Distribution Agreement

Three Essays on Financial Economics

By

Dexin Zhou
Doctor of Philosophy

Business

Narasimhan Jegadeesh, Ph.D.
Advisor

Jay Shanken, Ph.D.
Advisor

Tarun Chordia, Ph.D.
Committee Member

Ilia Dichev, Ph.D.
Committee Member

T. Clifton Green, Ph.D.
Committee Member

Accepted:

Lisa A. Tedesco, Ph.D.
Dean of the James T. Laney School of Graduate Studies

Date

Three Essays on Financial Economics

By

Dexin Zhou
BA, Bard College, 2009

Advisors:

Narasimhan Jegadeesh, Ph.D.
Jay Shanken, Ph.D.

An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy
in Business
2015

Abstract

Three Essays on Financial Economics

By Dexin Zhou

This dissertation examines the role of qualitative information in financial markets. Using textual analysis methodologies, I quantify the qualitative information in news media and corporate disclosures. The first essay (The Blame Game) examines the information in corporate executives' self-serving attribution behaviors. Using textual analysis, I construct a measure that identifies corporate executives' behaviors of blaming external factors such as economy or the industry. I find that the patterns of the blame behaviors are consistent with self-serving attribution bias. I also find that a high blame measure leads to low subsequent stock returns and low turnover-performance sensitivity. Blame behaviors also predicts negative earnings surprise and analyst downgrades. Further tests show that these results are robust after controlling for exposure to systematic risk factors. These results support the idea that investors underreact to firm-specific negative information when corporate executives blame external factors. The second essay (Analysts' Assimilation of Soft Information in the Financial Press), coauthored with Xue Wang and Mark Bradshaw, investigates the role of analyst in interpreting soft news from news media. We find that the quantity of news coverage of a firm is positively associated with subsequent analyst recommendation revision activity. Moreover, the recommendation revisions are more informative for firms with more intense news coverage. We also find that this relationship is mainly driven by soft news (news with low fraction of numeric information). These results shed new light on the source analysts' mosaic of information and the role of analysts. The third essay examines managers' (Good News in Numbers) use of numbers versus words in the conference call disclosure. I find that executives tend to use numbers when companies experience satisfactory performance and use words when they have to disclose poor performance. In addition, the ratio of numbers and words contains value-relevant information about the company. Market reacts positively when corporate executives use high fraction of numbers. However, the initial market reaction is incomplete. The stock prices continue to outperform in one quarter following the conference call when corporate executives use more numeric information in the conference calls.

Three Essays on Financial Economics

By

Dexin Zhou
BA, Bard College, 2009

Advisors:

Narasimhan Jegadeesh, Ph.D.
Jay Shanken, Ph.D.

A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy
in Business
2015

Acknowledgement

I am deeply grateful to my committee members Tarun Chordia, Clifton Green, Ilia Dichev and especially and especially my advisors Narasimhan Jegadeesh and Jay Shanken for their invaluable support and insights in the development of my dissertation. I would like to express my gratitude to Clifton Green and Breno Schmidt for their generous advice on effective presentation of my research.

In addition, I would like to thank Jeff Busse, Francisco Barillas, Ling Cen, Stephane Chretien, Jeffrey Coles, David Hirshleifer, Byoung-Hyoun Hwang, Russell Jame, Jim Kolari, Tim Loughran, Andrew Karolyi, Nadia Massoud, David Ng, Shiva Rajgopal, Oliver Randall, Breno Schmidt, David Solomon, Denis Sosyura, Zheng Sun, Siew Hong Teoh, Xue Wang, David Yermack, Steven Xiao, Soojin Yim, seminar participants at Emory University, Tulane University, DePaul University, Cornell University, University of Delaware, University of California-Irvine, Texas A&M University, University of Utah, Indiana University, University of Toronto, Hong Kong University of Science and Technology, Nanyang Technological University, Baruch College, and conference participants at 2014 NFA Meeting and 2015 AFA Annual Meeting for their helpful comments on my research. I am also thankful for my fellow PhD students Mengyao Cheng, Kiseo Chung, Badrinath Kottimukalur, Joonki Noh, Zhenping Wang, Quan Wen, Xing Zheng for their feedback on my presentation and writing. Last but not the least, I am indebted to my family and friends for their unwavering support throughout my doctoral studies.

Table of Contents

The Blame Game **1**

Introduction 2

Data and Methodology 8

Results 12

Determinants of Executives' Blame Behaviors 12

Predicting Post Conference Call Returns 16

Industry-Adjusted Portfolio 19

Predicting Future Earnings 20

Evidence from Analyst Recommendations 20

Contemporaneous Stock Returns 21

Executive Turnover 22

Conclusion 24

Analysts' Assimilation of Soft Information in the Financial Press **26**

Introduction 27

Background and Predictions 34

Background 34

Empirical Predictions 39

Data and Variable Measurement 43

Data 43

Variable Measurement 45

Empirical Results 48

Descriptive Statistics 48

News Coverage and Analyst Research Updates 49

News Coverage and Market Reactions to Analyst Recommendation Revisions 51

Analyst Interpretation of Hard versus Soft Information 55

Extensions and Diagnostics 60

Conclusion 63

Good News in Numbers **65**
Introduction 66
Hypotheses Development 71
Data 74
Main Results 77
Determinants of PCTNUM 77
Investor Responses to PCTNUM 80
PCTNUM and Information Precision 83
Conclusion 84

Appendix 86
Tables 86
Figures 114

References 116

List of Tables

The Blame Game

Table 1: Examples of Positive and Negative Description of Industry and the Economy 86
Table 2: Summary Statistics 87
Table 3: Determinants of BLAME Measure 88
Table 4: Predicting Post Conference Call Returns 89
Table 5: Calendar Time Portfolios 90
Table 6: Industry Adjusted Calendar Time Portfolio 91
Table 7: Predicting Future Earnings 92
Table 8: Recommendation Changes 93
Table 9: Contemporaneous Stock Returns 94
Table 10: CEO Turnover 95
Table A1: Determinants of BLAME Measure 96
Table A2: Comovement with Market and Industry Factors and Returns 97

Analysts' Assimilation of Soft Information in the Financial Press

Table 11: Summary Statistics for News Coverage 98
Table 12: Summary Statistics for Firm Level Variables 99
Table 13: News Coverage and Analyst Recommendation Change 100
Table 14: News Coverage Intensity and Announcement Return 102
Table 15: Types of News and Recommendation Announcement Return 104
Table 16: News Coverage Intensity, Tone of News and Recommendation Announcement Return 105
Table 17: Subsample Analyses: Recent News versus Distant News 106

Good News in Numbers

Table 18: Summary Statistics of Textual Variables 107

Table 19: Summary Statistics of Non-Textual Variables..108

Table 20: Determinants of PCTNUM 109

Table 21: Investor Reactions to PCTNUM 111

Table 22: Predicting Post Conference Call Returns 112

Table 23: PCTNUM and Information Precision 113

List of Figures

The Blame Game

Figure 1: Time Series of BLAME 114

Analysts' Assimilation of Soft Information

Figure 2: Recommendation CAR vs. News Coverage 115

The Blame Game

Dexin Zhou*†

Abstract

I propose a textual analysis-based measure to detect when corporate executives blame bad performance on external factors such as industry or the economy (BLAME measure). Using this methodology to analyze quarterly earnings announcement conference call transcripts, I find that: (1) executives are more likely to blame these external factors when their companies experience bad performance, but are unwilling to credit the external factors when they perform well; (2) a high BLAME measure predicts low returns subsequent to the conference call date after controlling for the tone of the transcripts and other known predictive variables. The hedged portfolio that takes long positions in companies with low BLAME measure and short positions in companies with high BLAME measure generates abnormal returns up to 6.8% per year; (3) the BLAME measure negatively predicts earnings surprises and analyst recommendation revisions in the subsequent quarter, indicating underreaction to firm-specific negative information; (4) a high BLAME measure reduces executive turnover-performance, implying that blaming external factors reduces the punishment on executives who underperformed. Overall, the evidence suggests that investors underreact to negative information when managers attribute negative performance to external factors.

*Emory University. E-mail: dexin.zhou@emory.edu

†I am grateful for the comments and suggestions from Mengyao Cheng, Stephane Chretien (NFA discussant), Tarun Chordia, Ilia Dichev, Clifton Green, Byoung-Hyoun Hwang, Russell Jame, Narasimhan Jegadeesh, Tim Loughran, Nadia Massoud, Joonki Noh, Breno Schmidt, Jay Shanken, David Solomon (AFA Discussant), Denis Sosyura, Xue Wang, Quan Wen, Steven Xiao, David Yermack and workshop participants at Emory University, Tulane University, Depaul University, Cornell University, University of Delaware, University of California-Irvine, Texas A&M University, University of Utah, Indiana University, University of Toronto, Hong Kong University of Science and Technology, Nanyang Technological University and Baruch College.

1 Introduction

This paper studies how self-serving attribution behaviors of corporate executives affect shareholders. In neoclassical economics, corporate executives are often modeled as corporate value maximizers. However, empirical literature shows that agency problems and behavioral characteristics could lead to diverging choices of corporate strategies (Bertrand and Schoar, 2011). One important behavioral characteristics that has been documented repeatedly in the psychology literature is the self-serving attribution bias, meaning that people tend to attribute success to internal factors and to blame failure on external factors (e.g., Tetlock and Levi (1982)). In this study, I analyze these self-serving attribution behaviors of corporate executives using an innovative textual analysis technique. I find that these behaviors lead to delayed responses to negative information.

There are several reasons to believe that these executive self-serving attribution behaviors may be value relevant for investors. First, the self-serving attribution behavior is believed to be a manifestation of self-presentation concern (Baumeister, 1982). People with self-presentation concerns tend to present a glossier image of their performance than the reality, which may mislead investors about the real value of the firm. In addition, psychology research indicates that self-serving attribution behaviors can be associated with impression management (e.g., Bradley (1978), Miller (1978)). For example, executives may direct the focus from potentially persistent problem within the company to relatively transient shocks to economy or industry. These behaviors may maintain confidence of shareholders towards the ability and plans of the management and lead to underreaction to negative information.

Second, research in psychology and management has indicated that biases in attribution may indicate negative managerial ability. This research predicts that attribution biases are likely to create impediments for problem solving at the firm. For example, past research shows that self-serving attribution bias may lead to failed course of action (Staw and Ross, 1978), because the decision maker is unable to correctly identify the causes of problems. In addition, psychologists also find that attribution biases decrease people's effectiveness in decision making (Janis, 1989, Janis and Mann, 1977). Finally, it is also shown that stake holders tend to commit less resources to executives when they are perceived to be attributing failures (Schwenk, 1990). Overall, existing literature suggests that self-serving attribution behaviors should relate to worse financial performance in the upcoming months.

As a result, if investors do not pay attention to the signs of self-serving attribution behaviors (e.g., Hirshleifer et al. (2009), Dellavigna and Pollet (2009)), stock returns are likely to experience sustained underperformance after executives' self-serving attribution behaviors.

An additional effect of attributing negative performance externally is that it may sway shareholders' and board members' decision to retain or replace the executives. Executives who tend to play the blame game in conference calls can also use similar excuses to appease the board members. Previous literature shows that executives are punished less when the bad performance is a result of external factors (e.g., Gibbons and Murphy (1990), Jenter and Kanaan (2006)). If the board members are convinced by their excuses, the executives are more likely to be allowed to stay and their salaries are less likely to be reduced following their bad performance than those who do not play the blame game. Thus, attribution behaviors may affect the turnover performance sensitivity.

Although executives' self-serving attribution behaviors are important for shareholders, there is limited existing research in this field. One reason for the lack of research is the difficulty in identifying these attribution behaviors. Existing literature largely avoids direct identification of these self-serving attribution behaviors in a large sample setting. In this paper, I infer attribution behaviors directly using transcripts from conference calls. Direct evidence can be established on how attribution bias affects corporate values.

Executives blaming negative impacts that are beyond their control is a sign of their attribution bias. In the corporate world, firms' fortunes are often tied to factors that cannot be managed by the executives. For example, the macroeconomic and industry fluctuations can impact results of individual firms. Few firms can avoid these negative shocks. As a result, macroeconomic performance and the factors related to the industry performance can be obvious scapegoats for corporate performances. For example, a company is experiencing headwinds in its operating results. The executives of the company have a choice of how to explain their performances. They can choose to discuss their companies' results in detail or they can simply attribute the bad performance to reasons such as luck. Whereas the impact of economic and industrial trends inevitably swing corporate performances up and down, these discussions are unlikely to be helpful for investors, since these factors impact all firms in the market or in the sector. Therefore, these discussions are likely to be signs of biases in attribution.

I use a sentence-based textual analysis to identify the sentences used to blame economy and industries in earnings conference calls. I first look for key words about industry and economy in the sentences of conference calls. Then, I count the number of positive and negative words in the same sentence. If there are more negative words than positive words in that sentence, it is considered as a sentence with a negative description of industry or the economy (or BLAME sentence). The overall tendency to attribute bad performance to external factors is measured by the percentage of BLAME sentences in the conference call (I will refer to this measure as BLAME measure hereafter). The BLAME measure is significantly negatively correlated with performance measures, such as returns and SUE, indicating that better performance reduces the need to attribute negative performances. However, in the placebo test, I do not find companies' past performance significantly correlates with the fraction of sentences with positive description about industry or the economy, consistent with the idea that blaming external factors is an impression management tactic of corporate executives. Consistent with investors underreacting to firm-specific negative news, I document that companies with high BLAME measures subsequently underperform those with low BLAME measures by up to 7% annually after risk-adjustment. Analyst recommendations in the quarter following the conference call support the hypothesis of underreaction in stock prices to BLAME measure.

In addition to returns, I also find that the BLAME measure changes CEO employment outcome. I show that blaming external factors reduces the sensitivity of executive turnover. These results indicate that blaming the industry and economy may shift the focus of board members away from the missteps of corporate executives and towards the factors beyond managers' controls. Thus, these managers are less likely to be punished through turnover.

This paper makes contributions on several fronts. First, this study documents a new executive behavioral bias and shows that this behavioral bias impacts the wealth of shareholders with a significant economic magnitude. Past research has documented a number of behavioral biases among corporate executives. The most prominent biases among them are overconfidence, optimism and hubris. These behavioral biases influence corporate operating and financial strategies significantly (Roll, 1986, Malmendier and Tate, 2005, 2008).[1] While self-serving attribution bias is closely related to overconfidence, this paper shows that it affects shareholder wealth in a very distinct way. A number of existing papers examine how managers' attribution bias or attribution behaviors affect their investment decisions and reporting behaviors. For example, Billett and Qian (2008) and Doukas and Petmezas (2007) investigate how self-attribution bias affects merger and acquisition decisions. Both papers argue that managers' overconfidence manifested in merger and acquisition activities is driven by self-attribution bias. Similar to this paper, Li (2010b) use a textual analysis method to extract terms for self-references such as "I" and "we" as a proxy for

[1]Other influential studies in corporate finance include Roll (1986), which associates value destruction in M&A with hubris, Baker et al. (2012) which document that reference prices affect the offer price for target company in mergers and acquisitions, Heaton (2002), which models pecking order of financing based on executives' optimism, and Aktas et al. (2010), which infer narcissism from CEO speeches and find that CEOs with narcissism tend to influence takeover decisions.

self-serving attribution. The paper finds self-attribution bias is positively related to firms' investment behaviors. In addition, Baginski et al. (2004) examine the attribution behavior of 900 earnings forecasts statements by manual classifications. There are several key difference between this paper and the aforementioned study. The Baginski et al. (2004) focus on the explanations of earnings forecasts, which is largely forward-looking. This paper explores earnings conference calls and the statements are related both to the companies' past performances and future expectations. Thus, this is a more general setting for managers' attribution behaviors. More importantly, the previous study's focus is on the determinants of attribution behaviors. This paper emphasizes the consequences of attribution activities in the earnings conference calls, including investors' underreaction to negative news and reduced sensitivity in turnover-performance. Furthermore, this paper provides a consistent argument that can jointly explains empirical observations in the attribution behaviors and its effect in stock returns and executive performance incentives. To my best knowledge, this is the first time to document that executive behavioral characteristics that is associated with future stock return.

Second, this study is broadly related to the literature on the information environment and the information content of corporate disclosure. Existing literature shows that changes in information environment may significantly change investor response. For example, Solomon (2012) finds that companies who hire an IR firm exhibit more ability to spin news and cause a delay in the incorporation of bad news. Cohen et al. (2013) find that analysts can cast their conference calls by calling friendly analysts. Li and Yermack (2014) document that evasive annual shareholder meetings predict low stock return. Other papers also find non-numerical information from earnings announcement conference calls informative. Hollander et al. (2010) find that silence during the conference call contains information. Matsumoto et al. (2011) find that the Q&A part of the conference calls is more informative than management discussions. Mayew and Venkatachalam (2012) find that tonal information from managers' voices contains information about firms' future performances. More closely related to this paper, Larcker and Zakolyukina (2010) find certain words in conference calls can be used to detect accounting misstatements. This paper builds on the existing research and shows that earnings conference calls also contain meaningful information about executive behavioral characteristics.

Third, this paper is also related to a set of papers that examine the executive turnover performance. Past literature documents that CEO turnover is significantly negatively related to stock returns (e.g., Kaplan and Minton (2006), Jenter and Kanaan (2006)). Moreover, Jenter and Kanaan (2006) document that negative industry shocks can lead to turnover. However, turnover sensitivity to industry shocks is lower than the sensitivity to companies' idiosyncratic performances. This paper adds to the literature and shows that the executives' explanations matter for the turnover decisions. Attributing negative performance can alleviate the pressure on executives by lowering turnover performance sensitivity. These results also complement the previous research on executives getting paid based on their luck (e.g., Bertrand and Mullainathan (2011)). While Bertrand and Mullainathan (2011) show that executives are sometimes paid for the sheer luck, this paper indicates that managers may also avoid blame by shifting the responsibility to external factors.

Finally, this paper also makes a methodological contribution.[2] Previous literature often uses pure dictionary method (e.g., Loughran and Mcdonald (2011), Jegadeesh and Wu (2013)) to capture the information from the texts. Li (2010a) show that using Naive Bayesian method to analyze words in the forward-looking sentences can extract useful information. This paper shows that sentence-based analyses, combining with a correctly specified dictionary, can provide additional information beyond

[2]Broadly speaking, the results from this paper add to a large literature related to textual and linguistic information in the financial markets. A number of papers document that tonal information in news articles contains information about firm fundamentals (eg Tetlock et al. (2008), Engelberg (2008)). In addition, it has also been shown that noninformative tonal information may also be incorporated into the asset prices (e.g., Tetlock (2011), Engelberg and Parsons (2011)). Finally, managers are able to manipulate the tone in the business press to affect the prices in the broad market.

pure word counts. While word count methodology has proved to be useful in capturing additional information to numerical information, simple word counts may miss important information from the context of sentences. This paper demonstrates that analyzing words in the context of sentences can provide insights into their context. For example, the sentence-based analysis helps provide information such as executive personal characteristics.

The rest of the paper will proceed as follows. Section 2 describes the source of the data and the construction of the BLAME measure in detail. The main results will be discussed in detail in section 3. Section 4 discusses the hypotheses about what cause the self-serving attribution bias. Section 5 concludes the paper.

2 Data and Methodology

The texts from conference call transcripts are used to analyze self-attribution biases in this study. Executives hold earnings conference calls to discuss the financial performances of the company in the fiscal quarter. Substantial amount of textual information is disclosed during the conference call. Past literature clearly indicates that the textual information in conference calls contains value relevant information in addition to the accounting information released by firms. Conference calls also offer opportunities for analysts and investors to interact with the management. In general, conference calls offer a valuable venue for managers to explain the companies' performances in detail to investors. Because of the rich linguistic information in the conference call, the language of disclosure may well shape the perceptions of the performance of the company.

One advantage of using conference calls to capture executive behavioral characteristics over using written materials such as letters to shareholders or annual reports (previous management literature such as Staw et al. (1983) and Clapham and Schwenk (1991)) is that written materials are often written by a committee rather than an individual. Therefore, the written materials are less accurate in capturing individual behavioral characteristics. Moreover, because of executives need to answer questions from the participating analysts, they are more likely to offer spontaneously reaction to the question. These spontaneous remarks are more likely to reveal executives' thinking processes.

The quarterly earnings conference call transcript data used in this study comes from two sources. I first download the available conference call transcripts from StreetEvents of Thomson One from 2003 to 2012. I supplement the missing observations with the data from Call Street, a unit of Factset. Combining these two sources, I obtain about 90,000 raw transcripts. After merging with CRSP, Compustat and IBES, the sample size reduces to around 70,000. I also delete the observations whose stock price is below 5 dollars in the month preceding the earnings announcement.

I parse the texts from these transcripts in the following way: I first split the text into sentences, by identifying the punctuation indicating the end of sentences, such as periods, question marks, semicolons and exclamations. For each sentence, I look for words related to economy and industry. Specifically, I look for "economy," "economic condition," "economic conditions," and "economic growth" for economic related descriptions and "industry" and "industries" as indicators for industry related descriptions.[3] The sentences identified as descriptions related to economy and industry performances are classified into positive, negative and neutral description sentences. I use the Loughran and Mcdonald (2011) financial dictionary to identify positive and negative words in the previously identified sentences. If there are more positive words than negative words in the sentence, it is classified as a positive sentence. Meanwhile, if there are more negative words than positive words, the sentence is classified as a negative sentence. Otherwise, the sentence is classified as neutral. In this paper, I focus on negative description of industry or economy to capture the

[3] I also consider other similar words, such as sector and segment as indicator for mentions of industry. By reading a random sample of conference call transcripts, the words "sector" and "segment" are most often referring to sector or segment within a company. Therefore, using these two words as indicator for mention of the overall industry condition will likely generate noisy results.

attribution behaviors. To better understand the negative sentences captured using this methodology, I have selected a number of these sentences in table 1. In the first two sentences, managers attribute negative performance to the economy. In the third example, executive attribute negative performances to industry. The program first captures the key words related to industry or economy (in bold letters). The program then identifies positive words (non-existent in the sentences displayed in these examples) and negative words (in red color). Since there are more negative words in these sentences than positive words, these sentences are classified as sentences with a negative description of industry or the economy (referred as BLAME sentences). Although this paper does not focus on the positive description of industry or economy, I have also examined a number of positive description sentences. The positive description sentences are a much noisier collection of sentences, since many executives proclaim that their companies are "industry-leading" or "better than the industry average." There are three sentences with positive descriptions of the economy and the industry exhibited in table 1. We can see that the last positive industry description sentence is really about the firm performance. The number of sentences with positive description of industry or economy (N(POSITIVE)), neutral description (N(NEUTRAL)) and negative description (N(BLAME)) are reported in the panel B of table 2. I find that there are more positive/neutral description sentences of industry or economy than negative descriptions, indicating a relatively high hurdle for sentences to qualify as a negative description sentence on industry or the economy. Overall, the number of BLAME sentences are not many. One may question whether managers can change investors' view of their companies with such few sentences. I argue that these sentences only serve as a proxy for the tendency to attribute failures. Thus, one should only view these BLAME sentences as red flags of attribution biases.

For each conference call, I calculate BLAME measure (Negative Description of Industry and Economy) in the following formula to capture the frequency of negative descriptions of industry and economic conditions:

$$BLAME = \frac{\text{N(BLAME Sentences)}}{\text{Number of Sentences}}.$$

In addition, I construct a measure for the fraction of sentences that with positive description about industry or economy as a placebo variable. Positive descriptions sentences are similar to BLAME sentences, except that they have more positive words than negative words in an industry or economy-related sentence. I construct a POSIE measure calculated as total number of positive sentences related to industry or economy. I also calculate the overall number of positive and negative words from the conference call. I intend to use the BLAME measure to proxy the tendency of attributing negative performance to external factors. To insure the BLAME measure captures the information independent of the tone of the overall text, I control the tone of the overall conference call using the following negativity measure[4]:

$$NEG = \frac{\text{Number of Negative Words}}{\text{Number of Words}}.$$

The parsed data is then merged with CRSP, Compustat and IBES to obtain the common financial measures such as market equity, book-to-market ratio, past return and Standardized Unexpected Earnings. The cumulative abnormal return (CAR) is calculated using the Fama-French 3-factor model (Fama and French, 1993). The beta of the factor loadings are estimated using the daily returns in the interval of [-180,-15] relative to the date of the conference call. Standardized unexpected earnings or SUE is calculated as

$$SUE_{i,t} = \frac{E_{i,t} - FE_{i,t}}{P_{i,t}},$$

where E represents realized quarterly earnings, FE represents the consensus analyst

[4]I have also examined a sentence-based tone measure. The measure is calculated as the total number of negative sentences dividend by the number of sentences in the conference call transcript, and negative sentences are the ones with more negative words than positive words. The results presented in this paper are robust when I use the alternative tone measure as a control.

forecast earnings and P is the stock price at the end of the IBES statistical period when consensus analyst earnings forecasts are calculated. The consensus analyst forecast expectation is formed on the closest IBES statistical period end date prior to the conference call. SUE is winsorized between -0.1 and 0.1. The key dependent variable is cumulative abnormal return or CAR. CAR is calculated using a 3-factor model, where the loadings on the Fama-French factors are estimated by returns from the prior 180 days to 10 days relative to the earnings announcement date. The results presented in the rest of paper are robust if market adjusted returns (calculated as firm returns minus market returns) are used as cumulative abnormal returns. Volatility is the estimated daily volatility one year prior to the conference call date. Share turnover is the monthly turnover in the month before the conference call date. Institutional ownership is formed based on the 13F data at the end of the quarter prior to the conference call. Executive employment information is obtained from Execcomp. Executive turnover date is based on the date that CEO steps down.

3 Results

3.1 Determinants of Executives' Blame Behaviors

Before proceeding to analyze the impact on returns, I first investigate the determinants of the BLAME measure (negative description of industry or the economy). I explore the time series variability of the BLAME measure to examine whether it is correlated with the macroeconomic fluctuations. I plot the BLAME measure (scaled up by 100), percentage firms with non-zero BLAME and the contemporaneous GDP growth data in figure 1. The plot clearly indicates that economic performance is negatively associated with BLAME measure. This trend is most clear during the period of the economic downturn around 2008-2010. This observation reflects that executives are more likely to discuss negative economy or industry performance when economic growth is slower.

The second test explores the cross-sectional variation of the BLAME measure. I hypothesize that several factors are positively associated with BLAME. First, firms that performed poorly are likely to be associated with higher BLAME measures. A firm with good performance has little incentive to discuss the negative impact of external factors, since they do not need to find any scapegoat for their performance. Second, firms of systemic importance are more likely to mention negative industry or economic factors, since the performance of these firms is more likely to be associated with higher economic performance and less likely to be associated with idiosyncratic performances. Third, firms with less external monitoring are more likely to be associated higher BLAME measures. These firms with less monitoring may play the blame game more often to shape a better self-image.

I run a tobit regression (dependent variable censored at 0) to explore what drives BLAME. To control for time series variations, I control for year-quarter dummies in the regression. The results are reported in table 3[5]. In addition to results, I also report the predicted signs for the coefficients. I find that consistent with the first hypotheses, firms with worse performance in either financial or accounting metrics tend to have higher BLAME measures. Specifically, I find that SUE is negatively associated with the BLAME measure, indicating that firms with lower earnings tend to mention negative effects of the economy and the industry more frequently. Similarly, lag returns are negatively associated with the BLAME measure, indicating that better stock performance reduces the need to blame the industry and the economy. The percentage of negative words, which can serve as a rough proxy for other negative information revealed linguistically, has a significant positive correlation with BLAME measure. Furthermore, valuation is negatively related to the BLAME measure, indicated by the positive coefficient from book-to-market ratio.

[5]An additional OLS regression with CEO fixed effects is reported in the appendix table A1. The idea is that some CEOs are habitually more likely to blame than others. Because of the fixed effect specification, tobit model cannot be used. The executive information is taken from Execcomp. The merged sample is roughly 2/3 the size of the original sample in the tobit regression. The result from the OLS regression is largely consistent with the tobit regression reported in the table 3.

Second, larger firms are associated with higher BLAME measures. This relationship is clearly indicated by the significantly positive coefficient of log market equity. This indicates that larger firms are more likely to encounter negative industry and economic shocks. In addition, I use the R^2 (see Roll (1988) for a discussion of the information content of R^2) from the following market and industry time series model to estimate the company's total exposure to industry and the economy factors:

$$\begin{aligned} RETRF_{i,t} = &\alpha_i + \beta^{(1)}_{MKT,i} MKT_{t-1} + \beta^{(2)}_{MKT,i} MKT_t + \beta^{(3)}_{MKT,i} MKT_{t+1} + \\ &\beta^{(1)}_{IND,i} IND_{t-1} + \beta^{(2)}_{IND,i} IND_t + \beta^{(3)}_{IND,i} IND_{t+1} + \epsilon_{i,t} \end{aligned}$$

where $RETRF$ is the difference between return and risk free rate, MKT is market return minus risk free rate and IND is value weighted industry return minus risk free rate. The industry return is defined using Fama-French 48 industry classification (Fama and French, 1997). The lead and lag industry and market returns are included to account for nonsynchronous trading (e.g., Dimson (1979)). The R^2 (estimated using daily return data with 1-year lag) estimated using the above model is significantly positively associated with the BLAME measure, indicating higher likelihood to mention industry and economy performance when a firm's exposure to macroeconomic performances is higher. This could also indicate that it is more convincing for executives of firms with higher exposure to systematic risk to blame industry and economy performance.

Third, analyst coverage is negatively associated with BLAME. High analyst coverage is associated with higher external monitoring as documented in the prior literature (Moyer et al., 1989). Analysts also confront the management about the bad performances from time to time. The negative coefficient of analyst coverage in this regression indicates intense external monitoring reduces the frequency of blaming external factors. Surprisingly, institutional ownership is positively associated the BLAME measure, though with less economic significance. Perhaps institutional investors do not usually field questions into the conference call, so they are less likely to be able to confront with the management during the conference call.

I repeat the same exercise with the POSIE measure as the dependent variable (fraction of positive sentences about industry or economy). I do not find significant evidence that past returns are associated positive descriptions of economy and the industry, which indicates that corporate executives do not attribute success to industry when their performance excels. This asymmetry may suggest that attributing negative performance to the industry is an impression management tactics used by the corporate executives when the companies underperform.

In the second specification, I use a regression discontinuity approach to detect whether there is a dramatic increase in BLAME at the cutoff point of meeting the analyst forecast revision if the companies slightly miss the analysts' consensus earnings estimates. The specification of the regressions discontinuity design is similar to the one proposed in Imbens and Lemieux (2008). The outcome variable (dependent variable) is BLAME and the assignment variable (independent variable) is SUE. Results are reported in the panel B of table 3. The need to play the blame game reduces significantly if the market expectations are met. Consistent with this hypothesis, I find that there is a significant difference in the mean at the cutoff point $SUE = 0$ and the coefficient of the jump is negative. In the placebo test, I do not find there is substantially more positive description about economy or the industry when companies experience good performance. In untabulated results, I repeat the same analysis for percentage negative words (NEG) as a placebo test. The null hypothesis that there is a cutoff at $SUE = 0$ cannot be rejected at conventional threshold. This suggests that this discontinuity is not driven by the behaviors of the assignment variable SUE or negative word counts. Summarizing the results from these regression discontinuity tests, BLAME seems to capture the tendency to present an optimistic picture when the performance falls short of expectations.

3.2 Predicting Post Conference Call Returns

The key test to confirm whether the "blame game" can be associated with delayed reaction to negative information is to examine whether BLAME can predict future returns. If the BLAME measure captures the tendency of companies' impression management of their performances during the conference call, market participants are likely to underreact to bad news. As a result, the stock is likely to experience negative performance after the earnings announcement. I first test this hypothesis using a Fama-Macbeth regression (Fama and MacBeth, 1973) specified as follows:

$$CAR[2,60]_{i,t} = \alpha + \beta BLAME_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

where $CAR[2,60]$ is the cumulative abnormal return calculated using the Fama-French 3 factor model. The standard errors are adjusted for serial correlations following Newey and West (1987). Because the earnings announcements are made on a quarterly basis, I group all earnings announcements made in one quarter as a cross-section. The predictive horizon is over the following 60 trading days after the earnings announcement. This trading horizon roughly covers 3 months. Past research used this predictive horizon in post earnings announcement drift, as information from earnings announcements is largely realized over this time horizon (Dellavigna and Pollet, 2009, Hirshleifer et al., 2009). These results are reported in table 4. The BLAME measure is the only independent variable in the first specification. The coefficient of the BLAME measure is negative with statistical significance below the 1% level. The economic magnitude implied by this regression is substantial. One standard deviation change in the BLAME measure corresponds to roughly 50 basis points change in return in the following 60 trading days[6].

In the second regression, I add a set of control variables to ensure the results from

[6] In the untabulated results, I also use positive industry and economy description as the independent variables. I find that while positive industry description is positively correlated with contemporaneous returns, but does not significantly predict future returns, consistent with the idea that the predictability is generated uniquely by the negative description.

the univariate regression is not driven by confounding effects of known predictive variables. These variables include book-to-market ratio, lag 6-month return, return volatility, standardized unexpected earnings, number of analysts, turnover and institutional ownership. In addition, I control overall negativity in the conference call transcript using NEG, percentage of negative words. Price et al. (2012) find that the conference call tone predicts future returns. Although the economic magnitude decreased, the BLAME measure still predicts the post earnings announcement returns with high statistical significance. Notably, the NEG measure is negatively correlated with post earnings announcement return, but the coefficient is statistically insignificant.[7] Hence, the results from the BLAME measure are independent of the negativity measure. In addition, BLAME measure captures further predictability under controlling the widely observed post earnings announcement drift (e.g., Bernard and Thomas (1989)), since controlling for SUE does not weaken the BLAME measure significantly. In terms of economic magnitude, the BLAME measure can generate return predictability comparable to the standardized unexpected earnings.

Next, I assess how much investors can profit from the information of BLAME measure by forming a calendar time portfolio following Lyon et al. (1999). I first take long positions in all the companies with a BLAME of 0. The short leg consists of companies with BLAME measure above 20% from the previous quarter, so that no forward-looking bias is driving the return results. All stocks are held in the portfolio for 60 trading days after the date of the conference call. The returns are equal weighted and at least 10 stocks are required in each portfolio. Then both Fama-French 3 factor models (Fama and French, 1993) and Carhart 4 factor models (e.g., (Carhart, 1997, Jegadeesh and Titman, 1993)) are calculated to assess the α from the hedged portfolio. The results are reported in table 5. The results indicate that the

[7]This results differ from Price et al. (2012). First, this paper investigates a larger sample, so this results is likely to be more accurate than the previous study. Second, Price et al. (2012) use OLS regression when predicting returns, while this study uses Fama-Macbeth regression. I find that NEG predicts future return significantly using the OLS specification, but not the Fama-Macbeth specification. This may imply that NEG does not have great power in predicting stock returns in the cross sectional setting.

hedged portfolio can generate substantial abnormal return. For example, the 3-factor alpha is 59 basis points per month or 7% per year. The four factor model alpha is 57 basis points or 6.8% per year. Both alphas are statistically significant at the 1% level. Thus, the information from the BLAME measure is highly valuable for investors.

To ensure that these results are not driven by post-earnings announcement drift, I form portfolios based on double sort. Specifically, I independently assign stocks into portfolios based on BLAME and SUE measures. Classification of high BLAME and low BLAME measures is the same as the single sort. High BLAME measure stocks are those with BLAME measures in the top 20% and low BLAME measure are those stocks with BLAME measures equal to 0. The break points for SUE are the top and bottom 30%. I first test the economic magnitude of BLAME portfolios for both low and high SUE stocks. In both cases, BLAME-sorted portfolios generate significant four factor alphas. However, the alpha of the BLAME sorted portfolios is much lower than in the low SUE stocks than in high SUE stocks. This indicates that the attribution to industry or the economy is more harmful for investors when the company experiences bad earnings. To compare the economic magnitude of BLAME measure and the post earnings announcement drift, I also exhibit the abnormal performance of taking long positions in high SUE and short position in low SUE firms. Across high BLAME and low BLAME measures, the SUE exhibit robust abnormal returns. These returns are slightly higher the returns in the portfolios sorted based on BLAME. These results are consistent with the findings of Fama-Macbeth regression.

In summary, both Fama-Macbeth regression and the calendar-time portfolio tests provide evidence that the BLAME measure significantly predicts negative return after the date of conference call. These results indicate that a high BLAME measure is associated with investors' delay in incorporating negative news about the firm.

3.3 Industry-Adjusted Portfolio

An alternative explanation for the previous cross-sectional and industry regression is that the BLAME measure contains information about future performance of industry or the economy and investors are underreacting to those warnings. First, if BLAME measure contains information about the overall economy and the stock market fails to react to this information, we still should not expect to find any cross-sectional predictability, since it should impact all firms in the economy. In the appendix table A2, I also show that the predictability does not concentrate in the companies with strong comovement with the market or the industry, since the interaction term between firms' time-series R^2 and its BLAME measure does not generate a significant coefficient in the predictability regression. As a result, it is unlikely that the predictability generated from BLAME measure is a result of underreaction to industry-wide negative information. Second, to address the possibility that the BLAME measure contains negative information about the industry of the firm, I form an industry-adjusted calendar time portfolio. Specifically, I calculate industry-adjusted return for each stock by subtracting matched Fama-French 48 industry return (IND) from the daily stock return:

$$RET_{i,t}^{ADJ} = RETRF_{i,t} - IND_t^{IND}.$$

These industry-adjusted returns are then used to form the calendar-time time portfolio using the procedure described in the previous paragraph. If the abnormal return observed in the previous calendar time portfolio is a result of underreaction to industry-wide negative information revealed by executives, the industry adjustment should eliminate the observed abnormal returns. Therefore, adjusting industry return should eliminate the abnormal returns in the calendar time portfolio not adjusted for return. The results of the industry-adjusted calendar time portfolio is reported in table 6. The portfolio indicates a significant α for both 3-factor and 4-factor models. The 3-factor alpha is 5.5% in annual term and the four factor alpha is 5.4%. Both alphas are significant at the 1% level. These economic magnitudes are slightly lower than the unadjusted portfolio, which may indicate BLAME also contains certain negative information about the industry. The overall evidence, however, is that BLAME measure contains information independent of overall industry performance.

3.4 Predicting Future Earnings

Next, I examine whether BLAME measure predicts future earnings. BLAME measure can be associated with future earnings in two ways. First, if high BLAME measure is a result of self presentation concern. The reported earnings can be inflated for presentation purpose, which then leads to subsequent reversals. Second, if high BLAME measure is driven by cognitive bias, the executives tend to be worse problem solvers. Therefore, it may take more time for them to address the problems present at the company and it will take longer for earnings to recover. Both possibilities predict a negative association between BLAME measure and future earnings. I test this hypothesis using the following Fama-Macbeth regression:

$$SUE = \alpha + \beta BLAME + \gamma X + \epsilon,$$

where SUE is standardized unexpected earnings and X is a vector of control variables.

The results from this set of regressions are reported in table 7. Consistent with the hypothesis, I find that BLAME significantly predicts next quarter SUE with p-value below 5%, indicating that analysts do not completely incorporate the negative information.

3.5 Evidence from Analyst Recommendations

In this section, I further explore whether stock prices underreact to negative information using changes in analyst recommendations. I look at whether the analysts recognize the displacement of stock prices after the earnings announcement by examining whether analysts change their recommendation after earnings announcement date. Specifically, I examine the first recommendation change to capture the initial reaction from analysts within 90 days after the earnings conference call. I use the Fama-Macbeth regression, similar to the specification in Jegadeesh et al. (2004). As indicated in the results reported in table 8, I find that the BLAME measure significantly predict this recommendation change measure with a negative sign, indicating that analysts gradually incorporate the information from the BLAME measure, as they realize that the stock prices of the firms with high BLAME are overvalued. Control variables do not reduce the significance level of the predictability results.

The evidence from the analyst recommendations are consistent with the idea that the broad market underreacts to the negative information when companies attribute negative performance to industry or economy. Analysts pick up the negative information subsequent to the earnings conference calls in the course of the next 90 days after the conference call. Thus, they tend to downgrade these firms in the following quarter for companies with high BLAME measures.

3.6 Contemporaneous Stock Returns

After looking at post earnings announcement returns, I analyze the announcement return at the date of the conference call. It is difficult to predict the sign of coefficient for the BLAME measure. On one hand, if high BLAME measure implies executives withholding some negative information, BLAME measure should be positively related to the conference call abnormal return. On the other hand, high BLAME measure means that there is negative information to assign blame, since it would be unnecessary to assign blame if there is no negative news. If this negative information is not captured by the control variables, then BLAME could be associated with negative contemporaneous return. Thus, I leave the verdict to the data.

The research setting is similar to the long-term return following the conference call. The dependent variable is the three-day cumulative abnormal returns from day -1 to day 1 relative to the earnings announcement date, adjusted using the Fama-French three factor model. The main independent variable of interest is BLAME. I run Fama-Macbeth style return regressions. Overall, I find that the BLAME measure is significantly associated with negative CAR, both with and without controls. In terms of economic magnitude, the coefficient in the regression with control variables is roughly one third that of the regression without control variables. Therefore, the lion share of negative information captured by the BLAME measure is correlated with the control variables. However, it is obvious that control variables do not capture all the negative information correlated with BLAME measure. These results, again, indicate that the BLAME measure is associated with negative firm-specific performance.

3.7 Executive Turnover

Results from the previous sections indicate that managers tend to attribute bad performances to external factors such as industry and economy. When the executives play the blame game, investors tend to underreact to the negative information. In this section, I provide evidence that the attribution behaviors significantly change the probability of executive turnover. Extensive research has documented that bad CEO performance (e.g., low stock returns) lead to higher executive turnover (e.g., Murphy and Zimmerman (1993)) and lower executive compensations (e.g., Gibbons and Murphy (1990)). Jenter and Kanaan (2006) document that bad industry performance also leads to executive turnover, but to a lesser extent. Similarly, Bertrand and Mullainathan (2011) document that CEO compensations are sometimes affected by the performance of the whole industry. The authors also find that this result is asymmetric: CEOs tend to be rewarded for good luck, but not blamed for bad luck. Thus, if executives can associate their performance with bad economic or industry environment, they are less likely to be held responsible for the bad performances. If executives attribute negative performance when they talk about their results in front of shareholders, they are also likely to use the same excuses when they face the board of directors. This possibility has been suggested in several previous contexts. For example, Duchin and Schmidt (2013) show that when executives make value-destructive mergers during merger waves, they are less likely to be fired than those who make bad merger decisions during the normal time, since the executives can argue that their peers all make similar decisions. In other words, the executives can blame the industry environment for the bad decisions that they made and board members tend to be more lenient on their bad decisions when these excuses are present. Nevertheless, this hypothesis has never been tested directly. I will empirically examine whether negative performances can reduce the pressure on the executives from the board members directly using the BLAME measure.

The specification in the form of Jenter and Kanaan (2006) is adopted to test whether attribution behaviors affect executive turnover performance sensitivity. I conduct a Probit regression. Similar to Jenter and Kanaan (2006), the dependent variable is CEO turnover in the next year. I also control ROA as additional control for firm performance. CEO age is also added as a control, as more CEO turnover may be observed when a CEO gets closer to retirement age. Similar to the intuition from the prior literature, lag one year return and ROA are negatively associated with CEO turnover. The proxy for attribution behavior is BLAMEDUM, a dummy variable that indicates whether there is attribution behavior during that year. I use this dummy variable as opposed to BLAME measure mainly because it is easier to interpret the economic magnitude of the interaction term. The statistical significance of the results reported in this table does not change significantly if the raw BLAME measure is used. The two variables of interests are BLAMEDUM and BLAMEDUM*LAGRET. BLAMEDUM itself is negatively correlated with executive turnover. However, this relationship is not statistically significant. The interaction variable BLAMEDUM*LAGRET is highly significant and positive. The positive coefficient indicates lower turnover performance sensitivity. The marginal effect of this coefficient is roughly one-third that of the coefficient of LAGRET, indicating a much lower likelihood for turnover if the performance is unsatisfactory.

Jenter and Kanaan (2006) show that executives are blamed less for the results from the negative performance of the industry. To make sure that this result is not driven by the possibility that the firms with high BLAME measure are in the industry with a negative shock, I separate the returns into two separate components: INDRET (the Fama-French 48 industry portfolio returns) and EXRET (difference between company returns and industry returns). The coefficient for the interaction term is still positive and highly significant. Thus, the reduced sensitivity is not a result of bad industry performance.

Taken together, attributing negative performance to external factors helps bad performing managers by reducing turnover performance sensitivity and the effect is the strongest when the firm's bad performance is not a result of industry shock.

4 Conclusion

Self-serving attribution bias is a widely documented behavioral bias. However, there is limited prior study on how it affects participants in the financial market. This paper uses textual analysis to capture the tendency to attribute failures to external factors. To my best knowledge, this is the first paper in the finance literature that provides direct evidence of executives' self-serving attribution bias. I find that managers attribute negative performances externally to industry and economy. These behaviors lead to underperformance of stock prices after the conference call. Further evidence from analyst recommendations is consistent with the idea that investors underreact to negative information when executives attribute negative performances. Using industry-adjusted calendar time portfolio, I show that these attribution activities do contain significant negative information about the industry. Thus, the underperformance is driven primarily by firm-specific negative information. Furthermore, executives who attribute negative performance to external factors are less likely to be fired in the next year, indicating that these executives are successful at lobbying board members by attributing bad performance externally. Thus, self-serving attribution bias affects both asset prices and corporate decisions. In summary, this study shows that behavioral characteristics of corporate executives have significant impact to shareholders.

Analysts' Assimilation of Soft Information in the Financial Press

Mark T. Bradshaw[a], Xue Wang[b] and Dexin Zhou[c]

[a] *Carroll School of Management, Boston College*
[b] *Fisher College of Business, The Ohio State University*
[c] *Goizueta Business School, Emory University*

Abstract

Prior research establishes that both sell-side analysts and the media act as information intermediaries in the capital markets. This study investigates whether sell-side analysts use information from firm-specific print news coverage and whether analysts' assimilation of this news leads to informative recommendations. We find that the quantity of news coverage of a firm is positively associated with subsequent recommendation revisions, and that the tone of the news predicts the direction of the revisions. Moreover, we document that the market reactions to analysts' recommendation revisions are stronger for firms with more frequent recent news coverage, suggesting a positive relation between the intensity of news coverage and the informativeness of analysts' recommendations. To understand the nature of news information useful to analysts, we classify news into soft and hard news based on qualitative and quantitative content, and find that the link between news coverage and market reactions to analysts' revisions is primarily driven by analysts' assimilation of soft news. Taken together, our paper sheds new light on the sources of analysts' mosaic of information and the role of analysts in the efficiency of the capital markets.

We appreciate helpful comments from Clifton Green, Narasimhan Jegadeesh, Lian Fen Lee, as well as workshop participants at the 2015 FARS Conference, Drexel University, George Mason University, Harvard Business School, and the Wharton School. We thank our respective schools for generous research support.

1. Introduction

This study examines whether sell-side analysts provide more informative research by assimilating information in the financial press. A long literature establishes that sell-side analysts act as a primary information intermediary in the capital markets (Womack 1996, Jegadeesh et al. 2004, Ramnath, Rock and Shane 2008). Understanding how analysts assemble and process the numerous types of value relevant of information available to them is the focus of numerous studies in both finance and accounting. More recently, a growing body of research investigates the media as another information intermediary. Beginning with studies like Miller (2006) and Tetlock (2007), finance and accounting researchers have become keenly interested in the direct role media plays in the flow of information within capital markets.[1] Bushee et al. (2010) conclude that the media serves as an information intermediary, which they define as “an agent that provides information that is new and useful to other parties” (pp. 1-2). We expect that the relation between these two information intermediaries is symbiotic, but there is no research of which we are aware that examines whether analysts exploit information from the media in their own role of providing new and useful information to investors.

Research demonstrates analysts’ extensive use of numerous information triggers, including market prices, financial information and management disclosures.[2] As a

[1] There are many finance and accounting studies on the role of the press, which precede the dates of these studies, and our intent with this statement is not to disregard earlier studies. Indeed, our literature review discusses many such studies. Nevertheless, beginning around 2006-2007, the studies on the role of the business press have grown into a well-defined area of the capital markets literature.

[2] For example, analysts rely on information garnered from prior earnings changes (Conrad et al. 2006, Ivković and Jegadeesh 2004), stock price changes (Abarbanell 1991), dividend changes (Denis, Denis and Sarin 1994), annual report disclosures (Hope 2003), management forecasts (Williams 1996), management guidance (Cotter, Tuna and Wysocki 2006), firm conference calls (Bowen, Davis and Matsumoto 2002), bond rating changes (Ederington and Goh 1998), broker-hosted investor conferences (Bushee, Jung and Miller 2011, Green et al. 2014), other analysts’ research (Trueman 1994), and so on. Together, these studies characterize analysts as processing multiple information signals.

practical example, Regulation Fair Disclosure presumes that analysts rely on multiple sources and types of information, claiming "Analysts can provide a valuable service in sifting through and extracting information that would not be significant to the ordinary investor to reach material conclusions." Given this, analysts should rely on information distributed through the media.[3] However, it remains an empirical question whether analysts are able to provide new and useful information to investors through their ability to process information contained in the financial press.

Analysts provide information to their clients by synthesizing these information sources and making useful recommendations. Analysts should possess a comparative information advantage because of their ability to generate assessments about the quality of a firm's fundamentals based on public information announcements. Public information conveyed by the media likely helps analysts to make informed opinions about a firm's fundamentals that are superior to those of other market participants (Kim and Verrecchia 1994, 1997), which are impounded into market prices. This is consistent with the evidence in Kross, Ro and Schroeder (1990) and Lys and Sohn (1990), who document that analysts' earnings forecasts are more informative when they are preceded by corporate accounting disclosures.

On the other hand, if print news and analyst reports are competing information channels, analysts' research based on media information may not be informative to

[3] It might be plausible to argue that analysts may choose not to rely on the information from the media. First, there is evidence that analysts ignore or only partially impound public information (Abarbanell and Bernard 1992, Bradshaw, Richardson and Sloan 2001). Much of the 'news' in news coverage is stale (Tetlock 2011), thus analysts may respond to either new or stale information, both, or neither. Third, to the extent that the media sometimes serves merely as an information conduit (i.e., pass-through of information) rather than an information intermediary (i.e., producer of information), it is possible analysts obtain the underlying information from more direct sources such as the firm itself (Hassell, Jennings and Lasser 1988) or newswires (Li, Ramesh and Shen 2011). Finally, Jensen (1979) expresses a sardonic characterization of news coverage as a form of entertainment, which diminishes the role of the media as a source of 'new and useful' information.

investors for a number of reasons. First, the mere existence of print news may reduce or 'crowd out' the informativeness of analyst reports (Ivkovic and Jegadeesh 2004). Second, studies like Lin and McNichols (1998) and Irvine, Lipson and Puckett (2007) argue that analysts' research has a marketing role, reducing the importance of any particular source of information, including that conveyed in the media. Third, while prior studies conclude that analysts are information agents with the ability to process information and affect stock prices (Womack 1996 and Michaely and Womack 2005), Altinkilic and Hansen (2009) characterize analysts' research as "information free" and argue that analysts "piggyback" on firm news and consequently issue uninformative reports. To the extent that the media sometimes serves merely as an information conduit (i.e., pass-through of information) rather than an information intermediary (i.e., producer of information), it is possible analysts obtain the underlying information from more direct sources such as the firm itself (Hassell, Jennings and Lasser 1988) or newswires (Li, Ramesh and Shen 2011).[4]

Much of our understanding of analysts' role in the capital markets is based on their quantitative outputs (i.e., earnings forecasts, discrete stock recommendations, or target prices), but these items are less important than qualitative factors such as their industry knowledge, management access, and written reports (Bradshaw 2013). Likewise, information conveyed through news coverage is both quantitative and qualitative. Petersen (2004) provides a thoughtful discussion of difference between 'soft' and 'hard' information, and concludes that there is a continuum and that a crisp dichotomy is unclear. However, hard information is almost always quantitative. Our examination of

[4] Of course, this is also a construct validity issue that we discuss later and attempt to address in our empirical design.

whether analysts respond to information in news coverage is focused on separately measuring the amount of soft versus hard information in firm-specific news coverage and, more importantly, examine which type of news is most strongly associated with analyst and investor reactions.

The first link we document is whether cross-sectional variation in the quantity of news coverage of a firm is associated with subsequent analysts' recommendation revision activity. We also examine whether any such association is conditional on the tone of news coverage. While a finding that analysts' revisions are positively associated with news coverage of the firm might not be surprising, we are not aware of any prior studies that document such a link.[5] The confirmation of the existence of such a link is important because it provides preliminary evidence consistent with analysts processing information conveyed by news coverage. However, such a relation could also reflect analysts processing the same information with a lag, analysts merely piggybacking off of public information disclosure, or some endogenous link between exogenous news and both media and analyst reactions. We address these alternative explanations through our primary analysis of how soft information in the financial press is associated with analysts' research and subject these analyses to numerous robustness tests.

We focus on stock recommendation revisions conditional on the type of information conveyed in the financial press. If analysts process information in news coverage, achieving information discovery, and this information that is not yet impounded into prices, we would expect more pronounced market reactions to analyst recommendation revisions subsequent to news coverage of a firm. If, however, analysts

[5] A recent study by Cao et al (2014) examines the effect of media competition on analyst forecast properties in an international setting, in which they stress the need to establish a connection between the press and analysts.

process information with a lag or piggyback on information releases, we should not see any permanent market reaction to the duplication of previously released news. Thus, we examine event window market reactions to analysts' stock recommendation revisions and investigate whether market reactions are stronger for firms with greater news coverage preceding the recommendation revision.

Our descriptive statistics are consistent with firm-specific news coverage being associated with higher levels of analysts' stock recommendation revision activity in the following 30-day window. A single news article is associated with a 1.66% increase in monthly revision activity, representing a 44% increase relative to the unconditional average revision frequency of 3.76%. In our primary tests, we document that the tone of the news corroborates the direction of revision activity. More importantly, we demonstrate that the market reaction to recommendation changes is stronger for firms with recent news coverage. A one standard deviation change in our variable capturing news coverage is associated with an incremental 0.6 percent negative return for downgrades and 0.4 percent positive return for upgrades. These incremental impacts are larger than several other mediating variables for stock recommendation reactions documented in previous literature, such as price momentum and herding (Loh and Stulz 2010). In our final analysis of the relative contribution of soft versus hard news to analysts' recommendation revisions and the associated stock price reactions, we substantiate an intuitive prediction that the stronger association between firm-specific news coverage and market reactions to recommendation revisions is driven primarily by analysts' interpretation of soft news.

Our study faces several empirical challenges, and we attempt to mitigate such concerns through our research design in several ways. One concern is that the media faces constraints in terms of news coverage, so there is selection bias in firm-specific news allocated valuable print media space. In our market reaction analyses, we control for factors that capture investor interest or firm visibility such as size, book-to-market, and momentum. A second, more important concern is that we assume the media is the source of the firm-specific news coverage, but such coverage could reflect the media merely transmitting firm-specific news releases. We omit newswires, which would capture direct firm releases, from our sampling procedures and rely instead on news coverage in the ten largest print newspapers. However, even if the news coverage we pick up is related to firm-specific disclosures, our focus is on analysts and market reactions in windows centered on analyst revisions, and these windows appear in the month following the associated news coverage. If news coverage is preceded by firm-specific disclosures through the newswires, the time lag to the analysts' revisions would be even longer and the expectation that investors would react to already public information would be even lower.[6] A third important concern is our implicit hypothesis that the news coverage forming the basis of our sample is the driver of the analyst revisions and the market reaction to those revisions. However, some unobservable aspect of the news coverage could be the driver of both the news coverage and the revisions and market reactions. Engelberg and Parsons (2011) describe how this identification problem hinders inferences in numerous studies on causal impacts of the media. We believe that our

[6] It is possible that analysts might use the same information from another source. 8-K disclosures are considered one of the important firm-specific disclosure channels. To test this possibility, we conducted a robustness check by including firm-specific 8-K disclosures during the same period as the news coverage period. Our results remain qualitatively similar as those presented in the paper (see section 4.5 for more details).

deliberate delay between the firm-specific news coverage and our sample analysts' subsequent revision activity observed in our sample minimizes concerns that any incremental market reaction to analysts' subsequent revision activity is merely a proxy for some unobservable aspect of the news coverage. The questionable alternative is that news would have to be very slowly processed by both analysts and investors for us to find significant incremental market reactions with our research design. Even if this were to be descriptive, our results still speak to the use of information in the print media by analysts. While it is fundamentally challenging to address the identification problem of news attribution, to the extent that the results from various sensitivity analyses support a general conclusion, the validity of our base-line results are enhanced.

Our results are consistent with various findings in the literature showing that analysts incorporate qualitative information into their analyses. For example, prior research demonstrates associations between analysts' recommendations and narrative annual report disclosures (Rogers 1996), an assessment of the quality of management (Barker 1999), a qualitative 'strengths-of-argument' variable (Asquith, Mikhail and Au 2005), and positive or negative affect in managerial presentations (Mayew and Venkatachalem 2012). More importantly, our study contributes to our understanding of the role of the media as an information intermediary in the capital markets. Bushee et al. (2010) examine news coverage of firms during earnings announcement windows and document a significant reduction in information asymmetry. We extend their research by demonstrating that one of the channels through which the media contributes to the information flow in the capital markets is through another intermediary – financial analysts. Our analysis links firm-specific news coverage to analyst revision activity and incremental impacts on stock price reactions to those revisions. Our study also extends the large literature on analysts' role as a primary user of financial information. Prior research analyzes how analysts differentially use various sources of information such as income statement versus balance sheet (Previts et al. 1994), audited versus unaudited information (Rogers 1996), and management sourced versus independently gathered information (Williams, Moyes and Park 1996). We document that firm-specific news coverage provides information that not only impacts analysts' firm-specific revision activity, but interacts with that revision activity to strengthen market reactions to analysts' revisions.

The paper proceeds as follows. The next section provides background and our empirical predictions. The third section discusses data and variable measurement. The fourth section presents results, and the final section concludes.

2. Background and predictions

2.1 Background

Our study is related to several strands of research. First, a growing body of research is interested in how market participants react to information disseminated through the media. A seminal study in this area is Cutler, Poterba and Summers (1988), who document on average small stock market reactions to major news events (and the reverse, limited news events to justify the largest stock price movements), which for many years cast doubt on the view that stock price movements are attributable to news coverage. However, recent empirical evidence suggests news coverage sometimes leads, and sometimes lags stock price movements. For example, using a popular *Wall Street*

Journal column "Abreast of the market," Tetlock (2007) documents that news coverage predicts stock market movements. Tetlock (2011) investigates investors' reaction to 'stale news stories,' and documents evidence of strong return reversals for stocks with above-average individual investor trading activity.

Existing empirical evidence suggests that news coverage contains value relevant information on firm fundamentals that is not directly impounded into stock prices (e.g., Tetlock, Saar-Tsechansky and Macskassy 2008, Engelberg 2008, and Tetlock 2011), which allows some market participants to obtain an advantage from processing this information (see Engelberg, Reed and Ringgenberg 2012 for short sellers, Bushman, Williams and Wittenberg-Moerman 2013 for banks, Chuprinin, Gaspar and Massa 2013 and Fang, Peress and Zheng 2013 for mutual funds, and Bonsall, Green and Muller 2013 for rating agencies).[7] We contribute to this line of research by investigating the extent to which financial analysts facilitate security price discovery in the capital markets through the incorporation of relevant information from news coverage into their research products.

Second, our research is related to the extensive literature on financial analysts (see Brown 1993 and Schipper 1991 for commentaries on early research, and Ramnath, Rock and Shane 2008 and Bradshaw 2013 for reviews on recent research). Financial analysts are considered sophisticated information intermediaries in the capital markets. Beyer et al. (2010) review recent literature on firms' financial reporting environment, and suggest that analysts provide 22% of accounting-based information about a firm. Prior research

[7] Recent commentators (Goldberg 2003) argue that major media outlets report news with a political bias. However, Mullainathan and Shleifer (2005) examine the determinants of media accuracy using a demand-side model, and find that in the aggregate readers should have an unbiased perspective if they have access to all news sources.

has almost exclusively focused on analysts' use of hard information, such as stock prices (Lys and Sohn 1990, Abarbanell 1991), financial information (Mendenhall 1991, Bradshaw, Richardson and Sloan 2001), and other performance measures (Han and Wild 1990).[8]

Analysts have access to other information such as private communication with managers and public information, including news coverage. Our objective in this paper is to shed light on whether and how analysts incorporate the information content of news coverage in their research outputs. The information in the financial press seems largely qualitative (i.e., "soft" information, as opposed to "hard" information that characterizes much of financial reports and earnings announcements). The cost of processing soft information is high (Petersen 2004 and Engelberg 2008), which presents an opportunity for analysts to transform such soft information into inputs for their research. Indeed, soft information is a key element of the "mosaic" of information discussed in Reg FD.

Our paper provides a unique setting to examine analyst efficiency, where the empirical literature provides mixed evidence. Many studies draw inferences about analyst efficiency by examining market reactions to analyst recommendation revisions. While the overall empirical evidence supports the view that analysts are information agents with the ability to process information and affect stock prices (Womack 1996 and Michaely and Womack 2005), recent research by Altinkilic and Hansen (2010) raises concern about the information role of analysts. Using intraday returns data and a narrow window around

[8] Prior studies also investigate the sources of the usefulness of analyst research, such as the discovery of private information and/or interpretation of public information (Ivkovic and Jegadeesh 2004, Asquith, Mikhail and Au 2005). While Francis, Schipper and Vincent (2002) document evidence supporting the complementarity of analyst research and earnings announcements, Chen, Cheng and Lo (2010) find that information discovery (interpretation) dominates in the week before (after) firms' earnings announcements, supporting the co-existence of both roles.

daytime revision announcements, they document insignificant price reactions to stock recommendation revisions. They also present evidence that financial analysts piggyback on recent news from other sources. Bradley et al. (2013) revisit the same issue by pointing out that the time stamps reported in IBES for analyst recommendations released during trading hours are systematically biased. By using the correct time stamps reported by newswires, they find strong price reactions of a narrow window around revision announcements. Li et al. (2014) employ intraday returns data to examine both regular-hour and after-hours revisions to investigate the piggyback conclusion in Altinkilic and Hansen (2009). [9] The results show that the after-hours revisions generate greater price reactions than regular-hour revisions, which they interpret as inconsistent with the piggyback story. We contribute to this recent debate by employing news coverage and focusing on how analysts interpret soft information.

Finally, our research is related to the broad literature concerning information flows in the capital markets. Given the complex nature of the capital markets, information flows in numerous directions between different parties. There is an extensive literature on the information flows among firms, investors, analysts, and other participants in the capital market.[10] Our focus is on the flow of information from the media to analysts, which is not explored in prior research.

---

[9] Our results complement those of Li et al. (2014), who focus on recommendation revisions within three days of corporate news. In contrast, we examine how firm-specific news coverage affects analysts' *subsequent* revision activity, requiring a delay of at least three trading days. This approach minimizes the concerns that any incremental market reaction to analysts' subsequent revision activity is merely a proxy for some unobservable aspect of the news coverage. Also, we focus on the type of news most strongly associated with the informativeness of analyst research (i.e., soft information).

[10] Research on information flows between firms and investors examines events such as earnings announcements (Ball and Brown 1968 and subsequent papers), stock repurchases (Ikenberry, Lakonishok and Vermaelen 1995), and dividends initiations and omissions (Michaely, Thaler and Womack 1995). On the other hand, research on the interaction between firms and analysts covers settings such as "earnings-guidance game" (Richardson, Teoh and Wysocki 2004) and conference calls (Bushee, Matsumoto and

Empirical evidence is generally consistent with the media providing news coverage of corporate events, creating new information, and disseminating the information (Dyck, Volchkova and Zingales 2008, Miller 2006, Bushee et al. 2010, and Ahern and Sosyura 2013). Further, the news coverage contains value relevant information on firm fundamentals and is processed and used by different players in the capital market. Bonner, Hugon and Walther (2006) document that media coverage of an analyst is positively related to investors' reactions to forecast revisions. Similarly, Rees, Sharp and Twedt (2013) study the determinants of news about individual analysts in the financial press and the effects of that news on the career outcomes of analysts, and their evidence suggests that media coverage provides valuable exposure for analysts. However, these two studies focus on the information flow from analysts to the financial press, which leaves open the question of the other direction of information flow. The media and analysts serve similar roles as information intermediaries, gathering, processing, and disseminating information. As a result, both are likely to use the outputs from each other.

Anecdotal evidence appears in analysts' formal reports and suggests that analysts consume and their opinions are shaped by news coverage. For example, Barclays analysts covering Apple (NASDAQ: AAPL) noted, "As we previously reported, according to the *Wall Street Journal* ('Apple Plots its TV Assault,' 12/19/11), Apple executives have been meeting with media executives to discuss the future of television" (Reitzes and Thorwart 2012). In a report on Wachovia Corp (NYSE: WB), a Punk, Ziegel & Company analyst states, "If published reports in the *Wall Street Journal* and *New York Times* are correct, it

---

Miller 2004 and Mayew 2008). Our research question is closely related to the literature on the interaction between investors and analysts (see Womack 1996 and others for investors' reactions to analyst recommendation revisions; and Conrad et al. 2006 for analysts' recommendation responses following large stock price movements) because we examine properties of investors' reactions to analyst recommendation revisions conditional on recent news coverage.

would appear that Wachovia's stock is about to plunge once again and stay down for an extended period. Both newspapers report that the company is close to a deal to acquire Golden West Financial" (Bove 2006). Finally, Janney Capital Markets analysts discuss a promising product for Crumbs Bake Shop (NASDAQ: CRMB) by referencing that, "A *Boston Globe* article describes the … croissant-doughnut hybrid as a food portmanteau. Ansel's Cronut has been featured on Late Night with Jimmy Fallon, The Today Show, Good Morning America, and Piers Morgan Live on CNN with host Anthony Bourdain" (Kalinowski and Babington 2013).

While anecdotal evidence shows analysts sometimes refer to the financial press in their reports, it is an open empirical question whether and how analysts assimilate information in financial press, and whether their research outputs incorporating such information facilitate security price discovery and improve efficiency in the capital market. Our objective is to provide evidence on this direct flow of information from the media to analysts.

2.2 Empirical predictions

Our empirical analysis proceeds in several stages. In the first stage, we provide descriptive baseline evidence about the link between the incidence of news coverage and analysts' recommendation revision activity. Our unit of analysis here is a firm and the population of analysts providing stock recommendations for that firm. It seems obvious that firm-specific news coverage is associated with subsequent analysts' recommendation revisions, as analysts assimilate information in the news coverage in their recommendations. We note that we are not aware of any empirical evidence on this association, but the confirmation of such a link is an important first step to investigate the role of media in providing information that is subsequently used by analysts in generating research.

After documenting the association between firm-specific news coverage and analysts' revision activity, our primary focus turns to evidence of information processing by analysts. As discussed previously, we are primarily interested in whether part of analysts' information set is information provided by the news coverage. If so, then the descriptive evidence would be consistent with news coverage possibly being used by analysts to trigger updates to existing stock recommendations. However, a stronger test is to examine whether the market reaction to analysts' revisions is incremental in the presence of recent news coverage on the firm being followed by the analyst. Altinkilic and Hansen (2010) argue that analysts tend to piggyback on public news about firms, so piggybacking may explain any association between news coverage and recommendation revision activity. Our primary prediction relies on investors' processing of analyst revisions. If analysts use superior information processing skills to convert information in the news coverage to inputs for stock recommendations, and if such information in the news coverage reflects aspects of firms' fundamentals that have not been impounded in stock prices, we would expect more pronounced market reactions to analyst recommendation revisions when there is more coverage of the firm. Our first hypothesis is as follows.

> *H_1: The association between analysts' stock recommendation revisions for a firm and stock returns is positively related to recent news coverage of the firm.*

We are also interested in capturing the nature of the information reflected in news coverage. One approach to characterizing the content of news would be to perform a content analysis, and manually code the specific types of information conveyed in news coverage (see, Asquith, Mikhail and Au (2005), for example). This is costly and subject to coding bias. An alternative that permits the processing of a large sample of news articles and extensive number of firms is to use machine-based textual analysis to characterize the composition of hard versus soft news and the tone of the information contained in the news coverage. These partitions are coarse relative to a manual content analysis, but they are popular in the literature due to their ease of computation and demonstrated ability to provide insights at a relatively low cost.[11]

We predict that the primary value obtained by analysts from consuming news coverage is in the soft information provided. Our argument is similar in spirit to that offered by Schneider (1972). He laments the lack of soft information in Securities and Exchange Commission filings because soft information is "highly relevant to investment decisions" (p. 254).[12] Accordingly, we believe that analysts' processing of information lies largely in the piecing together of various soft and hard information into a cogent opinion on the suitability of investing in a security. Analysts are typically viewed as quantitatively focused, using inputs from the financial statements. However, as noted in any text on financial analysis, much of the process is qualitative in nature, involving the selective processing of different strategic and economic conditions that are not amenable to quantification. Sedor (2002) discusses theories regarding information processing, and states that communication of information often takes place as "narratives." For example,

[11] See Tetlock, Saar-Tsechansky and Macskassy (2008), Kothari, Li and Short (2009), and Engelberg, Reed and Ringgenberg (2012) for the use of dictionary method to extract tonal information from news media. We use Loughran and McDonald's (2011) dictionary, which is more suitable for interpreting financial information based on 10-K filings.

[12] He acknowledges that there is no sharp dividing line between hard and soft information. For example, "Audited historical financial statements are normally considered to be a classic type of hard information. Accounting is not an exact science, however, and many subjective evaluations and other types of soft information must be considered in order to prepare audited financials." (p. 256)

narratives are used by managers in conference calls to discuss soft information like future plans, new products, timelines, and trends. Sedor (2002)'s fieldwork interviews of financial analysts also suggest that they generate forecasts by integrating historical quantitative financial information with qualitative, forward looking narratives from managers and other information sources (Webby and O'Connor 1996). As such, we predict that this type of information is the most likely to be useful to analysts assembling a mosaic of information that would trigger market reactions. Our second hypothesis is as follows.

> *H_2: The association between analysts' stock recommendation revisions for a firm and stock returns is more strongly related to soft news as opposed to hard news.*

Our final prediction relates to the tone of the news coverage. Tone has been examined in several contexts of financial disclosures. For example, Henry (2008) finds that the tone of earnings announcements significantly affects investors' reactions. She cites (Maat 2007), who explains that tone affects information processing because tone is "a stronger argument for a particular conclusion than the non-reinforced version" (p. 365). Similarly, Rogers, Van Buskirk and Zechman (2011) examine the impact of earnings announcement disclosure tone on shareholder litigation. Following this interpretation of the effect of tone on the receiver, we also predict that tone will affect analysts' use of the information. The differential impact of positive versus negative tone is more salient in the context of management press releases and disclosures, where strategic disclosure objectives may be present (e.g., Lang and Lundholm 2000).

In our empirical context, we are not aware of any evidence suggesting a strategic objective of financial news coverage. Further, we do not have any priors on whether analysts might differentially process positive versus negative tone. On one hand, analysts' ability to assemble and process a mosaic of information is expected to be neutral to the tone of the news coverage, so tone will be associated with the direction of recommendation changes, and by extension, market returns. On the other hand, it is well documented that sell-side analysts' forecasts are routinely optimistic. The typical explanation for this phenomenon is that analysts wish to maintain cordial relationships with the covered firms. If this is the case, the analysts might react more strongly to the positive tone of the news coverage relative to the negative tone of the news coverage.[13] Given that the investors are aware of analysts' optimism bias, the market is not expected to strongly react to analysts' recommendation revisions associated with good news. In contrast, the market is likely to respond strongly to react to analysts' recommendation revisions associated with bad news because such revisions are more credible. Given that we do not have a clear prediction related to the tone of the news coverage, we form our final hypothesis as a null hypothesis.

> *H_3: The association between analysts' stock recommendation revisions for a firm and stock returns is not correlated with the tone of the news.*

3. Data and Variable Measurement

3.1 Data

The financial news texts are downloaded from Factiva. Following Engelberg (2008) and Gurun and Butler (2012), we use Factiva's Intelligent Indexing to match firms and news, and require that the firm's name appear at least once in the article to ensure the

[13] It is also possible that analysts might strategically reference the media because of the need to provide cover, which would apply primarily for bad news coverage, i.e., news coverage with negative tone. We address this concern in section 4.4.

accuracy of matching.[14] We employ Factiva's algorithm on handling duplicates to ensure that the sample articles do not include duplicates. We omit newswires, which would capture direct firm releases, from our sampling procedures and rely instead on news coverage in the ten largest print newspapers. The news sources include top national newspapers (*Wall Street Journal*, *New York Times*, *Washington Post*, and *USA Today*) and top local newspapers (*Atlanta Journal Constitution*, *Boston Globe*, *Denver Post*, *Pittsburgh Post-Gazette*, *St Louis Post-Dispatch*, and *Minnesota Star Tribune*).[15] Following Tetlock (2011), we exclude news articles with fewer than 50 words to alleviate the concerns about articles being a short summary. We collect analyst data from I/B/E/S, stock return data from *CRSP*, and financial data from *Compustat*.

The sample period spans 1998 to 2012. We begin with 1998 because Intelligent Indexing is not reliable before 1998. We limit our firm universe to the S&P 1500 because smaller firms rarely receive any coverage in these larger publications. Our empirical tests are conducted at different samples, and we also impose restrictions on data as they become necessary in testing the hypotheses. As a result, our samples vary across different tests. We explain the sample details when we discuss the results of each empirical test.

[14] Given analysts' value as industry specialists (Kadan et al. 2012; Bradshaw 2013), news articles that contain macro or industry-specific information might be more useful to an analyst. However our sampling procedure on firm-specific news articles precludes us from including such articles in the sample. Along those lines, it would be interesting to examine how analysts incorporate information from industry trade journals because they contain a real cogent set of news that analysts would be in the position to capitalize upon. This is an appealing approach to investigate the interaction between analysts' industry expertise and industry level media coverage, but it is beyond the scope of the current paper.

[15] The initial list of newspapers is from Engelberg et al. (2011). When we collected data from the Factiva database, some local newspapers used in Engelberg et al. (2011) were not retrievable through the system. We thus only collected news articles available from the Factiva system at the time of data collection. We only consider the version of print news, but not online version or the blogs.

3.2 Variable Measurement

3.2.1 Media Variables

The key media variables used in the paper are the overall frequency of news coverage, the distribution of soft versus hard information included in news coverage, and the tone of the news. We proxy the frequency of press coverage for each firm as the number of news articles about the firm between days {-30, -3} centered on the analyst recommendation revision date (*#NEWS*). *#NEWS* is highly right-skewed, so we use a log transformation in the empirical analyses (*log#NEWS)*, calculated as log (1+*#NEWS*).

We also measure the frequency of soft versus hard information within news coverage. We designate textual information as soft and numerical information as hard, and construct a variable *HSRATIO*, equal to the number of numerical words (phrases consist of digits, decimal points, commas, percentage and/or dollar such as $1.08, 50% or 20,000) in an article divided by the sum of the number of positive words, negative words, and numerical words in the article. We use the classification method by Loughran and Mcdonald (2011) to identify positive and negative words.[16] We estimate *HSRATIO* for each article, and classify an article as a hard news article if *HSRATIO* is above 0.4, the median *HSRATIO* of all news articles, and as a soft news article otherwise. We then count the number of soft news articles and the number of hard news articles, and use a log transformation for the empirical analyses (*log#SOFTNEWS* and *log#HARDNEWS*).

Finally, we adopt a dictionary method to evaluate the tone of news article. We parse the news articles and count the number of positive and negative words using the

[16] Loughran and McDonald (2011) propose a new financial dictionary based on the words used in the 10-K filings. The authors manually classify the word lists into negative, positive, uncertainty, litigious, strong modal and weak modal categories, and we follow their approach to identify positive and negative words in the news article. On the other hand, numbers are identified using the following rule: the string needs to start with a space or a dollar sign, and then a string that combines digits, commas, and dots follows immediately. For example, $1.35 is considered as a number and FY13 is not counted as a number. To exclude numbers that mark the years, whole numbers from 1950 to 2020 are not included in the total counts.

classification method proposed by Loughran and Mcdonald (2011), who show that their word classification scheme is more suitable in the finance and economics context than the Harvard IV classification used in Tetlock (2010). We follow Tetlock (2007) and Dougal et al. (2012) to define several measures of the tone of articles: (1) the percentages of positive words (*%POS*) is defined as the number of positive words divided by the total number of words in the article, and the percentage of negative words (*%NEG*) is defined similarly; (2) the net tone of the article is defined as *TONE* = *%POS* − *%NEG*. *TONE* is constructed to capture the net effects from both the positivity and negativity of an article. In some regressions, we also include a variable *%HARD*, which is measured as the percentage of numerical words in an article, to capture the proportion of quantitative information (hard information) in the news coverage.

3.2.2 Analyst Variables

We focus on analyst recommendation revisions to make inferences on analysts' assimilation of useful information in the financial process. Specifically, we examine three recommendation revision variables during month t of any given year.

> $PROP\_REVISING_t$**:** The proportion of analysts revising their recommendation, calculated as the percentage of analysts revising recommendations (of all analysts covering the firm) during month t.
>
> ΔREC_t**:** The change in mean recommendation for firm i from month t-1 to month t. I/B/E/S defines recommendation level 1 as strong buy and 5 as strong sell, but we invert these measures so that higher numbers reflect higher recommendation levels. Thus, a higher ΔREC indicates a favorable recommendation revision.
>
> *CAR***:** The market reactions to analyst recommendation revisions, proxied by the abnormal stock returns upon analyst recommendation revisions. Following Loh and Stuz (2010), we use a two-day window (0, 1), and calculate abnormal stock returns upon analyst recommendation revisions as $CAR_i = \sum_{t=0}^{1} R_{it} - \sum_{t=0}^{1} R_{it}^{DGTW}$, where R_{it} is the return of firm i, and R_{it}^{DGTW} is the return on a

benchmark portfolio with the same size, book-to-market, and momentum characteristics as the stock (constructed in similar fashion as in Daniel et al. 1997 and Wermers 2003, DGTW hereafter).

3.2.3 Control Variables

In our regression analyses, we include a number of control variables as suggested in the prior research on analyst recommendation revisions (Jegadeesh et al. 2004 and Loh and Stulz 2010, among others). We explain the construction of the control variables as follows.

*logMV***:** The size of the firm, calculated as natural logarithm of market value, which equals to the number of shares outstanding times the price of the stock at the end of the previous year.

*#ANALYSTS***:** Analyst coverage, calculated as the number of analysts covering a firm in month t of any given year.

*logB/M***:** Book to market, calculated as natural logarithm of book value of equity divided by market value of equity measured at the end of the previous year.

*MOMENTUM***:** Momentum of the stock, calculated as the cumulative stock returns from six month before the recommendation revision date to one month before the revision date (Jegadeesh and Titman 1993). Loh and Stulz (2010) suggest that this variable is useful in explaining the impact of analyst recommendation revisions.

*logVOLATILITY***:** Stock return volatility, calculated as the standard deviation of daily returns over the past 60 days before the recommendation revision date. We include this variable to control the possibility that news coverage might increase or decrease uncertainty. Following Loh and Stulz (2010), we take the logarithm transformation in the regression analyses.

*TURNOVER***:** Average daily share turnover over the past 60 days before the recommendation revision date, calculated as average trading volume divided by the number of shares outstanding.

∆*EPS***:** An indicator variable that equals to one if the analyst who issued a recommendation also issued a new EPS forecast in the past three days before the recommendation revision date, and zero otherwise. Prior research suggests that a recommendation is more useful when it is accompanied by an EPS revision (Kecskes, Michaely and Womack 2013).

RECDEV: The deviation of the analyst's recommendation from the consensus recommendation, calculated as the analyst's recommendation on the inverted 1-5 scale minus the consensus recommendation (Jegadeesh and Kim 2010).

ACCRANK: The analyst's lagged earnings forecast accuracy, measured in month t-1. We sort analyst earnings forecast accuracy into quintiles with quintile five being the most accurate. Loh and Mian (2006) find that the opinions of accurate analysts are more informative.

lagRET: Lagged stock returns, calculated as as the returns in the past 30 days before the recommendation revision date.

PREEARN: Earnings announcement after recommendation revisions**,** an indicator variable that equals to one if the firm makes an earnings announcement in the 15 days after the recommendation revision date, and zero otherwise.

POSTEARN: Earnings announcement before recommendation revisions, an indicator variable that equals to one if the firm made an earnings announcement in the 15 days before the recommendation revision date, and zero otherwise.

4. Empirical Results

4.1 Descriptive Statistics

Table 11 reports descriptive statistics for each newspaper. *The Wall Street Journal* has the highest number of news articles followed by the *New York Times* and the *Washington Post*. Local newspapers in general have fewer number of articles compared to national newspapers. The average number of words per article ranges from 496 to 706 words. There are slightly more negative than positive words for each article, which might reflect the need to attract the attention of readers (Hamilton and Zeckhauser 2004). On the other hand, the levels of news tone do not appear to differ across publications.

Table 12 presents summary statistics on analyst recommendation revision and firm level variables used in the paper. The mean (median) Δ*REC* is -0.019 (0.000), and the mean (median) *CAR* is -0.385 (-0.039), indicating that our sample includes more downward revisions (50,983) than upward revisions (45,666). The table also shows that sample firms are quite heterogeneous on dimensions such as size, growth opportunity, and performance.

4.2 News Coverage and Analyst Research Updates

Our first set of analyses examines the link between firm-specific news coverage and analyst revisions. We perform the following regression analysis:

$$PROP\_REVISING_{i,t} = \alpha + \beta_1\, log\#NEWS_{i,t-1} + \beta_2\, |lagRET_{i,t-1}| + \beta_3\, logMV_{i,t-1} + \beta_4\, \#ANALYSTS_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

The dependent variable, *PROP_REVISING*, captures the likelihood of analysts revising their recommendations for firm i in month t. In this analysis, we start with S&P 1500 firms for a period of 15 years, and we arrive at sample of 268,197 firm-month observations after losing observations in the process of merging with CRSP, IBES, and the media data. *log#NEWS* is the variable of interest that captures the frequency of news coverage in the (-30, -3) window relative to the analyst revision month. In a different regression specification, we replace *log#NEWS* with two indicator variables, *I (#NEWS=1)* and *I (#NEWS>1)*, to capture the incidences when firms have one news article and when firms have more than one news article in month t. Control variables include the absolute value of lagged stock returns (|*lagRET*|), firm size (*logMV*), and the number of analysts covering the firm (*#ANALYSTS*). We standardize all continuous explanatory variables at mean 0 and standard deviation 1 to facilitate comparison of the economic magnitudes of coefficients.

Table 13 panel A presents the panel regression results, with standard errors clustered by year-month. Column (1) shows the results using indicator variables of news coverage, and column (2) reports the results using the continuous variable of news coverage *log#NEWS*. In column (1), we find that both indicator variables, *I (#NEWS=1)* and *I (#NEWS>1)*, are positive and statistically significant. Regarding economic significance, the coefficient on *I (#NEWS=1)* indicates that a single news article is associated with a 1.66% increase in monthly recommendation revision activity, representing a 44% increase relative to the regression intercept of 3.76%. Given that all independent variables are demeaned, the intercept therefore reflects the proportion of analysts revising for the mean firm in the sample. However, the coefficient on *I (#NEWS>1)* has similar magnitude and significance as that on *I (#NEWS=1)*. In column (2), we find a positive and significant coefficient on *log#NEWS*, supporting the intuition that firm-specific news coverage is associated with greater subsequent revision of analysts' recommendations.

We next investigate whether analysts' revisions are associated with the tone of recent news coverage. We restrict the sample to the firm-month observations with available news coverage in the prior month, thus the sample is reduced to 41,101 firm-month observations. We expect the direction of recommendation changes to be associated with the tone of the financial news. We perform Fama-Macbeth regressions of ΔREC on the lagged news tone measures along with control variables. The regression model is as follows:

$$\Delta REC_{i,t} = \alpha + \beta_1\, TONE_{i,t-1} + \beta_2\, \%HARD_{i,t-1} + \beta_3\, logMV_{i,t-1} + \beta_4\, logBM_{i,t-1} + \beta_5\, MOMENTUM_{i,t-1} + \beta_6\, lag\Delta \mathrm{REC}_{i,t-1} + \varepsilon_{i,t} \qquad (2)$$

Table 13 panel B presents the Fama-Macbeth regression results. Tone is measured as *%NEG*, *%POS*, and *TONE* in columns (1), (2), and (3), respectively. We again standardize all continuous explanatory variables at mean 0 and standard deviation 1 to facilitate comparison of the economic magnitudes of coefficients. Column (1) shows that the percentage of negative words in news coverage is associated with downward recommendation revisions with statistical significance at better than the 5% level. On the other hand, we find that the percentage of positive words in news coverage is associated with upward recommendation revisions, but the coefficient on *%POS* is not statistically significant. We control for *%HARD* when we examine the composite measure *TONE* in column (3). The results show a positive and statistically significant coefficient on *TONE*, supporting analysts' recommendations being associated the information content in news coverage. We control for *%HARD* and other control variables (listed in equation 2) in column (4). The inclusion of these control variables does not affect the sign and significance level on the tone measure, and we continue to observe a positive and significant coefficient on *TONE* in column (4).[17]

4.3 News Coverage and Market Reactions to Analysts Recommendation Revisions

The descriptive results in section 4.2 are consistent with the notion that analysts respond to news coverage by updating their recommendations, and that their recommendation revisions incorporate the qualitative signal from the news articles. Our primary set of analysis are discussed next, and focus on the market reactions to analyst recommendation revisions, which capture investors' processing of analyst research

[17] Note that the results in table 13 are also consistent with the strategic timing story, in which analysts await the arrival of news for cover. We provide additional analyses to address this possibility in Section 4.5.

updates. We perform separate regressions of *CAR* for recommendation downgrades and upgrades, and regressions of |*CAR*| for both upgrade and downgrade revisions.[18] The regression models are as follows:

$$CAR_{i,t} \text{ or } |CAR_{i,t}| = \alpha + \beta_1 \, log\#NEWS_{i,t-1} + \beta_2 \, logMV_{i,t-1} + \beta_3 \, logBM_{i,t-1} + \beta_4 \, MOMENTUM_{i,t-1} + \beta_5 \, logVOLATILITY_{i,t-1} + \beta_6 \, TURNOVER_{i,t-1} + \beta_7 \, \Delta EPS_{i,t} + \beta_8 \, RECDEV_{i,t} + \beta_9 \, ACCRANK_{i,t-1} + \beta_{10} \, lagRET_{i,t-1} + \beta_{11} \, PREEARN_{i,t} + \beta_{12} \, POSTEARN_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

where *CAR* is the DGTW adjusted abnormal announcement return to analyst recommendation revision, and |*CAR*| is the absolute value of the return. The variable of interest is *log#NEWS*. Similar to Loh and Stulz (2010), we include a number of control variables as listed in equation (3).

We note that the unit of analysis in this test is each individual analyst recommendation revision. This sample starts with the 268,197 firm-month observations in table 13. Given that each firm has an average of nine-analyst following and the mean proportion of analyst recommendation revision is 0.042, we arrive at a sample of 103,631 analyst recommendation revisions. Further requirements such as having necessary return data to calculate CAR reduces the sample to 96,649 recommendation revisions, with 50,983 upward and 45,666 downward revisions. A legitimate concern on this sample is that the fact that analysts do not revise recommendations does not suggest that they did not use the information from the media. However, restricting sample to recommendation changes makes empirical inferences feasible. That is why numerous prior research focuses identifiable rather than possible events (e.g., Beaver (1968), Loh and Stulz (2010)).

[18] Reiterations are excluded from our analyses.

Table 14 panel A reports the results from the regressions on the market reactions to analyst recommendation revisions for the event window [0, +1], with standard errors two-way clustered by firm and analyst. We standardize all continuous explanatory variables at mean 0 and standard deviation 1 to facilitate comparison of the economic magnitudes of coefficients. Columns (1) and (2) show the results for downgrade revisions, columns (3) and (4) show the results for upgrade revisions, and the last two columns include both upgrade and downgrade revisions. We find a negative and significant coefficient on *log#NEWS* for downgrade revisions (columns (1) and (2)), suggesting more negative market reactions to downgrade revisions when there is more news coverage on the firm. Likewise, we observe a positive and significant coefficient on *log#NEWS* for upgrade revisions (columns (3) and (4)), suggesting more positive market reactions to upgrade revisions when there is more news coverage on the firm. Finally, the coefficient on *log#NEWS* is positive and significant in columns (5) and (6) when we examine |*CAR*| for both upgrade and downgrade revisions. In terms of economic significance, the results indicate that a one standard deviation of *log#NEWS* is associated with a 0.59 percent change in abnormal returns for downward revisions (column 2), corresponding to roughly 19% of the mean abnormal returns in the two-day window. Similarly, the change in abnormal returns associated with one standard deviation of *log#NEWS* is 0.36 percent for upward revisions, equivalent to 14.5% of the mean abnormal returns in the two-day window (column 4). Collectively these results provide support for H_1.

The signs of coefficients on control variables are in general opposite to each other in downgrade and upgrade regressions. Large, high *BM*, high *MOMENTUM*, and low

VOLATILITY firms experience less negative returns upon downward revisions, and less positive returns upon upward revisions. When there is a concurrent EPS revision and when the revision deviates from consensus, the abnormal returns are more negative upon downward revisions, and more positive upon upward revisions. These results are in general consistent with those documented in prior studies.

The lag between our measurement of financial news and the analysts' subsequent recommendations lessens the likelihood that the revisions are merely piggybacking on financial press news. Moreover, these regression results documenting stronger reactions in the presences of recent press coverage are inconsistent with the piggybacking explanation of Altinkilic and Hansen (2009). However, the market price reactions at high volume news days could be a result of investor attention to content, rather than the revelation of firm fundamentals. For example, investors may impound recommendation information more timely when there is more news coverage, which leads to stronger price reactions around the event date. To explore this possibility, we investigate the price reaction from day 2 to day 5 after the analyst recommendation revision date. If higher price reactions are a result of investor attention, then we would expect the price reaction to reverse in day 2 to day 5. The results from these regressions are presented in panel B of table 15. We find that the coefficient on *log#NEWS* becomes smaller in magnitude and lacks statistical significance, but no evidence of price reaction reversals.

To illustrate the results, we estimate both upgrade and downgrade regressions of $\text{CAR}_{i,t} = \alpha + \beta \; log\#NEWS_{\,i,t-1} + \varepsilon_{i,t}$ for each trading day after the recommendation revision date. The first graph of Figure 2 shows the plot of the β coefficients (on the vertical axis) that correspond to the number of days after the recommendation revision day (on the horizontal axis). As is evident from the graph, the β coefficient has the largest magnitude at day 0, and declines rapidly over time. Taken together, these results are consistent with the view that analyst recommendation revisions, in particular those associated with more intense news coverage, are informative to the capital market.

4.4 Analyst Interpretation of Hard versus Soft Information

Although the collective empirical evidence thus far suggests that analysts incorporate firm-specific information from the news coverage in their research updates and such research updates are valuable to investors, it is not clear what type of information in the news coverage analysts primarily rely on to revise their research. While information conveyed by the financial press is both quantitative and qualitative, recent studies on media suggest that the media contains important soft information. The cost of processing soft information is considerably high (Petersen 2004), which creates a demand for analysts to process this type of information. On the other hand, soft information seems to be an important element of the “mosaic” of information discussed in Reg. FD. Our investigation of whether analysts respond to business press information allows us to separately measure the amount of soft versus hard information in the news coverage, and shed light on whether analysts respond to the information content of firm-specific soft information. Specifically we revisit the market reactions to analyst recommendation revisions, and examine whether the market reactions differ in response to quantitative versus soft information in press coverage. We implement the following panel regressions:

$CAR_{i,t}$ or $|CAR_{i,t}|$ =

$$\alpha + \beta_1 \, log\#SOFTNEWS_{i,t-1} + \beta_2 \, log\#HARDNEWS_{i,t-1} + \beta_3 \, \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t} \qquad (4)$$

where *CAR* is the DGTW adjusted abnormal announcement returns to analyst recommendation revisions. The variables of interest are *log#SOFTNEWS* and *log#HARDNEWS*. The vector ***X*** represents the same set of control variables as in equation (3).

Table 15 presents the results from the regressions on the market reactions to analyst recommendation revisions for the event window [0, +1], with standard errors two-way clustered by firm and by analyst. We again standardize all continuous explanatory variables at mean 0 and standard deviation 1 to facilitate the comparison of the economic magnitudes of the coefficients. Columns (1) and (2) show the results for downgrade revisions, columns (3) and (4) show the results for upgrade revisions, and the last two columns include both upgrade and downgrade revisions. For downward revisions (columns (1) and (2)), we find a negative and significant coefficient on *log#SOFTNEWS*, but an insignificant coefficient on *log#HARDNEWS*. The difference in the two coefficients is statistically significant at better than the 5% level. We interpret the results as more negative market reactions to downgrade revisions when there is more qualitative press coverage on the firm, but not quantitative coverage. For upgrade revisions (columns (3) and (4)), we observe positive and significant coefficients on both log *log#SOFTNEWS* and *log#HARDNEWS*. Although the coefficient on *log#SOFTNEWS* is larger in magnitude, the difference in the two coefficients is not statistically significant. When we examine |*CAR*| for both upgrade and downgrade revisions in columns (5) and (6), we find that the coefficient on *log#SOFTNEWS* is positive and significant, but the coefficient on *log#HARDNEWS* is not statistically significant. The difference in the two coefficients is statistically significant at better than the 1% level.

To illustrate the results, we estimate both upgrade and downgrade regressions of $\text{CAR}_{i,t} = \alpha + \beta\ log\#SOFTNEWS_{i,t-1} + \varepsilon_{i,t}$ and $\text{CAR}_{i,t} = \alpha + \beta\ log\#HARDNEWS_{i,t-1} + \varepsilon_{i,t}$ on each trading day after the recommendation revision date. The second graph of Figure 2 shows the plot of the β coefficients (on the vertical axis) of *log#SOFTNEWS* that correspond to the number of days after the recommendation revision day (on the horizontal axis), and the third graphs shows the plot of the β coefficients (on the vertical axis) of *log#HARDNEWS*. The β coefficient of *log#SOFTNEWS* has the largest magnitude at day 0, and declines rapidly over time. In contrast, we do not observe patterns on the β coefficients of *log#HARDNEWS*. Collectively, these results are consistent with H_2, supporting that analysts contribute to the security price discovery by sifting through and extracting soft information in news coverage.

Descriptive results in table 13 suggest that analyst impound the qualitative signal from news coverage (i.e. the tonal information) in their recommendation revisions. We now formally document that the stock market responds to the tonal information contained in analyst recommendation revisions. First, we note that our results from both table 14 and table 15 suggest that the market responds significantly to the amount of news coverage for both upward revisions and downward revisions. The upward (downward) revisions are generally triggered by the positive (negative) tone of the media coverage. The significant coefficients on *log#NEWS* in both upward and downward revision samples provide support that these revisions are informative to the investors. Second, we employ another research design to test such a link, and also consider the interactions between the tone measures and news coverage intensity. Given that we need news articles to calculate tonal measures, we remove all observations without news coverage, which results in a sample of 29,993 recommendation revisions. Specifically, we estimate the following panel regressions:

$$CAR_{i,t} = \alpha + \beta_1\, TONE_{i,t-1} + \beta_2\, log\#NEWS_{i,t-1} + \beta_3\, TONE_{i,t-1} * log\#NEWS_{i,t-1} + \beta_4\, \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t} \qquad (5)$$

$$CAR_{i,t} = \alpha + \beta_1\, TONE_{i,t-1} + \beta_2\, log\#SOFTNEWS_{i,t-1} + \beta_3\, TONE_{i,t-1} * log\#SOFTNEWS + \beta_4\, log\#HARDNEWS_{i,t-1} + \beta_5\, TONE_{i,t-1} * log\#HARDNEWS + \beta_6\, \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t} \qquad (6)$$

where *CAR* is the DGTW adjusted abnormal announcement returns to analyst recommendation revisions. The variables of interest are the tone measures and the interactions between the tone and news coverage measures. Again, the vector ***X*** represents the same set of control variables from equation (3).[19]

Table 16 presents the results from these panel regressions, with standard errors two-way clustered by firm and by analyst. We again standardize all continuous explanatory variables at mean 0 and standard deviation 1 to facilitate the comparison of the economic magnitudes of the coefficients. The results on the control variables are not tabulated for brevity, but they are in general consistent with those presented earlier in table 13. Columns (1) to (3) report the regression results with three different tone measures, *%POS*, *%NEG*, and *TONE*, but without news coverage measures. Consistent with the expectation (H_{A4}), we observe a positive coefficient on *%POS*, a negative coefficient on *%NEG*, and a positive coefficient on *TONE*, with all three coefficients

[19] Given that we are interested in the effect of tone measure, we pool all the recommendation revisions together to run the regression, which is different from the research design in tables 14 and 15.

highly statistically significant. We infer from the results that the stock market responds to the tonal information analysts extract from news coverage and impound in their research updates. Although we cannot completely rule out analyst optimistic bias as an alternative explanation of the results (note that the magnitude of coefficient on positive news coverage is less than that on negative news coverage), the positive and significant coefficient on positive news coverage variable suggests that analyst optimistic bias is not the primary driver of the results, which corroborates the results in tables 14 and 15,

Column (4) presents the results estimating equation (5). Our focus is on the interaction of the tone and the news coverage measures. The results reveal that *TONE* is no longer statistically significant, but there is a positive and significant coefficient on the interaction term. Thus, the qualitative signal in the news coverage has a significant market impact when the press coverage is more intense.

Column (5) presents the results estimating equation (6). Our focus is again on the interaction of the tone and the news coverage measures, but we also separate quantitative news coverage from qualitative news coverage. Similar to column (4), we do not find a significant coefficient on *TONE*. However, the coefficients on the two interaction terms are positive and statistically significant, although the coefficient on the *log#SOFTNEWS* interaction is higher in magnitude relative to that on the *log#HARDNEWS* interaction. This result implies that the tone signal in the news coverage has a significant market impact when the press coverage, in particular the qualitative press coverage, is more intense. Taken together, we interpret the empirical evidence in the paper as analysts extracting qualitative information from the news coverage, and providing such information to investors through recommendation revisions.

4.5 Extensions and Diagnostics

Finally, we address the concern that analysts might *strategically* reference the media because of the need to provide cover, which would apply primarily for bad news. Although the examination of the content of analyst reports is beyond the scope of the current study, we conduct the following analyses to investigate this possibility. First, we examine the timing (i.e. the number of days) of analyst revisions relative to the news articles, and how the timing differs with the direction of recommendation revisions. The mean (median) distance is 15.76 (15.55) days for upgrade revisions, and 15.58 (15.55) days for downgrade revisions. The lack of significant differences in the distance between up and downgrade revisions does not support the strategic cover-up story which predicts shorter distance for downward revisions (due to the need to cover up in particular for bad news). Second, although less likely, it might be possible that analysts need cover for good news. Thus we directly study whether the information content of recommendation revisions varies with the timing of the revisions relative to the news articles by including both good news and bad news articles. Revisions closer to the news articles are more likely to be those for which analysts are strategically citing them, whereas revisions with more distance are those that fit the "mosaic" theory, where analysts are expected to use and process the information from the media. As such, if the results are driven by analysts' processing of information from media, we would expect to find similar significant market reactions for recommendation revisions regardless of the timing differences. Alternatively, if our results are contaminated by the strategic cover-up story, we would expect to find stronger market reactions for the revisions closer to the news articles.

For each revision, we compute the mean distance between the news articles and the revision, and partition the sample into two subsamples using the sample median of the mean distance, the subsample of revisions closer to the news articles and those distant. We then estimate the regressions of model (3) on the market reactions to analyst recommendation revisions for the event window [0, +1] using the two subsamples separately, with standard errors two-way clustered by firm and by analyst. Table 17 reports the results. Columns (1) and (2) show the results for downgrade revisions, columns (3) and (4) show the results for upgrade revisions, and the last two columns include both upgrade and downgrade revisions. The results for the subsample of revisions closer to the news articles are presented in columns (1), (3), and (5), and those for the distant subsample are in columns (2), (4), and (6). We find a negative and significant coefficient on *log#NEWS* for downgrade revisions (columns (1) and (2)), a positive and significant coefficient on *log#NEWS* for upgrade revisions (columns (3) and (4)), and a positive and significant coefficient on *log#NEWS* in columns (5) and (6) when we examine |*CAR*| for both upgrade and downgrade revisions. Moreover, there are no significant differences in the *log#NEWS* coefficient between the two subsamples of interest, suggesting similar significant market reactions to revisions regardless of the timing between revisions and news articles. Collectively, our empirical evidence is more consistent with the "mosaic" story than the strategic reference cover alternative.

Next, an implicit assumption in our paper is that the media is the source of the firm-specific news coverage. However, such coverage could be a proxy of firm-specific news releases from other information sources and analysts could learn about this new information independently of the media coverage. To address this possibility, we consider the effects of firm-specific disclosure. Specifically, we collect data on firms' 8-K filings, which capture one of the important firm-specific disclosure sources. We additionally include the number of firm-specific 8-K filings during the same period as the news coverage period in the regression model and repeat the analyses. Although we do not find consistent results on the coefficient of the variable that captures the number of 8-K filings, our primary results on media coverage remain qualitatively similar as those presented in the paper.

Next, we further explore the market reactions to analyst revisions in response to national versus local news coverage. Given that national news coverage has greater impacts, the results are expected to be stronger for national news coverage. We conduct regressions of model (3) by including *log#NATIONAL_NEWS* and *log#LOCAL_NEWS*, along with other control variables. The results are not tabulated for brevity. We find a negative and significant coefficient on *log#NATIONAL_NEWS* for downgrade revisions, a positive and significant coefficient on *log# NATIONAL_NEWS* for upgrade revisions, and a positive and significant coefficient on *log# NATIONAL_NEWS* for both revisions. While the signs on *log# LOCAL_NEWS* are the same as those on *log# NATIONAL_NEWS*, the magnitudes are lower, and significant only for the upgrade revisions and the pooled revisions. This evidence suggests that the scope of news coverage is associated with analysts' assimilation of financial press information.

Finally, we perform several replications of our primary analysis to assess the robustness of our results to including various sample definitions and combinations of control variables.[20] We first consider the effects of other firm-specific correlated omitted variables by including firm fixed effects in the regression models; the inclusion of firm

[20] These results are not tabulated for brevity, but are available upon requests.

fixed effects does not change our main results on media coverage. Second, we consider the possibility that overlapping news coverage surrounding analyst revisions might contaminate our main results. We thus conduct a sensitivity analysis by removing from our sample revisions with overlapping news coverage, which leaves us with 41,135 downward revisions and 37,316 upward revisions. The regression results from this sensitivity analysis are similar to those reported in the paper. Third, we consider the effect of earnings surprises by including them in the market reaction regressions, and continue to find similar results as those reported in the paper. Fourth, we control for the direction of change in recommendation revisions in the market reaction regressions, and the inferences from this alternative specification are the same as those from the main specification reported in the paper.

5. Conclusion

To our knowledge, this is the first study to examine the role of the media in providing information that is subsequently used by analysts in generating informative research. There is a long literature on the efficiency of analysts with respect to numerous types of information. Whereas researchers most commonly presume that analysts primarily obtain information from financial reports and disclosures by firms, recent research has highlighted that analysts obtain non-financial information from alternative sources, such as manager forecasts (Hutton, Lee and Shu 2012), industry-level information (Kadan et al. 2012), broker-hosted investor conferences (Green et al. 2014), and nonverbal cues during manager presentations (Mayew and Venkatachalam 2012).

We extend these studies by examining analysts' use of information, especially soft information, from firm-specific print news coverage.

We investigate whether sell-side analysts use information conveyed by the financial press. Our specific examination is of the link between information disseminated by the media, its assimilation by analysts, and the communication of original analysis to investors. We document that analysts are more likely to revise their stock recommendations following greater news coverage of a firm. Moreover, investors' reactions to analysts' revisions are stronger when such revisions are linked to previous news coverage. Finally, we partition news by tone and type, and find not only that analysts and investors respond to both optimistic and pessimistic tone, but that the usefulness of news coverage by analysts and investors is primarily driven by soft information rather than hard information in the news. Our study primarily contributes to the general literature on the efficiency of capital markets, which is achieved through the free flow of information among participants in the capital markets.

Good News in Numbers

Dexin Zhou*

Abstract

This paper finds that the proportion of qualitative and quantitative information itself contains value-relevant information for investors, since executives tend to use qualitative information, which is less precise, to obscure their bad performance. I calculate the proportion of numbers to words in conference call transcripts as a proxy for the proportion of quantitative information. Using this measure, I find that the proportion of quantitative information is positively related to operating and financial performance. I also find that managers are more likely to talk up their performances when using lower proportion of quantitative information. In addition, a high proportion of quantitative information is associated with a more positive stock price reaction, suggesting that a high proportion of quantitative information itself contains positive information about the firm. Finally, investors do not fully incorporate this information in the stock prices. A high proportion of quantitative information predicts a sizable positive drift in stock returns after the conference call date.

*Emory University. E-mail: dexin.zhou@emory.edu

1 Introduction

While existing research indicates that both qualitative and quantitative information disclosed by managers are valuable to investors, there are also apparent differences: quantitative information tends to be more precise than qualitative information even if the numbers are only approximations (Hutton et al., 2003). Past research focuses on either quantitative information (e.g., Bernard and Thomas (1989)) or qualitative information (e.g., Li (2010) and Loughran and Mcdonald (2011)), but rarely considers the interaction between these two types of information. By investigating the determinants and consequences of the use of qualitative and quantitative information, this study finds support for the idea that the ratio of quantitative and qualitative information can also contain value-relevant information, since managers change their level of precision following their incentives to obscure negative information.

In previous literature, researchers have treated textual information such as word tones as qualitative information. The complement to qualitative information in the disclosure documents is quantitative information, including specific numbers or range of numbers. Quantitative information is considered more precise than qualitative textual information (Hutton et al., 2003), since numbers often indicate an exact point or a range and thus they leave little ambiguity about the information conveyed. In contrast, qualitative description can only indicate a direction (e.g., positive or negative) or a very wide range of numbers. The meaning of words may also be subject to interpretations in different contexts. Overall, qualitative information leaves more ambiguity to investors. For example, "good", "excellent" and "great" are all positive qualitative descriptions in Loughran and Mcdonald (2011) classification. However, when an executive discloses that they had a great quarter, it is difficult for investors to map these words to a specific range of numbers.

Precise information helps investors establish a solid understanding of companies. However, executives may disclose less precise qualitative information in lieu of more precise quantitative information for various reasons. First, executives themselves may not possess precise quantitative information on the subject that they are discussing. Thus, they cannot disclose inaccurate quantitative information to the shareholders. Second, managers may disclose qualitative information discretionarily even when they possess accurate numeric information. These discretionary decisions can be driven by executives' various incentives such as delaying negative information and toning up the positive information.

Empirically, I use percentage of numbers in an investment text as a proxy for the proportion of quantitative information in the document. The first part of the paper investigates the incentives that drives executives' choices of qualitative versus quantitative information in their conference call disclosures. First, past research shows that managers tend to delay or withhold the disclosure of negative news (e.g., Kothari et al. (2009b), Burgstahler and Dichev (1997)). I hypothesize that executives are more likely to use precise numeric information when the firms are reporting satisfactory financial or operating performances . When a company experiences bad performance, managers disclose less precise textual information to obscure negative performance information. Second, a reduced proportion of numbers can leave more room to influence investors' perception using qualitative statements. Third, executives disclose more quantitative information prior to share issuance and this relationship is most salient in companies with good performance.

The second part of the paper sheds light on investors' reactions to the mix of qualitative and quantitative information in the disclosures. Because executives tend to use more qualitative information when their performance is relatively unsatisfactory, a high proportion of qualitative information may alert investors about the negative performance of companies. The event return at the date of the conference call should be positively correlated with high proportion of quantitative information if some investors realize that a high proportion of quantitative information is associated with good performance. In addition, if investors underreact to this information the proportion of quantitative information may positively predict further positive returns after the information release. Finally, a higher proportion of quantitative information should be associated with more precise information. Using absolute analyst forecast error and analyst forecast dispersion to capture the ambiguity of information, a high proportion of quantitative information should imply a low forecast error and dispersion.

Towards these goals, I analyze a set of quarterly earnings conference call transcripts from 2003 to 2012. Conference calls provide significant additional information to written statements such as earnings releases (Matsumoto et al., 2011). In addition, conference call transcripts offer obvious advantages over the regulatory filings and earnings releases in my analysis. Since conference call transcripts do not contain any tables or XML appendices, calculating the proportion of qualitative and quantitative information in the disclosure becomes a much easier task. I use a ratio of numbers and total counts of numbers and words as a proxy for the ratio of quantitative to qualitative information (hereafter PCTNUM). First, I show that financial and operating performances are positively related with PCTNUM. In contrast, the tone of the conference call is negatively correlated with PCTNUM. These results may indicate that managers are more willing to disclose subjective information when they use more words in the disclosures. In addition, a higher proportion of qualitative disclosure is accompanied by soft talks aiming to influence investors' perception of the financial results. PCTNUM is also related to other strategic considerations. Managers disclose more quantitative information prior to SEO. Nevertheless, the firms with better operating performance tend to issue more quantitative information depending on share issuance in the next quarter. Second, I examine how investors react to the use of qualitative and quantitative information. The results indicate that the proportion of qualitative information and quantitative information also carries important information: high PCTNUM is correlated with positive market reaction. In addition, PCTNUM further predicts positive price reaction in the quarter after earnings announcement. Finally, confirming that the PCTNUM measure is a proxy for the precision of the information release, I find that this measure is positively correlated with analyst forecast dispersion and analyst forecast error for the incoming quarter.

This paper contributes to the existing literature in the following ways. First, this paper synthesizes the previous literature on the information content of qualitative and quantitative information. Prior literature documents that both qualitative (e.g., Li (2010), Price et al. (2012), Jegadeesh and Wu (2013), Demers and Vega (2014)) and quantitative information (e.g., Bernard and Thomas (1989), Richardson et al. (2005), Novy-Marx (2013)) disclosed by executives contain value-relevant information to investors. This paper shows that in addition to qualitative and quantitative information in the corporate disclosures, the proportion of qualitative and quantitative information itself also provides value-relevant information.

Second, this study contributes to a body of literature on disclosure. Previous literature documents that various incentives and investors' behavioral characteristics drive executives' reporting decisions. Related to previous literature, this is the first paper that shows the proportion of quantitative information in the voluntary disclosure is driven by managers' incentives. For example, Kothari et al. (2009b) find that executives tend to delay the disclosure of negative information. Burgstahler and Dichev (1997) document that earnings are managed upward to meet certain thresholds. Huang et al. (2013) find that executives may use tone to manipulate the perception of investors. Cohen et al. (2013) document that this behavior is related to executives trying to mask their bad performance. Overall, this literature indicates that executives tend to hide bad news and try to delay the disclosures of bad news hoping for the results to improve in the future. This paper shows that by changing the proportion of qualitative and quantitative information, managers can adjust the precision of their information disclosure. By disclosing less precise information when they experience bad performance, executives attempt to manage people's perception of the company's performance. Because of these incentives, the precision of information in the conference call itself contains value-relevant information. Imprecise information signals negative information to investors. Similar to this idea, there are a number of studies that examine the information precision and soft talk versus verifiable information in the management forecast (e.g., Baginski and Hassell (1997), Baginski et al. (1993), Hutton et al. (2003)). However, the price reaction to this variable is also distinctive from the variables examined in the prior research. Finally, in addition to the incentive to delay bad news, managers' decision to use qualitative or quantitative information in their disclosure can also be driven by strategic considerations such as share issuance (e.g., Hughes and Pae (2004)).

Third, this study contributes to the literature on how investors respond to information in disclosures. Bernard and Thomas (1989) document the post earnings announcement drift, indicating that investors underreact to quantitative information from the earnings announcements. Li (2010) and Tetlock et al. (2008) show that investors do not fully incorporate the qualitative textual information from regulatory filings and news reports. This paper further shows that although investors react in the right direction initially to managers' choice of qualitative and quantitative information in the disclosure, the price continues to drift after the conference call date. Thus, the evidence indicates that investors underreact to the information in PCTNUM.

Fourth, this paper provides supporting evidence that the proportion of qualitative and quantitative information measures the precision of information. Although not directly related to textual readability measures proposed in previous literature (e.g., Lehavy et al. (2011) and Loughran and Mcdonald (2014)), the measure used in this paper is also a direct measure of the difficulty in interpreting the disclosure material. The higher the percentage of numeric information the lower the difficulty in understanding disclosure texts. In addition, this paper provides supporting evidence to Chuprinin et al., who use the percentage of numbers in news coverage to proxy information tangibility. A high percentage of numbers is associated with more tangible information, since tangible information refers to information that is more precise and is easier to interpret and the proportion of numbers is positively correlated with information precision.

Finally, this paper is also linked to a literature on the information from earnings conference calls. This paper shows that the linguistic choices in conference call contains information in addition to previously documented variables. Existing papers find that conference calls are an informative disclosure channel (Matsumoto et al., 2011). In addition, investors react to various behavioral patterns such as whether executives stay silent over Q&A part (Hollander et al., 2010), structure of conference call narratives (Allee and DeAngelis, 2014) and attribution behavior (e.g., Zhou 2014). Mayew and Venkatachalam (2012) also show that the tone of voice is a useful signal for investors and investors underreact to that information. Larcker and Zakolyukina (2010) find that conference call can also help investors detect accounting irregularities.

The rest of the paper will proceed as follows. Section 2 develops empirically testable hypotheses. Section 3 provides a detailed description of textual and other data used in this study. Section 4 presents the main empirical findings of this paper. Section 5 concludes the paper.

2 Hypotheses Development

The first set of hypotheses are related to the determinants of the proportion of numbers used in conference calls. It is documented in the past that managers tend to delay revelation of bad news (e.g., Kothari et al. (2009b)). Managers also tend to spin bad news when the performance is unsatisfactory (e.g., Solomon (2012), Cohen et al. (2013)). I first hypothesize that managers reduce the use of quantitative information when their performance is less satisfactory. Thus, firm performances should negatively correlate with the proportion of quantitative information in the conference call. The first hypothesis is as follows:

- H1a: Operating and financial performance measures (such as SUE, ROA and lag return) are positively correlated with the use of quantitative information.

In addition, by increasing the proportion of qualitative information, executives will have higher ability to engage in tone management (e.g., Huang et al. (2013)). In other words, managers can use positive tones to influence investors' perception of the performance of their companies. The second hypothesis is

- H1b: The tone of the overall transcript is negatively correlated with the proportion of quantitative information.

In addition to the incentive to delay the revelation of bad news and tone management, executives' decisions to use qualitative or quantitative information in disclosure can also be driven by other strategic considerations. For example, managers may strategically reveal more quantitative information to reduce information asymmetry. However, this effect should only concentrate in the firms with good operating and financial performance. Hughes and Pae (2004) model firms' disclosure behaviors and find that companies disclose precise information when their value is high and less precise information when the value is low. Thus, firms that experience poor performance prefer to use qualitative information even if they need to issue shares. The testable hypothesis is that

- H1c: Firms that engage in SEO in the following quarter use more quantitative information. The effect is stronger for the firms with strong financial and operating performance.

The second set of hypotheses are related to investor responses to the use of qualitative and quantitative information. In order to hide certain unsatisfactory results, managers may simply choose to disclose using qualitative information even if they possess precise quantitative information. If executives choose to use less precise qualitative information when they experience bad performance, the ratio of qualitative and quantitative information itself can be informative about the performance of the company. A high percentage of qualitative information signals negative performance information about the firm to investors. On the other hand, high level of quantitative information shows executives' confidence in their numbers. Thus, a high percentage of qualitative information should receive negative investor responses. I hypothesize that

- H2a: A high proportion of quantitative information leads to positive stock price reaction at the announcement date.

Past research shows that investors do not fully react to information in the earnings numbers (Bernard and Thomas, 1989) and the tone of 10-K (e.g., Li (2010)). It is shown that investor inattention may explain the documented predictability. Investors tend to react more slowly to less salient information and less tangible information (e.g.,Cohen et al. (2010)). The ratio of quantitative information is arguably not salient or tangible. Thus, investors are less likely to fully incorporate the information in the stock prices immediately. If investors do not react to the information in the ratio of qualitative and quantitative information or underreact to this information, a low ratio of quantitative information will predict lower future stock returns. Thus

- H2b: A high percentage of quantitative information leads to positive stock returns after the earnings announcement date if investors underreact.

The final hypothesis is related to how the release of qualitative versus quantitative information affects the information environment. Prior studies have established that the style of disclosure can affect the precision of information received by the participants. The existing literature proposes several measures of readability of regulatory documents. For example, Lehavy et al. (2011) use FOG index to analyze 10-K documents. Their results indicate that a higher FOG index is associated with higher forecast error and analyst forecast dispersion. Loughran and Mcdonald (2014) propose the file size of the 10-K document submitted to the SEC is a better proxy for readability. They document that greater 10-K file size is also associated with larger analyst forecast dispersion and higher forecast error. I hypothesize that the high percentage of numbers in the conference call transcript has a similar effect on market participants. Quantitative information disclosed in conference calls generally reflects an accurate statement (e.g., 5%) or a specific range of band (e.g., 5% to 7%). In contrast, qualitative information only reflects a normative statement and can imply a broad range of values (e.g., the segment is expected to have strong growth in the following quarter). Therefore, a higher percentage of numbers in the conference call should associate with more precise information. This leads to the following hypothesis:

- H3: A higher percentage of numbers is negatively associated with analyst forecast dispersion and analyst forecast error.

3 Data

The conference call transcripts come from two sources: Thomson One's StreetEvent and Factset's Call Street. The sample period is 2003 to 2012. The combined sample covers roughly 60,000 firm-quarters. For each transcript, I extract the number of positive and negative words. In addition, I count the total number of words in the text. A word is only counted when it is included in the 10-K dictionary by Loughran and Mcdonald (2011). This information allows me to calculate the overall tone of the transcript. I also extract the numerical phrase in the transcripts. Both StreetEvents and Call Street record numbers in numeric form (i.e., 9% instead of nine percent) in their transcripts. I look for any number with a space or a dollar sign in the front. The rest of the number can consist of numeric characters (0-9), comma (,) and period (.). These requirements can effectively rule out many numbers in company names (such as L-3 Communications) and other non-informative numbers (e.g., FY09). At the same time, they can pick up most value-relevant numbers in the discussion (such as growth rate, EPS, revenue and so on). In addition, I exclude whole numbers from 1950 to 2020 to exclude the mention of year in the conference call discussions. I calculate the following measure to proxy for the proportion of quantitative information in the text:

$$PCTNUM = \frac{N(Numbers)}{N(Words) + N(Numbers)},$$

where $N(Numbers)$ are the total count of numbers in the whole transcript and $N(Words)$ is the total count of words in the transcript. In the additional analysis, I divide the transcripts into statement and Q&A components. Matsumoto et al. (2011) document that both statement and the Q&A components contain significant information about corporate value and Q&A component delivers more information relative to the statement component. I split each transcript into the statement and Q&A components by looking for a number of textual patterns that involve operator and question. I then calculate $PCTNUM_S$ and $PCTNUM_{QA}$ for both statement and $Q\&A$ components for further analyses.

The summary statistics related to the conference calls are presented in table 18. The key variable is PCTNUM. On average, numbers account for roughly 2.7 percent of the total words and numbers. The statement component contains a higher proportion of numbers than the Q&A components. On average, numbers account for 3.9 percent in statement components and about 2.2 percent in Q&A components. The mean count of numbers in each transcript is about 209. Also, more numbers are presented in the statement components (about 109 numbers). Interestingly, compared with other textual variables listed in the table, only $PCTNUM_S$ and $PCTNUM_{QA}$ are negatively correlated (-0.0472). All the other textual variables have positive correlations between the statement component and the Q&A component. This result shows that the quantitative information in the statements and the Q&A sections are generally substitutes for each other.

The other variables are constructed as follows. Compustat and IBES are merged to obtain the common financial measures such as market equity, book-to-market ratio, past return and Standardized Unexpected Earnings. The cumulative abnormal return (CAR) is calculated using the Fama-French 3-factor model (Fama and French, 1993). The beta of the factor loadings are estimated using the daily returns in the interval of [-180,-15] relative to the date of the conference call. Standardized unexpected earnings or SUEs are calculated as

$$SUE_{i,t} = \frac{E_{i,t} - FE_{i,t}}{P_{i,t}},$$

where E represents realized quarterly earnings, FE represents the consensus analyst forecast earnings and P is the stock price at the end of the IBES statistical period when consensus analyst earnings forecasts are calculated. The consensus analyst forecast expectation is formed on the closest IBES statistical period end date prior to the conference call. SUE is winsorized between -0.1 and 0.1. ROA is the return on assets. The analyst forecast dispersion, DISP, is calculated as the standard deviation of analyst forecast for the next quarter, scaled by price. CAR is calculated using a 3-factor model, where the loadings on the Fama-French factors are estimated by returns from the prior 180 days up to 10 days relative to the earnings announcement date. The results presented in the rest of paper are robust if market adjusted returns (calculated as firm returns minus market returns) are used instead of cumulative abnormal returns. Volatility is the estimated daily volatility one year prior to the conference call date. Share turnover is the monthly turnover in the month before the conference call date, calculated as the total number of shares traded divided by the number of shares outstanding. Institutional ownership is formed based on the 13F data at the end of the quarter prior to the conference call. The summary statistics of these variables are presented in table 19.

4 Main Results

4.1 Determinants of PCTNUM

I explore whether executives change the proportion of qualitative and quantitative information in their disclosures in response to various incentives in this section. Specifically, I test the set of hypotheses proposed in H1. I run a set of panel regressions with PCTNUM as the dependent variable. The results from these regressions are reported in table 20. The first hypothesis under H1 states that corporate performance influences the choice of linguistic style in disclosure. Executives are more willing to disclose specific numbers as opposed to more vague qualitative descriptions when they perform well. I use several measures to proxy the overall corporate performance. Both standard unexpected earnings (SUE) and lag return (LAGRET) are measures of firms' financial performance. SUE measures whether earnings can beat the analyst forecast. The lag return is a direct measure of the market's assessment of the firm's performance. I use ROA to proxy for the operating performance of the company, since ROA is a commonly used measure for profitability. I find that both SUE and LAGRET are strongly positively correlated with PCTNUM. This indicates that executives use more numbers in the conference call when there is strong financial performance. ROA is also strongly positively associated with PCTNUM, indicating a positive relationship between the firm's operating performance and the use of quantitative information in the conference call. These results confirm the empirical predictions in H1a that the firm's financial and operating performances are positively correlated with the use of numbers in the transcripts. In the same regression, I also include a set of variables related to the company characteristics, institutional ownership and analyst coverage as control variables. I find that institutional ownership is positively correlated with the use of numbers. This result is likely to be driven by institutional investors' demand more precise voluntary disclosure from the management. Another possibility is that more precise information disclosure attracts institutional investors (Bushee and Noe, 2000). Analyst following is negatively correlated with the PCTNUM. This result may seem at odds with the previous institutional ownership result, since institutional ownership is positively correlated with the use of numbers in the conference call. However, Lehavy et al. (2011) find that 10-K with lower readability is associated with higher analyst coverage, since there may be greater demand for analysts to interpret the puzzling financial statements. Similar explanations may explain the positive coefficients in this regression: low PCTNUM is related to less precise information. Therefore, there is higher demand for analysts' services to interpret information releases from the investors.

The second test investigates how other linguistic characteristics relate with PCTNUM. Firstly, if low percentage of numbers are related to managers' choice to disclose less precise information in response to poor performance, it leaves more room for executives to tone up the results. Therefore, high PCTNUM may be negatively related to the tone of the transcript. In the second regression of table 20, I find that TONE is negatively related to PCTNUM. This coefficient is highly statistically significant (t-stat = -16). Secondly, the regression reports that PCTNUM is negatively related to the length of the transcript, indicating that managers tend to be more verbose when they use less quantitative information in the disclosures. Finally, a high proportion of qualitative information is likely to be linked to more behavioral biases in the reporting such as self attribution bias. Zhou (2014) proposes that BLAME measure can proxy managers' behaviors to attribute negative performance externally. Thus, BLAME is predicted to be negatively correlated with PCTNUM. Moreover, I find that BLAME is negatively related to PCTNUM, indicating that a higher proportion of quantitative information is related to a lower proportion of sentences that attribute negative performance to negative factors. These results are consistent with the hypothesis H1b. Summarizing the results, PCTNUM is negatively associated with the tone of the conference call transcript, the length of conference call transcript and the BLAME measure, indicating that a high proportion of quantitative information in the conference call disclosure is associated with reduced tone management, more succinctness in discussions and potentially less biases in attributing negative performance.

Finally, I test if share issuance in the recent future can affect executives' use of quantitative and qualitative information in the disclosure. The result is reported in the third regression of table 20. The SEO dummy equals to one if the company engages in SEO activity in the quarter following the conference call. I find the SEO dummy is strongly associated with high PCTNUM in the transcript. This is consistent with the idea that executives tend to disclose more quantitative information prior to the SEOs. By providing more quantitative information, executives can reduce the information asymmetry between management and the investors for share issuance purpose (e.g., Lang and Lundholm (2000)). This effect also concentrates in the firms with better operating performance, since the interaction term of SEO and ROA is significantly positive. Firms with worse operating performance may prefer to avoid disclosing precise quantitative information. Because qualitative information is less precise, disclosing qualitative information may leave more room for managers to manage investors' perception of the firm value before share issuance. However, there is no evidence that the interaction of SEO and financial performance (e.g., SUE) is positively correlated with PCTNUM.

In the last column of this table, I include all the independent variables. Most coefficients remain significant in the kitchen-sink regression. The coefficient of log number of analyst estimate and share turnover become statistically insignificant, indicating that these variables have less robust relationships with the proportion of quantitative information.

In sum, executives choose the proportion of numeric information in response to a number of incentives. They tend to use more quantitative information and thus increase the precision of the information disclosure when their financial and operation performances excel. An increase in qualitative information is oftentimes accompanied by more positive tones, indicating the possibility that executives engage in tone management (Huang et al., 2013). Managers also strategically increase the proportion of quantitative information prior to SEO, but this effect is stronger in the companies with higher profitability.

4.2 Investor Responses to PCTNUM

The previous results show strong evidence that managerial incentives strongly affect the choice of proportion of qualitative and quantitative information in the disclosure. In this section, I explore the information in the ratio of qualitative and quantitative information in the conference calls. I start by examining how investors respond to PCTNUM information around the conference call date. More specifically, I test hypothesis H2a: investors react positively to the conference call transcripts with a high proportion of quantitative information, since a high proportion of quantitative information indicates that executives are not attempting to obscure negative information from the investors. I test this hypothesis H2a by running the Fama-Macbeth regression (Fama and MacBeth, 1973) with cumulative abnormal return in the 3-day window around the date of the conference call to test investors' initial reaction to the ratio of quantitative information. The regression takes the following specification:

$$CAR[-1,1] = \alpha + \beta PCTNUM + \gamma X + \epsilon,$$

where CAR is adjusted using 3 factor model in Fama and French (1993) and X represents a vector of control variables. The results are reported in table 21. The reported coefficient is the average coefficient of quarterly coefficients. The standard deviation is calculated using time series standard deviation with Newey-West standard error Newey and West (1987) with four lags. I find that PCTNUM is is positively correlated with 3-day abnormal returns. In the univariate specification, one standard deviation in PCTNUM is associated with 27 basis points change in the 3-day abnormal return (t-stat=6). The second regression includes a set of control variables. Specifically, I include variables such as SUE, ROA and accrual. These variables summarize the financial and operating performance of the firm during the fiscal quarter covered by the earnings release. In addition, I control for two linguistic related variables: TONE (measures the difference between the percentage of positive words and negative words in the transcript) and BLAME (the percentage of sentences that attribute negative performance to industry and economy). The coefficient for PCTNUM is still positive and statistically significant. This result supports the hypothesis *H2b*. The positive response to a high proportion of quantitative information indicates that managers' providing a high proportion of quantitative information itself is a positive signal about the firm performance, since high proportion of quantitative information shows that managers do not need to obscure negative results using qualitative information.

Previous literature documents that the statement component and the Q&A components both offer significant information. However, the Q&A component seems to be more informative. One possibility is that the statement component has high similarity with the earnings release. In general, the statement component is prepared and the Q&A component may be more spontaneous, since it is difficult to anticipate the questions from the analysts. I further explore whether the PCTNUM from these two components of earnings conference calls affect the stock prices differently. I further split the transcripts into statement component and the Q&A component. I then examine which component is responsible for the positive relationship of PCTNUM and CAR[-1,1]. While both $PCTNUM_S$ and $PCTNUM_{QA}$ are positively correlated with the cumulative abnormal return, $PCTNUM_S$ is much stronger correlated with CAR, indicating that investors deem the PCTNUM in the statement component to be more informative.

The second test in this section investigates whether investors fully incorporate the information of PCTNUM in the stock prices in a timely manner. If investors do not fully incorporate this information in the stock prices, investors can potentially use the PCTNUM as a signal for firm performance. The existing literature documents that the market tends to underreact to certain quantitative and qualitative information.

The underreaction tend to be more severe for less tangible and less salient information. The information contained in PCTNUM is likely to be intangible and less salient. Few market participants count the number of words and total count of numbers after each conference call. Thus, there is the possibility that the information in PCTNUM is not completely reflected in the stock prices. I use a similar specification as the short term return regression:

$$CAR[2,60] = \alpha + \beta PCTNUM + \gamma X + \epsilon.$$

The CAR[2,60] includes the 60 trading days following the conference call, which roughly matches to the next calendar quarter. Previous research generally uses this time frame to test investors' underreaction to the information from earnings announcements (e.g., Hirshleifer et al. (2009)). The results from this regression are tabulated in table 22. The first column in the table indicates that one standard deviation change in PCTNUM is associated with 35 basis points change in the abnormal return in the next quarter (t=4). This effect is economically larger than the effect on the announcement date. Two standard deviations of PCTNUM implies an 2.9% difference in annualized return. This effect is robust even after including control variables in the regression. Breaking down the PCTNUM into the statement component and Q&A component, both components can positively predict future returns. The economic magnitude and statistical significance are somewhat stronger for the coefficient in $PCTNUM_S$. These results indicate that the market underreacts to the information from the proportion of qualitative and quantitative information in both the statement and Q&A components of the earnings conference call. In sum, these results indicate a clear pattern of underreaction to executives' choice of qualitative and quantitative information in the conference call disclosures. These results confirm the empirical prediction of H3b.

Summarizing the results, the proportion of qualitative and quantitative information in conference calls contain information about firm performance. A high proportion of quantitative information is a positive signal to investors, as it shows that managers are not hiding negative information behind more ambiguous qualitative descriptions. Furthermore, investors do not fully incorporate this information in stock prices.

4.3 PCTNUM and Information Precision

The final set of empirical results explores how the ratio of qualitative and quantitative information affects the information precision of the analysts. Specifically, I examine whether higher PCTNUM is associated with higher information precision. Following previous literature (e.g., Lehavy et al. (2011), Loughran and Mcdonald (2014)), both absolute SUE and analyst forecast dispersions can proxy for the information environment of the market participants. If a high percentage of quantitative information is associated with more precise information, then a high PCTNUM should be negatively correlated with lower absolute SUE in the following quarter. In addition, a high percentage of quantitative information should lead to low analyst forecast dispersion, since more precise information about firms' fundamentals can reduce the disagreement about firms' fundamentals. I use the following panel regression specification to test the hypothesis:

$$|SUE| = \alpha + \beta PCTNUM + \delta X + \epsilon$$

$$DISPER = \alpha + \beta PCTNUM + \delta X + \epsilon$$

where X is a number of control variables that includes log size, book-to-market and so on. The results from these regressions are reported in table 23. The standard errors are clustered by PERMNO. Consistent with the hypothesis H3, the first regression in the table indicates a negative relationship between PCTNUM and absolute SUE next quarter (t=-3.8). PCTNUM is also negatively related to high dispersion (t=-3.12). This result indicates that the higher the percentage of quantitative information the higher the information precision on average. Decomposing the PCTNUM for the full transcript into statement and Q&A sections, I find that the PCTNUM in the statement component is mainly responsible for the negative relationship. These results indicate that proportion of quantitative information can affect the ambiguity in the disclosed information. This effect is similar to the readability measures such as FOG index (Lehavy et al., 2011) and the size of the regulatory filing (Loughran and Mcdonald, 2014).

The set of regressions indicate a negative relationship between analyst forecast dispersion and forecast dispersion and PCTNUM. These results are consistent with hypothesis H3. These results provide evidence that a high percentage of numbers is associated with lower disagreement among analysts. However, only the statement component of the transcript is associated negatively with the statement component in the transcript. Taken together, a high proportion of quantitative information is associated with more precise information in the information released from the voluntary disclosure.

5 Conclusion

This paper studies the ratio of qualitative and quantitative information in the quarterly earnings conference call. The research documents that the choice to disclose qualitative or quantitative information is driven by various incentives of managers. Executives tend to use more quantitative information when the companies perform well. In addition, a high proportion qualitative information is related to less positive tone , longer transcript and a lower proportion of external attribution. A high proportion of quantitative information is likely to be associated with less tone management and more objective reporting. Managers also tend to increase the proportion of quantitative information in their reporting prior to share issuance. It is consistent with executives' aim to reduce information asymmetry prior to share issuance. The increase is significantly stronger in firms with high profitability.

More importantly, the proportion of quantitative information in the conference call disclosure also contains firm value-relevant information. Since firms with lower performance avoid disclosing precise quantitative information, a high proportion of quantitative information indicates managers' confidence in their own performance. Thus, high proportion of quantitative information in disclosure is associated with more positive price reaction for the window around the conference call. Furthermore, I also document that investors underreact to this information. Therefore, a high proportion of quantitative information leads to subsequent positive price reaction. Finally, I find that the proportion of quantitative information is positively related to the precision of external information environment. Results indicate that the proportion of numeric information is negatively related with dispersion of analyst forecast and forecast error measured by absolute SUE.

Previous literature examines qualitative and quantitative information separately. To my best knowledge, this study is the first one that joins the two lines of literature and shows that the interaction of qualitative and quantitative information is also informative to shareholders about corporate value. These results suggest that it may be fruitful to explore how qualitative and quantitative information interplay in other contexts.

Appendix

Table 1: Examples of Positive and Negative Description of Industry and the Economy

This table exhibits examples of positive and negative descriptions of industry and the economy. The first three examples are negative descriptions and are considered as executives playing the blame game. The first two involves executives blaming economy conditions. The third one demonstrates when executives blame the industry. The fourth example is a positive sentence about the economy. The last two examples are positive descriptions of industry captured by the program. Negative words are colored with red, positive words are colored with green and key words for economy and industry are marked with bold letters. Words in the square brackets are from the preceding sentence.

Blaming the economy	
Watts Water Technologies 2009Q2	Sales into Eastern Europe has remained depressed due to poor **economy** conditions, customer credit risk remain a major issue in Eastern Europe.
Fuel Systems Solutions 2009Q2	[We continue to experience softness in our aftermarket business.] We believe this reflects mainly continued weakness in the global **economy**.
Blaming the industry	
Navigator 2011Q4	We view this as an acceptable outcome given the magnitude of the loss to the global insurance **industry**.
Positive Economy Sentence	
Microsoft 2010Q1	We should start to see that improve going forward as we see the **economy** recover.
Positive Industry Sentences	
Honeywell 2006Q4	I think it's in a good space, the **industry** is doing well, and we see it both with UOP and process solutions that that industry should continue to do well and I think it's a good part of Honeywell.
BEAM 2012Q1	Notably, that includes strong growth for our **industry**-leading bourbon portfolio, which starts with sustained growth for our core Jim Beam White product and accelerates up the price ladder, delivering favorable mix.

Table 2: Summary Statistics

This table reports summary statistics for variables used in the paper. Panel A reports the summary statistics of relevant variables from the return regressions. Panel B reports the number of positive, negative and neutral industry and economy description sentences and total number of sentences in the conference call texts. CAR[2,60] and CAR[-1,1] are cumulative abnormal returns from trading day 2 to 60 and -1 to 1 relative to the date of the conference call. The cumulative abnormal return is calculated using Fama-French 3 factor model. BLAME is percentage sentences attributing negative performance to industry or economy. POSIE is percentage of sentences attributing positive performance to industry or economy. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). NEG is the percentage negative words in the text. NUMEST is the number of analysts covering the firm. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. RSQ is the R-squared estimated using market and industry factors. N(POSIE), N(BLAME) and N(NEUIE) are number of sentences with positive, negative and neutral description on industry or economy. N(SENTENCE) is the total number of sentences from conference calls.

Panel A: Variables in regresion analyses

Variable	**Mean**	**Median**	**Std Dev**	**Q1**	**Q3**
CAR[2,60]	0.316	0.011	20.528	-9.296	9.422
CAR[-1,1]	0.347	0.249	10.115	-4.447	5.239
BLAME	0.201	0.000	0.329	0.000	0.293
POSIE	0.316	0.195	0.421	0.000	0.467
ACCRUAL	0.972	0.977	0.478	0.946	1.001
ME	4996017	863327	19108962	312097	2666794
NEG	1.092	1.046	0.315	0.872	1.262
NUMEST	8.524	7	6.515	4	12
SUE	-0.042	0.052	1.577	-0.103	0.243
BM	-0.790	-0.740	0.852	-1.264	-0.263
MOM	6.392	6.531	40.782	-11.215	23.629
TURN	0.211	0.155	0.220	0.092	0.260
INSTOWN	0.721	0.771	0.206	0.606	0.879
VOLATILITY	0.297	0.194	0.490	0.107	0.355
RSQ	0.417	0.410	0.243	0.215	0.602

Panel B: Conference call descriptive statistics

Variable	**Mean**	**Median**	**Std Dev**	**Q1**	**Q3**
N(POSITIVE)	1.505	1	2.004	0	2
N(BLAME)	0.953	0	1.546	0	1
N(NEUTRAL)	2.281	1	2.784	0	3
N(SENTENCE)	480.723	477	164.361	373	576

Table 3: Determinants of BLAME Measure

This table explores the determinants of BLAME measure. I also report the results for POSIE (Positive Description of Industry and Economy) as placebo tests. Panel A reports the relevant variables from the revision analyses. Panel A reports a tobit regression (censored at lower bound 0) with year-quarter dummies. The standard errors (reported in parenthesis) is clustered by quarter. Panel B reports the result from the Regression Discontinuity test. The outcome variable is BLAME and the assignment variable is SUE. BLAME is percentage sentences attributing negative performance to industry or economy. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). NEG is the percentage negative words in the text. NUMEST is the number of analysts covering the firm. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. RSQ is the r-squared estimated using market and industry factors. The first column reports the predicted sign. The second column predicts the results from the regression. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Tobit Regression

VARIABLES	Predicted Sign (BLAME)	BLAME	POSIE
SUE	-	-0.122***	-0.0308
		(0.0208)	(0.0303)
BM	+	0.446***	0.371***
		(0.0400)	(0.0297)
Log(ME)	+	0.526***	0.477***
		(0.0334)	(0.0417)
RET	-	-0.174***	0.00963
		(0.0422)	(0.0481)
ACCRUAL	+	0.128***	0.128***
		(0.0298)	(0.0266)
NEG	+	1.358***	-0.0509
		(0.0711)	(0.0386)
VOLATILITY	?	-0.188***	-0.265***
		(0.0668)	(0.0547)
INSTOWN	-	0.0518**	0.00746
		(0.0222)	(0.0290)
NUMEST	-	-0.154***	-0.00901
		(0.0410)	(0.0271)
TURN	?	-0.0915***	-0.0150
		(0.0304)	(0.0403)
RSQ	+	0.165***	-0.156***
		(0.0364)	(0.0362)
R-squared		0.037	0.0078

Panel B: Regression Discontinuity Design

Discontinuity at	-	-0.212***	0.0771
SUE = 0		(0.0731)	(0.0973)
Observations		64,950	64,950

Table 4: Predicting Post Conference Call Returns

This table reports results from return predictability regressions. The dependent variable is the cumulative abnormal return (adjusted using Fama-French 3 factor model) from trading day 2 to trading day 60 following the conference call. BLAME is percentage sentences attributing negative performance to industry or economy. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). NEG is the percentage negative words in the text. LNUMEST is the log of one plus number of analysts covering the firm. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. RSQ is the R-squared estimated using market and industry factors. The third regression regresses CAR[2,60] on two components of BLAME. P(BLAME) is the predicted values from cross-sectional regression with BLAME as dependent variable and Log(ME), RSQ as independent variables. R(BLAME) is the residual from the same regression. Newey-West adjusted standard errors are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	CAR[2,60]	CAR[2,60]
BLAME	-0.500***	-0.432***
	(0.125)	(0.103)
SUE		0.634***
		(0.205)
BM		-0.0869
		(0.118)
Log(ME)		-0.0625
		(0.161)
MOM		-0.134
		(0.287)
ACCRUAL		-1.075***
		(0.173)
NEG		-0.108
		(0.140)
VOLATILITY		-0.379
		(0.687)
INSTOWN		-0.0253
		(0.107)
LNUMEST		-0.449**
		(0.203)
TURN		0.0988
		(0.195)
R-squared	0.003	0.049
Number of groups	40	40

Table 5: Calendar Time Portfolios

This table presents various estimates of abnormal returns from portfolios sorted based on BLAME measure. The hold periods for these portfolios are trading day 2 to 60 after the date of conference calls. Panel A reports the hedged portfolio that takes long position in companies with BLAME equals to 0 and short positions in companies with BLAME greater than 80 percentile based on the previous quarter. Panel B reports the portfolio returns based on sorting independently on SUE and BLAME. Low SUE stocks are those with SUE below 30 percentile and high SUE stocks are those with SUE higher than 70 percentile. The intercepts reflect monthly returns. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Portfolio sorted by BLAME				
ALPHA	MKTRF	SMB	HML	UMD
Excess Return				
0.518***				
(0.193)				
3-Factor Model				
0.590***	-0.024***	0.010	-0.241***	
(0.181)	(0.007)	(0.015)	(0.016)	
4-Factor Model				
0.570***	0.003	-0.014	-0.153***	0.128***
(0.174)	(0.007)	(0.014)	(0.016)	(0.009)
Panel B: Portfolio sorted by SUE and BLAME				
ALPHA	MKTRF	SMB	HML	UMD
Low BLAME High SUE - High BLAME High SUE				
0.341*	-0.036***	-0.070***	-0.038***	0.107***
(0.185)	(0.008)	(0.015)	(0.018)	(0.010)
Low BLAME Low SUE - High BLAME Low SUE				
0.616***	0.009	-0.044***	-0.117***	0.098***
(0.198)	(0.008)	(0.016)	(0.019)	(0.011)
Low BLAME High SUE - High BLAME High SUE				
0.440***	0.040***	-0.038***	0.062***	0.228***
(0.176)	(0.007)	(0.014)	(0.016)	(0.009)
High BLAME High SUE - High BLAME Low SUE				
0.792***	0.084***	-0.013	-0.017	0.219***
(0.220)	(0.009)	(0.017)	(0.020)	(0.011)

Table 6: Industry Adjusted Calendar Time Portfolio

This table presents various estimates of abnormal returns from industry adjusted portfolios sorted based on BLAME measure. The hold periods for these portfolios are trading day 2 to 60 after the date of conference calls. The hedged portfolio that takes long position in companies with BLAME equals to 0 and short positions in companies with BLAME greater than 80 percentile based on the previous quarter. The individual stock returns are adjusted by subtracting the matched value weighted Fama-French 48 industry returns. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

ALPHA	MKTRF	SMB	HML	UMD
		Excess Return		
0.408**				
(0.165)				
		3-Factor Model		
0.460***	-0.030***	0.007	-0.133***	
(0.159)	(0.006)	(0.013)	(0.014)	
		4-Factor Model		
0.449***	0.014**	-0.008	-0.080***	0.078***
(0.157)	(0.006)	(0.013)	(0.015)	(0.008)

Table 7: Predicting Future Earnings

This table examines whether BLAME is associated with lower earnings in the following quarter. The dependent variable is standardized unexpected earnings (scaled up by 10000). BLAME is percentage sentences attributing negative performance to industry or economy. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). LNUMEST is the log of one plus number of analysts covering the firm. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. The specification of this regression is Fama-Macbeth regression. Newey-West standard errors are reported in the parentheses. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	SUE	SUE
BLAME	-4.219***	-3.810***
	(0.940)	(0.810)
NEG		-5.628***
		1.017
BM		-4.879***
		(1.798)
Log(ME)		1.772*
		(0.894)
MOM		7.381***
		(1.095)
ACCRUAL		-1.564
		(1.289)
INSTOWN		6.437***
		(1.535)
TURN		-3.876***
		(1.377)
R-squared	0.002	0.02
Number of groups	39	39

Table 8: Recommendation Changes

This table reports Fama-Macbeth regressions with mean recommendation change as dependent variable. The independent variable is the difference between consensus analyst recommencation at the end of the 3-month period after conference call and the consensus recommendation right after the conference call. Newey-West standard errors are reported in parenthesis. BLAME is percentage sentences attributing negative performance to industry or economy. NEG is the percentage negative words in the text. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. TURN is the average share turnover in the month preceding the conference call. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	MEANRECCHG	MEANRECCHG
BLAME	-0.0205**	-0.0236***
	(0.00772)	(0.00727)
NEG		-0.0168*
		(0.00874)
SUE		0.0265**
		(0.0101)
Log(ME)		0.0561***
		(0.00979)
BM		0.0340***
		(0.0102)
MOM		0.0572**
		(0.0229)
TURN		-0.00330
		(0.00708)
INSTOWN		0.00984
		(0.0237)
R-squared	0.001	0.0137
Number of groups	40	40

Table 9: Contemporaneous Returns

This table reports results from contemporaneous returns regressions. The dependent variable is the cumulative abnormal return (adjusted using Fama-French 3 factor model) from trading day -1 to trading day 1 relative to the conference call. BLAME is percentage sentences attributing negative performance to industry or economy. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). NEG is the percentage negative words in the text. LNUMEST is the log of one plus number of analysts covering the firm. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	CAR[-1,1]	CAR[-1,1]
BLAME	-0.363***	-0.105**
	(0.0429)	(0.0404)
SUE		2.049***
		(0.0930)
BM		0.131**
		(0.0614)
Log(ME)		-0.0219
		(0.0803)
MOM		-0.305***
		(0.0845)
ACCRUAL		-0.264***
		(0.0604)
NEG		-1.009***
		(0.0725)
VOLATILITY		-0.622***
		(0.219)
INSTOWN		0.0536
		(0.0554)
LNUMEST		-0.132**
		(0.0609)
TURN		-0.0466
		(0.0811)
R-squared	0.002	0.074
Number of groups	40	40

Table 10: CEO Turnover

This table reports results from logit regression. The dependent variable is CEO turnover. The independent variables are BLAMEDUM (equals to 1 if BLAME is greater than 1 for one of the quarters in year t). LAGRET is identical to momentum, which is defined as past 12 month returns. INDRET is the matched Fama-French 48 industry returns. EXRET is the difference between LAGRET and INDRET. ROA is return on assets. CEO Age is the age of CEO reported on Execcomp. RETIRE is a dummy variable indicating that CEO is in the range of retirement age (equal or above 60). Additionally, year dummies are added as controls, but not reported in the table. Standard errors are clustered by Fama-French 48 industries. The odd columns besides the coefficient columns report the marginal effects from the coefficient estimates. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	CEO TURNOVER	Margins	CEO TURNOVER	Margins
BLAMEDUM	-0.0126	-0.00104	-0.00609	-0.000988
	(0.0315)	(0.00262)	(0.0158)	(0.00256)
BLAMEDUM * LAGRET	0.0852***	0.00707***	0.0426***	0.00691***
	(0.0319)	(0.00261)	(0.0151)	(0.00242)
LAGRET	-0.245***	-0.0203***		
	(0.0288)	(0.00273)		
INDRET			-0.0995***	-0.0161***
			(0.0127)	(0.00226)
EXRET			-0.101***	-0.0164***
			(0.0307)	(0.00528)
ROA	-0.0753***	-0.00625***	-0.0393***	-0.00637***
	(0.0246)	(0.00212)	(0.0133)	(0.00223)
CEO Age	0.210***	0.0174***	0.113***	0.0183***
	(0.0480)	(0.00380)	(0.0253)	(0.00392)
RETIRE	0.321***	0.0267***	0.162***	0.0263***
	(0.0766)	(0.00625)	(0.0381)	(0.00612)
Pseudo R-Squared	0.0272		0.0273	
Observations	11,730	11,730	11,730	11,730

Table A1: Determinants of BLAME Measure

This table explores the determinants of BLAME measure. The table reports OLS regression with year-quarter dummies and CEO fixed effects. The standard errors (reported in parenthesis) is clustered by quarter. BLAME is percentage sentences attributing negative performance to industry or economy. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). NEG is the percentage negative words in the text. LNUMEST is the log of one plus number of analysts covering the firm. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. RSQ is the R-squared estimated using market and industry factors. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	BLAME
SUE	-0.0294*
	(0.0147)
BM	-0.0200
	(0.0482)
Log(ME)	0.0932
	(0.0992)
RET	-0.113***
	(0.0194)
ACCRUAL	0.0158
	(0.0153)
NEG	0.727***
	(0.0527)
VOLATILITY	-0.00356
	(0.0173)
INSTOWN	-0.0389***
	(0.0142)
NUMEST	0.0300
	(0.0352)
TURN	-0.0413**
	(0.0200)
RSQ	-0.0809
	(0.113)
Constant	2.231***
	(0.0570)
R-squared	0.341
Observations	41,084

Table A2: Comovement with Market and Industry Factors and Returns

This table reports results from return predictability regressions. The dependent variable is the cumulative return from trading day 2 to trading day 60 following the conference call. BLAME is percentage sentences attributing negative performance to industry or economy. RSQ is the R-squared estimated using market and industry factors. Newey West adjusted standard errors are reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	CAR[2,60]
BLAME	-0.660***
	(0.145)
RSQ	-0.168
	(0.163)
BLAME * RSQ	0.138
	(0.0884)
Number of groups	40
R-squared	0.006

Table 11: Summary Statistics for News Coverage

This table presents descriptive statistics on the number of articles for each newspaper, as well as the number of words and news tone measures per article: %NEG is the number of negative words over total number of words for each article. %POS is the number of positive words over total number of words for each article. SD and Mean are standard deviations and sample means of the news articles in the corresponding news outlets.

	# Articles	Mean(Words)	Mean(%NEG)	SD(%NEG)	Mean(%POS)	SD(%POS)
Wall Street Journal	306,824	641	0.018	0.014	0.007	0.006
New York Times	92,806	522	0.018	0.014	0.006	0.004
Washington Post	41,368	708	0.018	0.015	0.006	0.005
USA Today	17,496	685	0.017	0.014	0.008	0.006
Atlanta Journal-Constitution	20,110	706	0.015	0.013	0.007	0.005
Boston Globe	28,430	496	0.016	0.015	0.007	0.008
Denver Post	13,906	596	0.016	0.014	0.006	0.005
Star Tribune	18,383	649	0.016	0.014	0.007	0.006
Pittsburgh Post Gazette	27,440	645	0.017	0.013	0.007	0.006
St Louis Post Dispatch	30,760	527	0.016	0.014	0.006	0.006

Table 12: Summary Statistics for Firm Level Variables

This table reports summary statistics of firm level variables. CAR is the DGTW-adjusted two-day [0,+1] return around each recommendation change and $|CAR|$ is its absolute value . TURNOVER is average daily turnover calculated as average trading volume divided by number of shares outstanding over the past 60 days. VOLATILITY is the lag daily volatility over the past 60 days. lagRET is lag return over the past 1 month. ΔREC is the change in recommendation levels. BM is log of book-to-market ratio. MV is market equity in million dollars. TONE is the difference between $\%POS$ and $\%NEG$. MOMENTUM is the stock return over the past 6 months (skipping the most recent month). #ANALYSTS is the number of analysts that cover firm in month t. PREEARN is an indicator variable indicating the recommendation is issued within 15 days before an earnings announcement. PREEARN is an indicator variable indicating the recommendation is issued within 15 days after an earnings announcement. ΔEPS is an indicator variable of whether the analyst issued a change in EPS forecast within the past 3 days. RECDEV is the absolute difference between the recommendation and median analyst recommendation and it proxies for deviation from consensus. ACCRANK is the rank of analyst forecast accuracy. It is a discrete variable ranging from 1 to 5. $PROP\_REVISING$ is the proportion of analyst revise the recommendation in the next month. #NEWS is the number of news count. #HARDNEWS is the number of hard news count. #SOFTNEWS is the number of soft news count.

Variable	Mean	Median	Std Dev	Q1	Q3
$\|CAR\|$	4.987	2.667	7.719	1.133	5.767
CAR	-0.385	-0.039	9.182	-2.718	2.613
$TURNOVER$	2.064	2.099	0.917	1.472	2.694
$VOLALTILITY$	3.236	2.693	2.044	1.878	3.968
$lagRET$	0.985	0.776	13.653	-5.312	6.765
ΔREC	-0.019	0.000	1.289	-1.000	1.000
BM	0.594	0.427	0.898	0.247	0.697
MV	27,479.785	8,071.182	53,318.282	2,132.420	25,856.626
$MOMENTUM$	5.366	5.831	36.296	-9.868	21.062
$TONE$	-0.012	-0.010	0.014	-0.019	-0.003
$\#ANALYSTS$	9.236	8.000	6.718	4.000	13.000
$PREEARN$	0.135	0.000	0.117	0.000	1.000
$POSTEARN$	0.321	0.000	0.467	0.000	1.000
ΔEPS	0.496	0.000	0.499	0.000	1.000
$RECDEV$	0.906	1.000	0.757	0.000	1.000
$ACCRANK$	2.953	3.000	1.339	1.000	4.000
$PROP\_REVISING$	0.042	0.000	0.100	0.000	0.048
#NEWS	2.338	0.000	8.854	0.000	1.000
#HARDNEWS	1.169	0.000	3.309	0.000	1.000
#SOFTNEWS	1.169	0.000	6.080	0.000	0.000

Table 13: News Coverage and Analyst Recommendation Change

Panel A tests whether news coverage increases the analyst recommendation changes. The dependent variable is the proportion of analyst issuing a recommendation change in the following month. The independent variables include log#NEWS (log number of news), I(#NEWS = 1) and I(#NEWS > 1) (two indicator variables for number of news equals to 1 and number of news greater than 1), logMV and number of active analyst coverage (#ANALYSTS) and $|lagRET|$ (the absolute return in the previous month). Panel B presents Fama-Macbeth regressions on mean recommendation changes. %NEG is the number of negative words over total number of words for each article published in the month prior to the recommendation revisions. %POS is the number of positive words over total number of words for each article published in the month prior to the recommendation revisions. TONE is the difference between %POS and %NEG. %HARD is the percentage of hard news in the past one month. See Table 2 for the definition of other variables included in the regression. Estimates and standard error are based on the time series of cross-sectional regressions. Significance level: *** $p < 0.01$, $**\,p < 0.05$, * $p < 0.1$.

Panel A: News Coverage Intensity and Analyst Recommendation Revisions

VARIABLES	(1) $PROP\_REVISING$	(2) $PROP\_REVISING$
I(#NEWS = 1)	0.0166***	
	(0.000708)	
I(#NEWS > 1)	0.0167***	
	(0.00091)	
log#NEWS		0.00473***
		(0.000221)
$\|lagRET\|$	0.00421***	0.00428***
	(0.000180)	(0.000180)
logMV	-0.00255***	-0.00218***
	(0.000254)	(0.000255)
#ANALYSTS	0.00176***	0.00118***
	(0.000235)	(0.000232)
Constant	0.0376***	0.0399***
	(0.000197)	(0.000177)
Observations	268,197	268,197
Adjusted R^2	0.031	0.025

Panel B: Predicting Recommendation Change				
	(1)	(2)	(3)	(4)
VARIABLES	ΔREC	ΔREC	ΔREC	ΔREC
%NEG	-0.263**			
	(0.115)			
%POS		0.154		
		(0.109)		
TONE			0.271**	0.278**
			(0.114)	(0.116)
%HARD			0.0301	0.0945
			(0.124)	(0.123)
logMV				0.126
				(0.157)
logBM				-0.243**
				(0.119)
MOMENTUM				-0.658
				(0.693)
LAG(ΔREC)				-0.780***
				(0.172)
Constant	0.122	0.124	0.139	-0.0438
	(0.168)	(0.166)	(0.169)	(0.175)
Observations	41,101	41,101	41,078	41,078
Average R^2	0.001	0.001	0.001	0.001
Number of groups	179	179	179	179

Table 14: News Coverage Intensity and Announcement Return

This table presents the regression results on recommendation revision abnormal returns with panel A event window [0,+1] and panel B event window [+2, +5]. $CAR^{(-)}$ is DGTW-adjusted return for downward recommendation revisions. $CAR^{(+)}$ is DGTW-adjusted return for upward recommendation revisions. #NEWS is calculated as $\log(1 + \#NEWS)$, with $\#NEWS$ defined as the number of articles published in the prior month before recommendation revisions. log#HARDNEWS is log(1+#HARDNEWS), where #HARDNEWS is the number of hard news count. log#SOFTNEWS is log(1+#SOFTNEWS), where #SOFTNEWS is the number of soft news count. ΔEPS is an indicator variable on whether there is a concurrent EPS revision. RECDEV is the deviation of the recommendation from the consensus recommendation measure. ACCRANK is the earnings forecast accuracy rank for the analyst(range from 1 to 5). PREEARN is a dummy variable that indicates the firm is going to make an earnings announcement in the next 15 days. POSTEARN is a dummy variable that indicates that the firm made an earnings announcement in the past 15 days. See Table 2 for the definition of other variables included in the regression. Two-way clustered standard errors (by firm and by analyst) are reported in parentheses. Significance level: $p < 0.01$, $**\, p < 0.05$, $*\ p < 0.1$.

Panel A: Return Window (0,1)

VARIABLES	(1) $CAR^{(-)}$	(2) $CAR^{(-)}$	(3) $CAR^{(+)}$	(4) $CAR^{(+)}$	(5) $\lvert CAR\rvert$	(6) $\lvert CAR\rvert$
log#NEWS	-0.665***	-0.593***	0.404***	0.364***	0.825***	0.742***
	(0.132)	(0.123)	(0.0710)	(0.0741)	(0.0809)	(0.0702)
logMV	1.123***	1.130***	-1.150***	-1.070***	-1.520***	-1.421***
	(0.0886)	(0.0950)	(0.0590)	(0.0710)	(0.0608)	(0.0611)
logBM		0.675***		-0.174***		-0.605***
		(0.0788)		(0.0598)		(0.0520)
MOMENTUM		0.283***		-0.317***		-0.484***
		(0.0767)		(0.0515)		(0.0404)
logVOLATILITY		-0.791***		0.446***		1.180***
		(0.0838)		(0.0634)		(0.0525)
TURNOVER		-0.0953		0.0735		0.0836*
		(0.0718)		(0.0530)		(0.0475)
ΔEPS		-1.420***		0.333***		0.566***
		(0.103)		(0.0703)		(0.0592)
RECDEV		-0.297***		0.197***		0.00714
		(0.0459)		(0.0336)		(0.0435)
ACCRANK		-0.000311		-0.0162		-0.00145
		(0.0415)		(0.0308)		(0.0230)
lagRET		0.764***		-0.0978		-0.716***
		(0.0872)		(0.0697)		(0.0526)
PREEARN		0.134		0.206*		0.169*
		(0.173)		(0.117)		(0.0967)
POSTEARN		-0.707***		0.799***		1.031***
		(0.133)		(0.0958)		(0.0811)
Constant	-3.127***	-2.150***	2.500***	2.242***	4.544***	3.863***
	(0.0772)	(0.179)	(0.0501)	(0.124)	(0.0604)	(0.112)
Observations	50,983	46,753	45,666	41,720	96,649	88,473
Adjusted R^2	0.014	0.060	0.029	0.044	0.044	0.128

Panel B: Return Window (2,5)

VARIABLES	(1) $CAR^{(-)}$	(2) $CAR^{(-)}$	(3) $CAR^{(+)}$	(4) $CAR^{(+)}$	(5) $\|CAR\|$	(6) $\|CAR\|$
log#NEWS	0.0730	0.0465	0.0140	0.00863	0.351***	0.225***
	(0.0795)	(0.0744)	(0.0290)	(0.0309)	(0.0548)	(0.0430)
logMV	0.0545	0.0671	-0.154***	-0.110***	-0.574***	-0.290***
	(0.0449)	(0.0450)	(0.0275)	(0.0324)	(0.0306)	(0.0234)
logBM		-0.0499		0.00338		-0.0318
		(0.0378)		(0.0293)		(0.0211)
MOMENTUM		-0.0157		-0.0175		-0.209***
		(0.0456)		(0.0352)		(0.0271)
logVOLATILITY		-0.00977		0.159***		1.044***
		(0.0384)		(0.0379)		(0.0244)
TURNOVER		0.128***		-0.125***		-0.0417**
		(0.0414)		(0.0284)		(0.0201)
ΔEPS		-0.0741		-0.00767		-0.00284
		(0.0519)		(0.0430)		(0.0249)
RECDEV		0.00498		0.0360*		-0.00105
		(0.0239)		(0.0214)		(0.0230)
ACCRANK		0.0177		0.00967		-0.0127
		(0.0223)		(0.0212)		(0.0115)
lagRET		-0.108		-0.0168		-0.455***
		(0.0682)		(0.0466)		(0.0407)
PREEARN		0.246**		0.183**		0.657***
		(0.108)		(0.0800)		(0.0573)
POSTEARN		0.0827		0.0353		0.0750**
		(0.0656)		(0.0461)		(0.0304)
Constant	-0.159***	-0.245***	0.222***	0.135*	2.707***	2.571***
	(0.0290)	(0.0906)	(0.0219)	(0.0821)	(0.0259)	(0.0469)
Observations	51,044	46,811	45,824	41,854	96,868	88,665
Adjusted R^2	0.001	0.002	0.001	0.003	0.020	0.140

Table 15: Types of News and Recommendation Announcement Return

This table presents regression results on recommendation revision announcement returns, with event window [0,+1]. $CAR^{(-)}$ is DGTW-adjusted return for downward recommendation revisions. $CAR^{(+)}$ is DGTW-adjusted return for upward recommendation revisions. log#NEWS is calculated as log(1 + $\#NEWS$), with $\#NEWS$ defined as the number of articles published in the prior month before recommendation revisions. log#HARDNEWS is log(1+#HARDNEWS), where #HARDNEWS is the number of hard news count. log#SOFTNEWS is log(1+#SOFTNEWS), where #SOFTNEWS is the number of soft news count. The definition of soft news article and hard news article is discussed in the data section. ΔEPS is an indicator variable on whether there is a concurrent EPS revision. RECDEV is the deviation of the recommendation from the consensus recommendation measure. ACCRANK is the earnings forecast accuracy rank for the analyst(range from 1 to 5). PREEARN is a dummy variable that indicates the firm is going to make an earnings announcement in the next 15 days. POSTEARN is a dummy variable that indicates that the firm made an earnings announcement in the past 15 days. See Table 2 for the definition of other variables included in the regression. Two-way clustered standard errors (by firm and by analyst) are reported in parentheses. Significance level: $p < 0.01$, $**\,p < 0.05$, $^{*}\,p < 0.1$.

VARIABLES	(1) $CAR^{(-)}$	(2) $CAR^{(-)}$	(3) $CAR^{(+)}$	(4) $CAR^{(+)}$	(5) $\lvert CAR\rvert$	(6) $\lvert CAR\rvert$
log#HARDNEWS	0.0980	0.104	0.108*	0.0946*	0.00775	-0.0270
	(0.0931)	(0.0886)	(0.0560)	(0.0572)	(0.0561)	(0.0514)
log#SOFTNEWS	-0.427***	-0.383***	0.207***	0.185***	0.531***	0.494***
	(0.137)	(0.125)	(0.0616)	(0.0634)	(0.0792)	(0.0705)
logMV	0.952***	0.943***	-1.102***	-1.017***	-1.372***	-1.255***
	(0.0808)	(0.0854)	(0.0563)	(0.0663)	(0.0583)	(0.0557)
logBM		0.636***		-0.163***		-0.571***
		(0.0783)		(0.0591)		(0.0514)
MOMENTUM		0.284***		-0.313***		-0.480***
		(0.0769)		(0.0517)		(0.0406)
logVOLATILITY		-0.806***		0.448***		1.191***
		(0.0852)		(0.0635)		(0.0528)
TURNOVER		-0.152**		0.0946*		0.144***
		(0.0704)		(0.0534)		(0.0467)
ΔEPS		-1.437***		0.345***		0.591***
		(0.103)		(0.0704)		(0.0603)
RECDEV		-0.302***		0.198***		0.00106
		(0.0463)		(0.0336)		(0.0233)
ACCRANK		0.00396		-0.311***		0.0615
		(0.157)		(0.117)		(0.0928)
lagRET		0.767***		-0.0948		-0.713***
		(0.0877)		(0.0699)		(0.0530)
PREEARN		0.0682		0.223*		0.234**
		(0.172)		(0.116)		(0.0963)
POSTEARN		-0.703***		0.806***		1.030***
		(0.134)		(0.0967)		(0.0825)
Constant	-3.138***	-2.146***	2.497***	2.239***	4.546***	3.840***
	(0.0790)	(0.180)	(0.0501)	(0.124)	(0.0613)	(0.113)
Observations	50,983	46,753	45,666	41,720	96,649	88,473
Adjusted R^2	0.011	0.062	0.028	0.043	0.037	0.124
$\beta_{SOFT} - \beta_{HARD}$	-0.525***	-0.445**	0.0988	0.0902	0.524***	0.523***

Table 16: News Coverage Intensity, Tone of News and Recommendation Announcement Return

Panel regression on recommendation revision abnormal returns. CAR corresponds to DGTW-adjusted return for recommendation revisions. log#NEWS is calculated as $\log(1 + \#NEWS)$. log#HARDNEWS is log(1+#HARDNEWS), where #HARDNEWS is the number of hard news count. log#SOFTNEWS is log(1+#SOFTNEWS), where #SOFTNEWS is the number of soft news count. Control variables are included in the regressions, but are not reported in the table. Control variables include: logMV, logBM, MOMENTUM, logVOLATILITY, RECDEV, ACCRANK, lagRET, REEARN, and POSTEARN. See Table 2 for the definition of other variables included in the regression. Two-way clustered standard errors (by firm and by analyst) are reported in parentheses. Significance level: $p < 0.01$, $**\, p < 0.05$, $*\, p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	CAR	CAR	CAR	CAR	CAR
%POS	0.231***				
	(0.0758)				
%NEG		-0.404***			
		(0.0734)			
TONE			0.419***	-0.0268	0.103
			(0.0771)	(0.121)	(0.100)
TONE * log#NEWS				0.662***	
				(0.157)	
TONE * log#HARDNEWS					0.240***
					(0.0895)
TONE * log#SOFTNEWS					0.469***
					(0.131)
log#HARDNEWS					-0.115
					(0.0734)
log#SOFTNEWS					0.00948
					(0.0844)
log#NUMNEWS	-0.161	-0.162	-0.157	-0.115	
	(0.110)	(0.109)	(0.109)	(0.0980)	
Control Variables	YES	YES	YES	YES	YES
Observations	29,993	29,993	29,993	29,993	29,993
Adjusted R^2	0.018	0.020	0.020	0.024	0.024

Table 17: Subsample Analyses: Recent News versus Distant News

This table presents regression results on recommendation revision announcement returns, with event window [0,+1]. We partition the sample by the median distance (lag) between the news article and the analyst revision dates. The recommendation revisions with average distance below the sample medium are classified as revisions associated with "recent news." Otherwise they are classified as revisions associated with "distant news." For both the "recent news" revision sub-sample and the "distant news" revision sub-sample, we run separate regressions. $CAR^{(-)}$ is DGTW-adjusted return for downward recommendation revisions. $CAR^{(+)}$ is DGTW-adjusted return for upward recommendation revisions. log#NEWS is calculated as $\log(1 + \#NEWS)$, with $\#NEWS$ defined as the number of articles published in the prior month before recommendation revisions. ΔEPS is an indicator variable on whether there is a concurrent EPS revision. RECDEV is the deviation of the recommendation from the consensus recommendation measure. ACCRANK is the earnings forecast accuracy rank for the analyst(range from 1 to 5). PREEARN is a dummy variable that indicates the firm is going to make an earnings announcement in the next 15 days. POSTEARN is a dummy variable that indicates that the firm made an earnings announcement in the past 15 days. See Table 2 for the definition of other variables included in the regression. Two-way clustered standard errors (by firm and by analyst) are reported in parentheses. Significance level: $p < 0.01$, $**\, p < 0.05$, $*\ p < 0.1$.

VARIABLES	(1) Recent $CAR^{(-)}$	(2) Distant $CAR^{(-)}$	(3) Recent $CAR^{(+)}$	(4) Distant $CAR^{(+)}$	(5) Recent $\|CAR\|$	(6) Distant $\|CAR\|$
log#NEWS	-1.320***	-1.558***	0.393***	0.740***	1.010***	1.808***
	(0.299)	(0.282)	(0.126)	(0.188)	(0.161)	(0.174)
logMV	1.069***	1.009***	-0.780***	-0.896***	-1.109***	-1.400***
	(0.188)	(0.166)	(0.0929)	(0.122)	(0.102)	(0.0977)
logBM	0.610***	0.766***	-0.341**	-0.253*	-0.675***	-0.683***
	(0.176)	(0.221)	(0.152)	(0.153)	(0.114)	(0.130)
MOMENTUM	0.00729	0.0229***	-0.0129***	-0.00752*	-0.0165***	-0.0278***
	(0.00475)	(0.00661)	(0.00362)	(0.00403)	(0.00252)	(0.00351)
logVOLATILITY	-1.142***	-2.031***	1.011***	1.111***	1.973***	2.274***
	(0.280)	(0.354)	(0.234)	(0.270)	(0.174)	(0.219)
TURNOVER	0.224	0.501**	-0.229*	-0.338**	-0.173	-0.330**
	(0.210)	(0.231)	(0.134)	(0.148)	(0.119)	(0.145)
ΔEPS	-1.224***	-1.644***	0.422***	0.171	0.502***	0.188
	(0.207)	(0.244)	(0.141)	(0.163)	(0.112)	(0.134)
RECDEV	-0.425***	-0.158	0.0199	0.354***	0.260***	0.184**
	(0.118)	(0.143)	(0.0940)	(0.117)	(0.0717)	(0.0835)
ACCRANK	-0.0545	0.0122	-0.0294	-0.0881	-0.00787	0.0121
	(0.0799)	(0.110)	(0.0573)	(0.0703)	(0.0418)	(0.0556)
lagRET	0.0307***	0.0735***	0.0120	-0.0161	-0.0309***	-0.0697***
	(0.0103)	(0.0158)	(0.0109)	(0.0126)	(0.00656)	(0.0105)
PREEARN	0.738*	0.260	0.139	0.0946	0.0706	-0.550***
	(0.382)	(0.353)	(0.321)	(0.230)	(0.236)	(0.202)
POSTEARN	-0.200	-0.386	0.384**	0.718***	0.765***	0.447**
	(0.310)	(0.313)	(0.180)	(0.231)	(0.168)	(0.183)
Constant	-15.45***	-14.30***	13.34***	14.97***	17.88***	21.62***
	(3.005)	(2.739)	(1.432)	(1.985)	(1.615)	(1.597)
Observations	7,776	8,002	7,155	7,084	14,931	15,086
Adjusted R^2	0.072	0.110	0.057	0.051	0.144	0.197

Table 18: Summary Statistics of Textual Variables

This table presents the summary statistics on conference call linguistic characteristics. PCTNUM is percentage of quantitative information in the conference call (in %), calculated as N(Numbers)/(N(Numbers)+N(Words)). TONE is the difference between percentage positive and percentage negative words in the conference call. Positive and negative words are categorized in the Loughran and McDonald (2013). N(Words) is the number of words. N(Numbers) is the total count of numbers in the conference call. The subscripts S indicates statement component and QA indicates question and answer component of the conference call. The last column presents the correlations between the indicated measures of the statement component and the Q&A component.

Variables	**Mean**	**Median**	**Std Dev**	**Q1**	**Q3**	**CORR(S,QA)**
$PCTNUM$	2.758	2.674	0.722	2.277	3.152	-0.0472***
$PCTNUM_S$	3.933	3.480	3.650	2.786	4.332	
$PCTNUM_{QA}$	2.192	2.144	0.894	1.799	2.520	
$TONE$	2.584	2.553	0.479	2.250	2.882	0.349***
$TONE_S$	2.833	2.784	0.742	2.314	3.297	
$TONE_{QA}$	2.405	2.377	0.467	2.084	2.692	
$N(Words)$	7532	7539	2456	5898	8998	0.0185***
$N(Words)_S$	2894	2762	1240	2078	3549	
$N(Words)_{QA}$	4645	4555	2105	3282	5833	
$N(Numbers)$	208.5135	201	80.49659	155	251	0.109*
$N(Numbers)_S$	108.5856	100	54.05513	72	135	
$N(Numbers)_{QA}$	100.7825	95	52.89314	67	128	

Table 19: Summary Statistics of Non-Textual Variables

This table presents the summary statistics of financial variables. CAR[-1,1] is the 3-day event day return, adjusted by Fama-French 3 factors. CAR[2,60] is the post conference call abnormal returns, also adjusted using Fama-French 3 factor model. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). ROA is return on assets. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is the institutional ownership from the most recent quarter end. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. NUMEST is the number of analysts who actively cover the company. $|SUE|$ is the dependent variable. It is the absolute SUE (scaled up by 100) for the quarter following the conference call. DISP is the analyst forecast dispersion (scaled up by 100) after the earnings announcement.

Variables	**Mean**	**Median**	**Std Dev**	**Q1**	**Q3**
CAR[-1,1]	0.269	0.213	8.763	-3.939	4.738
CAR[2,60]	0.363	0.423	17.326	-8.198	9.295
ROA	0.034	0.048	0.139	0.014	0.086
ACCRUAL	0.977	0.980	0.496	0.951	1.001
Log(ME)	14.050	13.873	1.526	12.952	14.946
BM	0.594	0.463	0.753	0.278	0.732
TURN	2.183	1.617	2.149	0.988	2.680
MOM	0.083	0.077	0.372	-0.084	0.239
VOLATILITY	0.249	0.173	0.416	0.099	0.304
INSTOWN	0.560	0.680	0.330	0.343	0.829
BLAME	0.199	0.000	0.319	0.000	0.291
NUMEST	9.057	7	6.571	4	12
SUE	0.010	0.055	1.025	-0.072	0.217
$\|SUE\|$	0.444	0.163	1.041	0.060	0.409
DISP	0.479	0.196	0.905	0.090	0.483

Table 20: Determinants of PCTNUM

This table investigates the determinants of PCTNUM. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). ROA is return on assets. SUE is standardized unexpected earnings. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceeding the conference call. TURN is the average share turnover in the month preceeding the conference call. TONE is the percentage of positive words minus percentage negative words in the text. LNUMEST is the log of one plus number of analysts covering the firm. BLAME is percentage sentences attributing negative performance to industry or economy. SEO is a dummy variable that indicates whether the company engages in SEO in the following 90 days. I(QTR Q) is a dummy variable that indicates the fiscal quarter Q. The regression controls for year-quarter fixed effects. The standard errors are clustered by PERMNO. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	PCTNUM	PCTNUM	PCTNUM	PCTNUM
Financial Variables				
SUE	0.0171***			0.0101***
	(0.00362)			(0.00363)
ROA	0.0352***			0.0298***
	(0.00298)			(0.00280)
BM	0.00613**			0.0133***
	(0.00281)			(0.00245)
Log(ME)	-0.00421			0.0418***
	(0.00883)			(0.00774)
LAGRET	0.0255***			0.0227***
	(0.00439)			(0.00368)
ACCRUAL	-0.0193***			-0.0103**
	(0.00353)			(0.00392)
VOLATILITY	0.0000			0.000304
	(0.00265)			(0.00227)
INSTOWN	-0.00777***			0.00827***
	(0.00231)			(0.00266)
LNUMEST	-0.0517***			0.000518
	(0.00658)			(0.00647)
TURN	-0.00683**			-0.00508
	(0.00320)			(0.00307)
Textual Variables				
TONE		-0.105***		-0.113***
		(0.00657)		(0.00590)
LENGTH		-0.163***		-0.180***
		(0.00898)		(0.0130)
BLAME		-0.0122***		-0.0121***
		(0.00356)		(0.00364)
Issuance Variables				
SEO			0.115***	0.0910***
			(0.0241)	(0.0258)
SEO*ROA			0.0547***	0.0337***
			(0.0114)	(0.0119)
SEO*SUE			0.00505	-0.0157
			(0.0180)	(0.0171)
I(QTR 2)	0.0316	0.0439	0.0343	0.0417
	(0.0320)	(0.0301)	(0.0299)	(0.0296)

I(QTR 3)	0.0464	0.0625*	0.0530	0.0587*
	(0.0347)	(0.0313)	(0.0322)	(0.0311)
I(QTR 4)	0.342***	0.387***	0.353***	0.382***
	(0.0405)	(0.0379)	(0.0382)	(0.0372)
Observations	59,411	60,662	60,657	59,411
R-squared	0.146	0.206	0.137	0.212

Table 21: Investor Reactions to PCTNUM

This table tests investors' reactions to the proportion of quantitative information (PCTNUM) in conference call disclosures. The dependent variable is CAR (adjusted using FF 3-factor model) from trading day -1 to 1 relative to the date of the conference call. PCTNUM is percentage of quantitative information in the conference call. $PCTNUM_S$ is the percentage of quantitative information in the statement component. $PCTNUM_{QA}$ is the percentage of quantitative information in the Q&A section. SUE is the standard unexpected earnings, calculated as the difference between realized earnings and analyst forecast earnings and scaled by price. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). ROA is return on assets. SUE is standardized unexpected earnings. BM is log book-to-market ratio. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. BLAME is percentage of sentences with negative attribution to industry or economy. TONE is the difference between percentages of positive and negative words in the conference call. VOLATILITY is the annualized daily volatility calculated using the data from the month preceeding the conference call. TURN is the average share turnover in the month preceding the conference call. LNUMEST is the log of one plus number of analysts covering the firm. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]
PCTNUM	0.266***	0.181***	
	(0.0446)	(0.0435)	
$PCTNUM_S$			0.312***
			(0.0803)
$PCTNUM_{QA}$			0.00942
			(0.0621)
SUE		2.020***	2.034***
		(0.0880)	(0.0898)
ROA		0.156***	0.152***
		(0.0494)	(0.0486)
BM		0.0212	0.0215
		(0.0524)	(0.0541)
Log(ME)		-0.161**	-0.154**
		(0.0695)	(0.0698)
MOM		-0.242***	-0.239***
		(0.0653)	(0.0663)
ACCRUAL		-0.280***	-0.279***
		(0.0584)	(0.0587)
TONE		0.399***	0.390***
		(0.0495)	(0.0508)
BLAME		-0.298***	-0.314***
		(0.0410)	(0.0414)
VOLATILITY		-0.594***	-0.611***
		(0.188)	(0.194)
INSTOWN		0.0593	0.0684
		(0.0415)	(0.0431)
LNUMEST		0.0269	0.00726
		(0.0578)	(0.0571)
TURN		-0.130*	-0.143*
		(0.0746)	(0.0744)
Observations	60,297	60,075	59,264
R-squared	0.002	0.063	0.064
Number of groups	40	40	40

Table 22: Predicting Post Conference Call Returns

This table test whether investors underreact to the proportion of quantitative information (PCTNUM) in conference call disclosures. The dependent variable is CAR (adjusted using FF 3-factor model) between trading days 2 and 60 after the conference call date. PCTNUM is percentage of quantitative information in the conference call. $PCTNUM_S$ is the percentage of quantitative information in the statement component. $PCTNUM_{QA}$ is the percentage of quantitative information in the Q&A section. SUE is the standard unexpected earnings, calculated as the difference between realized earnings and analyst forecast earnings and scaled by price. Accrual is the accrued earnings divided by total assets ((IBCY-OANCFY)/ AT). ROA is return on assets. SUE is standardized unexpected earnings. BM is log book-to-market ratio. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. BLAME is percentage of sentences with negative attribution to industry or economy. TONE is the difference between percentages of positive and negative words in the conference call. VOLATILITY is the annualized daily volatility calculated using the data from the month preceeding the conference call. TURN is the average share turnover in the month preceeding the conference call. LNUMEST is the log of one plus number of analysts covering the firm.Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	CAR[2,60]	CAR[2,60]	CAR[2,60]
$PCTNUM$	0.351***	0.219***	
	(0.0871)	(0.0742)	
$PCTNUM_S$			0.330**
			(0.139)
$PCTNUM_Q$			0.280**
			(0.126)
SUE		0.615***	0.628***
		(0.213)	(0.215)
ROA		0.577***	0.571***
		(0.195)	(0.195)
BM		-0.0681	-0.0832
		(0.128)	(0.128)
Log(ME)		-0.155	-0.157
		(0.164)	(0.169)
MOM		-0.149	-0.157
		(0.296)	(0.296)
ACCRUAL		-1.199***	-1.209***
		(0.169)	(0.170)
TONE		0.146	0.170
		(0.154)	(0.157)
BLAME		-0.482***	-0.496***
		(0.104)	(0.106)
VOLATILITY		0.0410	0.0645
		(0.665)	(0.666)
INSTOWN		0.0295	0.0225
		(0.0845)	(0.0839)
LNUMEST		-0.416**	-0.446**
		(0.196)	(0.199)
TURN		0.0718	0.105
		(0.190)	(0.195)
Observations	60,296	60,074	59,263
R-squared	0.001	0.051	0.053
Number of groups	40	40	40

Table 23: PCTNUM and Information Precision

This table tests whether PCTNUM is significantly related to more precise information environment. The dependent variables are of $|SUE_{t+1}|$ for the quarter following the conference call and the analyst forecast dispersion (DISP) after the earnings announcement. BM is log book-to-market ratio. MOM is the lag 12 month cumulative return. INSTOWN is institutional ownership. VOLATILITY is the annualized daily volatility calculated using the data from the month preceding the conference call. TURN is the average share turnover in the month preceding the conference call. LNUMEST is the log of one plus number of analysts covering the firm. The regression controls for year-quarter fixed effects. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	$\lvert SUE_{t+1}\rvert$	$\lvert SUE_{t+1}\rvert$	DISP	DISP
$PCTNUM$	-0.0319***		-0.0243***	
	(0.00837)		(0.00778)	
$PCTNUM_S$		-0.0114*		-0.0145**
		(0.00587)		(0.00603)
$PCTNUM_{QA}$		-0.000120		0.0186**
		(0.00613)		(0.00855)
BM	0.129***	0.128***	0.134***	0.132***
	(0.0128)	(0.0127)	(0.0134)	(0.0133)
Log(ME)	-0.0947***	-0.0958***	-0.101***	-0.102***
	(0.0162)	(0.0162)	(0.0196)	(0.0195)
MOM	-0.0904***	-0.0895***	-0.0968***	-0.0971***
	(0.0101)	(0.0100)	(0.0116)	(0.0116)
VOLATILITY	0.0616	0.0604	0.107*	0.105*
	(0.0416)	(0.0408)	(0.0553)	(0.0543)
INSTOWN	0.000155	0.00166	0.00769	0.00763
	(0.00695)	(0.00694)	(0.00709)	(0.00709)
LNUMEST	-0.102***	-0.0994***	-0.0332**	-0.0302**
	(0.0126)	(0.0123)	(0.0145)	(0.0137)
TURN	0.125***	0.129***	0.174***	0.179***
	(0.0202)	(0.0188)	(0.0274)	(0.0251)
Observations	58,241	57,457	57,733	56,945
R-squared	0.098	0.097	0.148	0.149

Figure 1: Time Series of BLAME

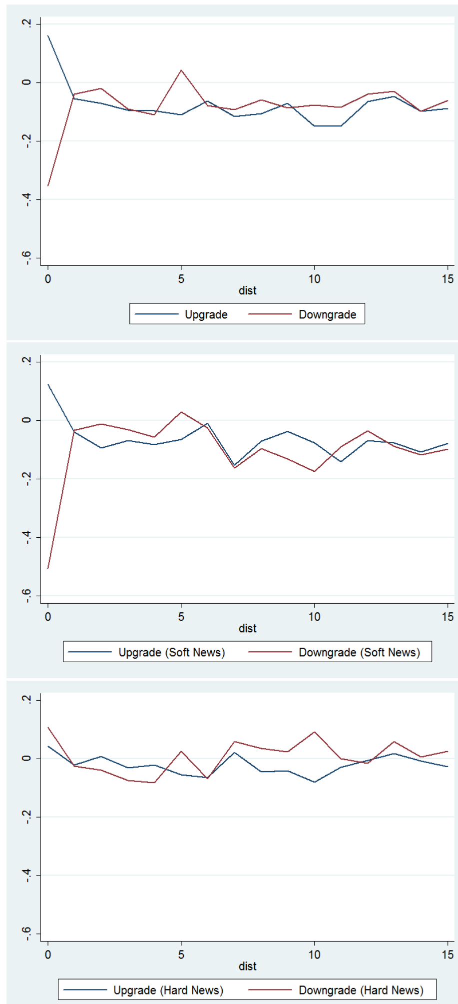

Figure 2: These plots are β coefficients from the regressions $CAR_t = \alpha + \beta log\#NEWS(TYPE) + \epsilon$, where t is the distance between the recommendation announcement date and TYPE is the type of news. The first graph, all news are counted. In the second figure, only the soft news are counted and in the third graph, only hard news are counted. All news variables are normalized with a mean 0 and standard deviation 1

References

Jeffery S. Abarbanell. Do analysts' earnings forecasts incorporate information in prior stock price changes? *Journal of Accounting and Economics*, 14(2):147–165, June 1991. ISSN 0165-4101.

Kenneth R. Ahern and Denis Sosyura. Who writes the news? Corporate press releases during merger negotiations. *Journal of Finance*, 2011.

Nihat Aktas, Eric De Bodt, Helen Bollaert, and Richard Roll. CEO Narcissism and the Takeover Process. *SSRN eLibrary*, July 2010. URL http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1638972.

Kristian D. Allee and Matt DeAngelis. The Structure of Voluntary Disclosure Narratives: Evidence from Conference Calls. SSRN Scholarly Paper ID 2375898, Social Science Research Network, Rochester, NY, January 2014. URL http://papers.ssrn.com/abstract=2375898.

Oya Altinkilic and Robert S. Hansen. On the information role of stock recommendation revisions. *Journal of Accounting and Economics*, 48(1):17–36, October 2009. ISSN 0165-4101.

Robert M. Arkin, Alan J. Appelman, and Jerry M. Burger. Social anxiety, self-presentation, and the self-serving bias in causal attribution. *Journal of Personality and Social Psychology*, 38(1): 23–35, 1980. ISSN 1939-1315(Electronic);0022-3514(Print).

Paul Asquith, Michael B. Mikhail, and Andrea S. Au. Information content of equity analyst reports. *Journal of Financial Economics*, 75(2):245–282, February 2005. ISSN 0304-405X.

Linda Babcock and George Loewenstein. Explaining Bargaining Impasse: The Role of Self-Serving Biases. *Journal of Economic Perspectives*, 11(1):109–126, 1997. URL http://ideas.repec.org/a/aea/jecper/v11y1997i1p109-26.html.

Stephen P. Baginski and John M. Hassell. Determinants of Management Forecast Precision. *The Accounting Review*, 72(2):303–312, April 1997.

Stephen P. Baginski, Edward J. Conrad, and John M. Hassell. The Effects of Management Forecast Precision on Equity Pricing and on the Assessment of Earnings Uncertainty. *The Accounting Review*, 68(4):913–927, October 1993.

Stephen P. Baginski, John M. Hassell, and Michael D. Kimbrough. Why Do Managers Explain Their Earnings Forecasts? *Journal of Accounting Research*, 42(1):1–29, March 2004. ISSN 1475-679X.

Malcolm Baker, Xin Pan, and Jeffrey Wurgler. The effect of reference point prices on mergers and acquisitions. *Journal of Financial Economics*, 106(1):49–71, October 2012. ISSN 0304-405X.

Ray Ball and Philip Brown. An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research*, 6(2):159–178, October 1968. ISSN 0021-8456.

Richard G. Barker. The role of dividends in valuation models used by analysts and fund managers. *European Accounting Review*, 8(2):195–218, July 1999. ISSN 0963-8180.

Roy F. Baumeister. A self-presentational view of social phenomena. *Psychological Bulletin*, 91(1): 3–26, 1982.

Roy F. Baumeister and Kenneth J. Cairns. Repression and self-presentation: When audiences interfere with self-deceptive strategies. *Journal of Personality and Social Psychology*, 62(5):851–862, 1992. ISSN 1939-1315(Electronic);0022-3514(Print). doi: 10.1037/0022-3514.62.5.851.

Victor L. Bernard and Jacob K. Thomas. Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? *Journal of Accounting Research*, 27:1–36, January 1989. ISSN 00218456. doi: 10.2307/2491062.

Marianne Bertrand and Sendhil Mullainathan. Are CEOS Rewarded for Luck? The Ones without Principals Are*. *Quarterly Journal of Economics*, 116(3):901–932, March 2011. ISSN 0033-5533.

Marianne Bertrand and Antoinette Schoar. Managing with Style: The Effect of Managers on Firm Policies*. *Quarterly Journal of Economics*, 118(4):1169–1208, January 2011. ISSN 0033-5533.

James R. Bettman and Barton A. Weitz. Attributions in the Board Room: Causal Reasoning in Corporate Annual Reports. *Administrative Science Quarterly*, 28(2):165–183, June 1983. ISSN 0001-8392.

Anne Beyer, Daniel A. Cohen, Thomas Z. Lys, and Beverly R. Walther. The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics*, 50(23): 296–343, December 2010. ISSN 0165-4101.

Matthew T. Billett and Yiming Qian. Are Overconfident CEOs Born or Made? Evidence of Self-Attribution Bias from Frequent Acquirers. *Management Science*, 54(6):1037–1051, June 2008. ISSN 0025-1909, 1526-5501.

Sarah E. Bonner, Artur Hugon, and Beverly R. Walther. Investor Reaction to Celebrity Analysts: The Case of Earnings Forecast Revisions. *Journal of Accounting Research*, 45(3):481–513, 2007. ISSN 1475-679X.

Bonsall, Samuel IV, Jeremiah Green, and Karl A. Muller, III. Business Press Coverage and Credit Rating Agency Monitoring. October 2013.

Bove, R.X. Say it isnt so, May 2006.

Robert M. Bowen, Angela K. Davis, and Dawn A. Matsumoto. Emphasis on Pro Forma versus GAAP Earnings in Quarterly Press Releases: Determinants, SEC Intervention, and Market Reactions. *The Accounting Review*, 80(4):1011–1038, October 2005. ISSN 0001-4826, 1558-7967.

Daniel Bradley, Jonathan Clarke, Suzanne Lee, and Chayawat Ornthanalai. Are Analysts Recommendations Informative? Intraday Evidence on the Impact of Time Stamp Delays. *The Journal of Finance*, 2013. ISSN 1540-6261.

Gifford W. Bradley. Self-serving biases in the attribution process: A reexamination of the fact or fiction question. *Journal of Personality and Social Psychology*, 36(1):56–71, 1978. ISSN 1939-1315(Electronic);0022-3514(Print).

Mark T. Bradshaw, Scott A. Richardson, and Richard G. Sloan. Do Analysts and Auditors Use Information in Accruals? *Journal of Accounting Research*, 39(1):45–74, 2001. ISSN 1475-679X.

Mark Thomas Bradshaw. Analysts Forecasts: What Do We Know after Decades of Work? SSRN Scholarly Paper ID 1880339, Social Science Research Network, Rochester, NY, June 2011. URL `http://papers.ssrn.com/abstract=1880339`.

Lawrence D. Brown. Earnings forecasting research: its implications for capital markets research. *International Journal of Forecasting*, 9(3):295–320, November 1993. ISSN 0169-2070.

David Burgstahler and Ilia Dichev. Earnings management to avoid earnings decreases and losses. *Journal of Accounting and Economics*, 24(1):99–126, December 1997. ISSN 0165-4101.

Brian J. Bushee and Christopher F. Noe. Corporate Disclosure Practices, Institutional Investors, and Stock Return Volatility. *Journal of Accounting Research*, 38:171–202, January 2000.

Brian J. Bushee, Dawn A. Matsumoto, and Gregory S. Miller. Managerial and Investor Responses to Disclosure Regulation: The Case of Reg FD and Conference Calls. *The Accounting Review*, 79 (3):617–643, July 2004. ISSN 0001-4826, 1558-7967.

Brian J. Bushee, John E. Core, Wayne Guay, and Sophia JW Hamm. The role of the business press as an information intermediary. *Journal of Accounting Research*, 48(1):1–19, 2010.

Brian J. Bushee, Michael J. Jung, and Gregory S. Miller. Conference Presentations and the Disclosure Milieu. *Journal of Accounting Research*, 49(5):1163–1192, December 2011. ISSN 1475-679X.

Robert Bushman, Zhonglan Dai, and Xue Wang. Risk and CEO turnover. *Journal of Financial Economics*, 96(3):381–398, June 2010. ISSN 0304-405X.

Robert M. Bushman, Christopher D. Williams, Wittenberg Moerman, and Regina. The Informational Role of the Media in Private Lending. SSRN Scholarly Paper ID 2374724, Social Science Research Network, Rochester, NY, December 2013. URL `http://papers.ssrn.com/abstract=2374724`.

Ying Cao, Sami Keskek, Linda A. Myers, and Albert Tsang. The Effect of Media Competition on Analyst Forecast Properties: Cross-Country Evidence. SSRN Scholarly Paper ID 2492716, Social Science Research Network, Rochester, NY, August 2014. URL `http://papers.ssrn.com/abstract=2492716`.

Mark M. Carhart. On Persistence in Mutual Fund Performance. *The Journal of Finance*, 52(1): 57–82, March 1997. ISSN 0022-1082.

Louis K. C. Chan, Narasimhan Jegadeesh, and Josef Lakonishok. Momentum Strategies. *The Journal of Finance*, 51(5):1681–1713, December 1996. ISSN 0022-1082.

Jing Chen, Elizabeth A. Demers, and Baruch Lev. Oh What a Beautiful Morning! The Time of Day Effect on the Tone and Market Impact of Conference Calls. SSRN Scholarly Paper ID 2186862, Social Science Research Network, Rochester, NY, July 2013. URL `http://papers.ssrn.com/abstract=2186862`.

Xia Chen, Qiang Cheng, and Kin Lo. On the relationship between analyst reports and corporate disclosures: Exploring the roles of information discovery and interpretation. *Journal of Accounting and Economics*, 49(3):206–226, April 2010. ISSN 0165-4101.

Oleg Chuprinin, Srgio Gaspar, and Massimo Massa. Adding Value Through Information Interpretation: News Tangibility and Mutual Funds' Trading. URL `http://www.aeaweb.org/aea/2014conference/program/retrieve.php?pdfid=996`.

Stephen E. Clapham and Charles R. Schwenk. Self-serving attributions, managerial cognition, and company performance. *Strategic Management Journal*, 12(3):219–229, 1991. ISSN 1097-0266.

L. Cohen, K. Diether, and C. Malloy. Misvaluing innovation. *Unpublished working paper, Harvard University, and Dartmouth University*, 2010.

Lauren Cohen, Dong Lou, and Christopher Malloy. Playing Favorites: How Firms Prevent the Revelation of Bad News. Technical report, National Bureau of Economic Research, 2013. URL `http://www.nber.org/papers/w19429`.

Terry Connolly, Hal R. Arkes, and Kenneth R. Hammond. *Judgment and Decision Making: An Interdisciplinary Reader*. Cambridge University Press, 2000. ISBN 9780521626026.

Jennifer Conrad, Bradford Cornell, Wayne R. Landsman, and Brian R. Rountree. How do analyst recommendations respond to major news? *Journal of Financial and Quantitative Analysis*, 41 (1):25, 2006.

Julie Cotter, Irem Tuna, and Peter D. Wysocki. Expectations Management and Beatable Targets: How Do Analysts React to Explicit Earnings Guidance?*. *Contemporary Accounting Research*, 23(3):593–624, September 2006. ISSN 1911-3846.

David M. Cutler, James M. Poterba, and Lawrence H. Summers. What moves stock prices? *The Journal of Portfolio Management*, 15(3):4–12, 1989.

Kent Daniel, Mark Grinblatt, Sheridan Titman, and Russ Wermers. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. *The Journal of Finance*, 52(3):1035–1058, 1997. ISSN 1540-6261.

Francois Degeorge, Jayendu Patel, and Richard Zeckhauser. Earnings Management to Exceed Thresholds. *The Journal of Business*, 72(1):1–33, January 1999.

Stefano Dellavigna and Joshua M Pollet. Investor Inattention and Friday Earnings Announcements. *The Journal of Finance*, 64(2):709–749, March 2009. ISSN 1540-6261.

Elizabeth A. Demers and Clara Vega. Understanding The Role of Managerial Optimism and Uncertainty in the Price Formation Process: Evidence from the Textual Content of Earnings Announcements. SSRN Scholarly Paper ID 1152326, Social Science Research Network, Rochester, NY, March 2014.

David J. Denis, Diane K. Denis, and Atulya Sarin. The Information Content of Dividend Changes: Cash Flow Signaling, Overinvestment, and Dividend Clienteles. *Journal of Financial and Quantitative Analysis*, 29(04):567–587, December 1994. ISSN 1756-6916.

Elroy Dimson. Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics*, 7(2):197–226, June 1979. ISSN 0304-405X.

Casey Dougal, Joseph Engelberg, Diego Garcia, and Christopher A. Parsons. Journalists and the Stock Market. *Review of Financial Studies*, 25(3):639–679, March 2012a. ISSN 0893-9454, 1465-7368.

Casey Dougal, Joseph Engelberg, Christopher A. Parsons, Van Wesep, and Edward Dickersin. The Path Dependence of Borrowing Costs. SSRN Scholarly Paper ID 1732559, Social Science Research Network, Rochester, NY, April 2012b.

John A. Doukas and Dimitris Petmezas. Acquisitions, Overconfident Managers and Self-attribution Bias. *European Financial Management*, 13(3):531–577, 2007. ISSN 1468-036X.

Ran Duchin and Breno Schmidt. Riding the merger wave: Uncertainty, reduced monitoring, and bad acquisitions. *Journal of Financial Economics*, 107(1):69–88, January 2013. ISSN 0304-405X.

Alexander Dyck, Natalya Volchkova, and Luigi Zingales. The Corporate Governance Role of the Media: Evidence from Russia. *The Journal of Finance*, 63(3):1093–1135, 2008. ISSN 1540-6261.

Louis H. Ederington and Jeremy C. Goh. Bond Rating Agencies and Stock Analysts: Who Knows What When? *Journal of Financial and Quantitative Analysis*, 33(04):569–585, December 1998. ISSN 1756-6916.

Joseph Engelberg. Costly Information Processing: Evidence from Earnings Announcements. *SSRN eLibrary*, 2008. URL `http://ssrn.com/paper=1107998`.

Joseph E. Engelberg and Christopher A. Parsons. The Causal Impact of Media in Financial Markets. *The Journal of Finance*, 66(1):67–97, 2011. ISSN 1540-6261.

Joseph E. Engelberg, Adam V. Reed, and Matthew C. Ringgenberg. How are shorts informed?: Short sellers, news, and information processing. *Journal of Financial Economics*, 105(2):260–278, August 2012. ISSN 0304-405X.

Eugene F. Fama and Kenneth R. French. The Cross-Section of Expected Stock Returns. *The Journal of Finance*, 47(2):427–465, June 1992. ISSN 00221082.

Eugene F. Fama and Kenneth R. French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56, February 1993. ISSN 0304-405X.

Eugene F. Fama and Kenneth R. French. Industry costs of equity. *Journal of Financial Economics*, 43(2):153–193, February 1997. ISSN 0304-405X.

Eugene F. Fama and James D. MacBeth. Risk, Return, and Equilibrium: Empirical Tests. *The Journal of Political Economy*, 81(3):607–636, May 1973. ISSN 0022-3808.

Lily Fang and Joel Peress. Media Coverage and the Crosssection of Stock Returns. *The Journal of Finance*, 64(5):2023–2052, October 2009. ISSN 1540-6261.

Lily Fang, Joel Peress, and Lu Zheng. Does Your Fund Manager Trade on the News? Media Coverage, Mutual Fund Trading and Performance. SSRN Scholarly Paper ID 1361771, Social Science Research Network, Rochester, NY, March 2009. URL `http://papers.ssrn.com/abstract=1361771`.

Ronen Feldman, Suresh Govindaraj, Joshua Livnat, and Benjamin Segal. Managements tone change, post earnings announcement drift and accruals. *Review of Accounting Studies*, 15(4):915–953, December 2010. ISSN 1380-6653, 1573-7136.

Jennifer Francis, Katherine Schipper, and Linda Vincent. Earnings announcements and competing information. *Journal of Accounting and Economics*, 33(3):313–342, August 2002. ISSN 0165-4101.

Dov Fried and Dan Givoly. Financial analysts' forecasts of earnings: A better surrogate for market expectations. *Journal of Accounting and Economics*, 4:85–107, 1982.

Robert Gibbons and Kevin J. Murphy. Relative performance evaluation for chief executive officers. *Industrial and Labor Relations Review*, 43(3):30–51, 1990. URL `http://ideas.repec.org/a/ilr/articl/v43y1990i3p30-51.html`.

Bernard Goldberg. *Bias: A CBS Insider Exposes How the Media Distort the News*. Regnery Publishing, July 2014. ISBN 9781621573111.

John R. Graham, Campbell R. Harvey, and Shiva Rajgopal. The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, 40(13):3–73, December 2005. ISSN 0165-4101.

T. Clifton Green, Russell Jame, Stanimir Markov, and Musa Subasi. Access to management and the informativeness of analyst research. *Journal of Financial Economics*, 114(2):239–255, November 2014a. ISSN 0304-405X.

T. Clifton Green, Russell Jame, Stanimir Markov, and Musa Subasi. Access to management and the informativeness of analyst research. *Journal of Financial Economics*, 114(2):239–255, 2014b.

Mark Grinblatt, Sheridan Titman, and Russ Wermers. Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior. *The American Economic Review*, 85(5):1088–1105, December 1995. ISSN 0002-8282.

Umit G. Gurun and Alexander W. Butler. Don't Believe the Hype: Local Media Slant, Local Advertising, and Firm Value. *The Journal of Finance*, 67(2):561–598, 2012. ISSN 1540-6261.

James T. Hamilton and Richard Zeckhauser. Media Coverage of CEOs: Who? What? Where? When? Why? *Unpublished working paper, Stanford Institute of International Studies*, 2004. URL `http://www.anderson.ucla.edu/faculty_pages/romain.wacziarg/mediapapers/HamiltonZeckhauser.pdf`.

Jerry C. Y. Han and John J. Wild. Unexpected Earnings and Intraindustry Information Transfers: Further Evidence. *Journal of Accounting Research*, 28(1):211–219, April 1990. ISSN 0021-8456.

Jay C. Hartzell and Laura T. Starks. Institutional Investors and Executive Compensation. *The Journal of Finance*, 58(6):2351–2374, December 2003. ISSN 1540-6261.

Paul M Healy and Krishna G Palepu. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, 31(13):405–440, September 2001. ISSN 0165-4101.

James B. Heaton. Managerial optimism and corporate finance. *Financial management*, pages 33–45, 2002.

Elaine Henry. Are Investors Influenced By How Earnings Press Releases Are Written? *Journal of Business Communication*, 45(4):363–407, October 2008. ISSN 2329-4884, 2329-4892.

David Hirshleifer and Siew Hong Teoh. Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(13):337–386, December 2003. ISSN 0165-4101.

David Hirshleifer, Sonya Seongyeon Lim, and Siew Hong Teoh. Driven to Distraction: Extraneous Events and Underreaction to Earnings News. *The Journal of Finance*, 64(5):2289–2325, October 2009. ISSN 1540-6261.

D. Eric Hirst, Lisa Koonce, and Shankar Venkataraman. Management Earnings Forecasts:A Review and Framework. *Accounting Horizons*, 22(3):315–338, September 2008. ISSN 08887993.

Stephan Hollander, Maarten Pronk, and Erik Roelofsen. Does Silence Speak? An Empirical Analysis of Disclosure Choices During Conference Calls. *Journal of Accounting Research*, 48(3):531–563, 2010. ISSN 1475-679X.

Vera Hoorens. Self-Favoring Biases, Self-Presentation, and the Self-Other Asymmetry in Social Comparison. *Journal of Personality*, 63(4):793–817, 1995. ISSN 1467-6494.

Ole-Kristian Hope. Disclosure Practices, Enforcement of Accounting Standards, and Analysts' Forecast Accuracy: An International Study. *Journal of Accounting Research*, 41(2):235–272, May 2003. ISSN 1475-679X.

Xuan Huang, Siew Hong Teoh, and Yinglei Zhang. Tone Management. *The Accounting Review*, page 131219095011009, December 2013. ISSN 0001-4826, 1558-7967.

John S. Hughes and Suil Pae. Voluntary disclosure of precision information. *Journal of Accounting and Economics*, 37(2):261–289, June 2004. ISSN 0165-4101.

Amy P. Hutton, Gregory S. Miller, and Douglas J. Skinner. The Role of Supplementary Statements with Management Earnings Forecasts. *Journal of Accounting Research*, 41(5):867–890, December 2003. ISSN 1475-679X.

Amy P. Hutton, Lian Fen Lee, and Susan Z. Shu. Do Managers Always Know Better? The Relative Accuracy of Management and Analyst Forecasts. *Journal of Accounting Research*, 50(5):1217–1244, December 2012. ISSN 1475-679X.

David Ikenberry, Josef Lakonishok, and Theo Vermaelen. Market underreaction to open market share repurchases. *Journal of Financial Economics*, 39(23):181–208, October 1995. ISSN 0304-405X.

Guido W. Imbens and Thomas Lemieux. Regression discontinuity designs: A guide to practice. *Journal of Econometrics*, 142(2):615–635, February 2008. ISSN 0304-4076.

Paul Irvine, Marc Lipson, and Andy Puckett. Tipping. *Review of Financial Studies*, 20(3):741–768, May 2007. ISSN 0893-9454, 1465-7368.

Zoran Ivkovic and Narasimhan Jegadeesh. The timing and value of forecast and recommendation revisions. *Journal of Financial Economics*, 73(3):433–463, September 2004. ISSN 0304-405X.

Irving L. Janis. Victims of groupthink: A psychological study of foreign-policy decisions and fiascoes. 1972.

Irving L. Janis and Leon Mann. *Decision making: A psychological analysis of conflict, choice, and commitment.* Free Press, 1977.

Irving Lester Janis. *Crucial decisions: Leadership in policymaking and crisis management.* Simon and Schuster, 1989.

Narasimhan Jegadeesh and Woojin Kim. Do Analysts Herd? An Analysis of Recommendations and Market Reactions. *Review of Financial Studies*, 23(2):901–937, February 2010. ISSN 0893-9454, 1465-7368.

Narasimhan Jegadeesh and Sheridan Titman. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, 48(1):65–91, March 1993. ISSN 00221082.

Narasimhan Jegadeesh and Di Wu. Word power: A new approach for content analysis. *Journal of Financial Economics*, 110(3):712–729, December 2013. ISSN 0304-405X.

Narasimhan Jegadeesh, Joonghyuk Kim, Susan D Krische, and Charles M. C Lee. Analyzing the Analysts: When Do Recommendations Add Value? *The Journal of Finance*, 59(3):1083–1124, June 2004. ISSN 1540-6261.

Jerald M. Jellison and Jane Green. A self-presentation approach to the fundamental attribution error: The norm of internality. *Journal of Personality and Social Psychology*, 40(4):643–649, 1981. ISSN 1939-1315(Electronic);0022-3514(Print).

Michael C. Jensen. Toward a Theory of the Press. In Karl Brunner, editor, *Economics Social Institutions*, number 1 in Rochester Studies in Economics and Policy Issues, pages 267–287. Springer Netherlands, 1979. ISBN 978-94-009-9259-7, 978-94-009-9257-3.

Dirk Jenter and Fadi Kanaan. CEO Turnover and Relative Performance Evaluation. Working Paper 12068, National Bureau of Economic Research, March 2006. URL `http://www.nber.org/papers/w12068`.

Ohad Kadan, Leonardo Madureira, Rong Wang, and Tzachi Zach. Analysts' industry expertise. *Journal of Accounting and Economics*, 54(23):95–120, October 2012. ISSN 0165-4101.

Kalinowski, M. and Babington, A. CRMB: Could the "crumbnut" eventually help to improve sales trend?, August 2013.

Steven N. Kaplan and Bernadette Minton. How has CEO Turnover Changed? Increasingly Performance Sensitive Boards and Increasingly Uneasy CEOs. Working Paper 12465, National Bureau of Economic Research, August 2006. URL `http://www.nber.org/papers/w12465`.

Ambrus Kecskes, Roni Michaely, and Kent Womack. What Drives the Value of Analysts' Recommendations: Earnings Estimates or Discount Rate Estimates? SSRN Scholarly Paper ID 1478451, Social Science Research Network, Rochester, NY, September 2009. URL `http://papers.ssrn.com/abstract=1478451`.

Eric K. Kelley and Paul C. Tetlock. How Wise Are Crowds? Insights from Retail Orders and Stock Returns. *SSRN eLibrary.* URL `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1668706`.

Oliver Kim and Robert E. Verrecchia. Market reaction to anticipated announcements. *Journal of Financial Economics*, 30(2):273–309, December 1991. ISSN 0304-405X.

Oliver Kim and Robert E. Verrecchia. Market liquidity and volume around earnings announcements. *Journal of Accounting and Economics*, 17(12):41–67, January 1994. ISSN 0165-4101.

Oliver Kim and Robert E. Verrecchia. Pre-announcement and event-period private information. *Journal of Accounting and Economics*, 24(3):395–419, December 1997. ISSN 0165-4101.

S. P. Kothari, Xu Li, and James E. Short. The Effect of Disclosures by Management, Analysts, and Business Press on Cost of Capital, Return Volatility, and Analyst Forecasts: A Study Using Content Analysis. *Accounting Review*, 84(5):1639–1670, September 2009a. ISSN 00014826.

S. P. Kothari, Susan Shu, and Peter D. Wysocki. Do Managers Withhold Bad News? *Journal of Accounting Research*, 47(1):241–276, March 2009b. ISSN 1475-679X.

Todd Kravet and Volkan Muslu. Textual risk disclosures and investors risk perceptions. *Review of Accounting Studies*, 18(4):1088–1122, December 2013. ISSN 1380-6653, 1573-7136.

William Kross, Byung Ro, and Douglas Schroeder. Earnings Expectations: The Analysts' Information Advantage. *The Accounting Review*, 65(2):461–476, April 1990. ISSN 0001-4826.

Richard Lambert, Christian Leuz, and Robert E. Verrecchia. Accounting Information, Disclosure, and the Cost of Capital. *Journal of Accounting Research*, 45(2):385–420, May 2007. ISSN 1475-679X.

Mark H. Lang and Russell J. Lundholm. Voluntary Disclosure and Equity Offerings: Reducing Information Asymmetry or Hyping the Stock?*. *Contemporary Accounting Research*, 17(4):623–662, December 2000a. ISSN 1911-3846.

Mark H. Lang and Russell J. Lundholm. Voluntary Disclosure and Equity Offerings: Reducing Information Asymmetry or Hyping the Stock?*. *Contemporary Accounting Research*, 17(4):623–662, December 2000b. ISSN 1911-3846.

David F. Larcker and Anastasia A. Zakolyukina. Detecting Deceptive Discussions in Conference Calls. *SSRN eLibrary*, July 2010. URL `http://papers.ssrn.com/sol3/Papers.cfm?abstract_id=1572705`.

Fiona Lee, Christopher Peterson, and Larissa Z. Tiedens. Mea Culpa: Predicting Stock Prices From Organizational Attributions. *Personality and Social Psychology Bulletin*, 30(12):1636–1649, December 2004. ISSN 0146-1672, 1552-7433.

Yen-Jung Lee, Kathy R. Petroni, and Min Shen. Cherry Picking, Disclosure Quality, and Comprehensive Income Reporting Choices: The Case of Property-Liability Insurers*. *Contemporary Accounting Research*, 23(3):655–692, September 2006. ISSN 1911-3846.

Reuven Lehavy, Feng Li, and Kenneth Merkley. The Effect of Annual Report Readability on Analyst Following and the Properties of Their Earnings Forecasts. *The Accounting Review*, 86(3):1087–1115, May 2011. ISSN 0001-4826, 1558-7967.

Edward Xuejun Li, K. Ramesh, and Min Shen. The role of newswires in screening and disseminating value-relevant information in periodic SEC reports. *The Accounting Review*, 86(2):669–701, 2011.

Edward Xuejun Li, K. Ramesh, Min Shen, and Joanna Shuang Wu. Do Analyst Stock Recommendations Piggyback on Recent Corporate News? An Analysis of Regular-Hour and After-Hours Revisions. SSRN Scholarly Paper ID 2441713, Social Science Research Network, Rochester, NY, January 2015. URL `http://papers.ssrn.com/abstract=2441713`.

Feng Li. The Information Content of Forward-Looking Statements in Corporate FilingsA Nave Bayesian Machine Learning Approach. *Journal of Accounting Research*, 48(5):1049–1102, 2010a. ISSN 1475-679X.

Feng Li. Managers self-serving attribution bias and corporate financial policies. *University of Michigan: working paper*, 2010b. URL `http://www.mccombs.utexas.edu/~/media/Files/MSB/Departments/Accounting/Workshop%20Papers/Li_Feng.pdf`.

Yuanzhi Li and David Yermack. Evasive Shareholder Meetings. SSRN Scholarly Paper ID 2409627, Social Science Research Network, Rochester, NY, March 2014. URL `http://papers.ssrn.com/abstract=2409627`.

Hsiou-wei Lin and Maureen F McNichols. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics*, 25(1):101–127, February 1998. ISSN 0165-4101.

Roger K. Loh and G. Mujtaba Mian. Do accurate earnings forecasts facilitate superior investment recommendations? *Journal of Financial Economics*, 80(2):455–483, May 2006.

Roger K Loh and Ren M Stulz. When Are Analyst Recommendation Changes Influential? *Review of Financial Studies*, October 2010. ISSN 0893-9454, 1465-7368.

Tim Loughran and Bill Mcdonald. When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *The Journal of Finance*, 66(1):35–65, 2011. ISSN 1540-6261.

Tim Loughran and Bill Mcdonald. Measuring Readability in Financial Disclosures. *The Journal of Finance*, pages n/a–n/a, March 2014. ISSN 00221082.

John D. Lyon, Brad M. Barber, and Chih-Ling Tsai. Improved Methods for Tests of Long-Run Abnormal Stock Returns. *The Journal of Finance*, 54(1):165–201, 1999. ISSN 1540-6261.

Thomas Lys and Sungkyu Sohn. The association between revisions of financial analysts' earnings forecasts and security-price changes. *Journal of Accounting and Economics*, 13(4):341–363, 1990.

Henk Pander Maat. How Promotional Language in Press Releases Is Dealt With by Journalists: Genre Mixing or Genre Conflict? *Journal of Business Communication*, 44(1):59–95, January 2007. ISSN 2329-4884, 2329-4892.

Ulrike Malmendier and Geoffrey Tate. CEO Overconfidence and Corporate Investment. *The Journal of Finance*, 60(6):2661–2700, December 2005. ISSN 0022-1082.

Ulrike Malmendier and Geoffrey Tate. Who makes acquisitions? CEO overconfidence and the market's reaction. *Journal of Financial Economics*, 89(1):20–43, July 2008. ISSN 0304-405X.

Dawn Matsumoto, Maarten Pronk, and Erik Roelofsen. What Makes Conference Calls Useful? The Information Content of Managers' Presentations and Analysts' Discussion Sessions. *The Accounting Review*, 86(4):1383–1414, July 2011. ISSN 0001-4826, 1558-7967.

William J. Mayew. Evidence of Management Discrimination Among Analysts during Earnings Conference Calls. *Journal of Accounting Research*, 46(3):627–659, 2008. ISSN 1475-679X.

William J. Mayew and Mohan Venkatachalam. The Power of Voice: Managerial Affective States and Future Firm Performance. *The Journal of Finance*, 67(1):1–43, 2012. ISSN 1540-6261.

Richard R. Mendenhall. Evidence on the Possible Underweighting of Earnings-Related Information. *Journal of Accounting Research*, 29(1):170–179, April 1991. ISSN 0021-8456.

Roni Michaely and Kent L. Womack. Brokerage recommendations: Stylized characteristics, market responses, and biases. *Advances in Behavioral Finance II*, pages 389–422, 2005.

Roni Michaely, Richard H. Thaler, and Kent L. Womack. Price Reactions to Dividend Initiations and Omissions: Overreaction or Drift? *The Journal of Finance*, 50(2):573–608, 1995. ISSN 1540-6261.

Dale T. Miller. What constitutes a self-serving attributional bias? A reply to Bradley. *Journal of Personality and Social Psychology*, 36(11):1221–1223, 1978. ISSN 1939-1315(Electronic);0022-3514(Print).

Gregory S. Miller. The Press as a Watchdog for Accounting Fraud. *Journal of Accounting Research*, 44(5):1001–1033, 2006. ISSN 1475-679X.

R. Charles Moyer, Robert E. Chatfield, and Phillip M. Sisneros. Security Analyst Monitoring Activity: Agency Costs and Information Demands. *Journal of Financial and Quantitative Analysis*, 24(04):503–512, 1989.

Sendhil Mullainathan and Andrei Shleifer. The Market for News. *The American Economic Review*, 95(4):1031–1053, September 2005. ISSN 0002-8282.

Kevin J Murphy and Jerold L Zimmerman. Financial performance surrounding CEO turnover. *Journal of Accounting and Economics*, 16(13):273–315, January 1993. ISSN 0165-4101.

Whitney K. Newey and Kenneth D. West. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3):703–708, May 1987. ISSN 0012-9682.

Austin Nichols. RD: Stata module for regression discontinuity estimation, June 2012. URL `http://ideas.repec.org/c/boc/bocode/s456888.html`.

Robert Novy-Marx. The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1):1–28, April 2013. ISSN 0304-405X.

Panos N. Patatoukas, Richard G. Sloan, and Jenny Zha. On the Pricing of Mandatory DCF Disclosures: Evidence from Oil and Gas Royalty Trusts. SSRN Scholarly Paper ID 2375552, Social Science Research Network, Rochester, NY, February 2015.

Mitchell A. Petersen. Information: Hard and soft. *Northwestern University, document de travail*, 2004.

Mitchell A. Petersen. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies*, 22(1):435 –480, January 2009.

Michael E. Porter. *Competitive Strategy: Techniques for Analyzing Industries and Competitors*. Simon and Schuster, June 2008. ISBN 9781416590354.

Gary John Previts, Robert J. Bricker, Thomas R. Robinson, and Stephen J. Young. A content analysis of sell-side financial analyst company reports. *Accounting Horizons*, 8:55–55, 1994. URL `http://elibrary.ru/item.asp?id=2052454`.

S. McKay Price, James S. Doran, David R. Peterson, and Barbara A. Bliss. Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking & Finance*, 36(4):992–1011, April 2012a. ISSN 0378-4266.

S. McKay Price, James S. Doran, David R. Peterson, and Barbara A. Bliss. Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking & Finance*, 36(4):992–1011, April 2012b. ISSN 0378-4266.

Sundaresh Ramnath, Steve Rock, and Philip Shane. The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting*, 24(1):34–75, 2008.

Lynn Rees, Nathan Sharp, and Brady Twedt. Whos Heard on the Street? Determinants and Consequences of Financial Analyst Coverage in the Business Press. *Determinants and Consequences of Financial Analyst Coverage in the Business Press (February 7, 2012). Mays Business School Research Paper*, (2012-30), 2011. URL `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1800822`.

Reitzes, B. A. and Thorwart, J. Apple Inc. Expecting Strong December Quarter with Conservative Guide for March, January 2012.

Scott Richardson, Siew Hong Teoh, and Peter D. Wysocki. The Walk-down to Beatable Analyst Forecasts: The Role of Equity Issuance and Insider Trading Incentives. *Contemporary Accounting Research*, 21(4):885–924, December 2004. ISSN 0823-9150.

Scott A. Richardson, Richard G. Sloan, Mark T. Soliman, and rem Tuna. Accrual reliability, earnings persistence and stock prices. *Journal of Accounting and Economics*, 39(3):437–485, September 2005. ISSN 0165-4101.

Marc Riess, Paul Rosenfeld, Valerie Melburg, and James T. Tedeschi. Self-serving attributions: Biased private perceptions and distorted public descriptions. *Journal of Personality and Social Psychology*, 41(2):224–231, 1981. ISSN 1939-1315(Electronic);0022-3514(Print).

Ritter, D. Morgan Stanley, July 2010.

Jonathan L. Rogers, Andrew Van Buskirk, and Sarah L. C. Zechman. Disclosure Tone and Shareholder Litigation. *The Accounting Review*, 86(6):2155–2183, July 2011. ISSN 0001-4826.

Rogers, R.K. An empirical investigation of financial analysts sources of information, 1996.

Richard Roll. The Hubris Hypothesis of Corporate Takeovers. *The Journal of Business*, 59(2): 197–216, April 1986. ISSN 0021-9398.

Richard Roll. R2. *The Journal of Finance*, 43(3):541–566, July 1988. ISSN 00221082.

Katherine Schipper. Analysts forecasts. *Accounting Horizons*, 5(4):105–121, 1991.

Carl W. Schneider. Nits, Grits, and Soft Information in SEC Filings. *University of Pennsylvania Law Review*, pages 254–305, 1972.

Catherine M. Schrand and Beverly R. Walther. Strategic Benchmarks in Earnings Announcements: The Selective Disclosure of PriorPeriod Earnings Components. *The Accounting Review*, 75(2): 151–177, April 2000. ISSN 0001-4826, 1558-7967.

Charles R. Schwenk. Illusions of Management Control? Effects of Self-Serving Attributions on Resource Commitments and Confidence in Management. *Human Relations*, 43(4):333–347, April 1990. ISSN 0018-7267, 1741-282X.

Lisa M. Sedor. An Explanation for Unintentional Optimism in Analysts' Earnings Forecasts. *The Accounting Review*, 77(4):731–753, October 2002. ISSN 0001-4826.

Douglas J. Skinner. Why Firms Voluntarily Disclose Bad News. *Journal of Accounting Research*, 32(1):38–60, April 1994.

Leonard C. Soffer, S. Ramu Thiagarajan, and Beverly R. Walther. Earnings Preannouncement Strategies. *Review of Accounting Studies*, 5(1):5–26, March 2000. ISSN 1380-6653, 1573-7136.

David H. Solomon. Selective Publicity and Stock Prices. *The Journal of Finance*, 67(2):599–638, 2012. ISSN 1540-6261.

Barry M. Staw and Jerry Ross. Commitment to a Policy Decision: A Multi-Theoretical Perspective. *Administrative Science Quarterly*, 23(1):40–64, March 1978. ISSN 00018392.

Barry M. Staw, Pamela I. McKechnie, and Sheila M. Puffer. The Justification of Organizational Performance. *Administrative Science Quarterly*, 28(4):582–600, December 1983. ISSN 0001-8392.

Paul C. Tetlock. Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *The Journal of Finance*, 62(3):1139–1168, June 2007. ISSN 0022-1082.

Paul C. Tetlock. Does Public Financial News Resolve Asymmetric Information? *Review of Financial Studies*, 23(9):3520 –3557, 2010. doi: 10.1093/rfs/hhq052.

Paul C. Tetlock. All the News That's Fit to Reprint: Do Investors React to Stale Information? *Review of Financial Studies*, 24(5):1481–1512, May 2011. ISSN 0893-9454, 1465-7368.

Paul C Tetlock, Maytal Saar-Tsechansky, and Sofus Macskassy. More Than Words: Quantifying Language to Measure Firms' Fundamentals. *The Journal of Finance*, 63(3):1437–1467, June 2008. ISSN 1540-6261.

Philip E. Tetlock and Ariel Levi. Attribution bias: On the inconclusiveness of the cognition-motivation debate. *Journal of Experimental Social Psychology*, 18(1):68–88, January 1982. ISSN 0022-1031.

Samuel B. Thompson. Simple formulas for standard errors that cluster by both firm and time. *Journal of Financial Economics*, 99(1):1–10, January 2011. ISSN 0304-405X.

B. Trueman. Analyst forecasts and herding behavior. *Review of Financial Studies*, 7(1):97–124, January 1994. ISSN 0893-9454, 1465-7368.

Richard Webby and Marcus O'Connor. Judgemental and statistical time series forecasting: A review of the literature. *International Journal of Forecasting*, 12(1):91–118, 1996.

Bernard Weiner. "Spontaneous" causal thinking. *Psychological Bulletin*, 97(1):74–84, 1985. ISSN 1939-1455(Electronic);0033-2909(Print).

Patricia A. Williams. The Relation between a Prior Earnings Forecast by Management and Analyst Response to a Current Management Forecast. *The Accounting Review*, 71(1):103–115, January 1996. ISSN 0001-4826.

Patricia A. Williams, Glen D. Moyes, and Kyungjoo Park. Factors affecting earnings forecast revisions for the buy-side and sell-side analyst. *Accounting Horizons*, 10:112–121, 1996.

Kent L. Womack. Do Brokerage Analysts' Recommendations Have Investment Value? *The Journal of Finance*, 51(1):137–167, 1996. ISSN 1540-6261.