ABSTRACT

Title of Document: THE HIDDEN FACE OF THE MEDIA: HOW FINANCIAL JOURNALISTS PRODUCE INFORMATION

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This study investigates how the media produces information. Using a sample of 296,497 *Wall Street Journal* news articles, I find that news articles written by experienced and reputable financial journalists are more informative about future earnings. I then examine the source of such information advantage by studying the detailed quotes from news articles. I further find that these journalists rely more heavily on first-hand access to management, institutional investors, and other external experts, an important channel through which they produce informative news. Interestingly, however, this information advantage is present *only* when the experienced and reputable journalists remain independent — for those journalists that repeatedly cover the same firm or rely primarily on information from management, the networking information advantage is completely muted.

Further, I perform two additional tests. In the first test, I employ news articles about firm fundamentals, and in the second I use a revised measure of information content by including *Dow Jones Business News.* I continue to find that the information advantage of experienced and reputable journalists obtains only when these journalists remain independent.

These results suggest that the quality of the media as an information intermediary depends critically on *individual* journalists' ability to access information from industry networks and provide unbiased news.

THE HIDDEN FACE OF THE MEDIA: HOW FINANCIAL JOURNALISTS PRODUCE INFORMATION

By

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Chapter 1: Introduction

A growing literature in accounting and finance examines the role of the media as an information intermediary and its effect on capital markets. While there is now ample evidence that the media matters, we know surprisingly little about the people who provide the news—financial journalists. As nicely put by Dougal et al. (2012), "the media is often modeled as a faceless institution, but its main product—news content—is generated by people." What is the role of individual financial journalist as an information intermediary and how do they produce information? The purpose of this paper is to bridge this gap in the literature by examining the effect of individual journalists on the informativeness of media news and their source of information.

Recent research shows that media plays an important role in providing value relevant information to capital market participants. For example, Miller (2006) provides evidence that the press serves as a watchdog for accounting fraud. Tetlock et al. (2008) show that media tone can predict firms' fundamentals. Dougal et al. (2012) find that the exogenous scheduling of *Wall Street Journal* (WSJ) columnists has a significant fixed effect on market returns. These findings suggest that at least some, if not all, journalists produce information. A natural question that follows is: What makes some journalists more informative than others, and more importantly, what are the channels through which they produce information? In this study, I first focus on two journalist attributes – experience and reputation – and examine whether journalists with more experience and a higher reputation generate more informative news.[1] I then investigate whether journalists' information advantage, if any, varies with access to information from industry networks and with firm-specific experience.

[1] In additional analyses, I further examine whether journalists' gender and education affect the informativeness of their news articles.

To address these questions, I obtain an initial sample of 296,497 WSJ news articles covering S&P 500, S&P MidCap 400, and S&P SmallCap 600 firms over the July 1995 to June 2012 period. Because the focus of the paper is on the effect of financial journalists, I exclude articles without an author, resulting in a sample of 132,107 WSJ news articles by 1,404 unique journalists.[2] I manually collect data on several journalist attributes, including experience, reputation, and other individual characteristics (e.g., gender, age, education), using LinkedIn and personal webpages, among other sources. To capture experience I use the number of years the WSJ author has been a journalist (not only at the WSJ). I proxy for reputation using two indicator variables, namely, whether the journalist has been a columnist and whether the journalist has received or been a finalist for a Pulitzer Prize, Gerald Loeb Award, or John Hancock Award. To measure the qualitative information of news articles, I construct the following two measures. First, I follow the approach of Tetlock et al. (2008) and use the fraction of negative words in firm-specific news articles to measure the "tone" of an article (hereafter, media tone). This measure, however, captures only one dimension of the qualitative information and it might not reflect the unique information content of a news article, which is important in the context of this study because there can be several news articles with similar tone that are released around the same time. In order to better capture the unique new information from an article, I follow an approach similar to that of Tetlock (2011), Hoberg and Phillips (2011), and Brown and Tucker (2011), and construct a second measure based on vector space model (VSM), which captures the extent to which an article is *dissimilar* to the most recent articles for the same firm.

[2] Due to the relatively high data collection cost, I restrict the sample of journalists to those that have at least 10 articles in the full sample .These authors account for 77% of the news articles.

I begin by replicating Tetlock et al. (2008), who find at the *firm level* that qualitative information as measured by a firm's aggregate tone across articles can predict earnings surprises around earnings announcements. I find consistent evidence using both measures of qualitative information (i.e., media tone and VSM). I next examine at the *article level* whether the observed earnings predictability varies across articles written by journalists with different attributes. The results show that articles written by journalists with more experience or a higher reputation have greater earnings predictability (after controlling for analyst forecasts), suggesting that these journalist attributes significantly affect the information content of news.

Given these findings, one might ask *why* these attributes matter, that is, what is the source of such information advantage? This raises a more fundamental question: How do journalists produce information? This is a particularly interesting question given that a vast majority of financial journalists are not trained in accounting or finance, and yet their articles predict firm fundamentals above and beyond analysts' forecast and historical accounting information. Conversations with journalists suggest that an important channel through which they generate first-hand information is through industry networks (e.g., networks with analysts, insiders, or professors). Ex ante, however, it is unclear that more experienced and reputable journalists' information advantage should be due to greater access to industry networks as analysts may have access to the same networks. Thus, whether the networking channel does indeed allow some journalists to produce news with incremental information content over other information intermediaries is an empirical question.

To shed light on the networking channel, I use quotes in the news articles to gauge the strength of a journalist's network and examine whether it affects the information content of news. To do so, I first extract sentences with quotes from each article. After carefully deleting quotes from public statements (e.g., annual reports, analyst reports) or speeches (e.g., conference calls), I identify four types of information sources: insiders (e.g., executives and directors), analysts, institutional investors, and other experts (e.g., professors, industry experts). I find that more experienced and reputable journalists are more likely to quote these external sources in their news reports. Moreover, although articles with quotes from analysts do not exhibit incremental earnings predictability over analyst forecasts, articles with quotes from the other types of sources do show greater earnings predictability on average. These results suggest that an important source of information advantage arises from journalists' ability to access *first-hand* information from their industry networks.

I next investigate whether the information advantage from the networking channel varies with a journalist's firm-specific experience (i.e., repeated coverage of the same firm). Unlike analysts, journalists tend to cover a wide spectrum of companies: an average journalist in the sample writes 82 articles but does not cover the same firm more than twice. A subset of journalists, however, do provide relatively extensive coverage of specific firms. On the one hand, such firm-specific experience may allow journalists to build closer ties with management and hence provide more informative news; on the other hand, closer ties with management may affect journalists' independence and in turn their ability to provide unbiased news. To examine this issue, I construct two measures of firm-specific experience that capture the volume of firm-specific coverage and the intensity of firm-specific insider access. First, I find that journalists with a relatively high volume of firm-specific coverage tend to rely more heavily on information from management. Further, for the subset of experienced and reputable journalists with relatively extensive firm-specific experience, the information advantage is completely muted—for those who repeatedly cover the same firm or obtain first-hand information from management their news articles do not exhibit significant earnings predictability. The information advantage of experienced and reputable journalists documented above thus obtains only when these journalists remain independent. Taken together, the results suggest that the quality of the information produced by individual financial journalists hinges not only on their ability to network, but also on their ability to provide unbiased news.

This study makes contributions to several literatures. First, this study adds to the growing literature that examines the role of the media as an information intermediary by investigating how individual financial journalists produce information. Specifically, prior research generally takes the media to be a homogeneous group. This study takes a first step to study what is inside the black box that we call "media" and argues that it is composed of heterogeneous journalists whose experience and ability can generate news with different information content. In particular, my results suggest that more experienced and reputable journalists, in part due to their networking ability, are likely to play a more important information creation role. Second, this study addresses a fundamental question that has received little attention in the literature, namely, how does the media produce information? My study suggests that financial journalists generate new information through their networking with management, experts, and other information intermediaries. Understanding the channels through which the media produces news content can enhance our understanding of its effect on the capital markets. Third, this paper documents that journalists' independence, a function of their firm-specific experience, matter. When journalists' independence is impaired, their networking information benefit is completely muted. Fourth, this paper also complements the literature that examines how attributes of managers, auditors, or analysts can affect their performance by showing that experience and reputation can have significant effects on the informativeness of media news.

The rest of the paper is organized as follows. Section 2 discusses background and develops hypotheses. Section 3 describes the sample and research design. Section 4 presents the empirical results. Section 5 concludes.

Chapter 2: Background and Hypotheses

2.1 The Media as an Information Intermediary

While a large literature examines the role of financial analysts and auditors as information intermediaries for the capital market, researchers have only recently focused on the role that the media plays as an information intermediary (Drake et al. 2014). Many early studies question the validity of media as an information intermediary. For instance, Jensen (1979) suggests that the media is not an information provider but rather a form of entertainment. Core et al. (2005) similarly conclude that media coverage has no impact on executive compensation. In similar spirit, Dyck and Zingales (2002) suggest that the media contributes to financial bubbles.[3] These studies argue that at best the media lacks the knowledge necessary to serve as an information intermediary and at worst it negatively affects the economy.

An emerging line of studies, however, show that the media is an important information intermediary for capital market participants. For instance, Miller (2006) finds that 29% of documented accounting frauds were first identified by the media. Bushee et al. (2010) define information intermediary as an agent that provides information that is new and useful to find that the media improves a firm's information environment by significantly reducing information asymmetry. They suggest that the media is a qualified information intermediary because it consistently provides information to not only sophisticated investors, but also individual investors and regulators.

[3] Some research even suggests that media may play a negative role in the economy. For example, DeAngelo et al. (1994, 1996) suggest that media induces a bias toward junk bond portfolio relative to the commercial real estate problems.

Consistent with this line of arguments, a growing research shows that the media is an important information intermediary to the capital market.[4] Tetlock (2007) finds that media tone predicts aggregate market valuation, i.e. market index and trading volume.[5] Tetlock et al. (2008) further provide evidence that media tone can predict fundamentals of individual S&P 500 firms. Drake et al. (2014) find that the media coverage of annual earnings announcement mitigates cash flow mispricing. Fang and Peress (2009) find that stocks with no media coverage earn higher returns than stocks with high media coverage. In addition, three recent studies document that media has a causal effect on the financial market. Engelberg and Parsons (2011) show that local media coverage predicts the magnitude of local trading. Dougal et al. (2012) find that the exogenous scheduling of Wall Street Journal columnists has a significant fixed effect on the Dow Jones Industrial Average returns that explains 35% of the time-series variation. Roger et al. (2013) find that media has a strong effect on trading volume.[6]

Despite the increasing interest in media in academic research and in practice, however, we know surprisingly little about the people that provide the news—financial journalists—that together form the media, as prior work generally takes the media to be a homogeneous group. This study takes a first step toward shedding light on the role of individual financial journalists.

[4] Li et al. (2011) find that Dow Jones alerts convey value-relevant information to investors.

[5] Garcia (2013) finds that the predictability of media tone for aggregate market returns concentrates in recessions.

[6] There is also a growing interest in the informational role of the media in practice. For example, many investment firms model include media tone as part in their strategy models.[7] For instance, prior empirical work finds that, relative to less experienced subjects, more experienced subjects: 1) have more highly developed cognitive structures (Chi et al. 1981), 2) search for more information, focusing in particular on more relevant information (Chiesi et al. 1979), 3) place greater (less) weight on relevant (irrelevant) cues (Brucks 1985; Shelton 1999), and 4) better understand uncertainty and the consequences of their decisions (Beach 1975).

2.2 Hypotheses

2.2.1 Experience and Reputation

Previous research suggests that individual-level attributes can help explain heterogeneity in corporate investment, financial reporting, and organizational practices (Bertrand and Shoar 2003; Ge et al. 2011), management forecast frequency and precision (Bamber et al. 2010), and audit quality (Gul et al. 2013). In this paper I examine whether two individual journalist attributes – experience and reputation – affect the informativeness of news content.

Extensive theoretical and empirical research in various disciplines examines the effect of experience on knowledge acquisition and on performance. "Learning-by-doing" theory (Anzai and Simon 1979; Arrow 1962) predicts that the cost of performing a task decreases as experience with the task increases, resulting in improved performance. Extensive empirical research in various disciplines finds supportive evidence. [7] In the analyst literature, Mikhai et al. (1997), Clement (1999), and Sinha et al. (1997) find that forecast accuracy is positively associated with analyst experience. Given that financial journalists have a similar information intermediary role as analysts, it is plausible that journalists with more experience produce higher quality, that is, more informative, news. This argument is consistent with Ahern and Sosyura (2014), who find that merger rumors are more likely to hold when the rumors are reported by journalists with more experience in the target industry.

However, while learning-by-doing suggests a positive relationship between experience and task performance, psychology researchers provide evidence that learning from experience is difficult (Fischhoff, 1982; Alpert and Raiffa, 1982; Thompson, 1990, 1991; Bonner and Walker

[7] For instance, prior empirical work finds that, relative to less experienced subjects, more experienced subjects: 1) have more highly developed cognitive structures (Chi et al. 1981), 2) search for more information, focusing in particular on more relevant information (Chiesi et al. 1979), 3) place greater (less) weight on relevant (irrelevant) cues (Brucks 1985; Shelton 1999), and 4) better understand uncertainty and the consequences of their decisions (Beach 1975).

1994),[8] and thus more experience may not necessarily lead to learning and in turn improved performance.[9] Even in the analyst literature the association between experience and performance is not without debate. Jacob et al. (1999), for instance, find no evidence of an improvement in forecast accuracy with experience once analyst aptitude and brokerage house characteristics are taken into account.[10]

There is also debate about the effect of experience on agents' risk-taking behavior. On the one hand, a number of theoretical models predict that managers become more risk-averse as they age. For instance, Prendergast and Stole (1996) suggest that junior agents overreact to new information, to signal that they have more information, while senior agents underreact to this information. Boyson (2003) further suggests that risk-aversion increases with age, leading to a reduction in risky behavior. On the other hand, several studies show that older agents take more aggressive or bold actions while younger agents herd or mimic other agents. For instance, Avery and Chevalier (1999) argue that as agents gain experience, they become more confident in their ability and hence take more risk. Further, Chevalier and Ellison (1999), Hong et al. (2000), and Lamont (2002) provide evidence that young agents herd more than older agents. In the context of financial journalists, to the extent that those journalists who are willing to take more risk are more likely to serve as watchdogs, their news articles are likely to be more informative.

Turning to reputation, reputation is a widely studied attribute in the analyst literature. For instance, Stickel (1992) finds that star analysts have better forecast accuracy because their ranking reflects their ability, and Bonner et al. (2007) show that the market overreacts to forecast revisions

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[8] Bonner and Walker (1994) find that performance improves only when experience is coupled with feedback.

[9] Indeed, Dawes (1988) suggests that success may have negative as well as positive results when people draw incorrect lessons from such experiences.

[10] Clement (1999) suggests that the conflict results between his paper and Jacob et al. (1999) may be due to differences in research design.

issued by star analysts. Journalists also have their “star” performers. For example, columnists are widely considered as knowledgeable journalists with a good reputation, and journalists awarded a Pulitzer Prize or Gerald Loeb Award are recognized for providing insightful commentary in addition to in-depth coverage of the facts. Thus, providing informative news can establish a journalist’s reputation (Starkman 2014). To the extent that reputation reflects a journalist’s ability, star journalists’ news articles should be more informative.[11]

Meanwhile, journalists are more likely to herd if they have a strong reputation. A number of theoretical models posit that if agents with a strong reputation are more likely to mimic others and provide less informative information. For instance, Scharfstein and Stein (1990), Zwiebel (1995), and Graham (2009) predict that career concerns make agents with a strong reputation more conservative. Consistent with these theoretical studies, Li (2002) suggests that analysts with a strong reputation are more likely to recommend less risky portfolios, and Chevalier and Ellison (1999) find that less reputable fund managers earn significantly higher returns than their more reputable colleagues. Overall, these studies predict that more reputable journalists are more likely to herd, in which case their articles should be less informative.

Taken together, whether more experienced and reputable financial journalists provide more or less informative news is ultimately an empirical question.

2.2.2 Information Channel

If individual attributes matter for journalists, the next question that arises is *why*, that is, what is the source of such information advantage? Conversations with journalists suggest that an important channel through which they generate first-hand information is through their industry sources (e.g., networks with analysts, insiders, or professors). Hence, a potential source of

[11] Meanwhile, several economic studies suggest that reputation affects product quality (Jin and Kato 2006, Jin and Leslie 2009).

information advantage, if any, may be their access to industry networks. Financial journalists conduct research on a wide range of areas and potentially have a broader set of sources relative to other types of information intermediaries. Further, since the business press is read by millions of people, it is a valuable exposure venue for managers, analysts, and fund managers (Blankespoor and deHaan 2014; Falato et al. 2012; Malmendier and Tate 2009; Rajgopal et al. 2006; Ree et al. 2015; Sirri and Tufano 1998 and Soloman et al. 2014).[12] Thus they have incentives to provide first-hand information to journalists. However, other information intermediaries (e.g., analysts) may have access to the same networks.[13] Further, prior evidence (Patterson 2013) suggests that financial journalists lack sufficient training in accounting or finance to digest and interpret the information provided by their sources. Therefore, ex ante it is unclear whether access to industry networks provides journalists an information advantage in producing incremental information.

2.2.3 Journalist Independence

Independence is a key principle of journalism. As Kovach (2001) states in his classic textbook *The Elements of Journalism*, "the critical step in pursuing truthfulness and informing citizens is not neutrality but independence." Given the importance of independence for journalists, another question that arises is whether the extent of a journalist's firm-specific coverage over time affects their information advantage, if any, from the networking channel. On the one hand, increased coverage of a firm over time allows a journalist to learn more about the firm and hence produce more informative news about the firm. This argument is consistent with evidence from prior research that analysts generate more accurate earnings forecasts and more profitable stock

[12] For example, Blankespoor and deHaan (2014) find that CEOs promote media coverage by quoting their names in firm press release.

[13] For example, Mayew et al. (2013) suggest that analysts can obtain superior private information by asking questions during earnings conference calls, and Green et al. (2014) find that analysts generate more informative research by accessing management at broker-hosted investor conferences. Overall, these studies suggest that analysts' information comes not only from their own analysis but also from their networks with information sources.

recommendations as their experience following a specific firm increases (Mikhail et al. 1997). In addition, as journalists develop closer ties with their sources, they may be able to obtain more first-hand information.[14]

On the other hand, prior journalism research suggests that journalist-reader is a form of principal-agency relationship (Fengler and Russ-Mohl 2008). Readers (the principal) delegate the work of producing information to journalists (the agent). They have an implicit contract that journalists are aligned with readers, who ultimately provide revenue. A priori, one might imagine that journalists serve the reader without exception, and thus should maximize information generation. However, it is difficult and expensive for readers to verify what journalists are actually doing and whether journalists have behaved appropriately. If journalists have developed close relationship with the company that they are reporting on, this relationship may impair journalist independence and thus create conflicts between journalists and readers. For example, journalists who have close relationship with a source can sometimes fail to ask the tough questions, the questions that should have been asked and answered to fully inform the readers (Pavlik 2004). In addition, as journalists become more reliant on a specific source, they may become more concerned about jeopardizing their relationship with the source and hence provide more conservative (i.e., less informative) reporting (Dyck and Zingales 2003; Pavlik 2004). Butler and Gurun (2012) suggest that local media has a more positive tone for local companies. In recent economic literature, Reuter and Zitzewitz (2006) find that mutual fund recommendations are correlated with past advertising in three personal finance publications (*Money Magazine, Kiplinger's Personal Finance,*

[14] Financial journalists are much more independent from the firm they cover compared with other information intermediaries, for example, financial analysts. First, journalists do not represent an employer who trades on a firm's securities. Second, financial journalists are news-oriented, and they do not tend to stay with the same firm for a long period of time. This characteristic is different from financial analysts, as analysts tend to report on the same firm repeatedly over time.

and *SmartMoney*) but not in two national newspapers (*New York Times* and WSJ), suggesting that the media is not always unbiased.[15]

In short, whether journalists remain independent as they gain firm-specific experience, and more importantly, how this relation costs journalist-reader relationship and affects the informative of their news content, is ultimately an empirical question.

[15] For example, many journalism studies examine how political preference biases reporting at both the individual and the media outlet level. Patterson and Donsbach (1996) find that the political preferences of individual journalists bias their decisions about story content and headlines. At the media outlet level, DellaVigna and Kaplan (2006) suggest that the Republican bias of Fox News convinced 3 to 8 percent of the viewers to vote Republican., and Groseclose and Milyo (2005) document a liberal bias among several major media outlets by counting the number of quotes from different policy institutes.

Chapter 3: Sample and Research Design

3.1 Main Variables

3.1.1 Dependent Variable

Following Tetlock et al. (2008), I measure a firm's quarterly earnings surprise using both standardized unexpected earnings (*SUE*) and standardized analyst forecasts errors (*SAFE*). In particular, I first standardize the seasonal earnings difference by subtracting the previous 20 quarters' mean and dividing by the previous 20 quarters' standard deviation of the seasonal earnings difference. I delete the observations with missing earnings data for the most recent 10 quarters. Similarly, I standardize the median analyst forecast error by dividing by the earnings volatility over the previous 20 quarters. I use the median analyst forecast from the most recent period in I/B/E/S before the earnings announcement. *SUE* and *SAFE* are winsorized at the 1% level.

3.1.2 Qualitative Information

I construct two proxies for the qualitative information content of news articles. First, I use the percentage of negative words. The classification of negative and positive words is based on the Loughran and McDonald (2011) dictionary (L&M hereafter). I use this dictionary due to its specialization to business texts. For example, the L&M dictionary excludes words that are typically not negative in a financial context, such as tax, cost, board, liability, foreign, vice, mine, cancer, crude, tire, and capital. Following Tetlock et al. (2008), I standardize the percentage of negative words in each news article by subtracting the prior year's mean and dividing by the standard deviation of the prior year's percentage of negative words. More specifically, the first measure of qualitative information content is given by:

$$NEG = \frac{No. of\ Negative\ words}{No. of\ Total\ words} \tag{1}$$

$$Neg = \frac{NEG - \mu NEG}{\sigma NEG}\,, \tag{2}$$

where μNEG is the mean of NEG and σNEG is the standard deviation of NEG over the prior calendar year. *NEG* and *Neg* are winsorized at the 1% level.

However, the percentage of negative words only picks up one dimension of qualitative information content, and thus may fail to capture the incremental information content of a news article. This is important in the current context because several news articles with similar tone may be released around the same time. To capture incremental information content, I construct a second measure of qualitative information that is based on vector space model. In particular, following the approach in Tetlock (2011), Hoberg and Phillips (2011), and Brown and Tucker (2011), I first calculate the similarity between news articles *j* and *j-k*, where $0 < k \leqslant 10$, with respect to firm *i*. To do so, I extract the text in each news article on the firm and construct a binary words vector. The vector length is equal to the number of unique words used across all news articles for the firm. For a given news article, an element of this vector is equal to one if the word associated with the element is in the news article. To reduce the dimension of vectors and thus computing time, I delete a set of common words such as “the”, “a”, “when”, and “while”, and I stem the remaining words using the Perl stemming algorithm to remove word tense and form; for example, “stemmer”, “stemming”, and “stemmed” would all be stemmed to “stem”. Next, for each news article I construct a binary vector V_j, with each element taking a value of one if the associated word is used in the given news article and zero otherwise. The similarity between news articles *j* and *j-k* is then defined by the dot product of their normalized vectors:

$$Similarity_{j,j-k} = \cos(\theta) = \frac{V_j}{||V_j||} \cdot \frac{V_{j-k}}{||V_{j-k}||}\,, \tag{3}$$

where θ is the angle between V_j and V_{j-k}, $0 < k \leqslant 10$, $||V_j||$ is the vector length of V_j, and $||V_{j-k}||$ is the vector length of V_{j-k}. The similarity score takes values between 0 and 1.

In the next step, I calculate a measure of the difference between dissimilarity according to

$$Information_{j,j-k} = 1 - Similarity_{j,j-k}. \quad (4)$$

Finally, for each news article, the VSM-based qualitative information measure is defined as the average difference relative to the previous 10 news articles for the same firm:

$$VSM = VSM_{i,j} = \frac{\sum_{k=1}^{10} Information_{i,j,j-k}}{10}. \quad (5)$$

3.1.3 Experience and Reputation

As a proxy for experience, I use the number of years that the WSJ reporter has been a journalist (*EXP*). I manually collect data on experience (as well as reputation and other individual characteristics, for example, gender, age, education) using LinkedIn and journalists' personal webpages, among other sources. For each year, I sort news articles into those by "experienced" versus "less experienced" journalists based on the median number of years' experience working as a financial journalist.

I use two measures to proxy for reputation. The first measure is journalist award. I manually collected the data on three major awards in financial journalist industry and match winner/finalist to the list of journalist in my sample. The three awards including in the study are Pulitzer Prize, Gerald Loeb Award and John Hancock Award[16]. I use these three awards because they are the most

[16] The Pulitzer Prize is a U.S. award for achievements in newspaper and online journalism, literature, and musical composition. It was established in 1917 by Joseph Pulitzer, and is administered by Columbia University in New York City. Prizes are awarded yearly in 14 journalism categories. The Gerald Loeb Award, also referred to as the Gerald

well-known awards for achievement in journalism. Gerald Loeb and John Hancock Awards are specifically in recognition of excellence in business and financial journalism. If a journalist has been a winner or a finalist for any of the three awards, I classify him/her as a reputable journalist. In particular, *AWARD* is equal to one if the journalist has been a winner or finalist of any of the three awards during the sample period, and zero otherwise. The second measure of reputation is an indicator for whether the journalist has been a columnist, as columnists write for a newspaper in a series and generally have a high reputation. Some columnists appear on a daily or weekly basis. For example, Spencer Jakab writes the "Ahead of the Tape" Column for the Wall Street Journal on a daily basis. In particular, *COLUM* is equal to one if the journalist has been a columnist during the sample period, and zero otherwise. Details on these variables are presented in Appendix I.

3.1.4 Information Source

Financial journalists often cite various sources in order to strengthen their arguments and establish credibility with their readers (Bonner et al. 2007; Twedt 2013; Blankespoor and deHaan 2014; Rees et al. 2015). In some cases, the quotes come second-hand from annual reports or conference calls. But in other cases, financial journalists obtain information first-hand through interviews or other interactions with their sources. To examine the impact of a journalist's sources, I first extract sentences with quotes from each news article. Next, I screen out quotes that come from public sources, such as annual reports, analyst reports, or conference calls. I then identify four types of sources: insiders (e.g., executives), analysts, institutional investors, and experts (e.g., professor, industry experts). In particular, I code a quote as coming from an insider if the sentence

Loeb Award for Distinguished Business and Financial Journalism, is recognition of excellence in journalism, especially in the fields of business, finance and the economy. The award was established in 1957 by Gerald Loeb to encourage reporters to inform and protect private investors as well as the general public in the areas of business, finance and the economy. http://www.anderson.ucla.edu/gerald-loeb-awards John-Hancock Award is sponsored by the American History of Business Journalism to recognize of Distinguished Business and Financial Journalism.

mentions firm executives or the firm's name right before or after the quote. I obtain executives' names from ExecuComp. I code a quote as coming from an analyst or institutional investor if the sentence mentions "analyst" or "fund manager" right before or after a quote. Finally, I code a quote as coming from experts if the sentence mentions a professor, institution, university, or research, or if it mentions "executive", "officer", "director", "vice president", etc. right before or after a quote but is not classified as from an insider. Details on this procedure are presented in Appendix II.

3.1.5 Journalistic Independence

I construct two measures of independence. The first captures a journalist's firm-specific experience. For each article, I define a journalist as having low independence if he or she has followed the same firm for at least two years and written more than ten articles. This group comprises 22% of the full sample. The second measure captures the intensity with which a journalist relies on an insider source. For each article, I define a journalist as having low independence if he or she has written more than ten articles about the same firm and more than 50% of his or her first-hand information comes from management. Again, only 23% of the sample observations fall into this category.

3.1.6 Control Variables

Results from prior research suggest that firm size, book-to-market, and trading volume should be taken into account when predicting future earnings. I use the log of market value and the log of book value to market value at the beginning of the calendar year to measure size and book-to-market, respectively. Trading volume is calculated as the log of annual shares traded divided by shares outstanding at the beginning of the calendar year. Next, I control for a firm's past returns using several measures following Tetlock et al. (2008) – in particular, I calculate abnormal returns using the Fama and French (1993) three-factor benchmark model, I regress a firm's raw return on the market excess return, a size factor (*SMB*), and a book-to-market factor (*HML*) over the 252 to 31 trading days prior to each earnings announcement, I estimate the cumulative abnormal return for the [-30,-3] trading day window ($CAR_{-30,-3}$), and I estimate the abnormal return on day -2 ($CAR_{-2,-2}$). I also control for the intercept from the benchmark model ($Alpha_{-252,-31}$), where $Alpha_{-252,-31}$ is the cumulative abnormal return over the 252 to 31 trading days prior to each earnings announcement. Next, I control for the median analyst earnings forecast revision (*REV*) and analyst forecast dispersion (*DISP*), where *REV* is the consensus I/B/E/S forecast in quarter *t* minus the consensus forecast in quarter *t*-1 for quarter *t*, and *DISP* is the standard deviation of analysts' earnings forecasts in the most recent quarter prior to the earnings announcement scaled by earnings volatility. All variables are winsorized at the 1% level.

3.2 Research Design

3.21 Journalist Attributes and Earnings Predictability

In a first set of tests, I follow Tetlock et al. (2008) and examine the association between journalist attributes and earnings predictability on a quarterly basis, as earnings are announced quarterly. I calculate the standardized $Neg_{-30,-3}$ using news stories from 30 to 3 trading days prior to each earnings announcement. I exclude the news articles for the 2 trading days prior to earnings announcement because Compustat earnings announcement dates may not be exact.

First, I regress the one-quarter-ahead earnings surprise (*SUE* or *SAFE*) on qualitative information as measured by $Neg_{-30,-3}$ or $VSM_{-30,-3}$, where day 0 is the earnings announcement release date, controlling for the current quarter's earnings surprise, firm size, book-to-market, trading volume, analyst forecast revision, analyst forecast dispersion, and cumulative abnormal stock return:

$$Earnings\ Surpise_t = \alpha_0 + \alpha_1 Neg_{-30,-3} + \alpha_2 Earnings\ Surpise_{t-1} + \alpha_3 LnMKT_{t-1} + \alpha_4 LnBM_{t-1} + \alpha_5 LnTV_{t-1} + \alpha_6 DISP_{t-1} + \alpha_7 REV_{t-1} + \alpha_8 Alpha_{-252,-31} + \alpha_9 CAR_{-30,-3} + \alpha_{10} CAR_{-2,-2} + \epsilon \qquad (1A)$$

$$|Earnings\ Surpise_t| = \alpha_0 + \alpha_1 VSM_{-30,-3} + \alpha_2 |Earnings\ Surpise_{t-1}| + \alpha_3 |LnMKT_{t-1}| + \alpha_4 |LnBM_{t-1}| + \alpha_5 |LnTV_{t-1}| + \alpha_6 |DISP_{t-1}| + \alpha_7 |REV_{t-1}| + \alpha_8 |Alpha_{-252,-31}| + \alpha_9 |CAR_{-30,-3|} + \alpha_{10} |CAR_{-2,-2}| + \epsilon \qquad (1B)$$

Second, I run analogous regressions at the *individual article* level. Regressions at the individual article level provide more powerful tests and allow me to control for different attributes in one model. Specifically, I regress the one-quarter-ahead earnings surprise (*SUE* or *SAFE*) on the individual article-level *Neg* or *VSM* and the control variables using the following models:

$$Earnings\ Surpise_t = \alpha_0 + \alpha_1 Neg + \alpha_2 LnEXP + \alpha_3 Neg * LnEXP + \alpha_4 Award + \alpha_5 Neg * Award + \alpha_6 Columnist + \alpha_7 Neg * Columnist + \alpha_8 Gender + \alpha_9 Neg * Gender + \alpha_{10} Economics + \alpha_{11} Neg * Economics + \alpha_{12} MBA + \alpha_{13} Neg * MBA + \alpha_{14} Top4Jschool + \alpha_{15} Neg * Top4Jschool + \alpha_{16} Journalism + \alpha_{17} Neg * Journalism + \alpha_{18} Artmajor + \alpha_{19} Neg * Artmajor + \alpha_{20} Earnings\ Surpise_{t-1} + \alpha_{21} LnMKT_{t-1} + \alpha_{22} LnBM_{t-1} + \alpha_{23} LnTV_{t-1} + \alpha_{24} DISP_{t-1} + \alpha_{25} REV_{t-1} + \alpha_{26} Alpha_{-252,-31} + \alpha_{27} CAR_{-30,-3} + \alpha_{28} CAR_{-2,-2} + \epsilon \qquad (1C)$$

$$|Earnings\ Surpise_t| = \alpha_0 + \alpha_1 VSM + \alpha_2 LnEXP + \alpha_3 VSM * LnEXP + \alpha_4 Award + \alpha_5 VSM * Award + \alpha_6 Columnist + \alpha_7 VSM * Columnist + \alpha_8 Gender + \alpha_9 VSM * Gender + \alpha_{10} Economics + \alpha_{11} VSM * Economics + \alpha_{12} MBA + \alpha_{13} VSM * MBA + \alpha_{14} Top4Jschool + \alpha_{15} VSM * Top4Jschool + \alpha_{16} Journalism + \alpha_{17} VSM * Journalism + \alpha_{18} Artmajor + \alpha_{19} VSM * Artmajor + \alpha_{20} |Earnings\ Surpise_{t-1}| + \alpha_{21} |LnMKT_{t-1}| + \alpha_{22} |LnBM_{t-1}| + \alpha_{23} |LnTV_{t-1}| + \alpha_{24} |DISP_{t-1}| + \alpha_{25} |REV_{t-1}| + \alpha_{26} |Alpha_{-252,-31}| + \alpha_{27} |CAR_{-30,-3}| + \alpha_{28} |CAR_{-2,-2}| + \epsilon. \qquad (1D)$$

Based on the discussion above, I predict that the coefficients on the interaction terms between negative media tone and journalist attributes, that is, $Neg * LnEXP$, $Neg * Award$, and $Neg * Columnist$, are negative, and that the coefficients on the interaction terms between information content and journalist attributes, $VSM * LnEXP$, $VSM * Award$, and $VSM * Columnist$, are positive.

3.22 Information Source

Next, I examine how financial journalists produce information about firm earnings. To test for industry network effects, I estimate the following two models at individual article level using articles written by more experienced or reputable journalists:

$$Earnings\ Surpise_t = \alpha_0 + \alpha_1 Neg + \alpha_2 Insider + \alpha_3 Neg * Insider + \alpha_4 Analyst + \alpha_5 Neg * Analyst + \alpha_6 Fund + \alpha_7 Neg * Fund + \alpha_8 Expert + \alpha_9 Neg * Expert + \alpha_{10} Earnings\ Surpise_{t-1} + \alpha_{11} LnMKT_{t-1} + \alpha_{12} LnBM_{t-1} + \alpha_{13} LnTV_{t-1} + \alpha_{14} DISP_{t-1} + \alpha_{15} REV_{t-1} + \alpha_{16} Alpha_{-252,-31} + \alpha_{17} CAR_{-30,-3} + \alpha_{18} CAR_{-2,-2} + \epsilon \quad \text{(2A)}$$

$$|Earnings\ Surpise_t| = \alpha_0 + \alpha_1 VSM + \alpha_2 Insider + \alpha_3 VSM * Insider + \alpha_4 Analyst + \alpha_5 VSM * Analyst + \alpha_6 Fund + \alpha_7 VSM * Fund + \alpha_8 Expert + \alpha_9 VSM * Expert + \alpha_{10}|Earnings\ Surpise_{t-1}| + \alpha_{11}|LnMKT_{t-1}| + \alpha_{12}|LnBM_{t-1}| + \alpha_{13}|LnTV_{t-1}| + \alpha_{14}|DISP_{t-1}| + \alpha_{15}|REV_{t-1}| + \alpha_{16}|Alpha_{-252,-31}| + \alpha_{17}|CAR_{-30,-3}| + \alpha_{18}|CAR_{-2,-2}| + \epsilon. \quad \text{(2B)}$$

I predict that the coefficients on the interaction terms between negative media tone and different types of information sources (α_3, α_5, α_7, α_9) are negative, and that the coefficients on the interaction terms between information content and the different types of information sources (α_3, α_5, α_7, α_9) are positive.

3.23 Independence and Information Advantage

In a third set of tests, I examine whether industry network effects are impacted by the extent of a journalist's firm-specific experience as measure by firm-specific coverage and network. In particular, I estimate the following two models at the article level using articles written by more experienced or reputable journalists:

$$Earnings\ Surpise_t = \alpha_0 + \alpha_1 Neg + \alpha_2 Low\ Independence + \alpha_3 Neg * Low\ Independence + \alpha_4 Earnings\ Surpise_{t-1} + \alpha_5 LnMKT_{t-1} + \alpha_6 LnBM_{t-1} + \alpha_7 LnTV_{t-1} + \alpha_8 DISP_{t-1} + \alpha_9 REV_{t-1} + \alpha_{10} Alpha_{-252,-31} + \alpha_{11} CAR_{-30,-3} + \alpha_{12} CAR_{-2,-2} + \epsilon \quad \text{(3A)}$$

$$|Earnings\ Surpise_t| = \alpha_0 + \alpha_1 VSM + \alpha_2 Low\ Independence + \alpha_3 VSM * Low\ Independence + \alpha_4|Earnings\ Surpise_{t-1}| + \alpha_5|LnMKT_{t-1}| + \alpha_6|LnBM_{t-1}| + \alpha_7|LnTV_{t-1}| + \alpha_8|DISP_{t-1}| + \alpha_9|REV_{t-1}| + \alpha_{10}|Alpha_{-252,-31}| + \alpha_{11}|CAR_{-30,-3}| + \alpha_{12}|CAR_{-2,-2}| + \epsilon. \quad \text{(3B)}$$

3.3 Sample and Data

Table 1, Panel A summarizes the sample selection. I start with all news articles from the WSJ between July 1995 and June 2012. I then focus on those articles about S&P 500, S&P MidCap 400, and S&P SmallCap 600 firms. I delete firm-specific articles that do not mention the firm's name at least once within the first 25 words, including the headline, and at least twice within the full story. In addition, I omit articles that do not contain at least 50 words, and at least 5 words that are either positive or negative. I obtain data on earnings, book value, market value, annual shares traded, and annual shares outstanding from Compustat, while S&P index constituents and stock price data come from CRSP. Analyst forecast information is from I/B/E/S. Using an automated program I extract the journalist's name from the news, omitting articles for which no authoring journalist is listed. To be included in the sample, I require that each journalist have at least 10 news articles. The final sample comprises 132,107 news articles on S&P 1500 firms representing 1,404 unique financial journalists.

Table 1, Panel B summarizes the number of news articles, the number of journalists, and the average number of news articles per journalist by year. The number of news articles and number of journalists are relatively stable during the sample period. On average, each year 496 journalists write 10,425 news articles.

Panel C of Table I presents descriptive statistics for the main variables of interest and the controls. The median *Neg* (*VSM*) is 0.021 (0.759). Panel D presents Pearson and Spearman correlations for the main variables over sample period. I find that *Neg* (*VSM*) has a strong negative (positive) and significant correlation with the one-quarter-ahead earnings surprise. This preliminary result implies that the qualitative information content of news articles contains incremental information for future earnings.

[Insert Table 1]

Table 2 presents descriptive statistics on the sample of WSJ financial journalists. The average WSJ reporter has been a journalist for 15 years. Fourteen percent of journalists have been winners or finalists of a Pulitzer Prize, Gerald Loeb Award, or John Hancock Award, while twenty percent of journalists have been a columnist. Thirty-eight percent of journalists are female. The most common undergraduate major is journalism (38%), followed by English (17%), history (10%), political science (8%), international studies (8%), and business (7%); these results suggest that the financial journalists at the WSJ have little finance or accounting background over the sample period.

[Insert Table 2]

Chapter 4: Empirical Results

Table 3 presents results for tests in which I replicate Tetlock et al. (2008) using the full sample. Consistent with Tetlock et al. (2008), in Panel A I find that the fraction of negative words predicts low earnings: the coefficient on $Neg_{-30,-3}$ is -0.015 (-0.006), significant at the 1% (5%) level in model 1 (2). Similarly, in Panel B the coefficient on $VSM_{-30,-3}$ is positive and significant (0.065 and 0.010). Overall, the results in Table 3 suggest that qualitative information content contains incremental information for future earnings.

[Insert Table 3]

As discussed above, although *VSM* is not without its own limitations, it captures multiple dimensions of news content and thus is more likely to capture the unique content of each news article, which is particularly important in the context of this paper. I therefore view it as my main measure of qualitative information content. To streamline the discussion, below I focus the discussion primarily on results using *VSM*.

4.1 Journalist Attributes and Earnings Predictability

Table 4 presents results on how experience and reputation affect the informativeness of news articles (Panel A for *Neg*, Panel B for *VSM*). In Panel B columns 1 and 3, *VSM * LnEXP* and *VSM * Columnist* have positive and significant coefficients (0.068, 0.037, 0.018, and 0.013 respectively), consistent with the predication that articles written by more experienced or reputable financial journalists are more informative about firm earnings. In untabulated results, the coefficient on *VSM * Award* is positive and significant if I do not control for experience and the columnist dummy, suggesting that the effect of experience and being a columnist subsumes the effect of receiving an award. In columns 2 and 4, I add additional attributes, for example, gender, economics major, MBA, top 4 journalism school, journalism major, and other liberal arts majors.

The coefficients on *VSM * LnEXP* and *VSM * Columnist* continue to be positive and significant. Interestingly, I find some evidence that female journalists or journalists with a major in journalism provide more informative news for firm earnings, as the coefficients on *VSM * Gender* and *VSM * Journalism* are positive and significant. Overall, the results suggest that experienced or reputable journalists have an information advantage compared with other journalists.

[Insert Table 4]

4.2 Information Channels

As Table 2 shows, only 7% of financial journalists have a business education. The puzzle lies in the fact that the financial journalists are not trained in accounting or finance yet their news articles predict firm fundamentals above and beyond analyst forecasts and historical accounting information. To shed light on the source of such information advantage I examine the detailed quotes from news articles. Table 5, Panel A presents descriptive statistics on news articles with quotes from different types of sources. The panel shows that the average percentage of articles that quote insiders, analysts, institutional investors, and experts is 14.2%, 8.5%, 12.1%, and 9.2%, with a standard deviation of 50.2%, 43.3%, 32.5%, and 39.2%, respectively. Panel B presents binary logit estimation results separately for news articles with quotes from the four types of sources. The estimation results provide some interesting insights. I show that the coefficients on *LnEXP* and *Columnist* are positive and significant across all models, suggesting that experienced and reputable journalists rely more heavily on first-hand access to management, analysts, institutional investors, and other external experts. Interestingly, I find that female journalists are more likely to quote management and experts while male journalists are more likely to quote analysts and institutional investors.

[Insert Table 5]

Table 6 provides regression results for Equations (2A) and (2B) for experienced (Panels A and B) and reputable (Panels C and D) journalists. Recall that for each year I define as experienced journalists the top 50% of journalists in terms of experience in journalism, and I define as inexperienced journalists the remaining journalist sample; similarly, I define reputable journalists as those who have been columnists. In Panel B columns 1 to 5, I find that the coefficients on *VSM * Insider*, *VSM * Analyst*, *VSM * Fund*, and *VSM * Expert* are all positive and significant, suggesting that first-hand access to management, analysts, institutional investors, and other external experts predicts firm fundamentals above and beyond historical accounting information. In columns 6 to 10, the results are generally similar except for quotes from analysts. Interestingly, the coefficient on *VSM * Analyst* is negative but insignificant in columns 7 and 10. This result implies that analysts have incorporated the information they share with journalists into their earnings forecasts, and thus the quotes from analysts do not have incremental predictability about firm earnings beyond analyst forecasts. I find similar results for columnists in Panel D, where the coefficients on *VSM * Insider*, *VSM * Analyst*, *VSM * Fund*, and *VSM * Expert* are 0.013, 0.016, 0.113, and 0.018, respectively, all significant at the 5% level. Taken together, these results are consistent with the hypothesis that an industry network is an important channel through which experienced or reputable journalists produce informative news.

[Insert Table 6]

4.3 Independence and Information Advantage

In my third set of tests, I investigate whether the information advantage arising from the networking channel is impacted by the extent of a journalist's firm-specific coverage or network. Table 7 presents descriptive statistics on news articles written by the same journalist on the same firm in a given year. On average, a journalist writes 1.762 news articles about a firm each year. In addition, less than 15% of journalist-firm pairs have more than three articles per year. These results suggest that unlike analysts, financial journalists do not tend to cover the same firm.

[Insert Table 7]

In Table 8, I report results for Equations (3A) and (3B) for experienced and reputable journalists. Panels A and B (C and D) present results for firm-specific coverage (firm-specific network). In Panel B, the coefficients on *VSM* High_cov* are all significant and negative, resulting in an insignificant coefficient on *VSM + VSM * High_cov*. For example, in column 1, the coefficient on *VSM + VSM * High_cov* is 0.006, with a p-value of 0.686. These results suggest that firm-specific coverage has a significant effect on the information advantage of an experienced or reputable journalist. I do not find information advantage for those who repeatedly cover the same firm. Similarly, in Panel D I do not find evidence of an information advantage for those whose information on a specific firm comes largely from firm insiders. Taken together, these findings suggest that the information advantage of industry networks is present only when the experienced or reputable journalists remain independent—for those who repeatedly cover the same firm or obtain first-hand information from management, the networking information advantage is completely muted. These results suggest that the quality of the information produced by individual financial journalists hinges critically on their ability to both network with sources and provide unbiased news.

[Insert Table 8]

4.4 Additional Analyses

In this section, I perform two additional tests. In the first test, I employ news articles about firm fundamentals, and in the second I use a revised version of *VSM*.

4.4.1 Earnings News

As discussed in Tetlock et al. (2008), news articles that mention the word stem “earn” are more likely to contain information about firm fundamentals than other news articles. I re-run Equations (1C), (1D), (2A), (2B), (3A), and (3B) using news articles that mention the word stem “earn”. Table 9 reports the results of this additional analysis. In Panel A columns 1, the coefficients on *VSM * LnEXP, VSM * Award, and VSM * Columnist* are 0.049, 0.039, and 0.027, respectively, all significant at 5% level. These results are consistent with Table 4. In Panel B column 1, I find that the coefficients on *VSM * Insider, VSM * Analyst, VSM * Fund,* and *VSM * Expert* are generally positive and significant, consistent with Table 6. Again, in column B I do not find that journalists have an information advantage beyond analysts if they obtain information largely from analysts. Similarly, in Panel C I do not find evidence of an information advantage for those journalists who repeatedly cover the same firm or obtain first-hand information from management of the firm they cover.

[Insert Table 9]

4.4.2 Including Dow Jones Business News

One limitation of the *VSM* measure is that it captures incremental information content relative to prior WSJ articles. To the extent that other media sources (in particular, more timely newswires) provide such information first, this measure may be misspecified. To address this problem, I construct a revised version of *VSM*, namely, *VSM2*, using an extended sample that includes articles in both WSJ and *Dow Jones Business News*.

Due to the high cost of downloading news articles, I only collect articles from *Dow Jones Business News* between January 2004 and June 2012. Again, I focus on articles about S&P 500, S&P MidCap 400, and S&P SmallCap 600 firms, I require that each firm-specific story mention the firm's name at least once within the first 25 words (including the headline) and at least twice within the full story, and I require that each news article contain at least 50 words and at least 5 words that are either positive or negative. I add the new observations to the sample used in the main analyses above. Then, as before, I calculate *VSM2* as 1 minus the similarity between news articles *j* and *j-k*, $0 < k \leqslant 10$, about firm *i*, where article *j* is still from WSJ but the 10 articles prior to *j* include news not only from WSJ but also from *Dow Jones Business News:*

$$VSM2 = \frac{\sum_{k=1}^{10} \text{Information}_{i,j,j-k}}{10}; \ \text{Information}_{j,j-k} = 1 - \text{Similarity}_{j,j-k}.$$

Table 10 reports the results using *VSM2*. The results are consistent with those presented in Tables 4, 6, and 8.

[Insert Table 10]

4.5 Robustness Test

In untabulated analyses, the news articles written by more experienced or reputable journalists get stronger market reaction for the news announcement day and the day after. This result is consistent that news articles written by experienced and reputable financial journalists are more informative. In addition, I find that the results are robust to an alternative measure of media tone, *Net*, which is the standardized fraction of net negative words (i.e., the number of negative words minus the number of positive words). The results are similarly unaffected when I define experienced journalists as the top 25% in terms of years of experience or when I use age to capture experience. As an additional check, I reestimate Equations (1C), (1D), (2A), (2B), (3A) and (3B) using only those news articles published on Page B3 of WSJ. This test addresses the self-selection concern that more experienced journalists' articles may be published on the front page. Again, the main results continue to hold.

Chapter 5: Conclusion

Recent research in accounting and finance suggests that the media plays an important role in the capital market. Most studies view the media collectively as a homogeneous group and we know little about the specific role that individual financial journalists play as an information intermediary, and more importantly, the channels through which they produce information. This study takes a first step to address these issues.

Using a sample of 296,497 *Wall Street Journal* (WSJ) news articles, I find that the news articles written by more experienced and reputable financial journalists are more informative about future earnings. Their articles are also more likely to include quotes from external sources such as management or institutional investors, suggesting that experienced and reputable journalists have access to a wider industry networks. I further find evidence that articles with more quotes from external sources are more informative. Interestingly, this information advantage is present *only* when the experienced and reputable journalists remain independent—for those who repeatedly cover the same firm or reply primarily on information from management, the networking information advantage is completely muted. Taken together, these findings suggests that the quality of the media as an information intermediary depends critically on *individual* journalists' ability to access information from industry networks and provide unbiased news.

Appendix I: Variable Definitions

Variable	*Definition*
Neg	Standardized negative tone of each news story;
$Neg_{-30,-3}$	Standardized negative tone using news stories from 30 to 3 trading days prior to each earnings announcement;
VSM	$VSM = \frac{\sum_{k=1}^{10} \text{Information}_{i,j,j-k}}{10}$, $\text{Information}_{j,j-k} = 1 - \text{Similarity}_{j,j-k}$
$VSM_{-30,-3}$	The mean of VSM for the news stories from 30 to 3 trading days prior to each earnings announcement.
SUE	Seasonal difference of earnings by subtracting the previous 20 quarters' mean and dividing by the previous 20 quarters' standard deviation of seasonal difference of earnings; |*SUE*| is the absolute value.
SAFE	Median analyst forecast error by dividing the earnings volatility during the past 20 quarters; |*SAFE*| is the absolute value.
$CAR_{-2,-2}$	Abnormal return for 2 trading day before each news release date; $\|CAR_{-2,-2}\|$ is the absolute value.
$CAR_{-30,-3}$	Cumulative abnormal return for 30 to 3 trading days before each news release date; $\| CAR_{-30,-3}\|$ is the absolute value.
EXP	The number of years of working experience as a business journalist;
Award	An indicator variable equal to 1 if the journalist has been the winner or finalist for any of the three awards, Pulitzer Award, Gerald Loeb Award and John Hancock Award, and 0 otherwise;
Columnist	An indicator variable equal to 1 if the journalist is a columnist and 0 otherwise;
Gender	An indicator variable equal to 1 if the journalist is a female and 0 otherwise;
Economics	An indicator variable equal to 1 if the journalist has an econ major and 0 otherwise;
MBA	An indicator variable equal to 1 if the journalist has a MBA degree and 0 otherwise;
Top4Jschool	An indicator variable equal to 1 if the journalist is graduated from top four journalism schools and 0 otherwise;
Journalism	An indicator variable equal to 1 if the journalist has a journalism major and 0 otherwise;
Artmajor	An indicator variable equal to 1 if the journalist has a major in English, History, Political Science, Communication, International Studies, Literature, Law, or Philosophy and 0 otherwise;
High_Cov	An indicator variable equal to 1 if the journalist has followed the same firm for at least two years and written more than ten articles;
High_InsiderInt	An indicator variable equal to 1 if 50% of the journalist's first-hand information is from management and the journalist has written more than ten articles about the firm.
LnMKT	Log of market value; | *LnMKT* | is the absolute value.
LnBM	Log of book value to market value; | *LnBM* | is the absolute value.
LnTV	Trading volume is calculated as the log of annual shares traded divided by shares outstanding at the beginning of the calendar year; | *LnTV* | is the absolute value.
DISP	DISP is calculated as the standard deviation of analysts' earnings forecasts in the most recent time period prior to the earnings announcement scaled by earnings volatility; | *DISP* | is the absolute value.

REV	REV is the consensus I/B/E/S forecast in quarter t minus the consensus forecast in quarter t-1 for quarter t; | *REV* | is the absolute value.
$Alpha_{-252,-31}$	In earnings predictability test, $Alpha_{-252,-31}$ is the cumulative abnormal return over the estimation window of 252 to 31 trading days prior to each earnings announcement. In return predictability test, $Alpha_{-252,-31}$ is the cumulative abnormal return over the estimation window of 252 to 31 trading days prior to each news release date; $\|Alpha_{-252,-31}\|$ is the absolute value.
Experienced	News articles are classified into two groups based on the journalist working experience and age. The first group represents news articles wrote by more experienced journalists ("experienced"), from 51 to 100 percentile in terms of the number of years of working experience as a business journalist;
Less Experienced	The second group represents news articles wrote by less experienced journalists ("less experienced") journalists, up to 50 percentile in terms of the number of years of working experience as a business journalist;
Analyst	An indicator variable equal to 1 if the news article quotes analysts;
Fund	An indicator variable equal to 1 if the news article quotes institutional investors;
Insider	An indicator variable equal to 1 if the news article quotes insiders, i.e., executives and directors;
Expert	An indicator variable equal to 1 if the news article quotes experts, i.e., professors, researchers, and industry experts;
VSM2	$VSM2 = \frac{\sum_{k=1}^{10} \mathrm{Information}_{i,j,j-k}}{10}$; $\mathrm{Information}_{j,j-k} = 1 - \mathrm{Similarity}_{j,j-k}$; The 10 articles include not only WSJ but also Dow Jones Business News;
Net	Standardized net negative tone of each news story;
$Net_{-30,-3}$	Standardized net negative tone using news stories from 30 to 3 trading days prior to each earnings announcement;

Appendix II: Data Collection

I first extract sentences with quotes and contain “said”, “say” or “says.” I screen out quotes that come from public sources, such as annual reports, analyst reports, or conference calls. In particular, I exclude the quotes if the sentences mentions “statement”, “conference call”, “annual report”, “announcement”, “speech”, “10-K”, “10-Q”, “8-K”, “Form D”, “S-1”, “Form 144”, “20-F”, “6-K”, “11-K”, “DEF 14-A” and “SEC filing” right before or after the quote.

I then identify four types of sources: insiders (e.g., executives), analysts, institutional investors, and experts (e.g., professor, industry experts). In particular, I code the quote as “insider” if the sentence mentioned the name of firm’s top executive right before or after a quote. The executives’ names are collected from ExecuComp. In addition, I code the quotes as “insider” if the sentence contains the firm name and mentions “executive”, ”officer”, “director”, “manager”, “president” or “chairman” right before or after the quote. I code the quote as “analyst” if the sentence mentions “analyst”, “broker”, or “brokerage” right before or after a quote. I then code the quote as “institutional investor” if the sentence mentions “trader”, “fund manager”, “money manager”, “portfolio manager”, “equity strategist”, “equity manager”, “money strategist”, “portfolio strategist”, “stock strategist”, “manager of hedge fund”, “head of trading”, “investment strategist”, “investment manager”, “market strategist”, “option strategist”, “trading strategist”, “fixed-income strategist”, “derivatives specialist”, “director of portfolio strategy”, “money management”, “capital management”, “asset management”, or “wealth management” right before or after a quote. Finally, I code the quote as experts if the sentence mentions “professor”, “faculty”, “university”, “research institute”, “expert”, “economist”, “scientist”, “physician”, “commissioner”, “former”, “specialist”, or mentioned “executive”, “officer”, “director”, “manager”, “president”, “chairman” right before or after a quote but is not classified as an insider.

Table 1: Sample Description

Table 1, Panel A presents the main sample selection criteria. Panel B presents the number of news articles, number of journalists, and average number of news articles written by each journalist per year. Panel C and presents descriptive statistics over the sample period from July 1995 to June 2012. In Panel D, Pearson correlations are presented above the diagonal and Spearman correlations are presented below the diagonal. Correlations in bold are statistically significant at the p<0.10 level, using two tailed tests. All variables are defined in the appendix I.

Panel A: Sample Selection

	Number of Observations
S&P 1500 News Articles	296,497
Less Articles without an author	(88,886)
Less Articles with an author who wrote less than 10 articles in the sample period	(33,102)
Less Articles without available attributes data	(35,959)
Less observations without available Compustat, CRSP or IBES data	(6,443)
Final Sample	132,107

Panel B: Sample with Author by Year

	Num of articles	Number of journalists	Number of articles per journalist
1995	2,928	235	12.460
1996	6,229	303	20.558
1997	6,769	344	19.677
1998	7,442	397	18.746
1999	7,305	496	14.728
2000	5,452	430	12.679
2001	8,171	547	14.938
2002	7,587	431	17.603
2003	6,009	364	16.508
2004	9,808	419	23.408
2005	10,119	464	21.808
2006	7,298	457	15.969
2007	7,701	479	16.077
2008	10,127	423	23.941
2009	10,517	482	21.820
2010	7,915	479	16.524
2011	8,037	420	19.136
2012	2,693	222	12.131

Panel C: Descriptive Statistics

Variable	NO.	Mean	Std	25%	50%	75%
Neg	132,107	0.231	1.112	-0.463	0.021	0.699
VSM	132,107	0.748	0.111	0.675	0.759	0.831
SUE	132,107	-0.011	0.252	-0.007	0.000	0.006
SAFE	132,107	0.003	0.090	0.000	0.000	0.001
LnMKT	132,107	9.608	1.919	8.212	9.832	11.106
LnBM	132,107	-1.004	0.854	-1.530	-0.965	-0.455
LnTV	132,107	13.053	0.896	12.413	13.008	13.685
DISP	132,107	0.318	0.734	0.019	0.050	0.283
REV	132,107	-0.050	0.287	-0.048	-0.004	0.017
$Alpha_{-252,-31}$	132,107	0.000	0.001	-0.001	0.000	0.001
$CAR_{-30,-3}$	132,107	0.000	0.099	-0.046	-0.003	0.045
$CAR_{-2,-2}$	132,107	0.001	0.023	-0.009	0.001	0.011

Panel D: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) SUE		**0.06**	**-0.06**	**0.05**	**0.01**	**0.02**	**0.04**	**0.04**	0.01	**-0.02**	**-0.01**	**0.01**	**0.02**	**0.01**	**0.03**
(2) SAFE	**0.36**		**-0.28**	**0.05**	**0.01**	**0.05**	**0.10**	**-0.02**	**0.01**	0.00	**-0.02**	**0.01**	0.00	**0.01**	**0.03**
(3) Neg	**-0.07**	**-0.08**		**-0.17**	**-0.01**	0.03	**-0.21**	**0.05**	0.00	**-0.02**	**-0.01**	**0.08**	**-0.06**	**0.11**	**0.18**
(4) VSM	**0.07**	**0.10**	**-0.11**		**0.34**	**0.18**	**0.21**	**0.02**	**-0.01**	**-0.07**	0.00	**0.05**	**-0.07**	**0.06**	**0.08**
(5) LnEXP	**0.02**	**0.01**	**-0.03**	**0.02**		**0.18**	**0.11**	**0.11**	**-0.02**	**0.06**	0.00	**0.01**	**0.02**	**-0.01**	**-0.02**
(6) Award	**0.02**	**0.04**	**0.06**	**0.06**	**0.09**		**0.30**	**-0.23**	0.00	**0.06**	**-0.02**	**0.12**	**0.05**	**0.01**	**-0.04**
(7) Columnist	**0.01**	**0.01**	**-0.01**	**0.04**	**0.10**	**0.13**		**-0.35**	**-0.04**	**0.07**	**-0.01**	**0.06**	**0.10**	**-0.06**	**-0.07**
(8) LnMKT	**0.07**	**-0.08**	**-0.03**	**0.02**	**0.02**	**0.02**	0.00		0.00	**0.02**	**0.03**	**0.02**	**-0.03**	**-0.03**	**0.09**
(9) LnBM	**-0.15**	**-0.15**	**0.13**	**-0.07**	**-0.02**	**0.06**	**-0.05**	**-0.35**		**0.13**	**0.11**	**0.04**	**-0.02**	**-0.01**	**-0.01**
(10) LnTV	**-0.07**	0.00	**0.09**	**-0.12**	**-0.04**	**0.05**	0.00	**-0.25**	**0.28**		**0.10**	**-0.06**	**0.05**	**-0.01**	0.00
(11) DISP	**-0.10**	**-0.11**	**0.09**	**-0.06**	**-0.02**	**-0.06**	**-0.02**	0.00	**0.29**	**0.28**		**0.02**	**0.03**	**0.01**	0.01
(12) REV	**0.30**	**0.35**	**-0.07**	**0.05**	**0.02**	**0.03**	**0.01**	**0.07**	**-0.19**	**-0.07**	**-0.23**		**-0.08**	**0.02**	**0.02**
(13) $Alpha_{-252,-31}$	**0.26**	**0.22**	**-0.09**	**0.08**	**-0.01**	**-0.03**	0.00	**0.05**	**-0.24**	**0.02**	**-0.09**	**0.24**		**-0.02**	**-0.03**
(14) $CAR_{-30,-3}$	**0.04**	**0.03**	0.00	**-0.01**	**-0.01**	0.00	**0.01**	0.00	**0.07**	**0.02**	**0.02**	**-0.02**	**-0.24**		**0.40**
(15) $CAR_{-2,-2}$	**0.04**	**0.04**	**-0.02**	**0.01**	0.00	0.00	**0.01**	**0.06**	**-0.03**	**-0.02**	**-0.01**	**0.03**	**-0.06**	**0.08**	

Table 2: Background Information of Financial Journalists

Table 2 presents descriptive statistics on attributes of financial journalists. All variables are defined in the appendix I.

Variable	No.	Mean	Std	25%	50%	75%
EXP	1112	15.774	9.241	9	14	21
Columnist	1404	0.201	0.401	0	0	0
Award	1404	0.139	0.347	0	0	0
Gender	1157	0.380	0.486	0	0	1
MBA	911	0.054	0.226	0	0	0
Master	911	0.440	0.497	0	0	1
Major						
Journalism	911	0.379	0.485	0	0	1
English	911	0.167	0.373	0	0	0
Econ/Business	911	0.071	0.258	0	0	0
History	911	0.097	0.296	0	0	0
International Studies	911	0.078	0.268	0	0	0
Communication	911	0.036	0.187	0	0	0
Literature	911	0.040	0.195	0	0	0
Law	911	0.016	0.127	0	0	0
Philosophy	911	0.010	0.099	0	0	0
Science	911	0.024	0.154	0	0	0
Political Science	911	0.081	0.273	0	0	0
Other	911	0.288	0.453	0	0	1

Table 3: Media and Earnings Surprises

Table 3 reports the results of Equation (1A) and (1B) for the full sample. Day 0 is the earnings announcement date. All variables are defined in the appendix I. In all specifications, standard errors are clustered by firm and quarter. P-values are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Media Tone	
	(1)	(2)
	SUE	SAFE
$Neg_{-30,-3}$	-0.015***	-0.006**
	(0.002)	(0.026)
SUE_lag	0.380***	
	(0.000)	
SAFE_lag		0.288***
		(0.000)
LnMKT	0.017***	0.002
	(0.001)	(0.401)
LnBM	0.009*	-0.004
	(0.072)	(0.303)
LmTV	-0.014**	-0.001
	(0.024)	(0.859)
DISP	-0.004	-0.003
	(0.526)	(0.636)
REV	0.129***	0.058***
	(0.000)	(0.003)
$Alpha_{-252,-31}$	39.721***	13.984***
	(0.000)	(0.000)
$CAR_{-30,-3}$	0.012**	0.019***
	(0.041)	(0.000)
$CAR_{-2,-2}$	0.007**	0.002
	(0.021)	(0.242)
Intercept	0.015	-0.016
	(0.821)	(0.831)
Obs	12,455	12,455
Adj R^2	0.162	0.091

	VSM	
	(1)	(2)
	|SUE|	|SAFE|
$VSM_{-30,-3}$	0.065**	0.010*
	(0.019)	(0.056)
|SUE_lag|	0.584***	
	(0.000)	
|SAFE_lag|		0.601***
		(0.000)
|LnMKT|	-0.051***	-0.043***
	(0.000)	(0.000)
|LnBM|	0.046***	0.009***
	(0.000)	(0.007)
|LmTV|	-0.033***	-0.022***
	(0.000)	(0.000)
|DISP|	0.020**	0.016**
	(0.022)	(0.018)
|REV|	0.060**	0.036**
	(0.034)	(0.048)
$\|Alpha_{-252,-31}\|$	13.125**	-0.189
	(0.021)	(0.877)
$\|CAR_{-30,-3}\|$	0.067	0.031
	(0.333)	(0.430)
$\|CAR_{-2,-2}\|$	0.116	0.241
	(0.591)	(0.245)
Intercept	1.891***	1.682***
	(0.000)	(0.000)
Obs	12,455	12,455
Adj R^2	0.351	0.424

Table 4. Article Level

Table 4 reports the results of Equation (1C) and (1D) at article level. Day 0 is the earnings announcement date. All variables are defined in the appendix I. In all specifications, standard errors are clustered by firm and quarter. P-values are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Media Tone

VARIABLES	(1) SUE	(2) SUE	(3) SAFE	(4) SAFE
Neg	-1.659**	-1.392*	-0.770***	-0.529*
	(0.021)	(0.083)	(0.005)	(0.084)
LnEXP	-0.007	-0.007	-0.002	-0.001
	(0.107)	(0.144)	(0.254)	(0.651)
*Neg * LnEXP*	-0.464**	-0.350**	-0.220***	-0.129**
	(0.022)	(0.032)	(0.004)	(0.035)
Award	0.005*	0.006**	-0.002	-0.003**
	(0.097)	(0.036)	(0.108)	(0.020)
*Neg * Award*	-0.023	-0.066	-0.066	-0.095*
	(0.150)	(0.154)	(0.147)	(0.054)
Columnist	0.000	0.001	0.001	0.002*
	(0.920)	(0.791)	(0.249)	(0.085)
*Neg * Columnist*	-0.242**	-0.229*	-0.102**	-0.121**
	(0.037)	(0.065)	(0.020)	(0.010)
Gender		-0.012***		-0.003***
		(0.000)		(0.010)
*Neg * Gender*		-0.082**		-0.090**
		(0.013)		(0.019)
Economics		-0.010*		-0.002
		(0.082)		(0.427)
*Neg * Economics*		-0.264		-0.094
		(0.283)		(0.317)
MBA		0.007		0.001
		(0.249)		(0.817)
Neg MBA*		-0.742**		-0.146
		(0.017)		(0.115)
Top4Jschool		-0.009**		-0.000
		(0.016)		(0.938)
*Neg * Top4Jschool*		0.390		-0.008
		(0.112)		(0.887)
Journalism		0.001		-0.004***
		(0.845)		(0.003)
*Neg * Journalism*		-0.077		-0.099*
		(0.563)		(0.052)
Artmajor		0.004		-0.000
		(0.117)		(0.740)
*Neg * Artmajor*		-0.096		0.028
		(0.334)		(0.457)
SUE_lag	0.410***	0.403***		
	(0.000)	(0.000)		
SAFE_lag			0.283***	0.275***
			(0.000)	(0.000)
LnMKT	0.010***	0.008***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
LnBM	0.007***	0.007***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
LmTV	-0.001	-0.003***	0.002***	0.002***
	(0.595)	(0.004)	(0.000)	(0.000)

DISP	-0.004***	-0.004***	-0.001**	-0.001**
	(0.000)	(0.001)	(0.027)	(0.032)
REV	0.033***	0.027***	0.010***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
Alpha$_{-252,-31}$	18.439***	18.537***	3.752***	3.446***
	(0.000)	(0.000)	(0.000)	(0.000)
CAR $_{-30,-3}$	0.048***	0.068***	0.016***	0.017***
	(0.000)	(0.000)	(0.000)	(0.000)
CAR $_{-2,-2}$	0.393***	0.361***	0.083***	0.064***
	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	-0.066***	-0.015	-0.006	-0.001
	(0.002)	(0.543)	(0.477)	(0.890)
Obs	132,107	96,055	132,107	96,055
Adj R^2	0.186	0.181	0.101	0.0966

Panel B. Information Content Based on Vector Space Model (VSM)

	(1)	(2)	(3)	(4)
VARIABLES	|SUE|	|SUE|	|SAFE|	|SAFE|
VSM	0.224***	0.134*	0.062**	0.037*
	(0.009)	(0.079)	(0.032)	(0.070)
LnEXP	-0.032*	-0.052***	-0.010*	-0.014**
	(0.050)	(0.004)	(0.078)	(0.028)
*VSM * LnEXP*	0.068***	0.041**	0.018**	0.012*
	(0.005)	(0.043)	(0.025)	(0.095)
Award	-0.014	0.006	-0.005	-0.004
	(0.171)	(0.585)	(0.106)	(0.246)
*VSM * Award*	0.015	0.008	0.006	0.005
	(0.155)	(0.189)	(0.174)	(0.277)
Columnist	-0.027***	-0.015	-0.009***	-0.008**
	(0.004)	(0.132)	(0.003)	(0.019)
*VSM * Columnist*	0.037***	0.022*	0.013***	0.010**
	(0.002)	(0.098)	(0.001)	(0.017)
Gender		0.032***		0.004
		(0.002)		(0.196)
*VSM * Gender*		0.037***		0.006
		(0.006)		(0.156)
Economics		0.017		-0.005
		(0.330)		(0.364)
*VSM * Economics*		0.028		0.003
		(0.242)		(0.719)
MBA		-0.014		0.006
		(0.525)		(0.379)
*VSM * MBA*		0.018		0.008
		(0.540)		(0.423)
Top4Jschool		0.006		-0.012***
		(0.650)		(0.006)
*VSM * Top4Jschool*		0.007		0.014**
		(0.661)		(0.012)
Journalism		-0.027**		-0.003
		(0.015)		(0.482)
*VSM * Journalism*		0.031**		0.002
		(0.034)		(0.723)
Artmajor		-0.035***		-0.003
		(0.000)		(0.299)

*VSM * Artmajor*		0.047		0.004
		(0.130)		(0.267)
|SUE_lag|	0.569***	0.565***		
	(0.000)	(0.000)		
|SAFE_lag|			0.615***	0.607***
			(0.000)	(0.000)
|LnMKT|	-0.024***	-0.024***	-0.008***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
|LnBM|	0.023***	0.023***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
|LmTV|	-0.017***	-0.015***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
|DISP|	0.005***	0.005***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
|REV|	0.026***	0.022***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
$\|Alpha_{-252,-31}\|$	3.793***	3.170***	-0.047	-0.618**
	(0.000)	(0.000)	(0.831)	(0.011)
$\|CAR_{-30,-3}\|$	-0.070***	-0.091***	-0.022***	-0.028***
	(0.000)	(0.000)	(0.000)	(0.000)
$\|CAR_{-2,-2}\|$	0.538***	0.634***	0.140***	0.176***
	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.558***	0.594***	0.141***	0.167***
	(0.000)	(0.000)	(0.000)	(0.000)
Obs	132,107	96,055	132,107	96,055
Adj R^2	0.391	0.389	0.498	0.488

Table 5 Descriptive Statistics. Financial Journalists and Quotes

Table 5 Panel A shows the descriptive statistics of news articles with four types of quotes, insider, analyst, institutional investor and experts. Panel B presents the binary logit estimation results for news articles with these four types of quotes. All variables are defined in the appendix I. In all specifications, standard errors are clustered by firm and quarter. P-values are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Descriptive Statistics

Variable	NO.	Mean	Std	25%	50%	75%
Insider	132,107	0.142	0.502	0	0	0
Analyst	132,107	0.085	0.413	0	0	0
Fund	132,107	0.121	0.335	0	0	0
Expert	132,107	0.092	0.392	0	0	0

Panel B. Journalist Attributes and Quotes

	(1)	(2)	(3)	(4)
VARIABLES	Logit(Insider=1)	Logit(Analyst=1)	Logit(Fund=1)	Logit(Expert=1)
LnEXP	0.149***	0.491***	1.754***	0.270***
	(0.003)	(0.000)	(0.000)	(0.000)
Columnist	0.125***	0.035*	0.543***	0.094***
	(0.000)	(0.062)	(0.000)	(0.000)
Award	0.054***	0.038*	0.295***	-0.072***
	(0.002)	(0.066)	(0.000)	(0.000)
Gender	0.023**	-0.059***	-0.296***	0.090***
	(0.017)	(0.002)	(0.000)	(0.000)
Economics	0.039*	0.296***	0.240***	-0.070*
	(0.092)	(0.000)	(0.000)	(0.067)
MBA	0.099***	0.133***	0.311***	0.086
	(0.005)	(0.001)	(0.000)	(0.114)
Top4Jschool	0.162	0.043*	0.481***	-0.011
	(0.102)	(0.084)	(0.000)	(0.522)
Journalism	0.038**	0.008	-0.131***	-0.007
	(0.037)	(0.7674)	(0.000)	(0.642)
Artmajor	-0.046***	-0.012	-0.187***	-0.061
	(0.001)	(0.528)	(0.000)	(0.120)
Intercept	-1.497***	-0.140	2.730***	-1.663***
	(0.000)	(0.326)	(0.000)	(0.000)
Obs	96,055	96,055	96,055	96,055
Pseudo R2	0.038	0.013	0.035	0.021

Table 6. Information Channels

Table 6 reports the results of Equation (2A) and (2B). Panel A and B (C and D) present the results using articles written by experienced journalists (journalists who have been columnists before). All variables are defined in the appendix I. In all specifications, standard errors are clustered by firm. P-values are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Media Tone

VARIABLES	(1) SUE	(2) SUE	(3) SUE	(4) SUE	(5) SUE	(6) SAFE	(7) SAFE	(8) SAFE	(9) SAFE	(10) SAFE
Neg	-0.038**	-0.013*	-0.027*	-0.019*	0.008	-0.031**	-0.030**	-0.028*	-0.023*	-0.040
	(0.047)	(0.065)	(0.089)	(0.064)	(0.894)	(0.048)	(0.038)	(0.071)	(0.083)	(0.172)
Insider	0.004				0.004	0.002				0.002
	(0.296)				(0.383)	(0.129)				(0.121)
*Neg * Insider*	-0.010**				-0.052*	-0.048*				-0.038*
	(0.045)				(0.071)	(0.065)				(0.072)
Analyst		0.004			0.003		-0.001			-0.001
		(0.493)			(0.578)		(0.781)			(0.621)
*Neg * Analyst*		-0.276*			-0.290*		-0.091			-0.082
		(0.082)			(0.087)		(0.192)			(0.231)
Fund			0.012		0.011			0.005		0.005
			(0.228)		(0.277)			(0.195)		(0.204)
*Neg * Fund*			-0.440***		-0.421***			-0.210**		-0.196**
			(0.008)		(0.009)			(0.037)		(0.042)
Expert				0.025*	0.024*				0.006	0.006
				(0.069)	(0.075)				(0.220)	(0.235)
*Neg * Expert*				-0.128**	-0.132**				-0.098**	-0.094**
				(0.028)	(0.042)				(0.040)	(0.041)
SUE_lag	0.396***	0.396***	0.396***	0.396***	0.396***					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
SAFE_lag						0.272***	0.272***	0.272***	0.272***	0.272***
						(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LnMKT	0.011***	0.011***	0.011***	0.011***	0.011***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LnBM	0.009***	0.009***	0.009***	0.009***	0.009***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LmTV	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.840)	(0.871)	(0.872)	(0.852)	(0.842)
DISP	-0.003*	-0.003*	-0.003*	-0.003*	-0.003*	0.000	0.000	0.000	0.000	0.000
	(0.075)	(0.073)	(0.073)	(0.070)	(0.076)	(0.462)	(0.468)	(0.471)	(0.496)	(0.471)
REV	0.037***	0.037***	0.037***	0.037***	0.037***	0.010***	0.010***	0.010***	0.010***	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Alpha_{-252,-31}$	15.944***	15.821***	15.918***	15.920***	15.907***	3.791***	3.773***	3.782***	3.786***	3.773***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$CAR_{-30,-3}$	0.019	0.019	0.019	0.019	0.019	0.019***	0.019***	0.019***	0.019***	0.019***
	(0.113)	(0.132)	(0.116)	(0.117)	(0.115)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$CAR_{-2,-2}$	0.173***	0.173***	0.174***	0.174***	0.174***	0.045**	0.046**	0.045**	0.045**	0.045**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.024)	(0.023)	(0.023)	(0.024)	(0.023)
Intercept	-0.049**	-0.049**	-0.050**	-0.050**	-0.050**	0.015*	0.016*	0.015*	0.015*	0.015*
	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.056)	(0.050)	(0.057)	(0.052)	(0.054)
Obs	74,179	74,179	74,179	74,179	74,179	74,179	74,179	74,179	74,179	74,179
Adj R^2	0.182	0.182	0.182	0.182	0.182	0.093	0.093	0.093	0.093	0.093

Panel B. Information Content Based on VSM

VARIABLES	(1) |SUE|	(2) |SUE|	(3) |SUE|	(4) |SUE|	(5) |SUE|	(6) |SAFE|	(7) |SAFE|	(8) |SAFE|	(9) |SAFE|	(10) |SAFE|
VSM	0.041**	0.042***	0.045*	0.044***	0.043*	0.012***	0.011***	0.012**	0.011**	0.009*
	(0.019)	(0.000)	(0.021)	(0.000)	(0.069)	(0.000)	(0.000)	(0.045)	(0.022)	(0.061)
Insider	-0.002				-0.002	0.003*				0.003*
	(0.749)				(0.772)	(0.091)				(0.082)
*VSM * Insider*	0.003**				0.003**	0.004*				0.004*
	(0.034)				(0.042)	(0.078)				(0.080)
Analyst		-0.001			-0.001		0.001			0.001
		(0.894)			(0.901)		(0.662)			(0.626)
*VSM * Analyst*		0.002*			0.002*		0.002			0.002
		(0.071)			(0.080)		(0.163)			(0.243)
Fund			0.023**		0.023**			0.007*		0.007*
			(0.048)		(0.047)			(0.062)		(0.056)
*VSM * Fund*			0.029**		0.027**			0.007**		0.007**
			(0.023)		(0.043)			(0.019)		(0.024)
Expert				-0.002	-0.002				-0.006	-0.006
				(0.934)	(0.903)				(0.498)	(0.476)
*VSM * Expert*				0.012*	0.011*				0.002**	0.003**
				(0.073)	(0.082)				(0.020)	(0.041)
|SUE_lag|	0.565***	0.565***	0.565***	0.565***	0.565***					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
|SAFE_lag|						0.643***	0.643***	0.642***	0.643***	0.643***
						(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
|LnMKT|	-0.025***	-0.025***	-0.025***	-0.025***	-0.025***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
|LnBM|	0.021***	0.021***	0.021***	0.021***	0.021***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
|LmTV|	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
|DISP|	0.004**	0.004**	0.003**	0.004**	0.004**	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.029)	(0.028)	(0.030)	(0.029)	(0.029)	(0.028)	(0.026)	(0.026)	(0.026)	(0.025)
|REV|	0.024***	0.024***	0.024***	0.024***	0.024***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\|Alpha_{-252,-31}\|$	0.564	0.571	0.575	0.563	0.582	-0.877**	-0.877**	-0.878**	-0.879**	-0.878**
	(0.604)	(0.591)	(0.597)	(0.604)	(0.591)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
$\|CAR_{-30,-3}\|$	-0.018	-0.018	-0.018	-0.019	-0.018	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.242)	(0.243)	(0.258)	(0.242)	(0.261)	(0.501)	(0.507)	(0.504)	(0.509)	(0.506)
$\|CAR_{-2,-2}\|$	0.305***	0.306***	0.306***	0.305***	0.308***	0.077***	0.077***	0.076***	0.077***	0.076***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	0.384***	0.385***	0.382***	0.384***	0.384***	0.094***	0.095***	0.095***	0.095***	0.095***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs	74,179	74,179	74,179	74,179	74,179	74,179	74,179	74,179	74,179	74,179
Adj R^2	0.382	0.382	0.382	0.382	0.382	0.481	0.481	0.481	0.481	0.481

Panel C. Media Tone

VARIABLES	(1) SUE	(2) SUE	(3) SUE	(4) SUE	(5) SUE	(6) SAFE	(7) SAFE	(8) SAFE	(9) SAFE	(10) SAFE
Neg	-0.131**	-0.122**	-0.119*	-0.161**	-0.113*	-0.046*	-0.046**	-0.057**	-0.057**	-0.038*
	(0.048)	(0.024)	(0.076)	(0.039)	(0.092)	(0.065)	(0.028)	(0.017)	(0.037)	(0.063)
Insider	0.007				0.007	0.002				0.002
	(0.174)				(0.197)	(0.244)				(0.301)
*Neg * Insider*	-0.063**				-0.055**	-0.060*				-0.051**
	(0.036)				(0.041)	(0.052)				(0.041)
Analyst		0.006			0.005		0.003			0.003
		(0.371)			(0.492)		(0.215)			(0.262)
*Neg * Analyst*		-0.166*			-0.140*		-0.091			-0.088
		(0.069)			(0.084)		(0.291)			(0.321)
Fund			0.011		0.010			-0.003		-0.001
			(0.367)		(0.391)			(0.935)		(0.895)
*Neg * Fund*			-0.605***		-0.586***			-0.117**		-0.126**
			(0.003)		(0.007)			(0.025)		(0.041)
Expert				-0.009	-0.010				0.004	0.004
				(0.626)	(0.585)				(0.559)	(0.574)
*Neg * Expert*				-0.189*	-0.199*				-0.060*	-0.055*
				(0.071)	(0.082)				(0.083)	(0.086)
SUE_lag	0.379***	0.379***	0.379***	0.379***	0.379***					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
SAFE_lag						0.292***	0.292***	0.292***	0.292***	0.292***
						(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LnMKT	0.014***	0.014***	0.014***	0.014***	0.014***	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.918)	(0.899)	(0.914)	(0.927)	(0.925)
LnBM	0.010***	0.010***	0.010***	0.010***	0.010***	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.113)	(0.121)	(0.114)	(0.112)	(0.117)
LmTV	0.002	0.002	0.002	0.002	0.002	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.288)	(0.293)	(0.279)	(0.295)	(0.264)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DISP	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*	0.000	0.000	0.000	0.000	0.000
	(0.078)	(0.077)	(0.074)	(0.071)	(0.070)	(0.783)	(0.788)	(0.789)	(0.811)	(0.801)
REV	0.039***	0.039***	0.039***	0.039***	0.039***	0.013***	0.013***	0.013***	0.013***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Alpha_{-252,-31}$	13.105***	13.081***	13.111***	13.091***	13.132***	2.366***	2.362***	2.367***	2.370***	2.362***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$CAR_{-30,-3}$	0.059***	0.059***	0.059***	0.060***	0.059***	0.018***	0.018***	0.018***	0.018***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
$CAR_{-2,-2}$	0.141**	0.141**	0.142**	0.142**	0.141**	0.000	-0.000	-0.000	-0.000	-0.000
	(0.043)	(0.042)	(0.042)	(0.042)	(0.043)	(0.995)	(0.989)	(0.999)	(0.994)	(0.989)
Intercept	-0.169***	-0.168***	-0.169***	-0.167***	-0.170***	-0.056***	-0.056***	-0.055***	-0.055***	-0.056***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs	32,733	32,733	32,733	32,733	32,733	32,733	32,733	32,733	32,733	32,733
Adj R^2	0.153	0.153	0.153	0.153	0.153	0.108	0.108	0.108	0.108	0.108

Panel D. Information Content Based on VSM

VARIABLES	(1) |SUE|	(2) |SUE|	(3) |SUE|	(4) |SUE|	(5) |SUE|	(6) |SAFE|	(7) |SAFE|	(8) |SAFE|	(9) |SAFE|	(10) |SAFE|
VSM	0.068**	0.073**	0.072**	0.071**	0.071*	0.025**	0.026***	0.023**	0.027**	0.025
	(0.011)	(0.019)	(0.040)	(0.031)	(0.052)	(0.020)	(0.000)	(0.035)	(0.042)	(0.108)
Insider	-0.007				-0.007	0.001				0.002
	(0.272)				(0.272)	(0.483)				(0.473)
*VSM * Insider*	0.013**				0.012**	0.003**				0.003*
	(0.017)				(0.039)	(0.016)				(0.065)
Analyst		0.014*			0.014*		0.001			0.001
		(0.092)			(0.086)		(0.772)			(0.762)
*VSM * Analyst*		0.016**			0.015**		0.001			-0.001
		(0.022)			(0.047)		(0.127)			(0.656)
Fund			0.005		0.005			0.003		0.003
			(0.737)		(0.744)			(0.606)		(0.578)
*VSM * Fund*			0.113***		0.111**			0.023***		0.023***
			(0.007)		(0.016)			(0.026)		(0.033)
Expert				-0.014	-0.013				-0.003	-0.002
				(0.581)	(0.621)				(0.755)	(0.786)
*VSM * Expert*				0.018**	0.017**				0.002**	0.001*
				(0.017)	(0.034)				(0.057)	(0.072)
|SUE_lag|	0.557***	0.557***	0.557***	0.557***	0.557***					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
|SAFE_lag|						0.652***	0.652***	0.652***	0.652***	0.652***
						(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
|LnMKT|	-0.029***	-0.029***	-0.029***	-0.029***	-0.029***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
|LnBM|	0.028***	0.028***	0.028***	0.028***	0.028***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
|LmTV|	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
|DISP|	0.005***	0.005***	0.005***	0.005***	0.005***	0.002**	0.002**	0.002**	0.002**	0.002**
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.015)	(0.015)	(0.016)	(0.015)	(0.014)
|REV|	0.029***	0.029***	0.029***	0.029***	0.029***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\|Alpha_{-252,-31}\|$	-3.086**	-3.051**	-3.025**	-3.054**	-3.048**	-1.975***	-1.960***	-1.961***	-1.965***	-1.967***
	(0.020)	(0.021)	(0.022)	(0.021)	(0.022)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\|CAR_{-30,-3}\|$	-0.019	-0.020	-0.019	-0.020	-0.019	-0.006	-0.006	-0.006	-0.006	-0.006
	(0.311)	(0.312)	(0.320)	(0.306)	(0.325)	(0.363)	(0.371)	(0.373)	(0.371)	(0.367)
$\|CAR_{-2,-2}\|$	0.383***	0.382***	0.386***	0.383***	0.385***	0.147***	0.148***	0.148***	0.147***	0.148***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.362***	0.357***	0.357***	0.359***	0.360***	0.088***	0.088***	0.087***	0.087***	0.088***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs	32,733	32,733	32,733	32,733	32,733	32,733	32,733	32,733	32,733	32,733
Adj R^2	0.376	0.376	0.376	0.376	0.376	0.519	0.519	0.519	0.519	0.519

Table 7. Descriptive Statistics

Table 7 presents descriptive statistics on news articles written by the same journalist on the same firm in a given year.

Year	NO.	Mean	Std	25%	50%	75%	90%
1995	1416	1.785	2.468	1	1	1	3
1996	3882	1.976	3.860	1	1	2	3
1997	4293	1.846	3.180	1	1	1	3
1998	4294	1.801	2.969	1	1	1	3
1999	4974	1.563	2.091	1	1	1	2
2000	5657	1.035	0.209	1	1	1	2
2001	5504	1.053	0.298	1	1	1	2
2002	3188	1.844	3.160	1	1	1	3
2003	3314	1.697	2.196	1	1	1	3
2004	4165	2.024	3.486	1	1	2	3
2005	4496	2.039	3.925	1	1	2	3
2006	4515	1.888	2.969	1	1	2	3
2007	4689	1.818	2.915	1	1	1	3
2008	4464	1.984	3.631	1	1	2	3
2009	4945	1.942	3.572	1	1	2	3
2010	4856	1.885	3.040	1	1	2	3
2011	4721	1.943	2.944	1	1	2	3
2012	2442	1.593	1.568	1	1	1	3

Table 8. Independence and Information Advantage

Table 8 presents the results for Equations (3A) and (3B) for experienced and reputable journalists. Panel A and B (Panel C and D) present results for firm-specific coverage (firm-specific network).

Panel A. High Firm-Specific Coverage (Media Tone)

	Experienced Journalists		Columnists	
	(1)	(2)	(3)	(4)
VARIABLES	SUE	SAFE	SUE	SAFE
Neg	-0.381***	-0.013***	-0.279**	-0.170***
	(0.000)	(0.006)	(0.021)	(0.000)
High_Cov	-0.001	-0.000	-0.010*	-0.002
	(0.841)	(0.997)	(0.084)	(0.322)
*Neg * High_Cov*	0.387**	0.017**	0.344**	0.198**
	(0.026)	(0.028)	(0.014)	(0.048)
Neg +	0.006	0.004	0.065	0.028
*Neg * High_Cov*	(0.970)	(0.982)	(0.875)	(0.731)
SUE_lag	0.398***		0.380***	
	(0.000)		(0.000)	
SAFE_lag		0.271***		0.293***
		(0.000)		(0.000)
LnMKT	0.010***	-0.002***	0.014***	0.000
	(0.000)	(0.000)	(0.000)	(0.901)
LnBM	0.009***	-0.002***	0.010***	-0.001
	(0.000)	(0.000)	(0.000)	(0.110)
LmTV	-0.004***	-0.000	0.002	0.004***
	(0.004)	(0.912)	(0.244)	(0.000)
DISP	-0.003*	0.000	-0.004*	0.000
	(0.073)	(0.431)	(0.077)	(0.714)
REV	0.037***	0.010***	0.040***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)
$Alpha_{-252,-31}$	15.902***	3.776***	12.931***	2.411***
	(0.000)	(0.000)	(0.000)	(0.000)
$CAR_{-30,-3}$	0.022*	0.020***	0.055***	0.018***
	(0.077)	(0.000)	(0.001)	(0.003)
$CAR_{-2,-2}$	0.161***	0.047**	0.139**	0.002
	(0.002)	(0.018)	(0.046)	(0.954)
Intercept	-0.049**	0.015*	-0.170***	-0.055***
	(0.020)	(0.065)	(0.000)	(0.000)
Obs	74,179	74,179	32,733	32,733
Adj R^2	0.182	0.093	0.153	0.108

Panel B. High Firm-Specific Coverage (VSM)

	Experienced Journalists		Columnists	
	(1)	(2)	(3)	(4)
VARIABLES	|SUE|	|SAFE|	|SUE|	|SAFE|
VSM	0.036***	0.015***	0.066***	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)
High_Cov	-0.009	-0.000	-0.012	-0.001
	(0.532)	(0.957)	(0.543)	(0.825)
*VSM * High_Cov*	-0.030**	-0.012*	-0.058**	-0.017***
	(0.021)	(0.076)	(0.046)	(0.001)
VSM +	0.006	0.003	0.008	0.002
*VSM * High_Cov*	(0.686)	(0.784)	(0.586)	(0.792)
|SUE_lag|	0.566***		0.559***	
	(0.000)		(0.000)	
|SAFE_lag|		0.619***		0.653***
		(0.000)		(0.000)
|LnMKT|	-0.026***	-0.008***	-0.028***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
|LnBM|	0.023***	0.005***	0.028***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
|LmTV|	-0.012***	-0.002***	-0.010***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
|DISP|	0.003**	0.001*	0.005***	0.002**
	(0.019)	(0.087)	(0.009)	(0.011)
|REV|	0.035***	0.008***	0.029***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
$\|Alpha_{-252,-31}\|$	1.018	-0.442	-3.374**	-1.805***
	(0.308)	(0.182)	(0.011)	(0.000)
$\|CAR_{-30,-3}\|$	-0.057***	-0.011**	-0.019	-0.007
	(0.000)	(0.023)	(0.330)	(0.273)
$\|CAR_{-2,-2}\|$	0.415***	0.093***	0.391***	0.146***
	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.387***	0.094***	0.357***	0.088***
	(0.000)	(0.000)	(0.000)	(0.000)
Obs	74,179	74,179	32,733	32,733
Adj R^2	0.382	0.481	0.376	0.519

Panel C. High Firm-Specific Network (Media Tone)

	Experienced Journalists		Columnists	
	(1)	(2)	(3)	(4)
VARIABLES	SUE	SAFE	SUE	SAFE
Neg	-0.376***	-0.049***	-0.243**	-0.138***
	(0.000)	(0.005)	(0.038)	(0.003)
High_InsiderInt	0.002	-0.001	-0.007	-0.003
	(0.659)	(0.515)	(0.286)	(0.265)
*Neg * High_InsiderInt*	0.398**	0.063**	0.422**	0.089**
	(0.042)	(0.012)	(0.036)	(0.039)
Neg +	0.022	0.014	0.179	-0.049
*Neg * High_InsiderInt*	(0.903)	(0.674)	(0.256)	(0.374)
SUE_lag	0.402***		0.380***	
	(0.000)		(0.000)	
SAFE_lag		0.270***		0.292***
		(0.000)		(0.000)
LnMKT	0.010***	-0.002***	0.014***	0.000
	(0.000)	(0.000)	(0.000)	(0.741)
LnBM	0.009***	-0.002***	0.010***	-0.001
	(0.000)	(0.000)	(0.000)	(0.145)
LmTV	-0.004***	-0.000	0.002	0.004***
	(0.002)	(0.891)	(0.320)	(0.000)
DISP	-0.003*	0.000	-0.004*	0.000
	(0.074)	(0.430)	(0.070)	(0.720)
REV	0.037***	0.010***	0.039***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)
$Alpha_{-252,-31}$	15.830***	3.821***	13.153***	2.386***
	(0.000)	(0.000)	(0.000)	(0.000)
$CAR_{-30,-3}$	0.021*	0.020***	0.060***	0.018***
	(0.088)	(0.000)	(0.000)	(0.003)
$CAR_{-2,-2}$	0.161***	0.044**	0.138**	0.003
	(0.002)	(0.027)	(0.047)	(0.922)
Intercept	-0.045**	0.015*	-0.164***	-0.056***
	(0.029)	(0.057)	(0.000)	(0.000)
Obs	74,179	74,179	32,733	32,733
Adj R^2	0.182	0.093	0.153	0.108

Panel D. High Firm-Specific Network (VSM)

	Experienced Journalists		Columnists	
	(1)	(2)	(3)	(4)
VARIABLES	|SUE|	|SAFE|	|SUE|	|SAFE|
VSM	0.037***	0.013***	0.055***	0.023***
	(0.000)	(0.000)	(0.000)	(0.000)
High_InsiderInt	0.004	0.004	0.013	0.015**
	(0.793)	(0.497)	(0.505)	(0.029)
*VSM * High_InsiderInt*	-0.036**	-0.013**	-0.050**	-0.028***
	(0.047)	(0.036)	(0.040)	(0.002)
	0.001	0.001	0.005	-0.005
	(0.987)	(0.975)	(0.689)	(0.721)
|SUE_lag|	0.567***		0.645***	
	(0.000)		(0.000)	
|SAFE_lag|		0.618***		0.651***
		(0.000)		(0.000)
|LnMKT|	-0.025***	-0.008***	-0.028***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
|LnBM|	0.023***	0.005***	0.028***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
|LmTV|	-0.013***	-0.002***	-0.010***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.001)
|DISP|	0.004**	0.001*	0.006***	0.002***
	(0.015)	(0.082)	(0.007)	(0.009)
|REV|	0.035***	0.008***	0.029***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
$\|Alpha_{-252,-31}\|$	1.123	-0.476	-3.267**	-1.875***
	(0.261)	(0.152)	(0.014)	(0.000)
$\|CAR_{-30,-3}\|$	-0.061***	-0.010**	-0.020	-0.005
	(0.000)	(0.034)	(0.305)	(0.400)
$\|CAR_{-2,-2}\|$	0.425***	0.092***	0.388***	0.142***
	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.390***	0.093***	0.350***	0.084***
	(0.000)	(0.000)	(0.000)	(0.000)
Obs	74,179	74,179	32,733	32,733
Adj R^2	0.382	0.481	0.376	0.519

Table 9. Earnings News

Table 9 reports the results from additional analysis using earnings news. All variables are defined in the appendix. In all specifications, standard errors are clustered by firm. P-values are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Experience and Reputation

	(1) |SUE|	(2) |SAFE|
VSM	0.205*	0.102*
	(0.277)	(0.059)
LnEXP	0.038	0.018
	(0.326)	(0.221)
*VSM * LnEXP*	0.050**	0.025**
	(0.043)	(0.024)
Award	-0.050**	-0.024***
	(0.036)	(0.006)
*VSM * Award*	0.058*	0.030**
	(0.074)	(0.015)
Columnist	0.032	0.003
	(0.142)	(0.686)
*VSM * columnist*	0.044**	0.004*
	(0.031)	(0.056)
|SUE_lag|	0.587***	
	(0.000)	
|SAFE_lag|		0.649***
		(0.000)
|LnMKT|	-0.031***	-0.012***
	(0.000)	(0.000)
|LnBM|	0.025***	0.008***
	(0.000)	(0.000)
|LmTV|	-0.026***	-0.005***
	(0.000)	(0.000)
|DISP|	0.009***	0.002*
	(0.003)	(0.099)
|REV|	0.030***	0.008***
	(0.000)	(0.001)
$\|Alpha_{-252,-31}\|$	4.806***	1.451**
	(0.003)	(0.019)
$\|CAR_{-30,-3}\|$	0.006	-0.006
	(0.804)	(0.448)
$\|CAR_{-2,-2}\|$	0.665***	0.147***
	(0.000)	(0.000)
Intercept	0.474***	0.101*
	(0.001)	(0.059)
Obs	32,392	32,392
Adj R^2	0.386	0.492

Panel B. Information Channels

VARIABLES	(1) |SUE|	(2) |SAFE|
VSM	0.013	0.026***
	(0.109)	(0.000)
Insider	-0.062***	0.003
	(0.000)	(0.434)
*Insider * VSM*	0.090***	0.023**
	(0.000)	(0.020)
Analyst	0.032	0.020
	(0.782)	(0.342)
*Analyst * VSM*	0.019*	0.013
	(0.078)	(0.331)
Fund	0.019	-0.001
	(0.279)	(0.559)
*Fund * VSM*	0.025***	0.021**
	(0.002)	(0.019)
Expert	0.083	0.043*
	(0.167)	(0.057)
*Expert * VSM*	0.021**	0.068**
	(0.044)	(0.028)
|*SUE_lag*|	0.588***	
	(0.000)	
|*SAFE_lag*|		0.668***
		(0.000)
|*LnMKT*|	-0.031***	-0.011***
	(0.000)	(0.000)
|*LnBM*|	0.027***	0.007***
	(0.000)	(0.000)
|*LmTV*|	-0.024***	-0.004***
	(0.000)	(0.000)
|*DISP*|	0.014***	0.001
	(0.000)	(0.340)
|*REV*|	0.032***	0.009***
	(0.000)	(0.000)
$\|Alpha_{-252,-31}\|$	5.352***	0.279
	(0.002)	(0.684)
$\|CAR_{-30,-3}\|$	0.006	0.024***
	(0.805)	(0.005)
$\|CAR_{-2,-2}\|$	0.584***	0.092**
	(0.000)	(0.016)
Intercept	0.604***	0.143***
	(0.000)	(0.000)
Obs	16,232	16,232
Adj R^2	0.402	0.513

Panel C. Independence and Information Advantage

VARIABLES	(1) |SUE|	(2) |SAFE|
VSM	0.043***	0.009***
	(0.109)	(0.000)
High_Cov	-0.013*	-0.003**
	(0.060)	(0.014)
High_Cov VSM*	-0.044***	-0.010**
	(0.000)	(0.011)
|*SUE_lag*|	0.586***	
	(0.000)	
|*SAFE_lag*|		0.666***
		(0.000)
|*LnMKT*|	-0.031***	-0.011***
	(0.000)	(0.000)
|*LnBM*|	0.028***	0.006***
	(0.000)	(0.000)
|*LmTV*|	-0.025***	-0.004***
	(0.000)	(0.000)
|*DISP*|	0.013***	0.001
	(0.000)	(0.690)
|*REV*|	0.031***	0.009***
	(0.000)	(0.000)
|$Alpha_{-252,-31}$|	5.360***	0.271
	(0.000)	(0.722)
|$CAR_{-30,-3}$|	0.006	0.024***
	(0.755)	(0.002)
|$CAR_{-2,-2}$|	0.586***	0.091**
	(0.000)	(0.044)
Intercept	0.633***	0.148***
	(0.000)	(0.000)
Obs	16,232	16,232
Adj R^2	0.402	0.513

Table 10 Additional Test Including Dow Jones Business News

Table 10 reports the results from additional analysis including Dow Jones Business News over the sample period from January 2004 to June 2012. All variables are defined in the appendix I. In all specifications, standard errors are clustered by firm. P-values are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Experience and Reputation

	(1) |SUE|	(2) |SAFE|
VSM2	0.119*	0.075*
	(0.059)	(0.068)
LnEXP	-0.026***	-0.010***
	(0.002)	(0.001)
*VSM2 * LnEXP*	0.042**	0.019***
	(0.014)	(0.005)
Award	-0.015***	-0.001
	(0.003)	(0.541)
*VSM2 * Award*	0.036***	0.002
	(0.006)	(0.157)
Columnist	0.001	-0.001
	(0.763)	(0.601)
*VSM2 *columnist*	0.016**	0.008*
	(0.030)	(0.094)
|*SUE_lag*|	0.556***	
	(0.000)	
|*SAFE_lag*|		0.612***
		(0.000)
|*LnMKT*|	-0.016***	-0.007***
	(0.000)	(0.000)
|*LnBM*|	0.022***	0.008***
	(0.000)	(0.000)
|*LmTV*|	-0.011***	-0.005***
	(0.000)	(0.000)
|*DISP*|	0.002***	0.002***
	(0.000)	(0.000)
|*REV*|	0.021***	0.005***
	(0.000)	(0.000)
|$Alpha_{-252,-31}$|	5.121***	1.562***
	(0.000)	(0.000)
|$CAR_{-30,-3}$|	-0.081***	-0.045***
	(0.000)	(0.000)
|$CAR_{-2,-2}$|	0.388***	0.218***
	(0.000)	(0.000)
Intercept	0.402***	0.163***
	(0.000)	(0.000)
Obs	72,970	72,970
Adj R^2	0.359	0.466

Panel B. Information Channels

VARIABLES	(1) |SUE|	(2) |SAFE|
VSM2	0.005*	0.008**
	(0.052)	(0.000)
Insider	-0.004	-0.000
	(0.336)	(0.845)
*VSM2 * Insider*	0.005**	0.001**
	(0.020)	(0.041)
Analyst	0.033	0.029
	(0.511)	(0.782)
*VSM2 * Analyst*	0.009**	0.008
	(0.021)	(0.192)
Fund	-0.000	-0.008***
	(0.976)	(0.000)
*VSM2 * Fund*	0.001**	0.018***
	(0.041)	(0.000)
Expert	0.005	0.001
	(0.691)	(0.826)
*VSM2 * Expert*	0.026**	0.004**
	(0.029)	(0.024)
|*SUE_lag*|	0.513***	
	(0.000)	
|*SAFE_lag*|		0.586***
		(0.000)
|*LnMKT*|	-0.021***	-0.007***
	(0.000)	(0.000)
|*LnBM*|	0.022***	0.007***
	(0.000)	(0.000)
|*LmTV*|	-0.011***	-0.004***
	(0.000)	(0.000)
|*DISP*|	0.004***	0.001***
	(0.000)	(0.000)
|*REV*|	0.026***	0.008***
	(0.000)	(0.000)
$\|Alpha_{-252,-31}\|$	2.852***	0.671**
	(0.000)	(0.015)
$\|CAR_{-30,-3}\|$	-0.060***	-0.042***
	(0.000)	(0.000)
$\|CAR_{-2,-2}\|$	0.394***	0.292***
	(0.000)	(0.000)
Intercept	0.312***	0.133***
	(0.000)	(0.000)
Obs	36,452	36,452
Adj R^2	0.372	0.483

Panel C. Independence and Information Advantage

VARIABLES	(1) |SUE|	(2) |SAFE|
VSM2	0.045***	0.019***
	(0.001)	(0.001)
High_Cov	0.001	0.001
	(0.949)	(0.818)
*VSM2 * High_Cov*	-0.035**	-0.022**
	(0.027)	(0.033)
|*SUE_lag*|	0.514***	
	(0.000)	
|*SAFE_lag*|		0.589***
		(0.000)
|*LnMKT*|	-0.021***	-0.008***
	(0.000)	(0.000)
|*LnBM*|	0.022***	0.006***
	(0.000)	(0.000)
|*LmTV*|	-0.012***	-0.005***
	(0.000)	(0.000)
|*DISP*|	0.005***	0.002***
	(0.002)	(0.000)
|*REV*|	0.027***	0.007**
	(0.000)	(0.012)
$\|Alpha_{-252,-31}\|$	2.805***	0.673**
	(0.002)	(0.021)
$\|CAR_{-30,-3}\|$	-0.059**	-0.041***
	(0.024)	(0.007)
$\|CAR_{-2,-2}\|$	0.391***	0.296***
	(0.000)	(0.000)
Intercept	0.313***	0.291***
	(0.000)	(0.000)
Obs	36,452	36,452
Adj R^2	0.372	0.483

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