negative) tone negatively (positively) predicts the forecast bias. Meanwhile, neither of them can predict an analysts' forecast accuracy.

To sum things up, information theory predicts a relationship between news tone and forecast accuracy, while sentiment story predicts a relationship between news tone and forecast bias.

3 Data and Key Variables

We collect analysts' quarterly earnings forecasts and actual earnings from Institutional Brokers' Estimate System (I/B/E/S) Detail History database spanning from January 1996 to December 2014 for U.S. firms. This database allows us to associate analyst characteristics with analyst forecast behavior. We also collect consensus (mean) quarter earnings-per-share (EPS) forecasts from the I/B/E/S summary database. The data for other firm fundamentals and stock market variables are respectively from the Compustat, CRSP and Thomson Reuters Institutional Holdings (Type 2) databases. We exclude the observations with share price less than 1 and analysts who only make one forecast for the same company.

To exclude data errors, we drop observations with an analyst code of zero, missing announcement date of the actual earnings or missing values for the actual earnings. In addition, we drop the observations where the forecast is announced or reviewed later than the day of the actual earnings announcement. Moreover, when one analyst makes more than one forecast for the same company in the same forecast period, we take the last forecast as his forecast announcement. To calculate the relative ranking, we require that at least four analysts make forecasts for the same company in the same forecast period. News articles that cannot be matched with a Compustat or CRSP CUSIP are excluded from the sample.

We drop the observations where the forecast release day is longer than 30 days before the actual earnings announcement. The reason is that, if the forecast is released too early, such as 90 days before the actual earnings announcement, the news before that analyst's forecast is almost irrelevant about earnings in current quarter. Including those observations will distort our analysis. Hence, only analysts who make earnings forecasts within 30 days before the actual earnings announcement are included in our sample. Moreover, to calculate the abnormal returns, we require a firm at least experiences more than 251 trading days when an analyst makes earnings forecast.

Finally, after removing missing values, we have the final quarterly news-analyst characteristic dataset including 92,003 observations, representing 1,295 firms and 4,952 analysts over January 1996 to December 2014. We also have monthly analyst consensus forecasts related to each firm fundamentals and news articles with 33,995 observations for the same companies and forecast period. These two datasets are used to process different empirical tests. Details are explained in the description of each table.

3.1 News Data

This paper uses data from Thomson Reuters' News Analytics (TRNA) database from January 1996 to December 2014 to compute a measure of firm specific news tone. TRNA uses a text processing engine to score a news item based on its content in real-time. Each news item receives a score for positive and negative tone, separately. The score for each type of tone ranges from 0 to 1. The scores capture the sentiment level expressed by the author about the subject matter being discussed (Thomson, 2013). In this case, a high positve (negative) score means the news contains more optimism (pessimism) sentiment of the firm. [2] Meanwhile, we also claim that the news tone can be proxy of the informativeness of news. A high negative (positive) tone indicates the firm's decaying (prosperous) future fundamentals under information story.

We then calculate the mean of news score within 3 to 30 days before the analysts' forecast release day/earnings announcement day as follows:

$$\text{Tone}_{t-30,t-3} = \frac{\sum_{d=-30}^{d=-3} \text{Tone}_d}{\text{Days of news}},$$

where $\text{Tone}_{t-30,t-3}$ stands for positive news score ($\text{Pos}_{t-30,t-3}$) or negative news score ($\text{Neg}_{t-30,t-3}$). The subscript stands for the number of days before the analyst forecast

[2] In the following section, we also use tone to stand for the news score, e.g, positive tone means positive score.

release day/earnings announcement day. In particular, we leave two days for analysts to fully incorporate the news effect into their forecast.

We also include a dummy indicating news coverage, $\text{NewsDummy}_{-30,-3}$, to differentiate firms with news coverage and those without media attention. Moreover, to aovid the situation that news paper includes hard information that can be easily collected from other resources, we further construct variable, Numeric Word, following Wang and Zhang (2015). It can be defined as number of numerical words (consist of digits, decimal points, commas, percentage and/or dollar such as $1.08, 50% or 20,000) in an article divided by the sum of the number of positive words, negative words, and numerical words in the article. We use the classification method by Loughran and Mcdonald (2011) to identify positive and negative words [3].

< Insert Figure 1 here >

Figure I plots the media coverage around earnings announcements. Specifically, for each firm-specific news story, we calculate the number of days until the firm's next earnings announcement and the number of days that have passed since the firm's previous earnings announcement. We plot a histogram of both variables back-to-back. Thus, each news is counted exactly twice in Figure 1, once after the previous announcement and once before the next announcement, except the stories that occur on the earnings announcement day. Overall, Figure I is consistent with Tetlock (2008) and provides us strong evidence that news stories concentrate around earnings announcement days.

[3] Loughran and McDonald (2011) propose a new financial dictionary based on the words used in the 10-K filings. The authors manually classify the word lists into negative, positive, uncertainty, litigious, strong modal and weak modal categories, and we follow their approach to identify positive and negative words in the news article.

3.2 Analyst Performance Measure & Characteristics

To measure the forecast performance of each individual analyst, we refer to the method provided by Walther and Willis (2013) to calculate forecast Bias and Accuracy as follows:

$$\begin{aligned} \text{Bias}_{i,j,t} &= \frac{\text{E}_{j,t} - \text{F}_{i,j,t}}{\text{P}_{j,t}}, \\ \text{Accuracy}_{i,j,t} &= -\frac{abs(\text{E}_{j,t} - \text{F}_{i,j,t})}{\text{P}_{j,t}}, \end{aligned}$$

where $\text{F}_{i,j,t}$ is the quarterly EPS forecast issued by analyst i for firm j in quarter t after the quarter t-1 earnings announcement, $\text{E}_{j,t}$ is the EPS excluding extraordinary items for firm j in quarter t, and $\text{P}_{j,t}$ is the share price for firm j in quarter t issued 30 trading days before the forecast release date. Negative forecast Bias implies optimism (actual EPS lower than forecasted EPS) while a lower forecast accuracy indicates less forecast precision.

In this paper, we consider seven analyst characteristics: forecast frequency, boldness, general working experience, firm-specific experience, forecast horizon, firm coverage, ranking and overconfidence.

Forecast frequency is the average number of quarterly earnings forecasts made per quarter by an analyst on all stocks he actively covers. Bold measures the fraction of forecast changes that move away from the consensus. To follow Womack et al (2015), we calculate boldness as a dummy variable equal to one if analyst i's forecast for firm j in quarter t is above his previous quarterly EPS forecast and the mean consensus forecast immediately before the forecast revision date or below both, zero otherwise.General experience (Firm specific experience) is defined as the log of number of days since an analyst first provide an earnings forecast (for the corresponding firm) on IBES.

O'Brien (1990), Jacob et al., (1999), and Clement (1999) document that analysts forecast horizon affects their forecast performance. We define horizon as the number of calendar days between the forecast issue date and the subsequent earnings announcement date. In particular, we restrict the forecast horizon within 30 days to make sure the analysts read the most relevant news.

Clement (1999) find that the number of stocks on which an analyst provides active forecasts is one of the measures representing the task complexity facing an analyst and finds that it reduce the forecast accuracy. Accordingly, we define firm coverage as the number of firms an analyst covers in previous quarter to reflect the task complexity.

Hong and Kubik (2003) find that the talented analysts are confident about their forecast so the herding behavior among the talented analysts is less serious than the less talented analysts. As the herding behavior drives the forecast optimism and damages the forecast accuracy, we need to control this effect in the regression as well. For each company and forecast period that an analyst issues an earnings forecast, the analyst is ranked on forecast accuracy relative to all other analysts covering the same company and forecast period. In addition, we require at least 4 valide analysts to issue forecasts for the same firm within the same forecast period. We also count the latest forecast to estimate the forecast accuracy ranking if the analyst has multiple forecasts for the same company in the same forecast period. Specifically, we define rank as

$$\text{Rank}_{itj} = 100 - \frac{\text{Relative Rank}_{ijt} - 1}{\text{Analyst Coverage}_{jt} - 1} \times 100,$$

where Relative Rank$_{itj}$ is analyst j's forecast accuracy ranking for firm i in forecast period t, and Analyst Coverage$_{jt}$ is the number of analysts issuing forecasts for firm i in the same forecast period. This percentile rank gives a fair comparison among analysts across different firms.

Our measure of analyst overconfidence is based on biased self-attribution, whereby analysts become overconfident after a short series of successes. We define overconfidence, in the same way as Daniel, Hirshleifer and Subrahmanyam (1998), as an individual who overestimates the precision of her private information signal, but not of public information signals. Many literatures document that overconfidence affects analyst forecast behavior.

For example, Michel and Pandes (2013) argues that if some analysts are overconfident about future earnings relative to other analysts at the same firm, then these analysts should arrive at differing forecasts since overconfident analysts overweight their private information compared to nonoverconfident analysts. In the paper, we follow Michel and Pandes (2013) to define $Overconfidence$ as the mean of a firms analyst Success, where Success follows Hilary and Menzly (2006) definition that an analyst's forecast accuracy is better than the median forecast for the same firm in the same quarter.

3.3 Financial Data

To examine earnings predictability, we use firm's standardized unexpected earnings (SUE) as the dependent variable. We follow the Bernard and Thomas (1989) and define SUE as:

$$\mathrm{UE}_t = \mathrm{E}_t - \mathrm{E}_{t-4}$$

$$\mathrm{SUE}_t = \frac{\mathrm{UE_t} - \overline{\mathrm{UE}}_\mathrm{t}}{\mathrm{Std}(\mathrm{UE}_t)},$$

where E_t is the firm's earnings in quarter t, and the trend and volatility of unexpected earnings (UE) are equal to the mean ($\overline{\mathrm{UE}}$) and standard deviation (Std(UE)) of the firm's previous 20 quarters of unexpected earnings data, respectively. We also include control variables such as firm's size, B/M, turnover, three measures of recent stock returns and analyst dispersion. We define firm size (Log(Market Equity)) and B/M (Log(Book/Market Equity)) at the end of the preceding calendar year, following Fama and French (1993). We compute turnover as the log of annual shares traded divided by shares outstanding (Log(Share Turnover)) at the end of the preceding calendar year. We also calculate analyst dispersion as the standard deviation of analysts' earnings forecasts within 3 to 30 days prior to the earnings announcement scaled by earnings volatility.

In terms of the 3 past return variables, we follow Tetlock (2008) to calculate them based on a simple event study methodology. To align the estimation window, we choose the analysts' forecast announcement day or earnings annoucement day as the event day in accordance with dependent variable. Specifically, the benchmark return is calculated using the Fama-French three-factor model with an estimation window of [-252,-31] trading days before the event day. We also calculate the cumulative abnormal return on day -2 before the event day, denoted as $\text{CAR}_{t-2,t-2}$ and the cumulative abnormal return from the [-30,-3] trading day window before the event day, denoted as $\text{CAR}_{t-30,t-3}$. We further include the abnormal return from the estimation window, denoted as $\text{AR}_{t-251,t-31}$. In particular, $\text{AR}_{t-252,t-31}$ is related to the Jegadeesh and Titman (1993) return momentum effect, which is based on firms' relative returns over the previous calendar year excluding the most recent month. In addition, all the three past returns are presented in percentage.

In addtion, to follow Druz, Wagner and Zeckhauser (2015), we add more firm characteristics and market condtions as control variables as following:

Market return is defined as the percent value-weighted market return for the period starting 5 days after an earnings announcement for the quarter t1 and ending 5 days prior to the earnings announcement for the quarter t. Momentum is defined as the firms buy-and-hold return over the prior 6 months. Illiquidity is defined as the absolute value of the stock return scaled by the product of volume and price. Leverage is defined as the long-term debt scaled by the sum of long-term debt and market capitalization. Institutional Ownership is defined as institutional share holdings scaled by shares outstanding. Monthly volatility is the monthly stock volatility computed from monthly return data over the previous 48 months and then classified into 10 quantiles. Besides, as standard control variables, we use the natural logarithm of market cap, as well as firm fixed effects, and year fixed effects.

3.4 Summary Statistics

Table II presents the summary statistics for the data. In general, the sample is consistent with prior research. The mean foreast accuracy is -0.31% and majority (over 75%) of the analysts has a good forecast accuracy above -0.3%. In terms of the forecast bias, both mean and median of this variable is negative (-0.02% and -0.03% respectively) which suggests that analysts are overall optimistic about their forecasts. Both forecast accuracy and forecast bias are reasonable compared to the previous studies. For example, Walther and Willis (2006) use Zacks Investment Research database and find the mean of accuracy is -0.95% for the firms listed from 1981 to 2004. This value suggest that analysts are relative more accurate in our sample (mean accuracy = -0.31%) than theirs. One of potential reason is that we restricted the Horizon to 30 days which increases the overall forecast accuracy. Meanwhile, we also find that public news is overall optimistic - on avearge, $\text{Pos}_{-30,-3}$ is 0.07 which is higher than $\text{Neg}_{-30,-3}$, 0.05. Table I also shows that sample firms are quite heterogeneous on dimensions such as SUE, $\text{CAR}_{-30,-3}$ and B/M.

< Insert Table II here >

Table III presents the Pearson correlation coefficients for the key variables. Both $\text{Pos}_{-30,-3}$ and $\text{Pos}_{-30,-3}$ are significantly positively related to the forecast accuracy negatively related with forecast bias. This evidence suggests that news may affect analysts' forecast behavior. What's more, negative news is significantly negatively related to the forecast bias, which is opposite to the prediction of sentiment story. In this case, we may expect that analysts are affected by the information of the negative tone so that their forecast behavior is different from the sentiment story.

We also note that the correlation between $\text{Pos}_{-30,-3}$ and $\text{Neg}_{-30,-3}$ is 0.716, suggesting a higher dependence between positive and negative news tones. This is because we consider number of news in calculating news tones. Winthin the same calculation window, firms with more news coverage should have more information or sentiment deliverred by news meida. Besides, we find some consistent results as previous studies. For example, the positive correlation between experience and accuracy/bias suggests that experienced analysts issue less optimistic and more accurate forecasts, which is consistent with Brown et al. 1987; Das et al. 1998; Kross et al. 1990; Lim 2001 and O'Brien 1988. However, the Pearson coefficient is negative between forecast frequency and accuracy, indicating that analysts who forecast more frequently are less accurate. This finding is inconsistent with Jacob et al. (1999) but consistent with the empirical results of Walther and Willis (2013). Walther and Willis explain the difference is due to the different measure of accuracy. Jacob. Jacob (1999) uses the rank of the absolute forecast accuracy while Walther and Willis use direct comparison between the actual earnings and forecast earnings to calculate the forecast accuracy. Intuitively, we follow Walther and Willis' method to measure the forecast accuracy and our result is consistent with them.

< Insert Table III here >

4 Empirical Results

4.1 News Tone and Standard Unexpected Earnings

Our first set of analyses examines the link between firm-specific news tones and actual earnings. We perform the following regression analysis:

$$\mathrm{SUE}_{jt} \;=\; \alpha + \beta_1 \mathrm{Tone}_{t-30,t-3} + \gamma^{'} \mathrm{X} + \epsilon_{jt},$$

where the dependent variable, SUE, measures each firm's standardized unexpected earnings following Bernard and Thomas (1989). In this analysis, we start with US 1,295 firms for a period from 1996 to 2014, and we arrive at sample of 33,335 firm-quarter observations after losing observations in the process of merging with COMPUSTAT, CRSP, IBES, and the media data. $\mathrm{Tone}_{-30,-3}$, is the variable of interest that captures the news tone ($\mathrm{Pos}_{-30,-3}$ or $\mathrm{Neg}_{-30,-3}$) in the (-30, -3) window relative to the earnings announcement day. Control variables include those suggested by Tetlock (2008), including firms' lagged earnings (proxied by last quarter's SUE, lagSUE), Size, B/M, Turnover, three measures of recent stock returns ($\mathrm{AR}_{t-252,t-31}$, $\mathrm{CAR}_{t-30,t-3}$ and AR_{t-2}), analysts' earnings forecast revisions (Forecast Revision), analysts' forecast dispersion (Analyst Dispersion). Besides, we further control other variables documented in related literatures (Jegadeesh et al. (2004) and Wagner et al. (2015), among others), including dummy variable of news coverage ($I_{newscoverage}$), Consensus Forecast, Management Forecast, Earnings Surprise, Return Volatility, Market Return, Institutional Ownership, Leverage, Momentum, Illiquidity and Overconfidence. Moreover, to argue that news provides incremental information, we further control news hard information, Numeric Word, following Wang and Zhou (2015) as hard information in news articles can be easily collected from other resources. Based on this setting, if news tone show significant prediction power on actual earnings, we may expect news provides valuable information to analysts.

Table IV presents the panel regression results, with standard errors clustered by firms. Column (1) and (2) shows the results based on bivariate regressions, column (3) and (4) report the results following Tetlock's setting and column (5) and column (6) present results using all control variables. We find that negative tones, ($Neg_{t-30,t-3}$) are negative and statistically significant across all regressions, implying negative tones contain incremental information about actual earnings. In contrast, positive tones seem to be insignificant, which mean positive tone may contain noise information. Overall, the results are consistent with Tetlock et al (2008) that negative tones are more informative than positive tones. Regarding economic significance, the coefficient on $Neg_{t-30,t-3}$ in column (6) indicates that one percent increase in $\mathrm{Neg}_{-30,-3}$ implies a 0.438% decrease in SUE given other control variables fixed.

< Insert Table IV here >

4.2 News Tone and Analyst Forecast Behavior

The empirical results in section 4.1 are consistent with the notion that negative tones contain valuable information about actual earnings. In this section, we further examine whether and how analyts deal with news tones. To answer this question, we investigate news tone effects on analysts' forecast behavior. We perform panel regressions of Accuracy and Bias on the lagged news tone measures along with control variables. The regression model is as follows:

$$\mathrm{Y}_{ijt} \quad = \quad \alpha + \beta_1 \mathrm{Tone}_{t-30,t-3} + \gamma^{`}\mathrm{X} + \epsilon_{ijt},$$

where Y_{ijt} stands for analysts' forecast performances, measured as $\mathrm{Accuracy}_{ijt}$ or Bias_{ijt}. The variable of interest is $\mathrm{Tone}_{-30,-3}$, which stands for positive tone, $\mathrm{Pos}_{-30,-3}$ or negative tone, $\mathrm{Neg}_{-30,-3}$ respectively. Different from regression (1), current news tone measure are calculated in the (-30, -3) window relative to the analysts' earnings forecast day. Namely, we allow 2 days for analysts to incorporate news information into their forecasts. On top of that, we further control analysts' characteristics, like General Experience, Firm Experience, Analyst Ranking, Analyst Boldness, Forecast Horizon, Forecast Frequency, Firm Coverage and Overconfidence. When having Analyst Ranking, we restrict valid sample to the firms that at least have 4 analysts issuing forecasts for the that firm in the same forecast period. Meanwhile, we restrict the Forecast Horizon not longer than 30 days to ensure the calculation window for news tones are not too far away from actual earnings announcement day [4]. Thus, the total sample has 73,884 analyst-firm-quarter observations.

Table V reports the results for the above regression - Panel A presents the bivariate regression results while Panel B shows the multi-variable regression results. Both panels

[4] Details can refer to the variable construction, section 3.4

show a similar estimation results so in the following analysis, we only focus on the multi-vavriable regressions.

< Insert Table V here >

First, we find that news tone measures are associated with analysts' forecast accuracy with statistical significance at better than 5% level shown in column (4) to (6), suggesting analysts tend to react to news tones. We then investigate how they deal with news tones. In column (1) to (2), we find both positive and negative tones do not affect analysts' forecast bias, namely, sentiment story is relative weak to explain analysts' behavior toward news tones. As a robustness check, we calculate $\text{Pos}_{t-30,t-3}$ - $\text{Neg}_{t-30,t-3}$ as news optimism to replace the news tone measures in column (3), and find that this variable again does not reduce the Forecast Bias, suggesting a weak sentiment effect.

On the contrary, we find both positive and negative tones increase analysts' forecast accuracy with significant coefficients, shown in column (4) and (5), suggesting both news tones are informative to analysts. This is an interesting finding which seems to be a contradiction to previous argument that positive tones contain noise information about actual earnings. In this case, we expect that positive tones contain both valuable and noise information. Meanwhile, analysts are able to differentiate valuable information from noise information so that they can benefit from positive tones as well. Moreover, it also means that both news tones are good proxies for news informativeness - a high positive or negative tone deliver more information to the analysts than otherwise. In column (6), we further calculate $\text{Pos}_{t-30,t-3} + \text{Neg}_{t-30,t-3}$ as news informativeness to replace the news tone measures and find it significantly increases analysts' forecast accuracy. This finding further confirms the argument that news tone is informative to analysts. In terms of economic significance, the result in column (4) indicates that a one standard deviation of $\text{Pos}_{t-30,t-3}$ is associated with a 0.014 improvement in forecast accuracy, equivalent to 5.3% of the mean Forecast Accuracy.

Overall, results in table V conclude that information story outperforms sentiment story in explaining analysts' behavior towards news tones and that analysts seem to asymmetrically react to news tones when they interpret news information.

4.3 Analysts' Characteristic and News Tone Effects

Although the collective empirical evidence thus far suggests that analysts incorporate firm specific information from the news tones in their research updates and such research updates are valuable in terms of their forecast accuracy, it is not clear what type of analysts rely on news information to improve their research. Hence in this section, the relationship between analysts' characteristics and news tone effects is revealed. Basically, we ask the question that which type of analysts tend to rely on public news to make forecasts. To answer the question, we classify analysts into different groups according to their characteristics, including general experience, firm experience, ranking performance, forecast frequency, firm coverage, boldness and overconfidence. For example, we define experienced analysts as those who have working explerience longer than (median of general working experience) or (median of firm working experience) for a specific firm at the time when they issue the forecasts. We then apply the same rule to other characteristics. For each type of analysts, we perform the same regression as equation (2) and compare the difference of news tone coefficients.

Table VI presents the coefficients of news tone for regressions on each type of analysts as well as the P value of the difference of coefficient between different groups. Panel A shows the results for $\text{Pos}_{t-30,t-3}$, Panel B shows the results for $\text{Neg}_{t-30,t-3}$ and Panel C shows the results for $\text{Pos}_{t-30,t-3} + \text{Neg}_{t-30,t-3}$. Results are quite robust across different news tone measures and we take $\text{Pos}_{t-30,t-3}$ as an example to illustrate the findings. In terms of coefficient significance, poor ranking analysts, less experienced analysts seem to be more sensitive to news tones than good ranking and more experienced analysts. This is consistent with argument that good ranking and experienced analysts have better information set so news information contributes little effect in improving their forecast accuracy. Meanwhile, analysts with heavy task complexity (high firm coverage) are also insensitve to news tones and we expect them to invest less effort in improving their forecast accuracy by analyzing news information. On the contrary, hard working analysts tend to improve their forecast by incorporating news information. Consistent with our expectation, bold analysts and overconfident analysts seem to rely more on their private information so their forecast accuracy is not sensitive to news tones. Among those characteristics, ranking performance and overconfidence are the most important characteristics that affect analysts' sensitivity toward news tones. For an instance, coefficients of negative tones of overconfident analysts are not statistically significant while for non-overconfident analysts, it is significantly positive at 5%, suggesting negative tones improve non-overconfident analysts' forecast accuracy by 0.26% of corresponding stock price given other variables fixed. And the difference between overconfident and non-overconfident analysts are statistically significant at less than 5%.

< Insert Table VI here >

4.4 Misweighting on Private Information and Public Information

Based on above analysis, news tones seem to be uninformative to some type of analysts, like good ranking and experienced analysts. However, it is also possible that news may provide incremental information to those analysts but due to their overweighting on private information, news information are not reflected by their forecasts. In this section, we investigate analysts' misweighting behavior by following Chen and Jiang (2006). According to their model, the relation between analysts forecast bias and his forecasts deviation from the consensus reveals information about how the analyst weights his signals. If analysts efficiently weights information (equal weight between private information and public information), forecast bias should not be predictable by available information. Hence, we perform the following regression:

$$\text{Bias}_{ijt} = \alpha + \beta_1 \text{Deviation}_{ijt} + \epsilon_{ijt},$$

Where Bias is the difference between actual earnings and analysts' forecast value. Deviatioin is the difference between the consensus and the forecast, in which consensus is an average of all prevailing forecasts available at time t. According to Chen and Jiang (2006), β_1 is a ratio of weights and is independent of the scales in forecast bias and deviation. Moreover, a positive (negative) β_1 suggests analysts overweight (underweight) their private information. Table VII reports coefficients of Deviation for different type of analysts and the P value of the coefficient difference. Consistent with our expectation, we find bold and overconfident analysts overweight their private information, which explains our empirical result that these analysts' forecasts are not sensitive to news tones. Since they do not show a better information set than others, we expect that it is their misweighting behavior that causes their insensitivity toward news tones.

< Insert Table VII here >

In the meantime, we also find anlysts with higher firm coverage tend to overweight their private information as well. As a result, misweighting behavior may also explains "uninformativeness of news tone effect" on those analysts' forecasting behavior. However, we are not able to exclude the possibility that those analysts put few effort in analyzing news information so that they do not find valuable information. Similar analysis can be applied to hard working analysts. The difference is that they benefit from interpreting news information but they do not underweight their private information. Hence, a reasonable explanation is that hard working analysts invest more effort in exploiting news information. These findings are also consistent with the notion that the cost of processing soft information is high (Petersen 2004 and Engelberg 2008).

However, overweigting on private information cannot explain good ranking and experienced analysts behavior. They seem to balance public information and private information better than other analysts, especially for good ranking analysts. Instead, poor ranking and less experienced analysts are more likely to misweighting their private information. The difference between good ranking and experienced analysts . As a result, we attribute insensitive reactions of good ranking and experienced analysts toward news tones to the fact that those analysts may have superior information set (connection with firm insiders and good economic model) so public news may not provide incremental information to them.

5 Alternative Explanations

Empirical evidence is generally consistent with the media providing valuable information to analysts, while it is also possible that analysts process the same information with some endogenous link between exogenous news and both media and analyst reactions. In the regression model, we controll all related public information coverred in previous literatures and even hard information in news articles, however, one of the possibility is that news reflects some private information where analysts collected from other resourses, like firm insiders, which is beyond the current setting. Indeed, it is diffcult to identify the private information but in the paper, we claim that the news information does not overlap with analysts' private information.

On the one hand, given news reflects some private information of analysts, we should expect that good ranking analysts and experienced analysts are more sensitive to news information as those analysts have superior information set and have a close connection with firm insiders, hence providing them more private information. In this case, good ranking analysts and experienced analysts benefit more from their news tone (proxy of private information) than other type of analysts. On the contrary, our empirical results reveal that poor ranking analysts and less experienced analysts improve their forecast accuracy more than others. As a result, we expect news information is not proxy of analysts' private information and it serves as public information that overall reduces information asymmetry among analysts.

On the other hand, we provide direct evidence that news information effect is quite different from private information in terms of affecting analysts' forecast behavior. We investigate the news effects on analysts forecast dispersion. According to theoretical models provided by Barry and Jennings (1992) and Barron et al. (1998), public information reduces forecast dispersion, while privately observed information is the only factor that drives information asymmetry among analysts. As a result, if news overlaps private information, it should increases forecast dispersion among the analysts. Hence, we perform the following regression:

$$\text{Analyst Dispersion}_{jt} = \alpha + \beta_1 \text{Tone}_{t-30,t-3} + \gamma^{`}\text{X} + \epsilon_{jt},$$

where analyst forecast dispersion is the dependent variable. In particular, as analysts' forecasts are more likely to be affected by most recent news, the analyst dispersion is based on the forecasts released within the calculation window of news tone. In this case, we test the association between analyst dispersion and news tone.

In terms of control variables, we consider all of the explanations related to analysts' forecast dispersion documented in previous literatures. For example, we control firm liquidity as Sadka and Scherbina (2007), who link dispersion to liquidity by showing that high disagreement coincides with high transaction costs. Michel and Pandes (2013) find that the firms analyst overconfidence mean and analyst overconfidence dispersion are the two most significant determinants of analyst forecast dispersion. We then also include them as two control variables [5]. Besides, we further include other firm fundamentals which we used in Table III as extra control variables. Table IX reports the corresponding estimation results.

< Insert Table VII here >

The first three columns illustrate the results of univariate regression while the last three columns presents multi-variate regression results. Indeed, results are quite consistent across different news tone measures - both $\text{Pos}_{t-30,t-3}$ and $\text{Neg}_{t-30,t-3}$ seem to be negatively associated with forecast dispersion, suggesting news tone provides public information to the analysts and decreases information asymmetry among the analysts.

A following question is that, news tones are different from public information and also does not overlap with private information, why good ranking and experienced analysts do not exploit this information to improve their forecast accuracy? This is an important question and it reveals how analysts utilize news information. We expect that news information is different from private information but it is also not informative as private information. In terms of actual earnings, news information is deliverred by journalists while private information can be collected from firm insiders or processed by analysts themselves, it is reasonable that news tone may not compete with private information in terms of predicting actual earnings. That is why good ranking analysts and experienced analysts are less sensitive to news information.

Besides, we also receive comments about reversal causality that analysts may strategically leak their information to journalists so that their forecasts are more impactful to the market. We agree with the point that due to career concern, analysts may seek market impact of their predictions but this incentive is strong for stock recommendations but not for earnings forecasts. Different from stock recommendation, forecast accuracy can

[5] More detailes can refer to Jean-Sbastien Michel and J. Ari Pandes (2013) who present detailed discussion on these control variables.

be easily evaluated. And to show a better forecast ability, analysts may not leak their private information to the public before they issue the forecasts.

6 Conclusion

In this article, we discussed the issue that whether news is informative to analysts. In particular, we start with the relationship between news content and Standard Unexpected Earnings. Consistent with Tetlock et al (2008), negative tones show significant effect in predicting actual earnings while positive tones do not. However, analysts seem to have the ability to differentiate valuable information from noise information and hence their forecast accuracy improves from processing both positive and negative tones. After that, we investigate the relationship between analysts' characteristics and news tone effects. Results suggest that good ranking and experienced analysts underreact to news information due to their superior information set. While bold and overconfident analysts overweight their private information so that their forecast accuracy are also insensitive to news tones. Different from hardworking analysts, analysts with heavy task complexity invest overweight their private information and also may invest less effort in analyzing news information so their forecast accuracy also does not react to news tones.

Overall, this study examines the public news effects on the analysts forecast behavior and results provide strong evidence to support the argument that analysts incorporate news information into their earnings prediction based on their understanding of news content rather than simply affected by the news sentiment.

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Figure I
Media coverage around earnings announcements

This figure depicts the relationship between the number of firm-specific news stories and the number of days away from a firm's earnings announcement. All stories included in the figure, covering 8,006 US companies, appear in Thomson Reuters from January 1996 through December 2014. For each news story, we calculate the number of days until the firm's next earnings announcement and the number of days that have passed since the firm's last earnings announcement. We plot a histogram of both variables back-to-back. Thus, each story is counted twice in the figure, once before and once after the nearest announcement, except the stories occurring on the earnings announcement day.

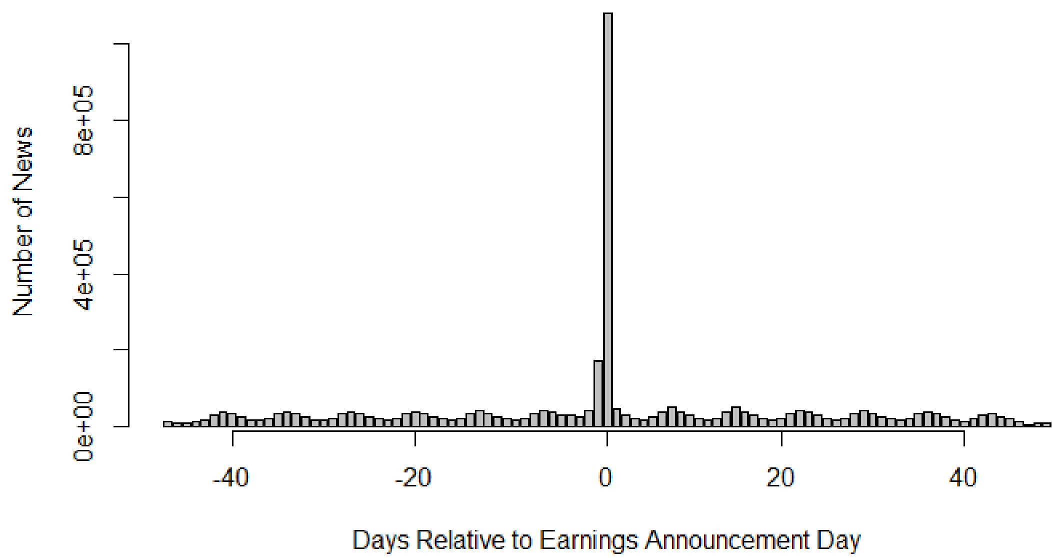

Table I
Main Variable Descriptions

Variable Name	Definition
Forecast Bias	Actual quarterly earnings-per-share (EPS) minus analyst forecast, divided by share price 30 trading days before the forecast release date, multiplied by 100.
Forecast Accuracy	Absolute value of forecast bias multiplied by -1. The forecast release day is within 30 days before the actual earnings announcement day to make sure the analysts read the most relevant news.
SUE	Firm's standardized unexpected earnings according to Bernard and Thomas (1989).
$\text{Pos}_{-30,-3}$	Mean of positive tone for firm j within 3 to 30 days before the analyst i's forecast release day[6].
$\text{Neg}_{-30,-3}$	Mean of negative tone for firm j within 3 to 30 days before the analyst i's forecast release day/earnings announcement day.
Analsyt dispersion	Standard deviation of analysts' earnings forecasts within 3 to 30 days prior to individual analyst's forecast day/earnings announcement day.
ForecastRevision	We compute the median analyst's 3-month earnings forecast revision following Chan, Jegadeesh, and Lakonishok (1996). [7] This revision variable is equal to the 3-month sum of scaled changes in the median analyst's forecast, where the scaling factor is the firm's stock price in the prior month.
Size	Log of market equity.
B/M	Log of book to market ratio at the end of the preceding calendar year.
Turnover	Log of annual shares traded divided by shares outstanding at the end of the preceding calendar year.
$\text{AR}_{-251,-31}$	Daily abnormal return of firm j in the past 251 days to 31 days before the analyst i's forecast release day [8] bassed on Fama and French (1993) three-factor model. Returns are presented in percentage.

[6]In Table IV and Table V, earnings announcement day is used to calculate this variable as the dependent variable in these two tables are SUE and corresponding analysts' dispersion which are calculated based on the earnings announcement day.

[7] Suggested by Tetlock (2008), we use 3-month revision periods rather than 6-month periods because these revisions capture new information after the forecast preceding last quarter's earnings announcement, which is already included in our regressions as a separate control.

[8]In Table IV and V, we choose the earnings announcement day as event day to calculate the past

$\text{CAR}_{-30,-3}$	Cumulative abnormal return of firm j 30 days and 3 days before the analyst i's forecast release day. Returns are presented in percentage.
$\text{CAR}_{-2,-2}$	Abnormal return 2 days before the analyst i's forecast release day. Returns are presented in percentage.
Consensus Forecast	The mean of most recent analyst forecasts for quarter t+1 recorded in IBES during the 1 day before the earnings announcement for the quarter t.
Management forecast	a dummy variable which equals 1 if there is a management annoucement before the actual announcement day. Management earnings forecasts are voluntary disclosures that provide information about expected earnings for a particular firm.
Analyst Boldness	Dummy variable: it equals one if analyst i's forecast for firm j in quarter t is above his previous quarterly EPS forecast and the mean consensus forecast before the forecast revision date or below both, and zero otherwise.
Forecast Horizon	Number of calendar days between the quarterly forecast release date and the quarterly earnings announcement date.
Forecast Frequency	Number of quarterly EPS forecasts analyst i issues for firm j during the previous forecast period.
Firm Experience	Log of number of working days for which analyst i has issued a quarterly EPS forecast for a specific firm as of the forecast release day.
Firm coverage	Number of companies for which analyst i has issued at least one quarterly EPS forecast in the previous forecast period.
Analyst Ranking	Percentile rank (ranging from a low of 0% for the least accurate analyst to 100% for the most accurate analyst), which is calculated as Hong and Kubik (2003).
$\text{NewsDummy}_{-30,-3}$	Dummy variable equals 1 if there is news coverage for firm j within 3 to 30 days before the analyst i's forecast release day/earnings annoucement day, equals 0 otherwise.
Earnings Surprise	Difference between actual and consensus forecast earnings (the mean of the most recent analyst forecasts recorded in IBES during the 90 days before the quarterly earnings announcement), divided by the share price 5 days before the earnings announcement.
Return Volatility	Monthly stock volatility computed from monthly return data over the past 48 months.

returns as the dependent variables in these two tables are SUE and corresponding analysts' dispersion which are calculated based on the earnings announcement day.

Market Return	Percent value-weighted market return for the period starting 5 days after an earnings announcement for the quarter t1 and ending 5 days prior to the analysts' forecast annoucement day/earnings announcement day for the quarter t.
Momentum	Firms buy-and-hold return over the prior 6 months.
Illiquidity	Absolute value of the stock return scaled by the product of volume and price multiplied by 10,000.
Leverage	Long-term debt scaled by the sum of long-term debt and market capitalization.
Institutional Ownership	Institutional share holdings scaled by shares outstanding.
Overconfidence	Mean of a firms analyst Success, where Success is a dummy which indicates an analyst's forecast accuracy higher than the median forecast accuracy for the same firm in the same quarter.
Overconfidence Dispersion	standard deviation of a firms analyst Success.
Numeric Word	We follow Wang and Zhou (2015) to control news hard information as number of numerical words in an article divided by the sum of the number of positive words, negative words, and numerical words [9] in the article. We use the classification method by Loughran and Mcdonald (2011) to identify positive and negative words.

[9] numeric words are identified using the following rule: the string needs to start with a space or a dollar sign, and then a string that combines digits, commas, and dots follows immediately. For example, $1.35 is considered as a number and FY13 is not counted as a number. To exclude numbers that mark the years, whole numbers from 1950 to 2020 are not included in the total counts. Detailed discussion can refer to Bradshawa, Wang and Zhou (2015).

Table II
Summary Statistics of Main Variables

This table provides descriptive statistics for company characteristics and analyst behavior. All variables are defined in Table 1. Variables in Panel A are related to analysts forecasts with all variables calculated corresponding to the analyst forecast issue date. Variables in Panel B are related to actual earnings with all variables calculated according to the earnings announcement day.

Panle A: Analyst Forecast	N	mean	sd	min	p25	p50	p75	max
Forecast Pessimism(%)	130,037	-0.02	1.21	-9.17	-0.14	-0.03	0.02	23.84
Forecast Accuracy(%)	130,037	-0.31	1.17	-23.84	-0.24	-0.09	-0.24	0.00
$\text{Pos}_{t-30,t-3}$	130,037	0.07	0.07	0.00	0.01	0.05	0.11	0.51
$\text{Neg}_{t-30,t-3}$	130,037	0.05	0.06	0.00	0.01	0.03	0.08	0.60
$\text{Pos}_{t-30,t-3}$ - $\text{Neg}_{t-30,t-3}$	130,037	0.02	0.05	-0.43	-0.00	0.01	0.04	0.48
$\text{Pos}_{t-30,t-3}$ + $\text{Neg}_{t-30,t-3}$	130,037	0.12	0.13	0.00	0.03	0.09	0.19	0.78
Analyst Dispersion	129,574	0.05	0.09	0.00	0.01	0.03	0.06	1.36
Forecast Revision	129,960	-0.00	0.01	-0.12	-0.00	0.00	0.00	0.03
Size Rank	117,992	5.52	2.87	1.00	3.00	6.00	8.00	10.00
B/M	117,958	1.83	1.23	0.55	1.12	1.44	2.08	13.73
Turnover	117,993	14.50	0.71	11.79	14.04	14.49	14.97	16.75
$\text{AR}_{t-252,t-31}$	130,021	-0.04	0.17	-0.94	-0.10	-0.02	0.05	0.74
$\text{CAR}_{t-30,t-3}$	129,997	-0.67	10.44	-81.27	-4.31	-0.03	4.03	44.70
AR_{t-2}	130,018	-0.01	1.60	-4.22	-0.91	-0.02	0.86	3.27
Analyst Boldness	130,037	0.57	0.50	0.00	0.00	1.00	1.00	1.00
Forecast Horizon	130,037	15.00	8.15	1.00	8.00	14.00	21.00	30.00
Forecast Frequency	130,037	2.04	0.88	1.00	1.00	2.00	2.00	7.00
General Experience	130,037	8.34	0.53	3.61	8.19	8.50	8.69	8.84
Firm Experence	130,037	8.57	0.34	2.30	8.49	8.68	8.77	8.84
Firm Coverage	130,037	7.87	5.75	1.00	3.00	7.00	11.00	52.00
Analyst Ranking	130,037	61.86	26.51	2.63	40.00	63.64	84.62	100.00
Overconfidence	130,037	0.44	0.18	0.00	0.36	0.45	0.52	1.00
Consensus Forecast	130,037	0.53	0.59	-2.95	0.19	0.41	0.75	5.26
Management Forecast	130,037	0.20	0.40	0.00	0.00	0.00	0.00	1.00
Earnings Surprise Rank	129,960	5.50	2.87	1.00	3.00	5.00	8.00	10.00
Return Volality	130,028	0.10	0.05	0.02	0.06	0.09	0.12	0.53
Market Return	130,037	0.00	0.04	-0.19	-0.02	0.01	0.03	0.11
Institutional Ownership	128,887	0.71	0.19	0.01	0.59	0.73	0.84	1.55
Illiquidity	114,193	0.04	0.27	0.00	0.00	0.00	0.01	8.00
Leverage	107,019	0.22	0.19	0.00	0.07	0.17	0.33	0.98
Momentum	129,982	-0.00	0.31	-2.82	-0.12	0.03	0.16	3.08
$\text{NewsDummy}_{t-30,t-3}$	130,037	0.83	0.38	0.00	1.00	1.00	1.00	1.00
Numeric Word	130,037	0.28	0.35	0.00	0.00	0.12	0.50	1.00

Panel B: Earnings Announcement	N	mean	sd	min	p25	p50	p75	max
SUE	33,335	0.22	1.48	-5.66	-0.53	0.12	0.85	7.64
Analyst Dispersion	33,009	0.04	0.06	0.00	0.01	0.02	0.04	0.50
$\text{Pos}_{t-30,t-3}$	33,335	0.06	0.06	0.00	0.01	0.04	0.09	0.52
$\text{Neg}_{t-30,t-3}$	33,335	0.04	0.05	0.00	0.00	0.02	0.05	0.56
Forecast Revision	33,335	-0.00	0.00	-0.04	-0.00	0.00	0.00	0.01
Size	31,431	8.15	1.67	2.76	7.00	8.11	9.29	12.09
B/M	31,425	1.85	1.21	0.66	1.13	1.45	2.10	10.28
Turnover	31,429	14.38	0.74	11.37	13.92	14.40	14.87	16.29
$\text{AR}_{t-252,t-31}$	33,334	-0.03	0.17	-0.81	-0.11	-0.02	0.06	0.70
$\text{CAR}_{t-30,t-3}$	33,326	-0.28	10.30	-52.69	-4.39	0.17	4.50	40.03
AR_{t-2}	33,332	0.05	2.09	-9.30	-0.88	0.02	0.96	10.23
Consensus Forecast	33,335	0.44	0.48	-0.85	0.15	0.35	0.63	2.49
Management Forecast	33,335	0.25	0.43	0.00	0.00	0.00	0.00	1.00
$\text{NumNews}_{t-30,t-3}$	33,335	0.81	0.39	0.00	1.00	1.00	1.00	1.00
Return Volality	33,335	0.11	0.05	0.04	0.08	0.10	0.14	0.42
Market Return	33,335	0.01	0.05	-0.19	-0.02	0.01	0.04	0.11
Institutional Ownership	33,326	0.69	0.20	0.01	0.57	0.72	0.84	1.18
Illiquidity	33,333	0.00	0.01	0.00	0.00	0.00	0.00	0.29
Leverage	31,387	0.21	0.19	0.00	0.06	0.16	0.32	0.88
Momentum	33,324	-0.00	0.30	-1.31	-0.12	0.03	0.16	1.08
Overconfidence	33,335	0.13	0.25	0.00	0.00	0.00	0.00	1.00
Overconfidence Dispersion	33,335	0.08	0.10	0.00	0.00	0.05	0.13	0.46
Numeric Word	33,335	0.19	0.33	0.00	0.00	0.00	0.25	1.00

Table III
Correlation Matrix of Key Variables

This table provides the Pearson correlation coefficients for the analysts' forecast performance, news tone and analyst's characteristics. Forecast bias is the actual quarterly earnings-per-share (EPS) minus analyst forecast, divided by share price 30 trading days before the forecast release date, multiplied by 100. Forecast accuracy is the absolute value of forecast bias multiplied by -1. The forecast release day is within 30 days before the actual earnings announcement day to make sure the analysts read the most relevant news. $\text{Pos}_{-30,-3}$ ($\text{Neg}_{-30,-3}$) stands for the mean of positive (negative) tone for firm j within 3 to 30 days before the analyst i's forecast release day. General Experience (Firm Experience) denotes the the log of number of working days for which analyst i has issued a quarterly EPS forecast for any (the same) firm as of the forecast release day. Analyst Ranking is the percentile ranks (ranging from a low of 0% for the least accurate analyst to 100% for the most accurate analyst), which is calculated as Hong and Kubik (2003). Firm Coverage is the number of companies for which analyst i has issued at least one quarterly EPS forecast in the previous forecast period. Bold is a dummy variable that equals one if analyst i's forecast for firm j in quarter t is above his previous quarterly EPS forecast and the mean consensus forecast before the forecast revision date or below both, and zero otherwise. Forecast Frequency stands for the number of quarterly EPS forecasts analyst i issues for firm j during the previous forecast period. Overconfidence is the mean of a firms analyst Success, where Success is a dummy which indicates an analyst's forecast accuracy higher than the median forecast accuracy for the same firm in the same quarter. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Variable	Forecast Bias	Forecast Accuracy	$\text{Pos}_{t-30,t-3}$	$\text{Neg}_{t-30,t-3}$	General Experience	Firm Experience	Analyst Ranking	Firm Coverage	Analyst Boldness	Forecast Frequency	Overconfidence
Forecast Bias	1										
Forecast Accuracy	-0.615***	1									
$\text{Pos}_{t-30,t-3}$	-0.0103***	0.00581**	1								
$\text{Neg}_{t-30,t-3}$	-0.00971***	0.00940***	0.716***	1							
Firm Experience	0.00652***	0.00603**	-0.0102***	-0.0163***	1						
General Experience	0.00315	0.00297	-0.00692***	-0.0104***	0.655***	1					
Ranking	0.000722	0.0960***	-0.00263	-0.00320	0.0166***	0.0137***	1				
Firm Coverage	-0.00770***	-0.0219***	0.00795***	0.00914***	-0.331***	-0.211***	-0.0372***	1			
Boldness	-0.00155	-0.0153***	0.00132	-0.00390*	0.00388*	0.000734	0.0582***	-0.00114	1		
Forecast Frequency	0.0100***	-0.0350***	-0.00406*	-0.00760***	-0.0359***	-0.0156***	-0.0295***	0.0939***	0.0427***	1	
Overconfidence	0.00794***	-0.00911***	-0.00522**	-0.0103***	-0.0331***	-0.0266***	0.221***	0.0316***	0.0581***	0.0285***	1

Table VI
Predicting Earnings Using News Tone

This table presents results from pooled least square regression of quarterly earnings (SUE) on news tone, firm fundamentals and other control variables. The regression model takes the following form:

$$\text{SUE}_{jt} \quad = \quad \alpha + \beta_1 \text{Tone}_{t-30,t-3} + \gamma^{`}\text{X} + \epsilon_{jt},$$

where SUE measures each firm's standardized unexpected earnings (SUE) following Bernard and Thomas (1989). $\text{Tone}_{t-30,t-3}$ stands for $\text{Pos}_{t-30,t-3}$ or $\text{Neg}_{t-30,t-3}$. X denotes other explanatory variables which are defined in Table I. We compute clustered standard errors at firm level. The robust t-statistics are in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable:					SUE				
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{Pos}_{t-30,t-3}$	0.235		0.958^{***}	-0.023		0.347	0.006		0.296
	(1.05)		(3.93)	(-0.11)		(1.49)	(0.03)		(1.26)
$\text{Neg}_{t-30,t-3}$		-2.107^{***}	-2.482^{***}		-1.147^{***}	-1.284^{***}		-0.964^{***}	-1.075^{***}
		(-7.70)	(-8.28)		(-4.74)	(-4.83)		(-3.93)	(-4.02)
Lag Sue	0.364^{***}	0.362^{***}	0.362^{***}	0.365^{***}	0.365^{***}	0.365^{***}	0.363^{***}	0.362^{***}	0.362^{***}
	(24.59)	(24.47)	(24.48)	(24.87)	(24.84)	(24.85)	(24.55)	(24.52)	(24.53)
Analyst Dispersion				-0.377^{**}	-0.317^{*}	-0.313^{*}	-0.328^{*}	-0.282	-0.278
				(-2.12)	(-1.77)	(-1.74)	(-1.80)	(-1.55)	(-1.52)
Forecast Revision				28.629^{***}	28.068^{***}	27.990^{***}	24.061^{***}	23.696^{***}	23.655^{***}
				(12.33)	(12.17)	(12.14)	(10.74)	(10.60)	(10.58)
Size				-0.013	-0.009	-0.011	-0.036^{*}	-0.029	-0.030
				(-0.76)	(-0.54)	(-0.60)	(-1.81)	(-1.49)	(-1.54)
B/M				0.001	-0.004	-0.003	-0.001	-0.005	-0.004
				(0.05)	(-0.29)	(-0.27)	(-0.10)	(-0.38)	(-0.35)
Turnover				-0.019	-0.011	-0.011	0.001	0.007	0.007
				(-0.90)	(-0.49)	(-0.50)	(0.03)	(0.33)	(0.32)
$\text{AR}_{t-252,t-31}$				1.350^{***}	1.329^{***}	1.325^{***}	1.078^{***}	1.073^{***}	1.073^{***}
				(26.26)	(25.56)	(25.45)	(18.09)	(17.99)	(17.98)
$\text{CAR}_{t-30,t-3}$				0.007^{***}	0.007^{***}	0.007^{***}	0.007^{***}	0.006^{***}	0.006^{***}
				(10.61)	(10.05)	(10.00)	(9.47)	(9.13)	(9.09)
AR_{t-2}				0.007^{**}	0.007^{**}	0.007^{**}	0.006^{**}	0.006^{**}	0.006^{**}
				(2.27)	(2.28)	(2.27)	(2.02)	(2.04)	(2.03)
Consensus Forecast							0.122^{***}	0.123^{***}	0.122^{***}
							(4.86)	(4.91)	(4.86)
Management Forecast							-0.043^{**}	-0.042^{**}	-0.042^{**}
							(-2.37)	(-2.29)	(-2.30)
NewsDummy							-0.072^{***}	-0.054^{**}	-0.059^{**}
							(-2.63)	(-1.99)	(-2.17)
Return Volatility							0.994	1.004	1.016
							(1.35)	(1.36)	(1.38)
Market Return							-0.517^{***}	-0.534^{***}	-0.532^{***}
							(-3.27)	(-3.38)	(-3.36)
Institutional Ownership							-0.223^{***}	-0.228^{***}	-0.226^{***}
							(-2.69)	(-2.76)	(-2.74)
Leverage							-0.160^{*}	-0.126	-0.130
							(-1.85)	(-1.46)	(-1.51)
Momentum							0.245^{***}	0.236^{***}	0.233^{***}
							(7.74)	(7.42)	(7.33)
Illiquidity							2.230^{***}	2.275^{***}	2.242^{***}
							(3.17)	(3.24)	(3.18)
Overconfidence							-0.064^{***}	-0.068^{***}	-0.067^{***}
							(-2.82)	(-2.99)	(-2.98)
Confidence Dispersion							-0.098	-0.090	-0.090
							(-1.50)	(-1.38)	(-1.38)
Numeric Word							0.028	0.028	0.028
							(1.33)	(1.30)	(1.31)
Intercept	0.039	0.075	0.063	0.496	0.369	0.374	0.440	0.306	0.315
	(0.78)	(1.48)	(1.25)	(1.55)	(1.15)	(1.17)	(1.30)	(0.90)	(0.93)
Year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	33,335	33,335	33,335	31,115	31,115	31,115	31,061	31,061	31,061
adj. R^2	0.183	0.185	0.185	0.248	0.248	0.249	0.251	0.252	0.252

Table V
News Tone Effect on Analyst Forecast Performance

This table presents results from pooled least square regression of forecast pessimism or forecast error on news tone, analyst characteristics, firm fundamentals and other control variables. The regression model takes the following way:

$$\mathrm{Y}_{ijt} \quad = \quad \alpha + \beta_1 \mathrm{Tone}_{t-30,t-3} + \gamma^{`}\mathrm{X} + \epsilon_{ijt},$$

where Y_{ijt} stands for analyst forecast bias or accuracy. Forecast bias is the actual quarterly earnings-per-share (EPS) minus analyst forecast, divided by share price 30 trading days before the forecast release date, multiplied by 100. Forecast accuracy is the absolute value of forecast bias multiplied by -1. The forecast release day is within 30 days before the actual earnings announcement day to make sure the analysts read the most relevant news. $\mathrm{Tone}_{t-30,t-3}$ stands for $\mathrm{Pos}_{t-30,t-3}$ or $\mathrm{Neg}_{t-30,t-3}$. $\mathrm{Pos}_{t-30,t-3}$ ($\mathrm{Neg}_{t-30,t-3}$) is the mean of positive (negative) tone for firm j within 3 to 30 days before the analyst i's forecast release day. X denotes other explanatory variables which are defined in Table I. Panel A reports the univariate regression results and Panel B reports multi-variable regression results. T-statistics are shown in parentheses. The underlying standard errors are clustered on the firm level and robust to heteroskedasticity. ***, ** and * indicate significance at 1%, 5%, and 10%, levels, respectively.

Dependent Variable	Bias			Accuracy		
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
$\mathrm{Pos}_{t-30,t-3}$	-0.14563*			0.27447**		
	(-1.89)			(2.34)		
$\mathrm{Neg}_{t-30,t-3}$		-0.14152*			0.27282**	
		(-1.75)			(2.39)	
$\mathrm{Pos}_{t-30,t-3}$ - $\mathrm{Neg}_{t-30,t-3}$			-0.05613			
			(-0.83)			
$\mathrm{Pos}_{t-30,t-3}$ + $\mathrm{Neg}_{t-30,t-3}$						0.16174**
						(2.42)
Lag Bias	0.15373***	0.15373***	0.15374***			
	(4.86)	(4.85)	(4.85)			
Lag Accuracy				-0.01380	-0.01380	-0.01380
				(-0.95)	(-0.95)	(-0.95)
Intercept	-0.04330**	-0.04611**	-0.05290***	-0.26334***	-0.25837***	-0.26404***
	(-2.39)	(-2.55)	(-2.93)	(-13.09)	(-12.91)	(-13.19)
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes	Yes	Yes	Yes
N	102,086	102,086	102,086	81,813	81,813	81,813
adj. R^2	0.068	0.068	0.068	0.159	0.159	0.159

Dependent Variable	Bias			Accuracy		
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Pos}_{t-30,t-3}$	-0.084			0.233**		
	(-1.08)			(2.46)		
$\text{Neg}_{t-30,t-3}$		-0.106			0.206**	
		(-1.26)			(2.13)	
$\text{Pos}_{t-30,t-3}$ - $\text{Neg}_{t-30,t-3}$			0.012			
			(0.19)			
$\text{Pos}_{t-30,t-3}$ + $\text{Neg}_{t-30,t-3}$						0.135**
						(2.38)
Lag Bias	0.135***	0.135***	0.135***			
	(3.80)	(3.80)	(3.80)			
Lag Accuracy				0.008	0.008	0.008
				(0.69)	(0.69)	(0.69)
Analyst Dispersion	1.690**	1.690**	1.690**	-2.758***	-2.758***	-2.757***
	(2.03)	(2.03)	(2.03)	(-3.32)	(-3.32)	(-3.32)
Forecast Revision	-17.119**	-17.130**	-17.128**	18.348***	18.382***	18.365***
	(-2.11)	(-2.11)	(-2.11)	(2.59)	(2.60)	(2.59)
Size	-0.002	-0.002	-0.002	0.036***	0.036***	0.036***
	(-0.21)	(-0.22)	(-0.21)	(2.96)	(2.97)	(2.96)
B/M	0.025***	0.025***	0.025***	-0.063***	-0.063***	-0.063***
	(2.99)	(2.99)	(3.00)	(-5.10)	(-5.11)	(-5.11)
Turnover	0.003	0.003	0.003	-0.091**	-0.091**	-0.091**
	(0.10)	(0.10)	(0.10)	(-2.46)	(-2.45)	(-2.46)
$\text{AR}_{t-252,t-31}$	-0.204**	-0.204**	-0.204**	0.182**	0.182**	0.182**
	(-2.04)	(-2.04)	(-2.04)	(2.13)	(2.13)	(2.13)
$\text{CAR}_{t-30,t-3}$	-0.004***	-0.004***	-0.004***	0.002*	0.002*	0.002*
	(-3.58)	(-3.58)	(-3.58)	(1.74)	(1.74)	(1.74)
AR_{t-2}	-0.005*	-0.005*	-0.005*	-0.001	-0.001	-0.001
	(-1.73)	(-1.73)	(-1.73)	(-0.34)	(-0.34)	(-0.34)
Consensus Forecast	-0.083*	-0.083*	-0.083*	0.132***	0.132***	0.132***
	(-1.88)	(-1.88)	(-1.88)	(2.92)	(2.92)	(2.92)
Management Forecast	-0.014	-0.014	-0.014	0.043***	0.043***	0.043***
	(-0.82)	(-0.82)	(-0.82)	(2.62)	(2.63)	(2.63)
Analyst Boldness	-0.017*	-0.017*	-0.017*	-0.003	-0.003	-0.003
	(-1.72)	(-1.72)	(-1.73)	(-0.31)	(-0.29)	(-0.30)
Forecast Horizon	0.000	0.000	0.000	-0.001*	-0.001*	-0.001*
	(0.44)	(0.44)	(0.44)	(-1.92)	(-1.93)	(-1.93)
Forecast Frequency	-0.001	-0.001	-0.001	0.011*	0.011*	0.011*
	(-0.09)	(-0.09)	(-0.09)	(1.70)	(1.70)	(1.70)
General Experience	-0.024**	-0.024**	-0.024**	0.006	0.006	0.006
	(-2.19)	(-2.19)	(-2.19)	(0.64)	(0.65)	(0.64)
Firm Experience	0.007	0.007	0.007	-0.000	-0.000	-0.000
	(0.37)	(0.37)	(0.37)	(-0.01)	(-0.02)	(-0.02)
Firm Coverage	-0.001	-0.001	-0.001	0.001*	0.001*	0.001*
	(-1.11)	(-1.11)	(-1.11)	(1.73)	(1.74)	(1.74)
Analyst Ranking	0.000	0.000	0.000	0.005***	0.005***	0.005***
	(1.00)	(1.00)	(1.00)	(14.02)	(14.01)	(14.01)
NewsDummy	0.010	0.010	0.003	-0.017	-0.010	-0.017
	(0.76)	(0.77)	(0.29)	(-1.25)	(-0.77)	(-1.21)
Earnings Surprise	-0.011***	-0.011***	-0.011***	-0.051***	-0.051***	-0.051***
	(-3.30)	(-3.29)	(-3.29)	(-12.51)	(-12.53)	(-12.52)
Return Volatility	-0.371	-0.372	-0.372	-2.373***	-2.371***	-2.372***
	(-0.94)	(-0.94)	(-0.94)	(-4.63)	(-4.63)	(-4.63)
Market Return	0.070	0.069	0.069	-0.582**	-0.581**	-0.582**
	(0.30)	(0.30)	(0.30)	(-2.12)	(-2.12)	(-2.12)
Institutional Ownership	0.262**	0.262**	0.262**	-0.071	-0.070	-0.070
	(2.07)	(2.06)	(2.07)	(-0.56)	(-0.56)	(-0.56)
Leverage	0.330**	0.329**	0.330**	-0.630***	-0.629***	-0.630***
	(2.28)	(2.27)	(2.27)	(-3.67)	(-3.66)	(-3.67)
Momentum	-0.020	-0.020	-0.020	0.227***	0.226***	0.227***
	(-0.35)	(-0.35)	(-0.35)	(3.51)	(3.51)	(3.51)
Illiquidity	0.001	0.001	0.001	-0.004***	-0.004***	-0.004***
	(1.16)	(1.16)	(1.16)	(-3.20)	(-3.20)	(-3.20)
Overconfidence	0.056**	0.056**	0.056**	-0.107***	-0.107***	-0.107***
	(2.48)	(2.47)	(2.49)	(-3.84)	(-3.83)	(-3.83)
Numeric Word	0.006	0.006	0.006	0.021**	0.021**	0.021**
	(0.57)	(0.57)	(0.57)	(2.29)	(2.29)	(2.30)
Intercep	-0.245	-0.242	-0.244	1.393**	1.385**	1.388**
	(-0.50)	(-0.49)	(-0.49)	(2.25)	(2.24)	(2.25)
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes	Yes	Yes	Yes
N	92,003	92,003	92,003	73,884	73,884	73,884
adj. R^2	0.104	0.104	0.104	0.295	0.295	0.295

Table VI
Analyst Characteristics and News Effects

Analysts are sorted into deciles according to Genearl Experience, Firm Experience, Analyst Ranking, Firm Coverage, Forecast Frequency, Boldness and Overconfidence. For each analyst characteristic, we compare the news coefficient of equation (2), with Forecast Accuracy as Dependent variables, between the bottom and top decile of that characteristic. Table VI reports the news tone coefficients for both bottom and top deciles analysts. The last column reports the p value of the coefficient diffence between top and bottom analysts.

Panel A	$\text{Pos}_{t-30,t-3}$	Upper Quantile	Low Quantile	P value diff
	Genearl Experience	0.0848	0.2658**	0.09*
	Firm Experience	0.1254	0.2686**	0.17
	Ranking	-0.0154	0.3389***	0.03**
	Firm coverage	0.0488	0.3533**	0.09*
	Boldness	-0.1865	0.2530**	-0.59
	Forecast Frequency	0.2434**	0.0495	0.06*
	Overconfidence	0.1031	0.2836***	0.10*
Panel B	$\text{Neg}_{t-30,t-3}$	**Upper Quantile**	**Low Quantile**	**P value diff**
	Genearl Experience	0.0897	0.2281**	0.35
	Firm Experience	0.0225	0.3336***	0.21
	Ranking	-0.0387	0.3369**	0.02**
	Firm coverage	0.0748	0.2827*	0.39
	Boldness	0.1576	0.2331**	0.61
	Forecast Frequency	0.2068*	0.1095	0.30
	Overconfidence	0.0979	0.2621***	0.04**
Panel C	$\text{Pos}_{t-30,t-3} + \text{Neg}_{t-30,t-3}$	**Upper Quantile**	**Low Quantile**	**P value diff**
	Genearl Experience	0.0521	0.1514**	0.16
	Firm Experience	0.0473	0.1888***	0.42
	Ranking	-0.01579	0.2062***	0.02**
	Firm coverage	0.0374	0.1958**	0.18
	Boldness	0.1059	0.1483**	0.59
	Forecast Frequency	0.1386**	0.0474	0.11
	Overconfidence	0.0615	0.1670***	0.06*

Table VII
Misweighting on Private Information and Public Information

Analysts are sorted into deciles according to Genearl Experience, Firm Experience, Analyst Ranking, Firm Coverage, Forecast Frequency, Boldness and Overconfidence. For each analyst characteristic, we compare the coefficient of Deviation in the following regression, with Forecast Bias as Dependent variables, between the bottom and top decile of that characteristic.

$$\text{Bias}_{ijt} = \alpha + \beta_1 \text{Deviation}_{ijt} + \epsilon_{ijt},$$

Table VII reports the coefficients of Deviation for both bottom and top deciles analysts. The last column reports the p value of the coefficient diffence between top and bottom analysts.

Analyst.Characteristic	Upper Quantile	Low Quantile	P value diff
Genearl Experience	0.0798	0.2231*	0.10*
	(0.34)	(1.66)	
Firm Experience	-0.0111	0.1452	0.22
	(-0.11)	(0.82)	
Ranking	-0.3267	0.7010**	< 0.01***
	(-0.39)	(6.36)	
Firm coverage	0.2382*	0.0592	0.03**
	(1.81)	(0.50)	
Boldness	0.3576***	0.0445	< 0.01***
	(2.75)	(0.32)	
Forecast Frequency	0.0985	0.905	0.43
	(0.79)	(1.33)	
Overconfidence	0.2469**	-0.2255	0.02**
	(2.13)	(-0.92)	

Table VIII
News Tone and Information Asymmetry

This table presents the regression of Analyst Dispersion on news tone and firm fundamentals. The regression model takes the following form:

$$\text{Analyst Dispersion}_{jt} = \quad \alpha + \beta_1 \text{Tone}_{t-30,t-3} + \gamma^{'} \text{X} + \epsilon_{jt},$$

where the dependent variable, analsyt dispersion stands for the standard deviation of analysts' earnings forecasts for firm j within 3 to 30 days prior to the earnings announcement. $\text{Tone}_{t-30,t-3}$ stands for $\text{Pos}_{t-30,t-3}$ or $\text{Neg}_{t-30,t-3}$. $\text{Pos}_{t-30,t-3}$ ($\text{Neg}_{t-30,t-3}$) stands for the mean of positive (negative) tone for firm j within 3 to 30 days before the actual earnings announcement day. X denotes other explanatory variables which are defined in Table I. Standard errors are clustered at firm level. The robust t-statistics are in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10%, levels, respectively.

Dependent Variable:			Analyst Dispersion			
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Pos}_{t-30,t-3}$	-0.0424**			-0.0357**		
	(-2.47)			(-2.25)		
$\text{Neg}_{t-30,t-3}$		-0.0472***			-0.0422***	
		(-2.92)			(-3.04)	
$\text{Pos}_{t-30,t-3}$ + $\text{Neg}_{t-30,t-3}$			-0.0249***			-0.0219***
			(-2.79)			(-2.67)
Forecast Revision				-3.6388***	-3.6419***	-3.6399***
				(-6.38)	(-6.38)	(-6.38)
Size				0.0028***	0.0028***	0.0028***
				(2.89)	(2.87)	(2.87)
B/M				0.0021***	0.0021***	0.0021***
				(2.80)	(2.83)	(2.81)
Turnover				0.0066***	0.0066***	0.0066***
				(2.80)	(2.79)	(2.80)
$\text{AR}_{t-252,t-31}$				-0.0156**	-0.0155**	-0.0156**
				(-2.47)	(-2.46)	(-2.47)
$\text{CAR}_{t-30,t-3}$				0.0000	0.0000	0.0000
				(0.30)	(0.31)	(0.31)
AR_{t-2}				0.0001	0.0002	0.0001
				(0.65)	(0.66)	(0.65)
Consensus Forecast				-0.0023	-0.0023	-0.0023
				(-0.46)	(-0.46)	(-0.46)
Management Forecast				-0.0038	-0.0038	-0.0038
				(-1.44)	(-1.44)	(-1.44)
NewsDummy				0.0013	0.0011	0.0014
				(0.70)	(0.63)	(0.79)
Earnings Surprise				0.0022***	0.0022***	0.0022***
				(5.84)	(5.86)	(5.84)
Return Volatility				0.0900***	0.0893***	0.0897***
				(3.39)	(3.37)	(3.38)
Market Return				0.0097	0.0095	0.0096
				(0.56)	(0.55)	(0.56)
Institutional Ownership				0.0202	0.0202	0.0201
				(1.52)	(1.52)	(1.52)
Leverage				0.0401***	0.0399***	0.0400***
				(4.13)	(4.10)	(4.11)
Momentum				0.0066**	0.0066**	0.0066**
				(2.15)	(2.14)	(2.14)
Illiquidity				-0.0000	-0.0000	-0.0000
				(-1.11)	(-1.11)	(-1.11)
Overconfidence				-0.0036	-0.0036	-0.0036
				(-1.00)	(-1.01)	(-1.01)
Numeric Word				0.0010	0.0010	0.0010
				(0.56)	(0.56)	(0.56)
Intercept	0.0429***	0.0425***	0.0430***	-0.1224***	-0.1216***	-0.1219***
	(16.90)	(18.48)	(17.70)	(-3.58)	(-3.57)	(-3.57)
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm effect	Yes	Yes	Yes	Yes	Yes	Yes
N	18,215	18,215	18,215	16,335	16,335	16,335
adj. R^2	0.225	0.225	0.225	0.276	0.276	0.276