Do Analysts Read the News?*

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Abstract

We examine whether and how the general supply of firm information via media news sources influences equity analysts' earnings forecast revisions. Combining large databases of U.S. firm-specific news stories and individual sell-side analysts' earnings forecast revisions during 2000 to 2010, we find that equity analysts' forecast revisions are significantly influenced by the tone of the news. The relation between news and forecast revision is stronger for news that contains information regarding firm fundamentals. Media reinforces analysts' revision decisions when firm information asymmetry is larger and when analysts face stronger conflicts of interest. Despite analysts' reaction to news, they generally respond to news with a low speed; and consequently, markets react less favorably when analysts' revisions are based on stale news.

1 Introduction

Financial analysts are primarily responsible for the analysis and interpretation of "relevant information" (Bradshaw, 2011). Prior research on sell-side equity analysts has examined different types of information events that shape analysts' earnings forecast and stock recommendation decisions. This literature has mostly focused on whether earnings forecasts are influenced by specific types of information events such as earnings surprises (e.g., Abarbanell and Bernard, 1992), major stock price movements (e.g., Abarbanell, 1991; Conrad, Cornell, Landsman, and Rountree, 2006; Clement, Hales, and Xue, 2011), firm disclosure (e.g., Jennings, 1987; Rogers and Grant, 1997; Bowen, Davis, and Matsumoto, 2002), and other analysts' forecasts (e.g., Welch, 2000; Clement et al., 2011). In this study, we use a comprehensive source of firm-specific news stories to measure the general supply of firm-specific information and thus measure the "relevant information" to financial analysts. We then investigate whether and how analysts react to the arrivals of information.

In addition to providing information regarding a wide variety of information events, firm-specific news stories may provide incremental "qualitative" information through the language of the report. The language (tone) of the news report may provide incremental information, for instance, because it reflects the analysis and interpretation of the financial press (e.g., Tetlock, Saar-Tsechansky, and Macskassy, 2008). This provides an opportunity to investigate whether equity analysts are influenced by other information intermediaries, in particular, the financial press. Prior work on the capital market role of the press focuses on equity investors' reactions to financial news reports (e.g., Pritamani and Singal, 2001; Tetlock, 2007, 2010; Bushee, Core, Guay, and Hamm, 2010; Tetlock, 2011; Engelberg and Parsons, 2011; Huang, Tan, and Wermers, 2014). There is, however, little research examining how financial news reports affect equity analysts.[1,2] This study aims to extend this literature by examining the effect of financial news reports on earnings forecasts. Since analysts are arguably one of the most sophisticated capital market participants, this study can be considered as a strong test of the role of the financial press.

[1] While there are studies (e.g., Frankel and Li, 2004) that examines the capital market impact of analysts and media separately, to the best of our knowledge, there is little research on how these two intermediaries affect each other.

[2] Notable exceptions include Kross, Ro, and Schroeder (1990); Bagnoli, Levine, and Watts (2005); Nichols and Wieland (2009). Kross et al. (1990) find that analyst's advantage over time series models increases with the amount of the Wall Street Journal coverage. Bagnoli et al. (2005) and Nichols and Wieland (2009) focus on the influence of firm-initiated news on analysts forecasting activity and market reaction to analyst forecast revisions. Unlike these studies we focus on the impact of financial news on the direction and magnitude of analysts' forecast revisions.

The main hypothesis of this study is that public news stories, though their tone, influences analysts' earnings expectations and result in EPS forecast revisions.[3] To test this hypothesis, we use a quantitative measure of news tone, which is the proportion of negative (net of positive) words, and document its influence on forecast revision. We combine a large database of U.S. firm-specific public news stories obtained from Factiva with individual analysts' earnings forecasts from I/B/E/S. We match every forecast revision, issued within one year prior to the actual announcement date, with financial news released between dates of the forecast revision and the previous forecast (i.e., news during the revision period). We first hypothesize that the direction and magnitude of forecast revisions are associated with the tone of the news stories released during the revision period. Furthermore, if analysts' reaction to public news is driven by the incremental information conveyed by the news, the association between the news tone and forecast revisions should be stronger for more informative news.[4] As a result, we also hypothesize that the tone of public news influences forecast revisions more strongly when the news is more likely to be informative, i.e., when the news contains information that is directly relevant to earnings. We test these hypotheses by removing news stories and analyst forecast revisions around earnings announcements, thus focusing on the effects of general news supply instead of major corporate events, and ameliorating the compounding effects of earnings announcements.

The results generally support these hypotheses. First, we find that both the direction and magnitude of revision are positively associated with the tone of financial news. Following revision periods dominated by positive (negative) news, forecast revision tends to be high (low), and upward (downward) revisions are more likely. Second, using the frequency of the word root "earn" as the news-informativeness proxy (Tetlock et al., 2008), we confirms that analysts react more strongly to more informative news. This finding suggests that the influence of news on earnings forecasts is at least partly driven by the fundamental information available from financial news stories.

We further identify a number of instances where media reinforces analysts' forecast revision. We find that the association between news tone and earnings forecast revisions is stronger when

[3]It is common in the analyst literature to use forecast revision to document the influence of an information event on earnings forecasts (e.g., Baginski and Hassell, 1990; Denis, Denis, and Sarin, 1994; Ely and Mande, 1996; Williams, 1996; Jennings, 1987; Conrad et al., 2006; Clement et al., 2011). The logic is that if the arrival of a new information event changes analysts' belief regarding their earnings forecasts, it will result in revision of the forecast. Thus, the information event should be associated with the forecast revision.

[4]This argument is in line with Clement et al.'s (2011) finding that analysts react more to stock prices and other analysts' forecasts when these events are more likely to be informative.

the information asymmetry of the underlying firm is higher, when the analyst is more experienced, and when the analyst possesses a higher degree of conflict of interest. These findings indicate that firm's information environment and analysts' attributes affect analysts' sensitivity to news. In particular, these results are consistent with general perceptions of information economics that treats information as a consumption goods—the sensitivity of information user to information is higher when the information quality is poor, when the information user is more capable, or when the information user is more motivated.

Lastly, we examine stock returns following news-driven analyst revisions. Consistent with prior literature, we document that analyst revision positively predicts stock returns for our sample of news-based revisions. We, however, find that despite analysts' reaction to news, they generally respond to news with significant time lapse. As a result, most of the analyst revisions are written on stale news. The positive association between revision and returns is reinforced only when analysts react to news in a very timely manner. Otherwise, when analysts write the revisions on stale news, the market reaction is much less favorable.

This study contributes to two branches of the accounting and finance literature. First, it contributes to the equity analyst literature by providing evidence on how analysts react to the general supply of public information, which includes news originating from a wide array of sources regardless of news type. It, thus, generalizes the results in prior research, which has focused on specific types of information events such as earnings announcements, management disclosures, dividend changes, and major stock price changes. Our results are obtained by removing earnings announcement periods and by controlling for firms' information environment and information shocks, and thus highlight the general information roles of financial news contents in shaping analysts' forecast revisions. Second, this study adds to the recent literature investigating the role of the financial press in capital markets. By documenting a significant impact of news tone on analysts' earnings forecasts this study provides strong evidence that firm-specific news stories contain incremental information and contribute to the firm information environment. Lastly, this study contributes to our understanding of the interactions between two major types of information intermediaries, namely, the business media and sell-side equity analysts. We document that the information sensitivity of analysts is higher when there are more information asymmetry and when they are ex-ante more incentivized.

The remainder of this paper is organized as follows. Section 2 discusses prior research and develops the hypotheses. Sections 3 and 4 present our main empirical results. Section 5 further identifies a number of cross-sectional differences in the response of analysts to news and Section 6 discusses the profitability of analysts' news-reading. Section 7 concludes the paper.

2 Related Research and Hypotheses Development

Equity analysts are important capital market information intermediaries. Their primary role is believed to be the analysis and interpretation of relevant information (e.g., Bradshaw, 2011), which leads to the question "*what information do analysts analyze?*".[5] Since only the outputs of the analyst decision process are readily observable, prior research has focused on investigating what type of information is incorporated in analysts' outputs such as earnings forecasts, stock recommendations, and reports (e.g. Previts, Bricker, Robinson, and Young, 1994; Ely and Mande, 1996; Rogers and Grant, 1997; Bowen et al., 2002; Asquith et al., 2005; Conrad et al., 2006; Clement et al., 2011; Agarwal and Hess, 2012). Following this line of research, we examine whether and how public news stories influence equity analysts' earnings forecasts. The main hypothesis is that public news stories provide *incremental* information to equity analysts, and therefore, influence their earnings forecasts. In this section we present the contrasting literature that public news may not or may contain incremental information, and then present our hypotheses.

2.1 Public News May Not Add to Analysts' Decision Process

The public news stories considered in this study include all types of firm-specific news stories and thus measures the general supply of corporate information. There are reasons to believe that this general supply of information may not provide a credible source to incrementally drive analysts' decision making, if i) analysts have private access to corporate information, ii) analysts focus on only specific event types and ignore other less influential and quantifiable events, and/or iii) the general information is built in other general measures of firm information environment and information arrival shocks. We discuss these elements in detail below.

[5] While the current study and most prior research focus on the analysis or information interpretation role of analysts, analysts are also shown to have a significant information discovery role (e.g., Asquith, Mikhail, and Au, 2005; Chen, Cheng, and Lo, 2010).

Equity analysts are believed to be experts with better access to information and better understanding of key industry and firm characteristics. Equity analysts have better access to information, for instance, through their relationship with management and other firm insiders. Bradshaw (2011) shows that industry knowledge and management access are among the top success factors for equity analysts, and that the importance of management access has increased from 1998 to 2005. The latter finding is particularly important since it shows management access remains a key factor in analysts' decision process even after the passage of Regulation Fair Disclosure (Reg FD) in 2000. While there is ample evidence suggesting that Reg-FD has succeeded in minimizing selective disclosure (e.g., Heflin, Subramanyam, and Zhang, 2003; Gintschel and Markov, 2004; Francis, Nanda, and Wang, 2006; Agrawal, Chadha, and Chen, 2006; Mohanram and Sunder, 2006), private meetings between management and analysts are still 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). Such access to private information together with better understanding of the firms' business may provide analysts with a superior information set compared to the financial press. Therefore, analysts are less likely to be influenced by financial news as the information and the press's analysis may not add to their private information set.

Secondly, the general firm-specific news stories may not be "eventful" enough to draw the attention of analysts, to the extent that they engage in earnings forecasts. Prior research has documented analysts' forecasts and recommendations consistently incorporate information contained in specific 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), mandatory disclosures such as financial statements and annual reports (e.g., Rogers and Grant, 1997), voluntary/management disclosures (e.g., Jennings, 1987; Baginski and Hassell, 1990; Williams, 1996; Bowen et al., 2002), other analysts' forecasts and recommendations (e.g., Welch, 2000; Bernhardt, Campello, and Kutsoati, 2006; Clement et al., 2011), and macroeconomic news (Agarwal and Hess, 2012). What differentiates these specific events and the general supply of financial news is that the former is believed to be more impactful, and is usually readily quantifiable. When news of major events is removed from the general supply of financial news, the rest of the financial news may be too "discolorful," and difficult to read because it usually lacks clear numbers to benchmark against.

Lastly, the contents embodied in the general supply of financial news may already be captured by readily observable market metrics that generally measure firms' information environment and information arrival shocks. Analysts' behaviors may thus be a function of the overall information environment and arrivals (e.g., Beyer, Cohen, Lys, and Walther, 2010). For example, Jiang, Xu, and Yao (2009) show that idiosyncratic volatility is negatively associated with analysts' forecast revisions; and Conrad et al. (2006) use stock price changes to proxy for major news arrivals and find that they significantly influence analyst forecast revisions.

To show that the general supply of news has an incremental effect on analysts' decision making, we control for major corporate events and firm information environment. Specifically, we remove financial news around earnings announcements and news related to M&A to avoid the compounding effects of major events; and we also control for a battery of variables that measure firms' information asymmetry and information arrival shocks, such as idiosyncratic volatility and prior stock price change. Our research design thus provides a cleaner picture on the incremental informativeness of the general news.

2.2 The Value of Public News and Financial Press

As previously discussed, the ability of the press to influence analysts' forecasts and recommendations depends on whether it incrementally contributes to firms' information contents. The press is valuable because of its roles in information production, assessment, and re-assessment. The press, as an information intermediary, may also engage in private information production through journalism (e.g., Bushee et al., 2010). The language in the news stories may as well contain additional information, possibly because it reflects opinions regarding the implications of the news (e.g., Tetlock et al., 2008).

Recent literature investigating the role of the financial press in capital markets presents evidence that the financial press is an important capital market information intermediary and contributes to firm information environment. Bushee et al. (2010) find that information asymmetry is lower for firms with higher media coverage; and they attribute these findings to the press's influence on firms' information environment through information discovery, packaging and dissemination of publicly available information. Pritamani and Singal (2001) and Chan (2003) document a significant long-run momentum in monthly stock returns subsequent to extreme price movements accompanied by public news. Tetlock (2007), Tetlock (2010) and Tetlock (2011) show that public news reduces information asymmetry in stock markets.[6] Engelberg and Parsons (2011) provide strong evidence of a causal effect of media coverage on investors trading behavior through the examination of the impact of the same news on investors with different access to media.

Recent literature also provides evidence that the press is valuable for both unsophisticated and sophisticated investors. Findings in Tetlock (2007) suggest that individual investors drive the relationship between news and stock prices, whereas (Huang et al., 2014) show that firm-specific news stories significantly affect institutional investors' trading activities. The roles of the press also exhibit cross-sectional variations, for example, the relationship between news and stock prices is more pronounced in small and growth stocks (Tetlock, 2007); and while a high fraction of negative words in financial news predicts low future earnings, the predictive ability of the news is stronger when the story is related to firm fundamentals (Tetlock et al., 2008).

The evidence discussed above indicates that financial news contains information that influences investors' information set and a wide array of capital market activities. While financial analysts are arguably among the most sophisticated users of information, the roles of financial news in the capital markets and the demand for their service plausibly motivate analysts to use financial news judicially. We analyze whether analyst forecasts are also driven by the contents embedded in the news, i.e., the "soft" information of the news. Regardless of whether analysts already have access to the news information prior to its release by the press, their analyses may be influenced by the contents of the news. Public news may, thus, affect equity analysts by providing new information or alternative interpretations of existing information.

2.3 Hypotheses

The above discussion leads us to empirically test whether financial news reports influence analysts' earnings forecasts. Following the literature which uses earnings forecast revision to measure the impact of information events on analysts' forecasts (e.g., Ely and Mande, 1996; Rogers and Grant, 1997; Conrad et al., 2006; Clement et al., 2011), we conduct the empirical tests using earnings forecast revision. As with the prior literature, we operationalize the contents of news by constructing a quantitative measure of news tone (e.g., Tetlock et al., 2008; Huang et al., 2014). Prior studies

[6] Tetlock (2011) also shows that investors remain to be influenced by stale news, such as reprints of the same story.

use either the proportion of negative words (e.g., Tetlock et al., 2008; Tetlock, 2010, 2011) or the net proportion of negative words (net of positive words) (e.g., Huang et al., 2014) as a measure of the news tone. If analysts incorporate information from financial news reports in their earnings forecasts, we would be able to observe a significant association between the tone of the news and their subsequent forecast revisions. More specifically, public news may affect analysts' forecast revision in two ways. First, it may influence the direction of revision, with upward (downward) revisions being more likely to follow positive (negative) news stories. Second, it may influence the (signed) magnitude of the revision. That is, the more positive (negative) the tone of the news, the higher (lower) the forecast revision. Collectively, these assertions are stated in the alternative form as follows:

Hypothesis 1. *A more positive (negative) news tone tends to be followed by i) higher (lower) earnings forecast revisions, and ii) a higher likelihood of upward (downward) earnings forecast revisions.*

While any relevant news is expected to influence analysts' forecast revisions, some news stories may provide a direct and more informative signal. For instance, Tetlock et al. (2008) find that the ability of news to predict earnings is higher when the news focuses on fundamentals. If analysts exhibit a reasonable level expertise, they should be able to identify and put higher weight on more informative news. Consistently, Clement et al. (2011) show that analysts respond more to stock price changes and to other analysts' forecasts when these signals are likely to be informative. Therefore, we hypothesize that more informative public news have greater impact on analysts' forecast revisions. While there may be many possible ways to measure the informativeness of public news, we follow Tetlock et al. (2008) and Huang et al. (2014) and use the frequency of the word root "earn" in the news story as a measure of news informativeness. This measure is designed to capture the relative strength of the signal, i.e., whether the news contains direct signals regarding earnings. This leads to the prediction that the association between financial news and analysts' forecast revisions is stronger when the news is more informative (i.e., news stories with relatively high frequency of the word root "earn").

Chan (2003), Tetlock (2007), and Tetlock et al. (2008) provide evidence of asymmetric effects of positive and negative financial news. Chan (2003) finds a strong downward stock price drift subsequent to bad news. Tetlock (2007) finds that media pessimism predicts a price decline, whereas the media optimism has weak predictive ability. Tetlock et al. (2008) find that negative words in financial news reports predict firm earnings, but the predictive ability of positive word is much weaker. Asymmetric reaction to positive and negative news is also observed in other economic literature (e.g., Brown and Ball, 1967; Veronesi, 1999). Consistently, we predict that the impact of financial news reports on analysts' forecast revision is stronger when the news is negative.

These two predictions are formally stated in the second hypothesis:

Hypothesis 2. *The association between news tone and earnings forecast revisions is stronger when:*

i) there is a higher frequency of "earn" in the news article; (H2A)

ii) the news has a negative tone. (H2B)

While the nature of news may influence analysts' interpretations, the firm's information environment and the analysts' attributes also plausibly affect their interpretation ability of the news. We attempt to isolate patterns when media reinforces analysts in their forecast revisions. The literature generally agrees that information quality reduces information asymmetry. For instance, Lang and Lundholm (1996) and Hope (2003) show that informative disclosure improves the accuracy of earnings forecasts, and Chen, Huang, and Jha (2012) document that accounting information quality arising from managerial discretion is negatively related to stock return volatility. Given the positive roles of information quality in reducing information asymmetry, the sensitivity of information users to information arrivals is arguably higher when: i) information asymmetry of the underlying firm is higher, ii) the information user is more capable of analyzing the information, and iii) the information user is more (ex-ante) motivated to analyze the information. This is consistent with the notion that analysts treat information (news) as a consumption goods—the marginal benefits of the goods (news) increase when the consumer (the analyst) or the goods (news) is more price-sensitive; for example, when analysts are more incentivized by potential conflict of interest. We accordingly state the third hypothesis:

Hypothesis 3. *The association between news tone and earnings forecast revisions is stronger when:*

i) information asymmetry of the underlying firm is higher; (H3A) *ii) the analyst is more experienced; (H3B)*

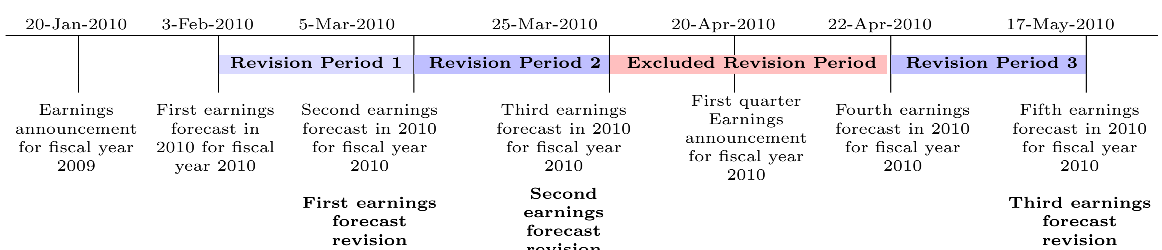
ii) the analyst possesses a higher degree of conflict of interest. (H3C)

$H3C$ emphasizes that analysts who have conflicts of interest are more motivated. Analysts are frequently subject to conflicts of interest due to business relationships with the covered firm. For example, the literature shows that analysts who are employed by banks with business ties with the covered firms tend to provide more optimistic stock recommendations (e.g., Dugar and Nathan, 1995; Lin and McNichols, 1998; Michaely and Womack, 1999; Dechow, Hutton, and Sloan, 2000). The ties that affiliated analysts enjoy with the covered firms may bring relative information advantage to the analysts by reducing the degree of information asymmetry between the covered firms and the analysts. Hence, if an analyst has stronger motives to follow the firm and also enjoys information advantage, she could be more responsive to firm news.[7]

3 Research Design and Sample Selection

3.1 Research Design

We test the hypotheses by examining how analysts' earnings forecast revisions are influenced by the tone of firm-specific public news released during the "revision period," which is the period between the previous and current earnings forecast dates.[8] Our time line of events can be demonstrated with the following analyst-firm specific example, assuming a December 31 fiscal year end and that the current fiscal year is 2010:



[7] One could also argue that the private knowledge of such affiliated analysts may lead to these analysts being less responsive to news, as they may be bound by their own private knowledge and discount the news more. Therefore, $H3C$ is ultimately an empirical issue.

[8] This research design is in line with Agarwal and Hess (2012), who investigate the influence of macroeconomic news on earnings forecasts.

In this time line, fiscal year-2009 earnings were announced on January 20, 2010. Subsequently, the analyst issued three forecasts of the firm's earnings for fiscal year 2010, respectively, on February 3, March 5, and March 25, 2010. The first earnings forecast is therefore on February 3, and the first and second revision dates are March 5, and March 25, 2010, respectively. The three forecasts create two revisions and two associated revision periods. The first revision is on March 5 with the first revision period between February 3 and March 5 (both exclusive); and the second revision is on March 25 with the second revision period between March 5 and March 25. We condition the forecast revision on news information during the previous revision period. For example, the first revision (March 5) is conditioned on news information during the first revision period.

We exclude earnings forecast revisions issued within [–3, +3] trading days around quarterly earnings announcement in order to limit the compounding effects of earnings announcements and sharpen our focus on the effects of news instead of major corporate events.[9] In our example, assume that the first quarter earnings announcement for fiscal year 2010 takes place on April 20. The analyst issues a forecast revision two days later on April 22. We exclude this forecast revision since it is within the [–3, +3] trading days window. In general, any forecast revision issued between April 15 and April 23 (both inclusive) would have been excluded since it is issued within [–3, +3] trading days window around the first-quarter earnings announcement. Associated with this exclusion, we exclude any news between the previous forecast date (March 25 in this example) and the right boundary of the [–3, +3] window (April 23 in this example).

We measure forecast revision in two ways. Our first measure is of forecast revision is the change in earnings forecast (Rev). Following the literature (e.g., Clement and Tse, 2005; Agarwal and Hess, 2012), we define forecast revision as the difference between the revised and the previous EPS forecasts scaled by stock price at the beginning of the fiscal year for a given firm-fiscal year and a given analyst. That is,

$$Rev = \frac{\text{Revised EPS forecast} - \text{Prior EPS forecast}}{Price} \times 100.$$

We also use the percentage of forecast revision (i.e., replace the denominator $Price$ with the Prior

[9]We choose the [–3,+3] trading days because we observe, in untabulated analyses, that both analysts and media significantly increase their activities around earnings announcement and this increase is concentrated within [–3,+3] trading days. Our results are also robust to other exclusion windows such as [–5,+5] trading days.

EPS forecast) and find our results robust. Our second measure is the direction of revision ($RevUp$), defined as an indicator variable which equals one when the revision is upward, and zero otherwise:

$$RevUp = \begin{cases} 1 & \text{if } Rev > 0 \\ 0 & \text{otherwise.} \end{cases}$$

We use Rev as our primary dependent variable, and use $RevUp$ to test the hypotheses regarding the direction of revision, and as a robustness check for the other hypotheses.

Following the literature, we measure news tone as the negative word ratio or net negative word ratio in a news article. We identify negative and positive words in the news using the word list of Loughran and McDonald (2011). The net negative word ratio for each news story (Huang et al., 2014) is:

$$NegNet = \frac{\text{No. of negative word occurrences} - \text{No. of positive word occurrences}}{\text{Total number of words in the news}}$$

The negative word ratio for each news story (Tetlock et al., 2008) is:

$$Neg = \frac{\text{No. of negative word occurrences}}{\text{Total number of words in the news}}.$$

As previously discussed, all news stories on the same day are grouped into a composite news story, and we take the mean of $NegNet$ and Neg across same-day news articles as the content measures of the composite news. We use $NegNet$ as our primary news contents variable and use Neg mainly for robustness check. Following Tetlock et al. (2008), we also count the number of occurrences of the word root "earn" in each news story ($EarnFreq$) and use it as a proxy for more informative news. Presumably, a larger value of $EarnFreq$ is indicative of more contents related to firm fundamentals. Appendix A presents the definitions of all variables.

3.2 Sample Selection

Our sample is composed of data from four major datasets. The news sample is obtained from Factiva. Individual analysts' annual earnings forecasts and other related information are obtained from the I/B/E/S details file, and the data for firm financials and stock market variables are respectively from the Compustat and CRSP databases.

We construct the news sample using all firm-specific news articles for all U.S. firms obtained from the Top Sources in the Factiva database between January 1, 2000 and December 31, 2010.[10] We provide a brief discussion of the news database here; for detail explanations refer to Huang et al. (2014). We retrieve 2.2 million news stories from Factiva that contain at least fifty words in total and mention a company identity in the first twenty five words (Tetlock et al., 2008). To minimize false identification of news to a firm, a news article is assigned to a particular company only if it mentions the company's identity three or more times. If a news article mentions two or more company identities, it is assigned to the firm that has the highest frequency of company-identity mentions in the article provided that the frequency of mentions of the second highest firm is less than 90% of that of the highest firm. Otherwise, the news is excluded from the sample. Moreover, observations that cannot be matched with a Compustat GVKEY are excluded from the sample. After these sampling screens, there are about 1.7 million news articles left. We then carry out textual analysis to read qualitative information embedded in each news story using the key word list of Loughran and McDonald (2011). We extract information about the tone of news and whether the news contains certain word roots. To the best of our knowledge, our news database provides the widest cross-section of news articles used in textual analysis in the literature.

We follow Huang et al. (2014) in dealing with potentially repetitive news stories in the same day by different media sources. We treat all news stories on the same day as "composite" news by taking the mean of textual analysis output measures (to be elaborated subsequently) across those news articles.[11] This results in about 1.1 million composite news observations for 15,650 firms. We keep the time stamp and source of the first news in the day as the time stamp and source of the composite news. Different from Huang et al. (2014) who only use wired news, we keep both wired news and non-wired news such as news from newspapers and magazines, as our definition of event window (to be elaborated subsequently) does not hinge critically on the within-day time. Figure 1 shows source of the news stories in our sample and the proportion of news we obtain from these sources. We note that the top three sources of news in our sample are Business Wire, PR Newswire,

[10]The Top Sources of Factiva include five major categories covering more than 150 individual media sources: Dow Jones Newswire, Major News and Business Publications, Press Release Wires, Reuters Newswire and The Wall Street Journal.

[11]26% of the sample contains more than one news article for a single firm in a single day.

and Dow Jones, contributing respectively 30%, 26%, and 22% of the news. The next two major sources, the Associated Press and the Wall Street Journal contribute respectively 6% and 4% of the news in our sample. Other sources include major US newspapers (e.g., The New York Times), Reuters, and M2 Newswire, each contributing approximately two or three percent of the news in our sample.

We then intersect the news data to analyst earnings forecasts in I/B/E/S. We consider annual EPS forecasts, as this is the most common type of analyst forecasts. While in principle analysts can start issuing annual EPS forecast for a given firm-year a number of years in advance, we note that during our sample period of 2000–2010, 62% of annual EPS forecasts for a given fiscal year are issued after the firm announces earnings of the previous fiscal year. We therefore focus on current year EPS forecasts and forecast revisions for the period starting from the the previous year earnings announcement. This leaves us with a sample of 843,045 news stories for 6,652 distinct firms.[12] Since news and EPS forecasts are likely to be dominated by earnings announcement events, we also remove news articles and analyst forecast revisions within the [–3,+3] trading days window around quarterly and annual earnings announcements.[13] Doing so ameliorates the compounding effects of earnings announcements and allows us to sharpen our focus on the effects of news instead of major corporate events. We further remove (a) observations for which our main dependent variable, forecast revision scaled by fiscal year opening price, could not be calculated, (b) penny stocks (stocks with fiscal year opening price less than $1), and (c) observations with missing values for total assets and market value at the beginning of the fiscal year. The final sample contains 330,331 news stories, 276,088 EPS forecast revisions made by 7,851 unique analysts for 3,461 firms. Panel A of Table I details the sample selection process.

[Table I about here.]

Panel B of Table I provides the firm-year summary statistics for the final sample. For the average firm in our sample, there are on average 22 (median=15) news stories, 6 (median=4) analysts following the firm, and 12 (median=14) EPS forecast revisions in a fiscal year.

[12] The large drop in the number of news stories (from 1.1 million to 843,045) is mainly due to the requirement of firm EPS-forecast availability in I/B/E/S, and not due to restricting the sample to next-year EPS forecast and forecast revisions for the period starting from the current-year earnings announcement.

[13] Our results are robust to other exclusion windows such as [–5,+5] trading days.

3.3 Summary Statistics

Table II presents the summary statistics for the data. In general, the sample is consistent with prior research. The mean (median) revision duration is 0.1951 or 71 calender days (0.1562 or 57 calender days), and a vast majority (over 75%) of the analysts revise their forecasts within three months.[14] Roughly 60% of the forecast revision are downward and the mean (median) value of *Rev* is –0.2198 (–0.0560). Thus, the average analyst revises down his/her earnings forecast every two months by about –0.22 % (of *Price*). This is consistent with prior literature; for example, Richardson, Teoh, and Wysocki (2004) document that analysts tend to 'walk down' to beatable forecasts over the fiscal year. The average firm, for a given fiscal year, has total assets of $4B ($\approx$ exp(8.37)), 17 ($\approx$ exp(2.83)) following analysts with an average price scaled forecast dispersion of 1.1%, and roughly 5 ($\approx$ exp(1.57)) news stories. These descriptive statistics closely resemble Agarwal and Hess's (2012).

[Table II about here.]

Table III presents the Pearson correlation coefficients for the main regression variables. $NegNet$ is significantly and negatively correlated with both *Rev* and *RevUp* implying, consistent with Hypothesis 1, that more negative news contents lead to downward revision. More strict tests of the hypotheses are presented in the next sections.

[Table III about here.]

4 Empirical Results on the Responsiveness of Analysts to News

4.1 The Regression Model

This section tests H1 and H2. We generally test the hypotheses by regressing a measure of forecast revision on news measures and control variables. The regression models take the form:

$$\text{Revision Variable} = \alpha + \beta_1 NegNet + \Phi' \text{CONTROLS} + \epsilon \quad (1)$$

[14] Note that forecast revisions around earnings announcement dates are not included in our sample.

where the revision variable is either the change in earnings forecast Rev or the direction of revision $RevUp$, $NegNet$ is the average net negative tone of news stories released during the corresponding revision period, and CONTROLS is a vector of control variables, which we elaborate below.

The literature generally agrees that Equity analysts are important components of the firm information environment, and their decisions shape and are shaped by the overall information environment (Beyer et al., 2010). Therefore, we broadly include four types of control variables that may affect the information flow that the analyst receives and the analyst's interpretation of the information: i) the information environment of the firm being analyzed, ii) information arrival shocks, iii) peer moves, and iv) analyst properties and other news properties than the news tone. We illustrate these four types of control variables in order below.

The first type of control variables are related to the information environment. Firm information environment presumably affects the availability and quality of earnings signals are presumably a function of firm information environment. The firm's information environment is thus likely to play a role in whether and how financial news stories influence analysts' forecast revision decisions. For instance, if SEC filings provide sufficiently informative signal to produce EPS forecasts with acceptable accuracy level, analysts may not rely on other information sources such as public news stories. Therefore, we include proxies of firm information environment, namely firm size, analyst following, analysts' forecast dispersion, illiquidity, and idiosyncratic return volatility. Amihud and Mendelson (1986), Kim and Verrecchia (1994), Leuz and Verrecchia (2000), Landsman and Maydew (2002), Francis, LaFond, Olsson, and Schipper (2005a), Francis, Schipper, and Vincent (2005b), Zhang (2006), and Houston, Lev, and Tucker (2010) are among the prior work that treats one or more of these variables as proxies for firm information environment. We control for both short- and long-term components of firm information environment; specifically, we control for these measures over the revision period and also over the previous fiscal year. We use subscripts ST and LT to denote the revision period and the previous fiscal year, respectively; for example, $Dispersion_{ST}$ ($Dispersion_{LT}$) refers to analyst forecast dispersion in the revision period (previous fiscal year). Since firm size[15] and analyst following tend to be sticky, we control for these two variables only in the previous fiscal year.

[15]We use the logarithm of book assets to proxy for firm size instead of the usually used market capitalization, since our main dependent variable uses price as the scalar, which is directly proportional to market capitalization.

Our second type of control variables are related to information arrival shocks. We have already excluded forecasts around earnings announcements to minimize the confounding effects of quarterly earnings announcements. Extant literature has shown, however, that analysts' forecast revisions are significantly influenced by other information events such as dividend changes (Denis et al., 1994; Ely and Mande, 1996), management disclosures (Jennings, 1987; Baginski and Hassell, 1990; Williams, 1996), and major stock price changes (Conrad et al., 2006). Following Conrad et al. (2006), who treat price changes as proxies for major public information events, we use stock return variables as controls for the amalgamation of other information events. We include the first and second moments of stock returns, i.e., cumulative abnormal stock returns and idiosyncratic volatility during the revision period. Note that idiosyncratic volatility doubles as a proxy for firm's information environment—that is, firm's information arrivals are related to firm's information environment.

In our third type of control variables we include measures capturing moves by peer analysts and the positioning of the analyst's forecast relative to peers. Analysts may revise their estimates not due to news information but simply due to observed peer moves; for instance, Welch (2000) shows that analysts tend to herd. We control for the revision activity by other analysts using the variables *PeerRevision*, which is the average revision by other analysts during the revision period. Following Clement and Tse (2005), we also include *Boldness*, which is the distance between the analysts' initial forecast and the consensus forecast during the revision period. *Boldness* captures the positioning of the analyst relative to her peers.

Lastly, we control for analyst properties and other news properties than the news tone. The ability of an analyst to efficiently gather and process information may also influence whether and how the analyst responds to public news stories. Such efficiency may depend on experience (considered as a proxy for expertise) and time constraint. We use the general and firm-specific analyst experience (measured as the logarithm of number of years of experience) to control for experience, and the number of firms the analyst follows to control for time constraint (Clement, 1999). The nature of our research design also necessitates controlling for additional news properties. News does not arrive, and neither do analysts revise their forecasts, on a regular basis. Therefore, the number of news stories during the revision period varies, and the revision period associated with each revision varies in length. To make sure that the relationship between the tone of news and forecast revision is not an artifact of these elements, we control for the number of news stories during the revision period $NumNews$, and the length of the revision period $RevDur$.[16]

4.2 Do Equity Analysts Incorporate Public News into their Earnings Forecast Revisions?

To test Hypothesis 1, we estimate Equation (1) for the dependent variables Rev and $RevUp$. Table IV presents the results. We first discuss the results with Rev, which are presented in Columns (1)–(5). In Column (1), we regress Rev on $NegNet$ without any control variables; and in Columns (2)–(5) we sequentially add control variables of different types. Consistent with Hypothesis 1, the coefficient estimate of $NegNet$ is all highly significantly negative, with robust t-statistics in the range of -7 to -12. These results suggest that analysts react to the tone of public news stories during the revision period, and that forecast revision tends to be lower (higher) following a revision period dominated by negative (positive) news.

[Table IV about here.]

The coefficients on the control variables are also by and large consistent with expectations based on prior research. On firm's information environment control variables, we note that analyst revise more conservatively for firms that exhibit higher information asymmetry. This is evident from the positive coefficient of the number of analysts following the firm ($AnalystFollow$), and from the negative coefficients on $Dispersion_{ST}$, $Illiquidity_{ST}$, and $IdioVolatility_{ST}$. The only exception to the information environment results are that $Assets$ in Columns (3) to (5) loads negatively, and $Illiquidity_{LT}$ loads positively, which we note are merely due to the confounding effects of other information asymmetry controls.[17] Other noteworthy results on the control variables are that Rev is positively related to cumulative abnormal return (CAR), peer revisions, analyst's own forecast boldness, and negatively related to her general experience and the duration of the revision period. The positive coefficient of CAR is consistent with the hypothesis that stock price movements contain information relevant to analysts' EPS forecasts (e.g., Conrad et al., 2006). The

[16] A similar variable to $RevDur$ is used in Agarwal and Hess (2012) to capture the walk down effect in analysts' earnings forecasts reported in Richardson et al. (2004). An alternative, but highly correlated control variable for the walk down effect is the length of the time interval between the forecast date and the actual announcement date. Our results remain robust if we use this variable to replace $RevDur$.

[17] The correlation matrix in Table III shows that $Assets$ is positively and $Illiquidity_{LT}$ is negatively correlated with Rev. Indeed, absent the controls of $Illiquidity_{ST}$ and $IdioVolatility_{ST}$, $Assets$ would have loaded significantly positively and $Illiquidity_{LT}$ would have loaded significantly negatively, as expected. In untabulated results, we also construct a principal factor to capture firm's information environment; and we find that the principal-component results are consistent with the findings that analysts revise less for more information-asymmetric firms.

positive coefficient of peer revision suggests that forecasting activity by other analysts is one of the important factors in analysts' forecast revision decision, consistent with prior work that documents herding in analysts' earnings forecasts (Welch, 2000). This evidence is strengthened by the results for analyst's own forecast boldness—the positive coefficient on boldness suggests that analysts tend to converge to the consensus. Lastly, the negative coefficient on the revision duration is consistent with the walk-down effect.

In Columns (6) and (7) of Table IV, we perform logistic regression analyses using $RevUp$ as the dependent variable. Consistent with the results of Rev, $NegNet$ loads significantly negatively on $RevUp$. The signs of the control variables in Columns (6) and (7) are mostly consistent with earlier columns, although the signs within the group of information environment variables are not always consistent. Again, we note that this is due to the confounding effects of many similar variables—a principal factor of information environment variables would instead load consistently. Lastly, the negative coefficient on analyst's firm experience ($FEXP$) suggests that analysts with more firm specific experience are more likely to revise their forecasts downward, which in turn suggests that these analysts are more likely to have issued more optimistic initial forecasts compared to the average analyst.

In sum, the results in Table IV show that analysts' forecast revision are significantly influenced by the tone of public news articles in a manner consistent with Hypothesis 1. Moreover, since we control for a host of variables designed to capture information in firm characteristics, analyst attributes, and other analysts' and stock market activities, this evidence suggests public news stories provide incremental information to analysts.

4.3 Does News Content Matter?

To test $H2A$, we extend Regression (1) to include a measure of news content and interact this measure with $NegNet$. The regression model takes the following form:

$$\text{Revision Variable} = \alpha + \beta_1 NegNet + \beta_2 EarnFreq + \beta_3 (NegNet \times EarnFreq) + \Phi' \text{CONTROLS} + \epsilon \tag{2}$$

where $EarnFreq$, the frequency of the word root "earn" in the news story, is used as a proxy for the informativeness of the news. $EarnFreq$ measures the extent to which the news contains fundamental information related to earnings. The estimation results for Regression (2) are presented in Table V. Table V shows that the interaction term $NegNet \times EarnFreq$ loads consistently on both Rev and $RevUp$ with a negative coefficient, supporting $H2A$. Furthermore, while the coefficients on $NegNet$ in Table V is significantly negative in all of the columns, providing additional support the main effect hypothesis $H1$, we note that the magnitude of the coefficient on $NegNet$ there is smaller compared to the results in Table IV. These results indicate that while general public news significantly influences the forecast revision, news related to firm fundamentals has a more significant impact.

[Table V about here.]

The results for the control variables are similar to those of Table IV in the previous section. We use the last specification of each revision variable in Tables IV and V, which incorporates all the control variables, as a benchmark model to test the remaining hypotheses and perform additional regressions.

4.4 Do Analysts React More to Negative News?

To test $H2B$ that analysts' reaction to news is asymmetric towards negative news, we perform two tests. In the first test, we use the "pure" negative word ratio, Neg, in lieu of the $NegNet$ (the negative word ratio net of positive word ratio). Neg does not consider any positive word and is used in the extant literature as a content measure (e.g., Tetlock et al., 2008). The results in Panel A of Table VI confirm that the pure negative tone also affects analyst forecast revision.

[Table VI about here.]

Since both pure negative tone and the net negative tone affect analyst decision, the negative tone may asymmetrically drive analyst revision. To test this hypothesis, we create a dummy variable $NegDummy$ to flag news with $NegNet > 0$, i.e., news with a net negative tone. The asymmetric response to negative news, if any, would imply significant coefficient estimates on the interaction terms $NegNet \times NegDummy$ and $NegNet \times EarnFreq \times NegDummy$ in regressions of revision variables Rev and $RevUp$. Panel B of Table VI presents the results. We note that while the main effects $NegNet$ and $NegNet \times EarnFreq$ remain significantly negative, none of these

$NegDummy$-interaction terms is significant. These results indicate negative news, whether general or more related to firm fundamentals, does not asymmetrically affect analyst revisions. Thus, the evidence provided in Table VI does not seem to provide support for $H2B$. Different from what is implied in the literature (Chan, 2003; Tetlock, 2007; Tetlock et al., 2008), Table VI suggests that negative and positive news contents are, by and large, equally informative on shaping analysts' earnings revision decisions.

5 When do Analysts React more to News Contents?

We have established that analysts read the news in their earning forecasts and are more sensitive to fundamentals-related news. In this section we test $H3$ that analysts exhibit higher forecast responsiveness to news when information asymmetry of the underlying firm is higher ($H3A$), when the analyst is more experienced ($H3B$), and when the analyst has a higher degree of conflict of interest ($H3C$). We also include in this section a key robustness check to differentiate which type of news source has a higher impact on analysts.

5.1 Information Asymmetry and Analyst Experience

We begin by testing $H3A$ and $H3B$. Earlier our literature review suggested that analysts operate in an information environment consisting of the following key components: i) the information nature of the firm being analyzed, ii) information arrival shocks, and iii) the analyst's own traits. In line with $H3A$ and $H3B$, we now dissect analysts' cross-sectional news response along these dimensions. Our strategy involves partitioning the sample, each year, according to these dimensions, and examining whether the magnitude of revision, Rev, responds to new contents differently in the resulting sub-samples. While our results are generally robust to different group-partitioning, for ease of exposition we choose a binary group partition based on the median value, and we label the group with the larger value "$HiGroup$." We therefore augment our main Regressions (1) and (2) with the terms $NegNet \times HiGroup$ and/or $NegNet \times EarnFreq \times HiGroup$.

To examine the effect of the firm information environment, we construct a principal factor out of our menu of information environment measures of firm size, analyst following, analysts' forecast dispersion, illiquidity, and long-term idiosyncratic volatility, such that a higher value of the principal factor indicates poorer information. Panel A of Table VII shows that when Regression (1) is augmented with $NegNet \times HiGroup$, the coefficient estimate of $NegNet$ is smaller in magnitude as compared to Table IV, and the coefficient estimate of $NegNet \times HiGroup$ is significantly negative. Further, when Regression (2) is augmented with $NegNet \times HiGroup$ and $NegNet \times EarnFreq \times HiGroup$, the coefficient estimate of $NegNet \times EarnFreq \times HiGroup$ is significantly negative; and the significance of both $NegNet \times EarnFreq$ and $NegNet \times HiGroup$ is subsumed. In untabulated results, we can also report that individual components of the principal factor, such as analyst forecast dispersion and long-term idiosyncratic volatility, behave similarly with the principal factor. Collectively, these results indicate that i) analysts react more to news from firms with poorer information environment; and that ii) much of this reaction seems to be driven by the fundamental contents of the news. The evidence offers support to $H3A$.

[Table VII about here.]

Another way to test $H3A$ is to examine short-term information shocks. In Panel B of Table VII, we examine the effect of information arrival shocks using our earlier proxies of cumulative abnormal stock returns and short-term idiosyncratic volatility (i.e., idiosyncratic volatility during the revision period). The former indicates the direction, and the latter indicates the magnitude of the shocks. Panel B shows that the results of short-term idiosyncratic volatility are not different from those of the information-environment principal factor—which is not surprising because idiosyncratic volatility can also be thought of as a measure of information asymmetry. The interaction terms $NegNet \times HiGroup$ and $NegNet \times EarnFreq \times HiGroup$ do not load significantly on groups partitioned on cumulative abnormal stock returns. These results suggest that the magnitude instead of the direction of information shocks impacts how analysts read the news; and that analysts pay more attention to news when the covered firm experiences larger shocks. The results offer further support for $H3A$.

We test $H3B$ about analyst experience in Panel C of Table VII. We use both general industry experience and firm-specific experience as proxies for analyst expertise. $NegNet \times HiGroup$ load significantly negatively for both general experience and firm-specific experience, and $NegNet \times EarnFreq \times HiGroup$ loads negatively for analyst's general industry experience. These results suggest that analyst expertise translates into sensitivity towards news contents, supporting $H3B$.

In sum, we identify a number of instances where media reinforces analysts' revision decisions when reading the news. These instances include when the firm's information environment is more opaque, when the firm experiences larger short-term information shocks, and when analysts are more experienced. The degree of sensitivity of analysts to news is thus dependent on both the information asymmetry of the firm being analyzed and the analysts who are following the firm. In particular, when firm information asymmetry is larger and when analysts are more experienced, media would reinforce analysts' earnings-forecast revision decisions.

5.2 Conflict of Interest and Future Business Opportunities

We now turn to testing $H3C$ that analysts are more responsive to news when they face higher degrees of conflict of interest. Extant literature frequently measures the existence of conflict of interest using the existing relationship variable, for example, whether the analyst's employer served as lead underwriter or co-manager for the covered firm in the past three years (e.g., Bradshaw, Richardson, and Sloan, 2006). This measure, however, is backward-looking and captures only the past business relationships. Conflict of interest rests on continuing or potential business and personal gains; hence analysts are arguably more motivated by expected gains than by historical gains. Existing relationships lead to conflict of interest, to the extent that the analyst or her employer will continue to benefit from this relationship. Relative to historical relationship, the future potential benefits arising from either maintaining an existing relationship or winning a new one often result in higher levels of conflict of interest.

We employ a number of forward-looking measures of conflict of interest that are designed to capture potential future business opportunities. Our first measure for future business opportunities is a look-ahead version of the investment banking indicator of Bradshaw et al. (2006), namely, an indicator variable for whether the analyst's employer serves as lead underwriter or co-manager for the covered firm's equity or debt offerings in the *next* three years based on Thomson One Banker. This variable captures the realized future business relationship. Our second and third measures for future business opportunities relate to firm's potential needs for investment banking business. Bradshaw et al. (2006) document that analysts tend to issue more optimistic forecasts of earnings, stock recommendations, and target prices on firms with larger external financing needs, perhaps in hopes to win over business. We use two measures of external financing needs, namely Frank and Goyal's (2003) financing deficit measure and Bradshaw et al.'s (2006) financing need measure. Consistent with the investment-banking relationship indicator variable and also with Section 5.1, we use indicator variable for firms with above-median external financing needs. Our fourth measure is $PureBroker$, which takes the value of one if the brokerage house that employs the analyst is a pure broker that has no investment banking business.[18] The literature shows that pure brokers tend to issue more optimistic forecasts in order to generate trading business (Cowen, Groysberg, and Healy, 2006). For ease of exposition, we label these measures as a group of conflict of interest measures "CC." To test $H3C$, we augment our main Regressions (1) and (2) with the terms $NegNet \times CC$ and $NegNet \times EarnFreq \times CC$.

Table VIII presents the results. The first two columns of table VIII examine the impact of past and future investment banking relationships on analysts' responsiveness to news. $NegNet \times CC$ does not load significantly for past investment banking relationship. In contrast, $NegNet \times CC$ loads significantly for future investment banking relationship (Column two). These results suggest that analysts' responsiveness to news increases with potential (future) investment banking relationship but not with past investment banking relationship. This is consistent with our expectation that analysts' conflict of interest is stronger when it arises from business-to-be-won relative to business-already-won, and the stronger conflict of interest associated with potential future business increases analysts' responsiveness to news. The results in the remaining columns, based on other forward-looking measures of conflict of interest, further support the above interpretation. In Columns (3) and (4), $NegNet \times CC$ loads significantly for firm's potential financing needs; and in Column (5), $NegNet \times CC$ loads significantly for pure broker, indicating that analysts employed by pure broker firms respond to news more strongly. $NegNet \times EarnFreq \times CC$ generally does not load significantly, suggesting that conflicts of interest exist regardless of whether news is related to fundamentals or not. Overall, the results show that analysts react to news more strongly when they are motivated by conflicts of interest arising from potential future business opportunities.

[Table VIII about here.]

[18] We define a pure broker to be a broker that does not have underwriting business in Thomson One Banker during our sample period.

5.3 Does the News Source Matter?

Our news database contains a broad category of news including firm-initiated news (i.e., press releases by corporations) and press-initiated news. We do not so far differentiate between firm- and press-initiated news. It is, however, possible that the results we document in Tables IV and V are mainly driven by firm-initiated news, since news directly from the firm itself may contain more value-relevant information. If this is the case the information intermediary role of the business press, in the context of this study, may be limited to the dissemination of firm-initiated news. On the other hand, press-initiated news may also contribute to firms' information environment since it incrementally contains the media's analyses of the firm. We, therefore, perform the following to test if our results are mainly driven by firm-initiated news. Following Bushee et al. (2010), we classify all news released through Press Release Newswire, Business Wire and Federal Filings Newswire as firm-initiated news. Once we identified firm-initiated news, we create three variables to measure the extent to which a revision period is dominated by firm-initiated news stories. First, we create an indicator variable $InitialNewsFI$, which takes the value one when the first news story in a revision period is firm-initiated. Second, we create a variable $ProportionNewsFI$ that captures the proportion of firm-initiated news stories relative to all news stories during a revision period. Third, we create a variable $TotNumNewsFI$, which is the total number of firm-initiated news stories during a revision period. We then augment the main regression models (1) and (2) with these variables (one at a time) and their interactions with the other news variables.

The results are presented in Table IX. The first three columns present the results for augmented model (1) where we interact our main news variable $NegNet$ with the three news source variables above. The interaction of $NegNet$ with each of the news source variables is statistically insignificant in all of the three cases, while the coefficient on $NegNet$ remains negative and significant. These results indicate the influence of news content on analysts' EPS revision is not driven by firm-initiated news stories. The last three columns present the results for augmented model (2). In two out of the three cases, the interaction term $NegNet \times EarnFreq \times$ (the news source variable) has a significantly negative coefficient, suggesting that firm-initiated news stories with earnings-related content influence analysts' EPS forecast revisions to a greater extent compared to other types of news. Overall, Table IX suggests that our results are not driven by firm-initiated news stories; however, firm-initiated, earnings-related news stories may have larger effects on analysts' EPS forecast revisions than their press-initiated counterparts.

[Table IX about here.]

6 The Speed of Reaction to News and the Profitability of News-Driven Analyst Revisions

In this section, we examine stock returns following news-driven analyst revision, and link such returns to analysts' speed of reaction to news. Our earlier investigation (Table II) suggests that analysts probably do not react promptly to news. Although we showed that news drives forecast revision, the impact of the revision on returns, if any, should be smaller for news that is stale. In this section we empirically confirm this conjecture.

6.1 Returns on News-Driven Analyst Revisions

We first examine the return performance of analyst forecast revisions when the revisions are associated with news. Early research (e.g., Givoly and Lakonishok, 1979; Stickel, 1991; Francis and Soffer, 1997) investigates the association between analyst forecast revisions and stock returns around the revision date and finds a positive association, which is consistent with analysts' forecast revisions providing additional information to market participants. We run the following regressions of returns on analyst revisions for our sample of post-news analyst revisions:

$$\text{Abnormal Return} = \alpha + \beta_1 Rev + \Phi'\text{CONTROLS} + \epsilon \tag{3}$$

We use (cumulative) returns over the following horizons: days 0, 1, 2, and 3 to 5. Specifically, we collect the within-day time stamp of each analyst forecast and match it to trading hours. Day-0 return is the return on the same trading day as the forecast announcement.[19] We then adjust

[19] We use the time stamp on the forecast announcement to determine the trading day that the forecast belongs to. If the forecast is announced before-market (after-market including holidays), day-0 return refers to the return of the stock on the same (next) trading day. We treat forecasts announced in the middle of the trading hours as before-market, assuming that pre-announcement daily returns are due to market risks and therefore contain no abnormal return. In our sample 19.9% (9.9%) of analyst revisions are released in the hours of 12:00 (14:00) to 15:59. Removing these observations does not affect our conclusions.

returns by the Fama-French three-factor risks, namely, market, size, and book to market, where we calculate factor betas from the past one year daily stock returns. The control variables include: i) firm attributes of return momentum (cumulative abnormal return during the revision period), Amihud illiquidity, idiosyncratic volatility, and total assets; ii) analyst characteristics of revision duration, analyst forecast dispersion, number of following analysts, and the analyst's own revision boldness; and iii) news intensity during the revision period (number of news stories).

Table X presents the results. In line with prior research, *Rev* is significantly positively associated with abnormal returns on the day of the revision and the first two days subsequent to the revision. The association between abnormal returns and analyst forecast revision is insignificant when we measure abnormal return over the three to five days interval subsequent to the revision date.

[Table X about here.]

6.2 Speed of Reaction to News, News Staleness, and Returns on News-Driven Analyst Revision

Lastly, we examine analysts' speed of reaction to news and the profitability of the news-driven analyst EPS revisions. Earlier Table II shows that analysts on average wait, *between revision periods*, on five news stories in 71 calendar days to issue a new forecast. To give a more accurate picture of how fast analysts respond to news, we now measure analysts' reaction in trading days. Given that the revision period often has multiple news days, we use two measures for the speed of reaction: i) the distance, in trading days, between the first news in the revision period and the analyst revision date ($Rev2FirstNews$); and ii) the average trading days between all of the news days in the revision period and the analyst revision date ($Rev2News$). Panel A of Table XI presents the distribution of these two measures. The medians of $Rev2FirstNews$ and $Rev2News$ are, respectively, 27 and 18 days; and their means are, respectively, 38 and 25 days. In other words, on average it takes more than a month (of calendar time) for analyst to issue a new EPS forecast in response to news. The 10^{th} percentile of $Rev2FirstNews$ ($Rev2News$) is 5 (4), or a week (close to a week) of calendar time. The fifth percentile of both measures is 2. With the speed of market reaction to general news being fast—for example, Tetlock et al. (2008) document only one-day return to negative news tone on S&P 500 firms—it appears reasonable to treat news with an age of one week and above as stale. We therefore use the fifth percentile of $Rev2FirstNews$

and $Rev2News$ as a cutoff for news being "fresh," labeled by the dummy variable $Fresh$.

[Table XI about here.]

We interact news staleness with returns on news-driven analyst revisions. Analyst revision presumably reinforces (weakens) media news if the pair are in the same (opposite) direction. Consequently, the relation between analyst revision and return that we documented in Table X could be subject to whether the analyst issues a news-conforming forecast. The following parsimonious partition of news and analyst revision illustrates this point:

	Relatively good revision	Relatively bad revision
Relatively bad news	Quadrant 1: Return relation weakened	Quadrant 2: Return relation reinforced
Relatively good news	Quadrant 3: Return relation reinforced	Quadrant 4: Return relation weakened

As illustrated, the return relation between news contents and analyst revision is likely more pronounced in Quadrants 2 and 3. Accordingly, we partition the sample by the median value of $NegNet$ and the median value of Rev, and create a dummy variable, $Q23\_dummy$, that equals one if the observation falls into either Quadrant 2 or Quadrant 3 of the above partition. We then augment the return regressions Equation (3) with the news tone variables $NegNet$, the interaction term $Rev \times Q23\_dummy$ to introduce the interactive effect of news tone and analyst reaction, and the triple interaction term $Rev \times Q23\_dummy \times Fresh$ to examine whether the interactive effect of $Rev \times Q23\_dummy$ is driven by news freshness.

Panels B and C of Table XI present the results for $Fresh$ variable defined on, respectively, $Rev2FirstNews$ and $Rev2News$. We make two observations. First, the interaction term $Rev \times Q23\_dummy$ is negatively significant in predicting abnormal returns of days 0 and 1. Thus somewhat surprisingly, instead of reinforcing the positive return association between revision and returns, making a news tone-consistent revision would instead tamper the positive return reactions. However, our second observation—news staleness—would explain this seemingly puzzle observation. There, the triple interaction term, $Rev \times Q23\_dummy \times Fresh$, loads significantly positively on returns of days 0, 1, and 2, suggesting that when news is fresh, analyst writing a news-conforming revision would compound the return effects of the revision. Otherwise, when news is stale and loses its timeliness, analyst writing a news-conforming revision would only weaken the revision effect on returns—which explains the positive sign of $Rev \times Q23\_dummy$. In addition, the magnitude of the coefficient estimate of $Rev \times Q23\_dummy \times Fresh$ is much larger than that of $Rev \times Q23\_dummy$.

Aggregating these two coefficients will give a measure of the net effect of revision-on-fresh-news on stock returns—in untabulated results, we confirm that the sum of these two coefficients is indeed significantly positive.

To further confirm the news staleness argument, we find that as we loosen the freshness cutoff to higher percentiles of $Rev2FirstNews$ or $Rev2News$, the magnitude and significance of $Rev \times Q23\_dummy \times Fresh$ are weakened. For example, in untabulated results, if we define $Fresh$ using the 25th percentile cutoff, $Rev \times Q23\_dummy \times Fresh$ is no longer significant in predicting days 0 and 1 returns. In sum, the return results in this section demonstrate that when an analyst updates her forecast on "fresh" news, the subsequent return reaction of the stock is reinforced; however, when the analyst updates her forecast on stale news, the staleness of the news will discount the analyst's own revision and reduce the subsequent return reaction of the stock.

7 Conclusions

Business media and sell-side equity analysts are two major types of information intermediaries in the capital market. This study provides a general test of the informational roles of business media on analysts. We match a comprehensive sample of financial news on U.S. firms from major news sources with individual analysts' earnings forecasts for the sample period 2000 to 2010, and examine whether and how the directions and magnitudes of analysts' earnings forecast revisions are associated with the tone of previously-released financial news. Different from extant literature that emphasizes specific information events, our sample distinctly features general news stories originating from an exhaustive list of major news sources and directly measures the overall supply of firm-specific public information. We further remove news around earnings announcement periods and control for firms' information environment and information shocks. Our study thus highlights the general information roles of financial news contents in shaping and driving analysts' EPS forecast revisions.

Our overall conclusions are that news incrementally drives analyst forecast revisions. We find that both the direction and magnitude of forecast revision are positively associated with the tone of the news. The association between the news tone and forecast revision is stronger when i) the news contains earnings-related fundamental content, ii) the information asymmetry of the underlying firm is higher, iii) the analyst is more experienced, and iv) the analyst possesses a higher degree of conflict of interest looking forward. That analysts are more sensitive to news under these circumstances supports the notion that analysts treat news as a consumption goods; that is, the marginal benefits of the goods (news) increase when the consumer (the analyst) or the goods (news) is more price-sensitive. We therefore conclude that the general supply of firm-specific information influences analysts' earnings forecast revisions. Our results suggest that financial news contains relevant information that affects decisions by one of, if not the most, sophisticated capital market participants.

We also examine stock returns following news-driven analyst revisions. Despite analysts' reaction to news, they generally respond to news with significant time lapse, and thus, most analyst revisions are written on stale news. We find that revision positively predicts returns; however, the positive association between revision and returns is reinforced only when analysts react to news in a very timely manner. Otherwise, when analysts write the revisions on stale news, the market reaction is much less favorable.

A Variable Descriptions

Variable	Description
Main Variables	
Rev	Analyst EPS forecast revision, defined as the difference between the revised and the previous EPS forecasts for a given fiscal year end scaled by stock price at the beginning of the fiscal year.
$RevUp$	An indicator variable for a upward revision, which equals one if the revised EPS forecast is greater than the previous EPS forecasts and zero otherwise.
$NegNet$	The proportion of total negative words count, net of total positive words count, relative to the total number of words in a news report, averaged over all the firm-specific news stories released during the revision period. We use the negative and positive word list from Loughran and McDonald (2011).
Neg	The proportion of total negative words count relative to the total number of words in a news report, averaged over all the news stories released during the revision period.
$EarnFreq$	The proportion of the word root "earn" relative to the total number of words in a news report, averaged over all the news stories released during the revision period.
Control Variables	
$AnalystFollow$	The logarithm of the number of analysts following the firm during the previous fiscal year.
$Assets$	The logarithm of the total assets at the beginning of the current fiscal year.
$Boldness$	The difference between the median estimate (consensus) and the analysts' initial forecast (outstanding forecast prior to revision) scaled by price at the beginning of fiscal year.
CAR	Cumulative abnormal stock return during the revision period.
$Dispersion_{ST}$	The standard deviation of analysts' EPS forecasts, for a given firm, issued during the revision period.
$Dispersion_{LT}$	The standard deviation of analysts' EPS forecasts, for a given firm, for the previous fiscal year.
$FollowFirms$	The number of firms an analyst covers, measured during the previous fiscal year.
$GEXP$	General analyst experience, defined as the difference between the revision date and the date of the first EPS forecast in IBES issued by the same analyst, expressed in log years.
$FEXP$	Firm-specific analyst experience, defined as the difference between the revision date and the date of the first EPS forecast in IBES for the same firm issued by the same analyst, expressed in log years.
$Horizon$	EPS Forecast horizon, defined as the difference between the actual announcement date and the revision date scaled by 365.
$IdioVolatility_{ST}$	Idiosyncratic stock price volatility during the revision period.
$IdioVolatility_{LT}$	Idiosyncratic stock price volatility during the previous fiscal year.
$Illiquidity_{ST}$	Amihud's (2002) illiquidity measure over the revision period
$Illiquidity_{LT}$	Amihud's (2002) illiquidity measure over the previous fiscal year.
$NumEst$	The total number of EPS forecasts issued for a given firm during the revision period scaled by the total number of EPS forecasts issued for the same firm during the previous fiscal year.
$NumNews$	The total number of news stories assigned to a given firm during the revision period scaled by the total number of news stories assigned to the same firm during the previous fiscal year.

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Variable	Description
$PeerRevision$	The average of forecast revisions (Rev) issued during the revision period by other analysts following the same firm.
$Price$	The stock price at the beginning of the fiscal year.
$RevDur$	The length of the revision period (in days) scaled by 365.
	Other Variables Used in Additional Analysis
$InitialNewsFI$	An indicator variable, which equals one when the first news during a revision period is firm-initiated. We classify news from Press Release Newswire, Business Wire, or Federal Filings Newswire as firm-initiated.
$ProportionNewsFI$	The proportion of firm-initiated news stories during the revision period relative to the total number of news stories assigned to the same firm during the revision period.
$TotNumNewsFI$	The total number of firm-initiated news stories assigned to the same firm during the revision period.
$NegDummy$	An indicator variable for news with negative net tone, which equals one when $NegNet > 0$.
$PastIBRelation$	An indicator variable that equals one if the analyst's employer serves as lead underwriter or co-manager for the covered firm's equity or debt offerings in the past three years based on Thomson One Banker.
$FutureIBRelation$	An indicator variable that equals one if the analyst's employer serves as lead underwriter or co-manager for the covered firm's equity or debt offerings in the next three years based on Thomson One Banker.
$FinancingDeficitFG$	Frank and Goyal (2003) financing deficit measure: cash dividend + change in net working capital + investments – internal cash flow.
$FinancingDeficitBRS$	Bradshaw et al. (2006) financing needs measure: change in equity (net sale of common and preferred stock minus cash dividend) plus change in debt (net long-term debt issuance minus current debt changes).
$PureBroker$	An indicator variable which equals one if the brokerage house that employs the analyst is a pure broker that has no investment banking business.
$AR[i]$	Abnormal Return for a given firm on the i^{th} day relative to the revision date.
$AR[i,j]$	Abnormal Return for a given firm for the $[i,j]$ days window relative to the revision date.
$Rev2FirstNews$	The number of trading days between the first news in the revision period and the EPS forecast revision date.
$Rev2News$	The average number of trading days between all of the news days in the revision period and the EPS forecast revision date.
$Q23\_Dummy$	An indicator variable that equals one when a relatively bad EPS forecast revision is released subsequent to relatively bad news or a relatively good EPS forecast revision is released subsequent to relatively good news.

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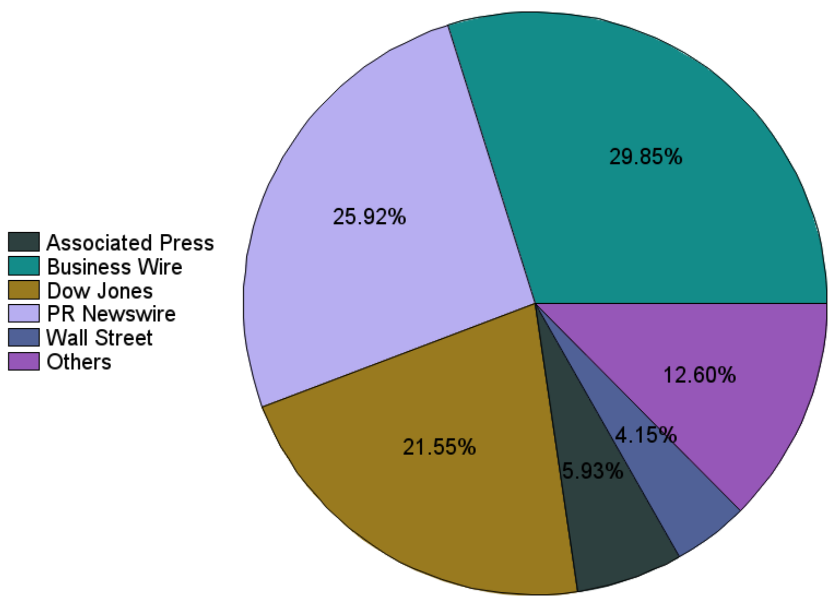
Figure 1: Media Sources of the News



This figure presents the frequency of news from the following news sources: Dow Jones Archive Newswire ("Dow Jones"), Press Release Newswire ("Press Release"), Business Newswire, Associated Press Newswire ("Associated Press"), the Wall Street Journal, and all other sources ("Others"). The category "Others" includes media sources such as Reuters (2.1%) and major US newspapers (2.8%).

Table I: **Sample Selection**

Panel A: Sample Selection Process

		Number of distinct news articles	Number of firms	Number of analysts	Number of analyst forecasts
(1)	Initial news dataset	1,142,114	15,650		
(2)	Firms with analyst forecast data in I/B/E/S unadjusted details file with forecast dates between Jan 01, 2000 and Dec 31, 2010 [a,b]	846,250	6,752	10,461	1,580,680
(3)	Remove analyst forecasts released prior to the announcement of earnings for the previous fiscal year [c]	843,045	6,652	10,412	986,189
(4)	Remove news stories and forecasts released within [-3,+3] trading days around quarterly earnings announcements	472,708	6,360	9,711	411,634
(5)	Remove observations for which the main dependent variable, forecast revision scaled by fiscal year opening price, could not be calculated	332,003	3,476	7,861	276,725
(6)	Remove observations for which the fiscal year opening price is either missing or lower than $1	330,386	3,462	7,852	276,118
(7)	Remove observations with missing values for total assets and market value at the beginning of the fiscal year	330,331	3,461	7,851	276,088

Panel B: Descriptive Statistics (Per Firm-year)

			Percentiles		
	Mean	**Std**	**25**	**50**	**75**
Number of distinct news articles	21.72	24.39	7	15	26
Number of following analysts	6.11	6.16	2	4	8
Number of analyst forecasts	12.84	19.90	2	6	14
Total number of firm-year observations	21,508				

[a] We also remove analyst forecasts when there appears to be a data entry error, e.g., analyst forecasts with announcement date after the actual announcement date.

[b] While we initially obtain forecasts and actuals earnings values from the unadjusted IBES details file, we adjust these variables (and other variables measured at per share basis) for subsequent stock splits and dividends using CRSP daily cumulative adjustment factor. The adjustment aligns all per share variables to be on the basis of shares outstanding as at the end of our sample period (Dec 31, 2010).

[c] This step limits the sample to forecasts of earnings for the current fiscal year that are issued subsequent to the annual earnings announcement date of the previous fiscal year. This is equivalent to restricting the sample to forecasts when IBES fiscal period indicator (FPI) equals 1. Note that this filter does not affect the news sample with the following exception. If all analyst forecasts for a given firm-year are issued prior to the announcement of earnings for the previous fiscal year (IBES FPI = 2), andt there are no forecasts issued subsequent to the announcement of earnings for the previous fiscal year (IBES FPI=1), this filter will remove the entire firm-year. This leads to removal of the associated news stories for that specific firm-year.

Table II: **Summary Statistics - Regression Variables**

	Mean	**StD**	**Min**	**P1**	**P25**	**P50**	**P75**	**P99**	**Max**
Rev	-0.2198	1.3885	-7.5515	-7.5515	-0.3865	-0.0560	0.1595	4.5	4.5
$RevUp$	0.4224	0.4939	0	0	0	0	1	1	1
$NegNet$	0.0018	0.0118	-0.0255	-0.0255	-0.0053	0.0000	0.0075	0.0414	0.0414
Neg	0.0106	0.0094	0	0	0.0039	0.0082	0.0148	0.0463	0.0463
$EarnFreq$	2.3574	4.2606	0.0000	0.0000	0.0000	0.6667	3	25	25
$Assets$	8.3737	1.9509	0.4737	4.0284	7.0154	8.3170	9.6805	13.1832	14.9357
$AnalystFollow$	2.8283	0.5992	1.0986	1.0986	2.4849	2.9444	3.2581	3.8712	3.8712
$Dispersion_{LT}$	0.0111	0.0174	0.0004	0.0004	0.0025	0.0054	0.0120	0.1202	0.1202
$Dispersion_{ST}$	0.0059	0.0162	0.0000	0.0000	0.0007	0.0022	0.0058	0.0593	1.3591
$Illiquidity_{LT}$	0.0951	0.3372	0.0004	0.0004	0.0052	0.0140	0.0457	2.7805	2.7805
$Illiquidity_{ST}$	0.0615	0.1898	0.0003	0.0003	0.0042	0.0115	0.0362	1.4888	1.4888
$IdioVolatility_{LT}$	0.0238	0.0123	0.0073	0.0073	0.0150	0.0208	0.0295	0.0682	0.0682
$IdioVolatility_{ST}$	0.0294	0.0189	0.0076	0.0076	0.0167	0.0240	0.0357	0.1084	0.1084
CAR	0.0013	0.1993	-0.5611	-0.5611	-0.0997	0.0035	0.1000	0.6781	0.6781
$PeerRevision$	-0.1928	1.0106	-5.5411	-5.5411	-0.3163	-0.01548	0.1044	2.9429	2.9429
$Boldness$	-0.1349	1.2384	-6.3551	-6.3551	-0.2861	0.0000	0.1290	4.6154	4.6154
$GEXP$	1.5797	1.0226	-1.5958	-1.5958	1.0227	1.7493	2.3192	3.2335	3.2335
$FEXP$	0.7166	1.2030	-2.6041	-2.6041	-0.0306	0.8442	1.6012	2.9619	2.9619
$FollowFirms$	10	8	1	1	4	9	14	36	70
$NumNews$	1.5723	0.7913	0.6931	0.6931	0.6931	1.3863	2.0794	3.8501	3.8501
$RevDur$	0.1951	0.1636	0.0110	0.0110	0.0932	0.1562	0.2301	0.9616	0.9616
Observations	276,088								

This table presents the summary statistics of all variables considered in this study. Detailed variable definitions are provided in Appendix A. The "P" in the column headings stands for "Percentile", e.g., P1 stands for the first percentile.

Table III: **Correlation Matrix - Main Regression Variables**

		(1)	(2)	(3)	(4)	(5)	(7)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	Rev	1												
(2)	$RevUp$	0.495*	1											
(3)	$NegNet$	-0.053*	-0.060*	1										
(4)	Neg	-0.064*	-0.061*	0.861*	1									
(5)	$EarnFreq$	-0.022*	-0.004*	0.055*	0.084*	1								
(6)	$Assets$	0.029*	0.009*	0.182*	0.196*	0.161*	1							
(7)	$AnalystFollow$	0.071*	0.037*	0.080*	0.106*	0.083*	0.496*	1						
(9)	$Dispersion_{LT}$	-0.057*	0.033*	0.017*	0.005*	-0.090*	-0.051*	-0.127*	1					
(9)	$Dispersion_{ST}$	-0.109*	0.001	0.028*	0.027*	-0.038*	0.010*	-0.015*	0.421*	1				
(10)	$Illiquidity_{LT}$	-0.035*	-0.007*	-0.053*	-0.069*	-0.037*	-0.319*	-0.435*	0.065*	0.012*	1			
(11)	$Illiquidity_{ST}$	-0.075*	-0.037*	-0.053*	-0.066*	-0.040*	-0.337*	-0.455*	0.043*	0.006*	0.810*	1		
(12)	$IdioVolatility_{LT}$	-0.084*	-0.009*	-0.065*	-0.046*	-0.081*	-0.414*	-0.141*	0.393*	0.258*	0.180*	0.152*	1	
(13)	$IdioVolatility_{ST}$	-0.184*	-0.164*	-0.002	0.023*	-0.075*	-0.229*	-0.084*	0.139*	0.200*	0.052*	0.102*	0.440*	1
(14)	CAR	0.237*	0.308*	-0.025*	-0.042*	0.021*	0.002	-0.025*	0.041*	0.038*	0.033*	0.001	0.029*	-0.210*
(15)	$PeerRevision$	0.468*	0.286*	-0.070*	-0.083*	0.005*	0.009*	0.048*	-0.059*	-0.154*	-0.002	-0.037*	-0.105*	-0.233*
(16)	$Boldness$	0.545*	0.298*	-0.038*	-0.045*	-0.021*	0.007*	0.028*	-0.036*	-0.082*	-0.004	-0.023*	-0.057*	-0.122*
(17)	$GEXP$	-0.009*	-0.014*	0.007*	0.014*	0.047*	0.091*	0.023*	-0.016*	-0.006*	-0.038*	-0.026*	-0.060*	-0.035*
(18)	$FEXP$	-0.006*	-0.010*	0.036*	0.044*	0.079*	0.186*	0.119*	-0.023*	-0.010*	-0.081*	-0.056*	-0.125*	-0.080*
(19)	$FollowFirms$	0.017*	0.002	0.035*	-0.036*	-0.024*	0.122*	-0.003	0.060*	0.042*	0.021*	0.022*	-0.067*	-0.037*
(20)	$NumNews$	-0.025*	-0.004*	0.057*	0.130*	0.504*	0.342*	0.259*	-0.036*	0.031*	-0.127*	-0.134*	-0.088*	-0.073*
(21)	$RevDur$	-0.059*	-0.009*	-0.041*	-0.032*	0.430*	-0.085*	-0.163*	-0.048*	-0.008*	0.103*	0.132*	-0.018*	-0.083*

		(14)	(17)	(17)	(18)	(19)	(20)	(21)
(15)	$PeerRevision$	0.175*						
(16)	$Boldness$	0.141*	1					
(17)	$GEXP$	0.007*	-0.013*	1				
(18)	$FEXP$	0.013*	-0.009*	0.632*	1			
(19)	$FollowFirms$	0.023*	-0.005*	0.200*	0.127*	1		
(20)	$NumNews$	-0.004*	-0.023*	0.059*	0.116*	-0.054*	1	
(21)	$RevDur$	0.067*	-0.036*	0.053*	0.083*	0.007*	0.433*	1

This table provides the Pearson correlation coefficients for the main regression variables. Detailed variable definitions are provided in Appendix A. * indicates significance at 5% level.

Table IV: **Corporate News and Analyst Forecast Revision**

Dep. Var.	(1) *Rev*	(2) *Rev*	(3) *Rev*	(4) *Rev*	(5) *Rev*	(6) *RevUp*	(7) *RevUp*
$NegNet$	-8.373***	-8.127***	-5.440***	-2.062***	-2.135***	-9.66***	-9.75***
	(-11.79)	(-9.26)	(-10.40)	(-7.46)	(-7.34)	(-6.50)	(-6.41)
$Assets$		0.005	-0.025**	-0.010*	-0.013*	0.016	0.0086
		(0.81)	(-2.00)	(-1.85)	(-1.92)	(1.12)	(0.62)
$AnalystFollow$		0.071***	0.093***	0.054***	0.046***	0.0050**	0.0043**
		(3.07)	(4.21)	(4.39)	(4.03)	(2.42)	(2.09)
$Dispersion_{LT}$		-1.699	-0.265	-0.883	-1.036	1.48	1.33
		(-1.19)	(-0.22)	(-1.15)	(-1.31)	(0.85)	(0.78)
$Dispersion_{ST}$		-8.044***	-7.055**	-2.272*	-2.094	3.28***	3.39***
		(-2.66)	(-2.42)	(-1.72)	(-1.60)	(3.78)	(3.94)
$Illiquidity_{LT}$		0.417***	0.296***	0.164***	0.152***	0.21***	0.20***
		(5.10)	(6.94)	(4.03)	(3.74)	(3.22)	(3.15)
$Illiquidity_{ST}$		-0.956***	-0.816***	-0.590***	-0.545***	-0.40***	-0.36***
		(-6.79)	(-9.17)	(-6.98)	(-6.82)	(-4.37)	(-4.40)
$IdioVolatility_{LT}$			-2.656	-1.593	-1.710	9.23***	8.93***
			(-0.80)	(-0.89)	(-0.89)	(5.64)	(5.21)
$IdioVolatility_{ST}$			-8.108***	-2.251*	-2.585**	-12.6***	-12.9***
			(-2.73)	(-1.79)	(-2.21)	(-5.21)	(-5.46)
CAR			1.570***	0.945***	0.970***	3.30***	3.34***
			(15.35)	(8.71)	(8.17)	(14.67)	(14.23)
$PeerRevision$				0.344***	0.346***	0.74***	0.74***
				(24.11)	(23.72)	(5.71)	(5.70)
$Boldness$				0.462***	0.459***	0.77***	0.77***
				(21.60)	(21.11)	(5.32)	(5.30)
$GEXP$				-0.007*	-0.008**	-0.0028	-0.0029
				(-1.91)	(-2.09)	(-0.22)	(-0.23)
$FEXP$				0.002	0.004	-0.036***	-0.034***
				(0.28)	(0.74)	(-2.86)	(-2.71)
$FollowFirms$				0.002	0.002	0.0023	0.0023
				(1.42)	(1.55)	(1.32)	(1.38)
$NumNews$					0.001		0.029
					(0.24)		(1.52)
$RevDur$					-0.453***		-0.42**
					(-3.26)		(-2.54)
Constant	-0.175**	-0.384***	0.287	0.031	0.156	-0.52***	-0.40***
	(-1.98)	(-3.41)	(1.34)	(0.32)	(1.25)	(-3.26)	(-2.95)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276,088	211,684	211,681	203,624	203,624	203,624	203,624
Adjusted/Pseudo R^2	0.027	0.047	0.110	0.405	0.408	0.210	0.210

This table reports the regression results testing whether analysts revise their earnings forecasts in reaction to firm-specific news stories, Hypothesis 1. The regression model takes the form

$$\text{Revision Variable} = \alpha + \beta_1 NegNet + \Phi' \text{CONTROLS} + \epsilon$$

where the dependent variable is either *Rev* or *RevUp*. *Rev* is forecast revision (i.e. change in EPS estimate) scaled by the stock price at the beginning of the fiscal year. *RevUp* is an indicator variable for an upward revision, which equals one if *Rev* is greater than zero. $NegNet$ measures the net proportion of negative words in the news stories released during the revision period. Detailed definitions of all variables are provided in appendix A. We estimate a probit model when the dependent variable is *RevUp*. The industry classifications for the fixed effects are based on two-digit SIC code. All standard errors are clustered by analyst and year. t-stats are in parentheses. *** , **, and * indicate significance at the 1%, 5% and 10% levels respectively.

Table V: **The Effect of News Informativeness**

Dep. Var.	(1) *Rev*	(2) *Rev*	(3) *Rev*	(4) *Rev*	(5) *Rev*	(6) *RevUp*	(7) *RevUp*
$NegNet$	-6.674***	-6.637***	-4.509***	-1.706***	-1.765***	-6.99***	-7.05***
	(-10.03)	(-7.83)	(-9.69)	(-5.38)	(-5.64)	(-5.11)	(-5.06)
$EarnFreq$	-0.003	-0.007	-0.010**	-0.008***	0.001	0.0032	0.010***
	(-0.66)	(-1.45)	(-2.38)	(-2.82)	(1.03)	(1.05)	(4.31)
$NegNet \times EarnFreq$	-0.933***	-0.825***	-0.489***	-0.169**	-0.216***	-1.60***	-1.64***
	(-8.85)	(-8.00)	(-3.24)	(-2.09)	(-2.83)	(-13.04)	(-13.19)
$Assets$		0.010	-0.019*	-0.006	-0.013*	0.019	0.011
		(1.40)	(-1.68)	(-1.32)	(-1.87)	(1.30)	(0.77)
$AnalystFollow$		0.073***	0.096***	0.056***	0.046***	0.0049**	0.0041**
		(3.13)	(4.35)	(4.53)	(4.00)	(2.33)	(2.03)
$Dispersion_{LT}$		-1.749	-0.343	-0.940	-1.032	1.53	1.41
		(-1.19)	(-0.28)	(-1.20)	(-1.31)	(0.88)	(0.82)
$Dispersion_{ST}$		-8.004***	-7.006**	-2.240*	-2.098	3.23***	3.37***
		(-2.65)	(-2.41)	(-1.69)	(-1.61)	(3.71)	(3.92)
$Illiquidity_{LT}$		0.416***	0.296***	0.164***	0.152***	0.21***	0.20***
		(5.10)	(6.97)	(4.03)	(3.74)	(3.21)	(3.14)
$Illiquidity_{ST}$		-0.948***	-0.808***	-0.585***	-0.544***	-0.40***	-0.35***
		(-6.86)	(-9.30)	(-7.05)	(-6.81)	(-4.29)	(-4.31)
$IdioVolatility_{LT}$			-2.757	-1.678	-1.680	9.45***	9.25***
			(-0.81)	(-0.91)	(-0.87)	(6.00)	(5.68)
$IdioVolatility_{ST}$			-8.071***	-2.240*	-2.573**	-12.5***	-12.8***
			(-2.75)	(-1.81)	(-2.20)	(-5.16)	(-5.47)
CAR			1.575***	0.950***	0.969***	3.30***	3.34***
			(15.29)	(8.69)	(8.14)	(14.64)	(14.26)
$PeerRevision$				0.344***	0.346***	0.73***	0.73***
				(24.22)	(23.80)	(5.74)	(5.72)
$Boldness$				0.461***	0.459***	0.77***	0.77***
				(21.58)	(21.12)	(5.32)	(5.31)
$GEXP$				-0.007*	-0.008**	-0.0032	-0.0037
				(-1.77)	(-2.10)	(-0.25)	(-0.29)
$FEXP$				0.002	0.005	-0.036***	-0.034***
				(0.35)	(0.75)	(-2.86)	(-2.71)
$FirmsFollow$				0.002	0.002	0.0023	0.0024
				(1.44)	(1.55)	(1.33)	(1.40)
$NumNews$					0.001		0.018
					(0.17)		(0.89)
$RevDur$					-0.457***		-0.49***
					(-3.35)		(-2.93)
Constant	-0.176**	-0.428***	0.239	0.001	0.153	-0.55***	-0.41***
	(-2.01)	(-3.57)	(1.15)	(0.01)	(1.23)	(-3.36)	(-2.95)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276,088	211,684	211,681	203,624	203,624	203,624	203,624
Adjusted/Pseudo R^2	0.028	0.048	0.111	0.406	0.408	0.210	0.210

This table reports the regression results testing the first part of the second hypothesis (*H2A*), whether analysts differentiate between core and non-core news. The regression model takes the form

$$\text{Revision Variable} = \alpha + \beta_1 NegNet + \beta_2 EarnFreq + \beta_3 (NegNet \times EarnFreq) + \Phi' \text{CONTROLS} + \epsilon$$

where the dependent variable is either Rev or $RevUp$. Rev is forecast revision (i.e. change in EPS estimate) scaled by the stock price at the beginning of the fiscal year. Rev is forecast revision (i.e. change in EPS estimate) scaled by the stock price at the beginning of the fiscal year. $RevUp$ is an indicator variable for a upward revision, which equals one if Rev is greater than zero. $NegNet$ measures the net proportion of negative words in the news stories released during the revision period. $EarnFreq$ is the number of times the word root "earn" appears in the news, averaged over news stories released during the revision period. Detailed definition of all variables are provided in appendix A. We estimates a probit model when the dependent variable is $RevUp$. The industry classifications for the fixed effects are based on two-digit SIC code. All standard errors are clustered by analyst and year. t-stats are in parentheses. *** , **, and * indicate significance at the 1%, 5% and 10% levels respectively.

Table VI: **Does Negative News Asymmetrically Affect Analyst Decision?**

Panel A: Neg Ratio

Dep. Var.	(1) Rev	(2) Rev	(3) RevUp	(4) RevUp
Neg	-2.66***	-2.24***	-8.66***	-6.14***
	(-7.24)	(-6.15)	(-5.30)	(-3.90)
$EarnFreq$		0.0033**		0.0065*
		(1.97)		(1.80)
$Neg \times EarnFreq$		-0.26*		-1.49***
		(-1.83)		(-16.08)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	203,624	203,624	203,624	203,624
Adjusted R-squared	0.408	0.408	0.200	0.210

Panel B: Dummy Interactions

	(1) Rev	(2) Rev	(3) RevUp	(4) RevUp
$NegNet$	-1.259**	-0.831	-10.6***	-8.65***
	(-2.02)	(-1.25)	(-3.51)	(-2.69)
$NegNet \times NegDummy$	-1.328	-1.437	1.30	2.30
	(-1.56)	(-1.43)	(0.37)	(0.57)
$EarnFreq$		0.000		0.010***
		(0.33)		(2.64)
$NegNet \times EarnFreq$		-0.308***		-1.48**
		(-3.84)		(-2.18)
$NegNet \times EarnFreq \times NegDummy$		0.145		-0.13
		(1.37)		(-0.13)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	203,624	203,624	203,624	203,624
Adjusted R-squared	0.408	0.408	0.210	0.210

This table presents the regression results testing the second part of the second hypothesis (*H2B*). Panel A presents the estimation of regression Models (1) and (2) using the "pure" negative word ratio, Neg, in lieu of $NegNet$ (the negative word ratio net of positive word ratio). Panel B presents the estimation of regression Models (1) and (2) augmented with the variables $NegNet \times NegDummy$ and $NegNet \times EarnFreq \times NegDummy$. $NegDummy$ is an indicator variable that equals one when $NegNet > 0$, i.e., news with a net negative tone. In all panels, the regression models include all control variables as well as year and industry fixed effects. The industry classifications for the fixed effects are based on two-digit SIC code. All standard errors are clustered by analyst and year. t-stats are in parentheses. *** , **, and * indicate significance at the 1%, 5% and 10% levels respectively.

Table VII: **Information Asymmetry and Analyst Experience**

Panel A: Information Environment

	Model 1	Model 2
$NegNet$	-1.361***	-1.281***
	(-4.86)	(-4.97)
$NegNet \times HiGroup$	-1.483***	-0.772
	(-2.80)	(-1.11)
$NegNet \times EarnFreq$		-0.049
		(-0.64)
$NegNet \times EarnFreq \times HiGroup$		-0.464***
		(-3.32)
Controls	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes

Panel B: Information Shocks

	$Idio.Volatility_{st}$		CAR	
	Model 1	Model 2	Model 1	Model 2
$NegNet$	-1.482***	-1.537***	-2.344***	-2.093***
	(-3.67)	(-3.99)	(-5.83)	(-6.49)
$NegNet \times HiGroup$	-1.236**	-0.345	0.456	0.702
	(-2.19)	(-0.50)	(0.71)	(1.25)
$NegNet \times EarnFreq$		0.013		-0.154*
		(0.17)		(-1.66)
$NegNet \times EarnFreq \times HiGroup$		-0.499***		-0.127
		(-5.18)		(-1.48)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes

Panel C: Analyst Experience

	$GEXP$		$FEXP$	
	Model 1	Model 2	Model 1	Model 2
$NegNet$	-1.533***	-1.396***	-1.660***	-1.398***
	(-7.53)	(-5.08)	(-4.62)	(-3.29)
$NegNet \times HiGroup$	-1.089***	-0.683*	-0.773***	-0.609**
	(-3.22)	(-1.93)	(-2.96)	(-2.09)
$NegNet \times EarnFreq$		-0.095		-0.170
		(-0.88)		(-1.58)
$NegNet \times EarnFreq \times HiGroup$		-0.200***		-0.066
		(-3.17)		(-0.75)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes

This table presents the regression results testing the first two parts of the third hypothesis (*H3A* and *H3B*). We partition the sample into two groups based on a composite information environment proxy (Panel A), proxies of information shocks (Panel B), and analyst experience (Panel C). In each Panel, *HiGroup* is an indicator variable that equals one when the variable of interest has a value higher than its median. Using these binary groups we augment the main regression Models (1) and (2) with the terms $NegNet \times HiGroup$ and/or $NegNet \times EarnFreq \times HiGroup$. Panel A presents the regression results testing *H3A* using a composite information environment measure. We form a composite measure of firm information environment by performing a principal component analysis on the following variables: firm size, analyst following, analysts' forecast dispersion, illiquidity, and idiosyncratic volatility. A higher value of the principal factor indicates poorer information. Panel B presents regression results testing *H3A* based on two of our measures of information shocks, $IdioVolatility_{st}$ and CAR. Panel C presents the regression results testing *H3B* based on the analyst's general and firm specific experience. The industry classifications for the fixed effects are based on two-digit SIC code. All standard errors are clustered by analyst and year. *t*-stats are in parentheses. *** , **, and * indicate significance at the 1%, 5% and 10% levels respectively.

Table VIII: Conflict of Interest

	Conflict of Interest Measure									
	(1)		(2)		(3)		(4)		(5)	
	$PastIBRelation$		$FutureIBRelation$		$FinancingDeficitFG$		$FinancingDeficitBRS$		$PureBroker$	
NegNet	-2.133***	-1.762***	-2.018***	-1.644***	-1.125***	-0.941***	-1.208***	-1.023***	-1.898***	-1.481***
	(-6.73)	(-5.10)	(-7.46)	(-5.47)	(-4.75)	(-2.90)	(-4.70)	(-4.37)	(-6.28)	(-4.92)
NegNet x CC	0.049	0.031	-1.936**	-1.937**	-1.798***	-1.439*	-1.901**	-1.505*	-2.581***	-3.103***
	(0.04)	(0.02)	(-1.96)	(-1.97)	(-2.75)	(-1.76)	(-2.42)	(-1.67)	(-3.87)	(-3.88)
EarnFreq		0.001		0.001		0.001		0.001		0.001
		(1.01)		(0.98)		(0.90)		(0.96)		(1.02)
NegNet x EarnFreq		-0.219***		-0.220***		-0.112		-0.115		-0.243***
		(-2.70)		(-3.15)		(-0.98)		(-1.25)		(-2.98)
NegNet x EarnFreq x CC		0.043		0.072		-0.209		-0.218*		0.276
		(0.23)		(0.45)		(-1.54)		(-1.82)		(1.36)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results testing *H3C* using various measures of conflict of interest. CC is an indicator variable taking the value one when the analyst faces potential conflict of interest as measured by the variable of interest described in the column headers. In column (1), CC represents the indicator variable for past investment banking relationship ($PastIBRelation$) based on whether the analyst's employer served as either lead underwriter or co-manager for the covered firm in the past three years. In column (2), CC represents the indicator variable for future IB relationship ($FutureIBRelation$) based on whether or not the analyst's employer served as either lead underwriter or co-manager for the covered firm in the next three years. We use equity and debt offering from Thomson One Banker to identify investment banking relationships. In columns (3) and (4) CC represents the indicator variables for high financing needs based on Frank and Goyal's (2003) financing deficit measure ($FinancingDeficitFG$) and Bradshaw et al.'s (2006) financing need measure ($FinancingDeficitBRS$), respectively. These indicators take the value one if the variable of interest has a value higher than its median and zero otherwise. In column (5), the CC represents the indicator variable for $PureBroker$, i.e., if the analyst's employer is a pure brokerage firm. Using these binary groups for conflicts of interest, we augment the main regression models (1) and (2) with the terms $NegNet \times CC$ and/or $NegNet \times EarnFreq \times CC$. In all panels, the regression models include all control variables as well as year and industry fixed effects. The industry classifications for the fixed effects are based on two-digit SIC code. All standard errors are clustered by analyst and year. t-stats are in parentheses. *** , **, and * indicate significance at the 1%, 5% and 10% levels respectively.

Table IX: **The Effect of News Source**

	(1)	(2)	(3)	(4)	(5)	(6)
$NegNet$	-2.263***	-2.486***	-2.061***	-2.062***	-2.317***	-1.874***
	(-6.74)	(-5.78)	(-9.01)	(-4.28)	(-4.35)	(-6.75)
$EarnFreq$				0.001	0.000	0.001**
				(0.62)	(0.37)	(2.00)
$NegNet \times EarnFreq$				-0.111	-0.053	-0.227***
				(-1.07)	(-0.68)	(-4.62)
$InitialNewsFI$	-0.017**			-0.017**		
	(-2.32)			(-2.17)		
$NegNet \times InitialNewsFI$	-0.134			0.331		
	(-0.19)			(0.47)		
$NegNet \times EarnFreq \times InitialNewsFI$				-0.304**		
				(-2.47)		
$MeanNumNewsFI$		-0.032***			-0.031***	
		(-2.87)			(-2.83)	
$NegNet \times MeanNumNewsFI$		0.010			0.525	
		(0.01)			(0.60)	
$NegNet \times EarnFreq \times MeanNumNewsFI$					-0.443**	
					(-2.29)	
$TotNumNewsFI$			-0.003*			-0.003**
			(-1.84)			(-2.12)
$NegNet \times TotNumNewsFI$			-0.139			-0.023
			(-0.84)			(-0.12)
$NegNet \times EarnFreq \times TotNumNewsFI$						-0.005
						(-1.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	203,945	203,945	203,945	203,945	203,945	203,945
Adjusted R-squared	0.399	0.399	0.399	0.399	0.399	0.399

This table presents the regression results testing for the effects of news source. A news story is classified as firm initiated if it is carried on Press Release Newswire, Business Wire of Federal Fillings Newswire (Bushee et al., 2010). $InitialNewsFI$ is an indicator variable which equals one when the first news story in a revision period is firm-initiated. $ProportionNewsFI$ is the proportion of firm-initiated news stories during a revision period. $TotNumNewsFI$ the total number of firm-initiated news stories during a revision period. Detailed definitions of all other variables are provided in appendix A. In all panels, the regression models include all control variables as well as year and industry fixed effects. The industry classifications for the fixed effects are based on two-digit SIC code. All standard errors are clustered by analyst and year. t-stats are in parentheses. *** , **, and * indicate significance at the 1%, 5% and 10% levels respectively.

Table X: **Return on News-driven Analyst Forecast Revisions**

	(1) $AR[0]$	(2) $AR[1]$	(3) $AR[2]$	(4) $AR[3,5]$
Rev	0.158***	0.055***	0.012*	-0.025
	(7.77)	(3.68)	(1.74)	(-1.40)
CAR	2.897***	-0.254***	-0.276***	-0.834***
	(9.76)	(-3.04)	(-4.06)	(-7.23)
$Illiquidity_{LT}$	-0.012	-0.042	0.056	-0.091
	(-0.22)	(-0.66)	(0.93)	(-0.88)
$Illiquidity_{ST}$	0.282***	0.157	0.010	0.233
	(2.81)	(1.09)	(0.09)	(1.23)
$IdioVolatility_{LT}$	-2.811	-3.766	-5.000*	-16.764
	(-0.95)	(-1.29)	(-1.81)	(-1.56)
$IdioVolatility_{ST}$	-0.448	2.548	0.904	8.710
	(-0.17)	(1.22)	(0.38)	(1.04)
$Assets$	0.024	0.001	0.007	-0.007
	(1.59)	(0.20)	(1.01)	(-0.41)
$RevDur$	-0.036	-0.008	0.011	0.079
	(-0.18)	(-0.22)	(0.23)	(0.51)
$Dispersion_{LT}$	1.541	-0.900**	0.194	-0.213
	(1.55)	(-2.03)	(0.36)	(-0.10)
$Dispersion_{ST}$	-0.456	0.466**	-0.827	5.032**
	(-0.61)	(2.41)	(-1.49)	(2.13)
$AnalystFollow$	0.002	0.024	-0.012	-0.011
	(0.06)	(1.53)	(-0.55)	(-0.16)
$Boldness$	0.027***	-0.016***	-0.009**	-0.007
	(3.04)	(-3.12)	(-2.09)	(-0.89)
$NumNews$	0.002	-0.002	-0.003	-0.036
	(0.09)	(-0.21)	(-0.24)	(-1.46)
Constant	0.172	-0.462**	0.056	-1.527**
	(0.53)	(-2.37)	(0.26)	(-2.33)
Year fixed effects	yes	yes	yes	yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	211,676	211,674	211,673	211,670
R-squared	0.046	0.018	0.019	0.056

This table presents the results for the regression of stock returns on analyst forecast revision. The dependent variable is the (cumulative) abnormal returns around the forecast revision date. In column (1), the dependent variable $AR[0]$ is the abnormal stock return on the day of the forecast revision. Similarly, in columns (2) and (3), the dependent variables $AR[1]$ and $AR[2]$ are respectively the abnormal stock returns on the first and second day following the day of the forecast revision. In column (4), the dependent variables $AR[3,5]$ is the cumulative abnormal returns over the 3-5 interval following the day of the forecast revision. The independent and control variables are as defined in Appendix A. The industry classifications for the fixed effects are based on two-digit SIC code. All standard errors are clustered by analyst and year. t-stats are in parentheses. *** , **, and * indicate significance at the 1%, 5% and 10% levels respectively.

Table XI: **News Staleness and Return on Fresh-news-driven Forecast Revision**

Panel A: Distribution of Analysts' Speed of Reaction to News (in trading days)

		Percentiles							
	Mean	1st	5th	10th	25th	Median	75th	95th	99th
Rev2FirstNews	38.6	1	2	5	13	27	47	116	227
Rev2News	24.6	1	2	4	9.3	18	30.2	71	132.6

Panel B: Return on Fresh-News-Driven Forecast Revisions (for *Rev2FirstNews***)**

	$AR[0]$	$AR[1]$	$AR[2]$	$AR[3,5]$
Rev	0.210***	0.067***	0.007	-0.022
	(6.64)	(3.79)	(1.08)	(-0.84)
NegNet	0.970	0.971	1.437*	5.601***
	(0.87)	(1.24)	(1.93)	(2.81)
$Rev \times Q23\_Dummy$	-0.102***	-0.025***	0.007	0.004
	(-3.64)	(-3.43)	(0.64)	(0.18)
$Rev \times Q23\_Dummy \times Fresh$	0.167**	0.054*	0.060***	-0.072
	(2.31)	(1.73)	(3.58)	(-1.21)

Panel C: Return on Fresh-News-Driven Forecast Revisions (for *Rev2News***)**

	$AR[0]$	$AR[1]$	$AR[2]$	$AR[3,5]$
Rev	0.210***	0.067***	0.007	-0.022
	(6.64)	(3.79)	(1.09)	(-0.84)
NegNet	0.975	0.974	1.444*	5.705***
	(0.87)	(1.24)	(1.93)	(2.84)
$Rev \times Q23\_Dummy$	-0.104***	-0.025***	0.006	-0.000
	(-3.57)	(-3.23)	(0.59)	(-0.01)
$Rev \times Q23\_Dummy \times Fresh$	0.168**	0.056*	0.064***	-0.026
	(2.05)	(1.85)	(3.94)	(-0.46)

This table presents the results for the analyses of the impact of news staleness on market reaction to analyst earnings forecast revisions. Panel A presents the distribution of the time lag between news and revision, where *Rev2FirstNews* is the number of trading days between the first news in the revision period and the EPS forecast revision date, and *Rev2News* is the average number of trading days between all of the news days in the revision period and the EPS forecast revision date. Panels B and C present the return regressions with the three-way interaction $Rev \times Q23\_Dummy \times Fresh$ included in the model, where $Q23\_Dummy$ is an indicator variable that equals one when a relatively bad EPS forecast revision is released subsequent to relatively bad news or a relatively good EPS forecast revision is released subsequent to relatively good news, and *Fresh* is an indicator variable that takes the value one if the time interval between news and revision is equal to or below the 5^{th} percentile based on *Rev2FirstNews* and *Rev2News* respectively. In both panels B and C, the dependent variable is the (cumulative) abnormal returns around the forecast revision date, as shown in the column titles. $AR[0]$ is the abnormal stock return on the day of the forecast revision, and similarly for other *AR* horizons. The actual regression models presented in Panels B and C include all of the control variables as in Table X; the coefficients for the control variables are omitted for brevity. All standard errors are clustered by analyst and year. t-stats are in parentheses. *** , **, and * indicate significance at the 1%, 5% and 10% levels respectively.