How do analysts gather information about the firms they follow?

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December 2022

We examine how analysts gather information based on their public interactions with firm managers. We use measures of textual similarity to capture the uniqueness of an individual analyst's question(s) on a firm's quarterly earnings conference call relative to 1) the questions of other analysts on the same call, 2) same analyst on prior firm calls, and 3) the management-prepared narrative. We first examine the associations between the uniqueness of analysts' questions and analysts' characteristics. We observe that the uniqueness of individual analysts' questions varies systematically with analysts' experience, broker size, forecast frequency, and number of firms followed. Next, we examine how differences across analysts' questions impact analysts' revisions and accuracy, and the market's reaction to the conference call, focusing on the sign of the quarterly earnings surprise. Overall, we provide evidence on analysts' information gathering to help form their forecasts and how the market interprets differences across analysts' public interactions with firm managers.

JEL classification: G3, G17, M4, M41

Keywords: Analysts, Forecast Revisions, Conference Calls, Forecast Accuracy, Textual Analysis

We thank Bill McDonald, Stephannie Larocque, Beverly Walther, and Hansol Yoon for helpful comments. Allee acknowledges the support of the Doyle Z. Williams Chair in Professional Accounting at the Walton College of Business. †Corresponding author: 220 North McIlroy Avenue, Sam M. Walton College of Business, Fayetteville, AR 72701; Tel: (479) 575-5227.

1. Introduction

In the competitive financial markets, a great deal of information is available simultaneously to anyone with internet access. Even with research department cutbacks, many firms are still followed by several sell-side analysts – not to mention the coverage of the financial press and social media. As a result, it is likely that sell-side analysts who follow firms try to differentiate themselves not only in their published research (e.g., forecasts and recommendations) but also in their information-gathering processes. We seek a better understanding of how analysts publicly gather information about the firms they follow. We do so in order to learn more about the information-gathering process, including whether different information gathering behaviors are translated into earnings forecasts, and the market's reaction to analysts' information gathering.

While we cannot observe analysts' private conversations and thoughts, we can observe how analysts gather information from their public interactions with firm managers. We seek to examine the associations between analysts' information-gathering behavior, characteristics, and forecast revisions as well as the market's reaction. Many studies document results consistent with analysts' herding behavior (e.g., Trueman 1994; Clement and Tse 2005), which is the tendency for analysts to issue forecasts or recommendations in line with their peers. Hong, Kubik, and Solomon (2000) find that inexperienced analysts are more likely to be terminated when their forecasts are "bolder", suggesting that there are costs to standing out from the crowd. Thus, absent private information, an analyst is more likely to mimic the forecasts issued by other (strong) analysts than to forecast something that differs from the consensus. We argue that differential information gathering behaviors represent a public signal of analyst's attempt to convey to the market their credibility (Twedt and Rees 2012). Accordingly, we expect the market to infer analyst's private data-gathering from their public behavior.[1]

We focus on firms' quarterly earnings conference calls which are frequent and public calls in which firms communicate their plans and expectations with outsiders and where interested participants, typically sell-side analysts, can ask questions of firm managers. Conference calls have been associated with analysts' forecast accuracy (Bowen, Davis, and Matsumoto 2002) and have been shown to have information content incremental to that presented in firms' earnings press releases and mandatory quarterly and annual filings (Matsumoto, Pronk, and Roelofsen 2011). While not the only place to observe analysts' behavior, conference calls are presumably representative of analysts' information-gathering activities more generally.[2]

We use textual analysis to compare an individual analyst's question(s) during a firm's quarterly earnings conference call to the questions of other analysts on the same call, as well as the same analyst on the same firm's previous calls, and the management-prepared narrative (MPN) on the same call. In particular, we use cosine similarity, a correlation-like measure that has been used in prior accounting and finance literature (Brown and Tucker 2011; Hoberg and Phillips 2016; Lang and Stice-Lawrence 2015) which, simply put, measures whether the words used by one speaker are the same words used by another speaker (see Loughran and McDonald 2016).

We begin by exploring whether analysts' characteristics, such as their experience, brokerage size, forecast frequency, and number of firms followed are associated with the

[1] We recognize that analysts may not be able to signal their credibility during a firm's conference call due to limitations placed by management. That is, Mayew (2008) and others (e.g., Cohen, Lou, and Malloy 2020) find that conference calls are "casted" such that more favorable analysts are invited to participate during the question and answer (Q&A) session of the call.

[2] We note that the public nature of this type of information-gathering activity may change the nature of analysts' behaviors. However, research in behavioral and experimental economics (e.g., Benz and Meier 2008) documents that behavior in experimental labs (i.e., when subjects know they are being watched) is correlated with behavior in the field. Thus, while our proxy for analysts' information-gathering activities may not be completely representative of their thoughts and behaviors in a more private setting, it should be correlated with those behaviors to some reasonable degree.

uniqueness of analysts' questions on a conference call. We then test how differences in information-gathering, i.e., the uniqueness of individual analysts' questions, translate into analysts' forecast revisions. Specifically, we test for an association between how unique an individual analyst's questions are and how likely the analyst is to revise their earnings forecast for the firm following the conference call. We also examine the extent to which the analysts' differential data gathering activities are associated with the size of their forecast revisions and the accuracy of their forecasts. Finally, we consider the market's reaction to the conference call as a function of how much analysts on the call differ in what they ask and whether they differ from what managers have already offered.

We find that the uniqueness of individual analysts' questions varies with their individual characteristics, controlling for firm and conference call characteristics as well as the order in which the analyst has the opportunity to pose a question during the call. In particular, more experienced analysts appear more willing and able to ask unique questions relative to those they have asked in the past on that firm's prior earnings calls and relative to other analysts asking questions on the same call. The questions posed by analysts from larger brokers and those who forecast more frequently are less unique, while the questions posed by analysts who follow more firms are more unique.

Turning to the frequency and quality of analysts' outputs and the market's reaction to analysts' information gathering in conference calls, we first zero in on analysts' revisions and forecast accuracy. In doing that, we are particularly interested in analysts' differential data gathering behavior and its effects on their revision behavior and accuracy when firms have positive versus negative earnings surprises. We observe that, when analysts ask more unique questions relative to their own prior questions and relative to the management prepared narrative (MPN), they are more likely to revise their forecasts immediately following the conference call. This is even more so when firms report an earnings surprise. Furthermore, in additional analyses, the magnitude of the revision from analysts asking unique questions appears to be associated with the size of the earnings surprise. That is, the greater the earnings surprise, the greater the revision from analysts who ask unique questions during conference calls.

Moreover, the accuracy of analyst forecast appears to be associated with their differential data gathering activities on conference calls, though the results are little more nuanced. Specifically, analysts who ask questions that differ more from their peers' are more accurate in the absence of an earnings surprise. However, we find evidence that forecast accuracy is greater for the analysts whose questions on the call differ more from themselves in prior calls, in the absence of an earnings surprise, but even more so when there is an increasingly large earnings surprise. Finally, analysts who ask questions that are different from the MPN are only more accurate when the earnings surprise is larger. This evidence emphasizes the effect the news has on analysts in terms of their differential data gathering proclivities and the news' effect on their outputs.

The market appears to respond to the uniqueness of analysts' questions when there is a negative earnings surprise. That is, investors do not appear to react to analysts' differential information gathering activities in conference calls when the news is good or at least neutral. On the other hand, when earnings surprise is negative (i.e., the news is bad), and when analysts ask questions that differ from their own questions in prior calls and from the MPN, cumulative abnormal returns are decreasing with the magnitude of earnings surprise. These results suggest that analysts who ask questions that differ from their own questions in prior calls and from the MPN are likely able to push managers to release additional negative information that they may have attempted to or at least preferred to withhold. Furthermore, using "real-time" analysis and data from millisecond trading data, we find that the question and answer (Q&A) session on an earnings conference call is more informative in the presence of unique analyst's questions—relative to their own prior questions and relative to the Q&A.

Our study contributes to the sell-side analyst literature. Mikhail, Walther, and Willis (2007) examine who trades on security analyst stock recommendations by extending prior research to focus on investor-specific responses to analyst forecast revisions. They find that both large and small traders react to analyst reports; however, large investors appear to trade more than small traders in response to the information conveyed by the analyst's recommendation and earnings forecast revision (proxied by the magnitudes of the recommendation change and the earnings forecast revision, respectively). Our paper also focuses on analysts' behavior but instead of focusing on their reports, we examine their questions on conference calls as an indication as to whether/if this behavior will then affect their earnings forecast revisions and the market's reaction to the call. Participating analysts may want to know and be aware of how their public interactions are associated with the quality of their outputs and how the market perceives their behavior.

We also provide insights into analysts' forecasting behavior based on earnings conference calls, and to the market's use of analysts' information in interpreting earnings information. Recent research (Mayew, Sethuraman, and Venkatachalam 2020) examines whether and to what extent individual analysts' ex ante stock recommendations and earnings forecasts affect the information content of analyst-manager conversations and finds that manager dialogues with bearish analysts whose forecasts are missed are more informative. Our paper contributes to this literature by documenting that there is significant nuance in the interactions between managers and analysts, as well as within analysts, and there is an association between analysts' interactions and analysts' forecasting behavior as well as the market's reaction.

Additionally, our study contributes to the literature that examines earnings conference calls at the conversation level (Allee, DeAngelis, and Merkley 2019; Mayew et al. 2020). Research on conference calls tends to examine the content of conference calls overall or by section (i.e., MPN vs. Q&A) (Price, Doran, Peterson, and Bliss 2012; Chen, Hribar, and Melessa 2018; Milian, Smith, and Alfonso 2017) without considering features of individual dialogues between managers and specific analysts or within the analysts themselves. Finally, Matsumoto et al. (2011) document that the Q&A portion of the earnings conference call is informative primarily due to analyst involvement. We build on this finding by providing additional evidence on the comparability of analysts' questions on the calls and how this differential information gathering may be associated with analysts' characteristics, as well as their forecast revisions and the market's reaction to the earnings conference call.

2. Literature review and development of research questions

In a post-Regulation Fair Disclosure (Reg FD) world, a great deal of information is made available by firms to the public.[3] Conference calls are one of firms' primary means of two-way communication with external stakeholders and with sell-side analysts in particular. While all publicly traded firms issue quarterly earnings reports, as well as other mandated disclosures, an increasing number of firms regularly schedule conference calls to follow the release of their quarterly earnings (Brown, Hillegeist, and Lo 2004; Matsumoto et al. 2011). In 2016, the overwhelming majority of respondents to a National Investor Relations Institute (NIRI) Earnings Process Practices Research Survey reported that they held earnings calls (97%), nearly identical to the findings from NIRI's 2014 and 2011 studies.[4] These calls typically include a prepared, uninterrupted management discussion (aka the management-prepared narrative or "MPN") followed by a question-and-answer session ("Q&A") in which participants, largely sell-side

[3] Effective October 2000, Regulation Fair Disclosure, or "Reg FD", requires that firms issue material, non-public information to the public and not just to selective individuals or institutions.
[4] See https://www.niri.org/NIRI/media/Protected-Documents_ExcludeGlobalSubs/Analytics%20Reports/Analytics_Guidance/NIRI-Earnings-Process-Practices-Report-2016.pdf.

analysts, are invited to ask questions of management. According to Heinrichs, Park, and Soltes (2019), conference calls are consumed (i.e., their transcripts are accessed) by a large cross-section of investors, both those who hold a position in the firm and those who do not.

Theoretical research documents that when analysts lack private information to produce accurate forecasts or recommendations, either through lack of effort or ability, they will tend to mimic outputs from other analysts (Trueman 1994; Arya et al. 2005). This herding behavior among analysts is an attempt to obfuscate the observable effects of their lack of information and is documented in several empirical studies (e.g., Hong et al. 2000; Clement and Tse 2005; Mensah and Yang 2008).

Prior literature finds that conference calls provide relevant information to the financial markets. Early work by Bowen et al. (2002) finds analysts' forecast accuracy increases and forecast dispersion decreases following firms' conference calls. Bushee, Matsumoto, and Miller (2003) find that small trades increase in number following open conference calls, consistent with individual investors trading on information released during the call.[5] Information released during the call is also found to reduce information asymmetry among investors (Brown et al. 2004), with the Q&A portion of the call being more informative, or explaining more of the total return related to the call, relative to the MPN (Matsumoto et al. 2011; Gomez, Heflin, Lee, and Wang 2018).

Some research suggests that conference calls are somewhat "staged," or orchestrated by firm managers and/or investor relations. Mayew (2008) concludes that managers choose which analysts are invited to participate in the Q&A portion of earnings conference calls, and that they discriminate by choosing the analysts with more favorable recommendations for the firm's stock as well as the more prestigious analysts. Moreover, the analysts who are invited to participate

[5] Prior to Reg FD, firms hosted conference calls that were either closed (i.e., available to a limited audience) or open to everyone. Following Reg FD, all firms' conference calls are open, with transcripts available to the public through firms' websites as well as from services like Seeking Alpha and The Motley Fool.

during the conference call Q&A issue more accurate and timelier earnings forecasts, relative to the analysts who are not invited to participate (Mayew, Sharp, and Venkatachalam 2013). Milian, et al. (2017) further find that the analysts who use more favorable language on a firm's conference call subsequently issue more accurate earnings forecasts.

Focusing on managers' conference call comments, Lee (2016) concludes that market participants infer negative information about future firm performance when managers appear to adhere to predetermined scripts when responding to questions during the Q&A. Mayew et al. (2020) find that manager dialogues with disfavored analysts during the Q&A are more informative. Finally, some research focuses on deception by management during conference calls (Larcker and Zakolyukina 2012; Burgoon et al. 2016).

We are interested in individual analysts' behavior on firms' conference calls. While conference calls are just one way in which analysts gather information about firms, we assume that individual analysts' interactions with managers and information-gathering activities on public conference calls might provide clues about how these same analysts gather information in other settings. In particular, we focus on the uniqueness of the questions posed by an individual analyst during the Q&A portion of a firm's earnings conference call, relative to other analysts and to the management-provided narrative on the same call, as well as relative to the same analyst on the same firm's prior calls.

First, we consider the characteristics of individual analysts. Prior analyst-related research finds that individual analysts' outputs (including forecasts, recommendations, and target prices) vary with their characteristics. In particular, analysts with more experience and more resources, and those who forecast more frequently, generally provide higher-quality outputs (Mikhail, Walther, and Willis 1997; Clement 1999; Clement and Tse 2003). In our setting, we are interested in whether those characteristics are associated with the uniqueness of the individual analysts' questions. To some extent, we are interested both analysts' inputs (i.e., the unique information they collect about firms) and their outputs (e.g. their forecasts). We expect that analysts characteristics are likely related to whether they are willing and able to ask unique questions and, over time, vary the types and topics of questions that they may have for managers on public earnings conference calls.

RESEARCH QUESTION 1. *Does the uniqueness of individual analysts' questions on firms' earnings conference calls vary with analysts' characteristics?*

Second, we investigate the individual analyst's reaction to the conference call based on their information-gathering activities on the call. A firm's earnings conference call provides a public forum for the firm's management to discuss its recent earnings release, as well as to respond to the street's inquiries about the release and any other topics. Prior research finds that analysts revise their earnings forecasts following firms' earnings releases (Brown and Rozeff 1979). It is also likely that conference call participants, and in particular sell-side analysts, respond to the firms' quarterly earnings conference call by revising their forecasts. In our setting, we are interested in whether analysts are more likely to revise their forecasts when they participate in the call in a manner that differentiates themselves from other analysts on the same call, and from their own questions on prior calls by the same firm.

RESEARCH QUESTION 2. *Is the uniqueness of an individual analyst's question(s) on a firm's earnings conference call associated with the likelihood that the individual analyst revises their forecast?*

Prior research by Bowen et al. (2002) and Mayew et al. (2013) finds that analysts become more accurate following firms' conference calls, which suggests that conference calls provide useful information to analysts. We seek to build on this, by investigating whether analysts, by asking more unique questions, issue more accurate forecasts.

RESEARCH QUESTION 3. *Is the uniqueness of an individual analyst's question(s) on a firm's earnings conference call associated with the accuracy of the analyst's post-call earnings forecast?*

Finally, we consider the market reaction to the conference call, taking into account the extent to which analysts' questions differ on the call. That is, more analyst "disagreement" on the call could produce more information for investors, but could also be seen as more uncertainty and a lack of a consistent message coming from managers. Thus, conditional on the earnings news, the market could respond favorably to the additional information gathering activities of analysts or consider it a bad sign that analysts (and managers) cannot coalesce on a shared message for the quarter.

RESEARCH QUESTION 4. *To what extent, if any, does the market reaction to the conference call vary based on the uniqueness of analysts' questions?*

3. Research Design

3.1 Parsing procedures

To examine our research questions, we analyze and compare specific segments of text within the transcripts of earnings conference calls. This section describes the parsing procedures that were used to isolate and clean these segments of text.

The raw transcripts obtained from SeekingAlpha consist of four different sections: the section that identifies the participants on the call, the management prepared narrative (MPN), the question-and-answer (Q&A) with analysts, and the legal disclaimer. As they do not represent actual discussions on the call, we remove the identification section and the legal disclaimer. The identification section is defined as the text between the beginning of the transcript and the first statement by any speaker. The legal disclaimer is defined as the text between the last statement by any speaker and the end of the transcript. In most transcripts, the MPN and the Q&A are separated by the phrase "Question and Answer Session." In the instances where the phrase is not present, we set our parsing script to search for the second time that the operator speaks and parse out all words spoken by the operator.[6]

At this point, the parsing procedure yields two segments of text for each transcript: the MPN and the Q&A. In the MPN, the executives speak uninterrupted. Therefore, no further parsing is needed for the MPN. In the Q&A, an analyst asks a question, which is followed by the executive's answer. This pattern repeats until every analyst that wants to speak has the chance to do so or the time is up on the call. Every time the speaker changes in the Q&A, the transcript starts a new line of text with the speaker's name first and followed by the text of the speech (e.g., "John Smith: [Speech text]"). Because this study focuses on the analysts' behaviors in conference calls, the most important segments of text are those related to the analysts' questions in the Q&A. To identify a line of text as an analyst's question, we check to see if the speaker is listed as an analyst in the identification section. Because the speaker's names and the names in the identification section are not always exactly the same, we do both exact and fuzzy matches.

Once we match a line of text with an analyst, we collect the text as follows. All words spoken are considered to be part of the question, not just the sentence that ends in the question mark. Analysts typically raise several points to preface a question. These points are key to understanding the context of the question and the analyst's strategy to potentially influence the executive's answer. If two consecutive lines of text are from the same analyst, we consider both lines to be one question. The order that each analyst appears in the transcript is the order in which they speak in the actual conference calls.[7] This order is important for the computation of a variable of interest and a control variable described later in the paper.

[6] The operator typically speaks once at the beginning to welcome listeners and does not speak again until the Q&A and while they are an agent of the firm, they only facilitate the calls and do not speak about the firm's performance.
[7] We manually verify this assumption by downloading and listening to several audio files of conference calls.

For each transcript in the sample, the parsing procedure yields one text file for the MPN and one text file each for each unique analyst question. As the final parsing step, we remove the names of the speaker from the text as well as all stop words such as "the", "an", and "in" which would affect the measurement of the key variables of interest described in the next section.

3.2 Variables of interest

To capture the uniqueness of an analyst's question, we compare an analyst's question during an earnings conference call to three items: the questions of other analysts on the same call that come before the original analyst's question, the same analyst on the same firm's previous calls, and the MPN on the same call.

To measure the statistical difference between the different strings of text, we use cosine similarity, a widely used methodology in computer science (Salton, Wong, and Yang 1975) and more recently in accounting and finance (Hoberg and Phillips 2010; Brown and Tucker 2011; Peterson, Schmardebeck, and Wilks 2015). The model converts text into a vector based on the unique words found in the text (after removing stop words). The value for a particular word in the vector is 1 if the stemmed word occurs in the text, and 0 if missing. Two different texts can then be compared by measuring the cosine of the angle between the vectors. The cosine's range is [0,1], where 0 means the two texts have no similarity, and 1 means the texts use identical words (Peterson et al. 2015). We use the cosine similarity measure to calculate the degree of similarity between the vectors of analysts' words on the earnings call and then invert them to analyze the differences (Brown and Tucker 2011).[8]

The first measure, *Differ_Others*, is the cosine similarity between the text of an individual analyst's question and the text of the questions of all other analysts on the same call that come

[8] As noted in prior research, however, there are some limitations to this relatively objective and intuitive measure. The most apparent limitations are: 1) it is insensitive to semantics, in that the use of words with similar meanings will result in non-matches, 2) it is based on words, not phrases, and 3) it treats every word as equally important.

before the original analyst's question. Because *Differ_Others* is intended to capture the extent that analysts "copy" each other, we only consider the questions of other analysts that each analyst can observe (i.e., questions that already occur). In the computation of *Differ_Others*, all other valid analysts' questions are consolidated into one string of text. The second measure, *Differ_Self*, is the cosine similarity between the text of an individual analyst's question and the text of the same analyst's question on the most recent previous earnings conference call of the same firm. For example, John Smith's question in the conference call of Apple in quarter 3 of year 2010 will be compared to John Smith's question in the conference call of Apple in quarter 2 of year 2010. We set the script to go back only as far as a calendar year. In the example above, the oldest conference call transcript that the program searches for a question from John Smith is quarter 3 of year 2009. We set this restriction because questions that are more than a year apart are unlikely to address the same financial issues. The third and final measure, *Differ_MPN*, is the cosine similarity calculated by comparing the analyst's words on the firm's conference call with the words spoken by management on the same call during the MPN. We consider only executives' words in the MPN and exclude all words spoken by the executives in the Q&A.

3.3 Regression models

To investigate our first research question, we estimate versions of the following equation:

$$Differ_{i,j,q,t} = \beta_0 + \Sigma\beta(AnalystCharacteristics)_{i,j,t} + \Sigma\beta(FirmCharacteristics)_{j,q,t} + \Sigma\beta(CallCharacteristics)_{q,t} + \Sigma\beta(Year_t) + \Sigma\beta(Quarter_q) + \Sigma\beta(Firm_j) + \varepsilon_{i,j,q,t} \quad (1)$$

In all equations presented in this section, the subscripts *i, j, q,* and *t* denote analyst, firm, quarter and year, respectively. The dependent variable *Differ* represents one of the three measures of analyst's uniqueness described in section 3.2: *Differ_Others*, *Differ_Self,* and *Differ_MPN*. Thus, there are three different iterations of equation (1). The unit of observation for equation (1) is an analyst-firm-quarter. We include fixed effects for firm, year, and fiscal quarter. Control variables are discussed below.

Our first research question relates to the association between analysts' data gathering activities and their fundamental characteristics. Thus, we include as our variables of interest four analyst characteristic measures common to the analyst literature (Mikhail et al. 1997; Clement and Tse 2005). Specifically, $Bsize_{i,t}$ is the number of analysts appearing in I/B/E/S during year *t* from analyst *i*'s brokerage house. $Fexp_{i,j,t}$ is the number of consecutive years for which analyst *i* appears in I/B/E/S following firm *j* as of year *t*. $Freq_{i,j,t}$ is the number of EPS forecasts that analyst *i* issues for firm *j* during year *t*. $Nfirms_{i,t}$ is the number of firms followed by analyst *i* in I/B/E/S during year *t*.

In this initial determinants analysis we control for firm characteristics including the earnings surprise for the quarter (*SUE*), firm size (*Size*), book-to-market ratio (*BtM*), leverage (*Lev*), the standard deviation of analysts' earnings forecasts (*STD*), analyst following (*AF*), and return on assets (*RoA*). Further, we control for characteristics of the conference call including tone, the number of words spoken, and each analyst's position on the call that might be associated with our main variables of interest. $PositionPerc_{i,j,q,t}$ is analyst *i*'s position on the call (i.e., the order in which he/she asks a question) relative to and as a percentage of all analysts.[9] $Analyst\_WC_{i,j,q,t}$ is the total word count for analyst *i* on the call. $AnNetOpt_{i,j,q,t}$ is the net analyst optimism on the call (i.e., the total number of positive words less negative words spoken by all analysts on the call, divided by total positive and negative words combined). $AdjAnNetOpt_{i,j,q,t}$ is analyst *i*'s optimism on the call, adjusted for net analyst optimism on the call.

[9] When the analyst speaks more than once during the Q&A session, we use the average of his/her appearances in the order.

Finally, because the cosine similarity technique used to compute the *Differ* variables is susceptible to influence by the length of the referent texts, we include various "length" variables as controls. $AnTotalCount_{i,j,q,t}$ is the natural log of the total number of words spoken by all other analysts, excluding analyst *i*, on firm *j*'s call. $RelSelfCount_{i,j,q,t}$ is the natural log of the total number of words spoken by analyst *i* on the previous call for firm *j*. $MPNWordCount_{i,j,q,t}$ is the natural log of the total number of words spoken during the management-prepared narrative on the call for firm *j*. Thus, *AnTotalCount*, *RelSelfCount,* and *MPNWordCount* are essentially the word counts of the string of text that the analyst's question is compared to for each of the *Differ* variables.

To investigate our second research question, we estimate the following equation:

$$Revise_{i,j,q,t} = \beta_0 + \beta_1 Differ_{i,j,q,t} + \beta_2 |SUE|_{j,q,t} + \Sigma\beta_3 Differ \times |SUE| + \Sigma\beta(AnalystCharacteristics)_{i,j,t} + \Sigma\beta(FirmCharacteristics)_{j,q,t} + \Sigma\beta(CallCharacteristics)_{q,t} + \Sigma\beta(Year_t) + \Sigma\beta(Quarter_q) + \Sigma\beta(Firm_j) + \varepsilon_{i,j,q,t} \quad (2)$$

In equation (2), the dependent variable $Revise_{i,j,q,t}$ refers to an indicator variable that takes the value 1 if analyst *i* revises their forecast of the upcoming fiscal year's earnings for firm *j* in a 14-day window following the earnings conference call for firm *j* that takes place during quarter *q* of year *t*. Thus, we compare the analyst's latest forecast in a 14 day window following the earnings conference call with the same analyst's latest forecast made preceding the same earnings conference (and also preceding the earnings release associated with the conference call), while taking care that the latter forecast is made following the preceding quarter's earnings release. In addition, we analyze the analyst's signed revision relative to the differ variables, using the following equation:

$$Revision_{i,j,q,t} = \beta_0 + \beta_1 Differ_{i,j,q,t} + \beta_2 |SUE|_{j,q,t} + \Sigma\beta_3 Differ \times |SUE| + \Sigma\beta(AnalystCharacteristics)_{i,j,t} + \Sigma\beta(FirmCharacteristics)_{j,q,t} + \Sigma\beta(CallCharacteristics)_{q,t} + \Sigma\beta(Year_t) + \Sigma\beta(Quarter_q) + \Sigma\beta(Firm_j) + \varepsilon_{i,j,q,t} \quad (3)$$

In equation (3), the dependent variable $Revision_{i,j,q,t}$ represents analyst *i*'s signed revision of their forecast of the upcoming fiscal year's earnings for firm *j* made in a 14-day window following the earnings conference call for firm *j* that takes place during quarter *q* and year *t* and scaled by price. For non-revising analysts (where *Revise* equals zero), we set *Revision* equal to zero as well. In both equation (2) and equation (3), we include the interactions between the *Differ* variables and the absolute value of *SUE*, the earnings surprise for the quarter. We do this as it is likely that analysts' data gathering activities on a call and their subsequent forecast activities vary with the extent of earnings news being discussed on the conference call. To aid interpretation of the interaction terms, we dichotomize the *Differ* variables. Whenever the dichotomous versions of *Differ* are used, they are denoted with an *I* suffix in the tables. All other elements of equation (2) and (3) are similar to those previously discussed with equation (1).

To investigate our third research question, we estimate the following equation:

$$Accuracy_{i,j,q,t} = \beta_0 + \beta_1 Differ_{i,j,q,t} + \beta_2 |SUE|_{j,q,t} + \Sigma\beta_3 Differ \times |SUE| + \Sigma\beta(AnalystCharacteristics)_{i,j,t} + \Sigma\beta(FirmCharacteristics)_{j,q,t} + \Sigma\beta(CallCharacteristics)_{q,t} + \Sigma\beta(Year_t) + \Sigma\beta(Quarter_q) + \Sigma\beta(Firm_j) + \varepsilon_{i,j,q,t} \quad (4)$$

In equation (4), the dependent variable $Accuracy_{i,j,q,t}$ represents the accuracy of an analyst's earnings forecast following a firm's conference call, which is calculated as the difference between actual earnings for the upcoming year and the analyst's forecast of those earnings, made in the same 14-day window following the conference call, scaled by price and multiplied by -1 so that the measure is increasing in accuracy relative to actual earnings. All other elements in equation (4) are as previously discussed.

To investigate our fourth research question, we estimate versions of the following equation:

$$CAR_{j,q,t} = \beta_0 + \beta_1 Differ_{i,j,q,t} + \beta_2 |SUE|_{j,q,t} + \Sigma\beta_3 Differ \times |SUE| + \Sigma\beta(AnalystCharacteristics)_{i,j,t} + \Sigma\beta(FirmCharacteristics)_{j,q,t} + \Sigma\beta(CallCharacteristics)_{q,t} + \Sigma\beta(Year_t) + \Sigma\beta(Quarter_q) + \Sigma\beta(Firm_j) + \varepsilon_{i,j,q,t} \quad (5)$$

In equation (5), the dependent variable $CAR_{j,q,t}$ is the three-day abnormal return for the days preceding, including, and following the conference call. We investigate the association between the market response to analysts' unique questions on the conference call by regressing the three-day, market-adjusted cumulative abnormal return surrounding the conference call date (the day before, the day of, and the day after) on a summed inverse measure of analyst cosine similarity. Equation (5) is the first instance in the study in which we no longer investigate only analysts' characteristics and/or behaviors in and out of the conference calls. $CAR_{j,q,t}$ is a measure of the reaction of equity investors, a different set of stakeholders. Because equity investors have financial stakes in the firms, it is likely that the nature of the news (i.e., the sign of the earnings surprise) influences their reactions. Thus, we estimate three versions of equation (5): the whole sample, the sample with positive *SUE*, and the sample with negative *SUE*. All other elements in equation (5) are as previously discussed.

3.4 Sample Construction

To form the sample, we obtained 99,902 conference call transcripts from SeekingAlpha from 2004 to 2017. From this group, we perform several screens to maintain data integrity. First, many transcripts contain only a webcast link without the actual text of the calls. Therefore, these webcast transcripts are deleted. Second, we retain only earnings conference call transcripts and delete transcripts of other types of conference calls.[10] Finally, each earnings call transcript on SeekingAlpha is identified by company name, stock ticker, year, and quarter. To ensure appropriate matching, we delete all observations without all key identifiers.

We then match the names of the analysts who ask questions during the Q&A portion of the calls to analysts providing forecasts in I/B/E/S, based on the analyst's name and broker name, which we obtain by matching the broker translation file to the I/B/E/S detailed forecast file

[10] Special conference calls that do not follow earnings release typically occur because of a major event (merger, litigation, etc.). Because they do not follow the typical format of an earnings conference call, they represent noise in the analysis if included.

downloaded during March 2018.[11] Given the challenges in matching names between I/B/E/S, we limit the sample to those analysts whom we can match with some degree of certainly (i.e., a match on analyst name as well as affiliation). As in other conference call studies, we observe only the analysts who participate on the call, and not the analysts who listen to the call without asking questions (Mayew 2008).

From I/B/E/S, we obtain the necessary data to measure analysts' characteristics (experience, forecast frequency, broker size, and number of firms followed) as well as whether analysts revise their forecast following the earnings conference call. From CRSP, we obtain market returns. From Compustat, we extract firm characteristics. Appendix B provides a detailed description of the sample selection process. Panel B describes the analyst-call sample that is used in the main analyses. Panel C describes the call-level sample that is used in the additional analysis.

4. Descriptive statistics and empirical results

4.1 Descriptive analysis

Summary statistics for our variables of interest are included in Table 1. We observe that analysts generally ask questions that differ from each other, from their prior questions on earlier calls, and from managements' prepared narrative. Specifically, mean (median) values of *Diff_Others*, *Diff_Self*, and *Diff_MPN* are 0.739 (0.739), 0.767 (0.772), and 0.808 (0.816), respectively. The analysts we are able to identify on the call come from brokerage houses with an average of 75.040 brokers, have an average of 4.956 years forecast experience for firm *j*, issue an average of 5.861 forecasts a year for firm *j*, and cover on average 17.989 unique firms. On average analyst asks questions with 69.269 words (the mean of *Analyst_WC* presented in Table 1 has been converted using natural logarithm), which suggests that analysts often setup their questions with

[11] According to Wharton Research Data Services (WRDS), Thomson Reuters began randomizing some analyst codes in October 2018. Thus, we rely only on detailed forecasts and individual analyst codes obtained prior to that date. We thank Stephannie Larocque for access to downloaded data before the randomization occurred.

some context and/or interject statements into their questions, seeing as this is approximately the length of the average paragraph.

Table 1 further reports that there is an analyst revision of more than a penny in nearly half (47.2 percent) of the analyst-firm-quarter observations in our sample and the revision is on average a downward revision of about 0.068 percent of share price. Finally, the average (median) earnings surprise is slightly negative (equal) when comparing the actual reported earnings to pre-call forecasted amounts. That is, firms usually just barely meets or beats (*SUE*) the estimates forecasted by analysts prior to the conference call. This is noteworthy as we later condition analysts' news gathering activities on the earnings news.

Correlations among our variables of interest are included in Table 2. We observe that the three *Differ* variables are positively correlated, which is expected as each of the measure is the cosine similarity that is based on the same analyst's question. There is some evidence of significant correlations between the *Differ* variables and the analyst characteristic variables (i.e., *Fexp*, *Freq*, *Bsize*, and *Nfirms*) as well as between the *Differ* variables and the revision variables (i.e., *Revise* and *Revision*) and the accuracy variable, *Accuracy*. At the same time, it is important to control for both conference call and firm characteristics when investigating these associations. We thus proceed to the multivariable regression analyses.

4.2 Results

To examine our first research question, whether the uniqueness of individual analysts' questions on firms' earnings conference calls varies with analysts' characteristics, we estimate equation (1). The results from this estimation are presented in Table 3. Columns 1 through 3 evaluate the association between each of the three differ variables and analysts' characteristics, controlling for conference call and firm characteristics. Beginning with *Differ_Others* in column 1, we observe positive and significant coefficients on each of *Fexp* and *NFirms* and negative and significant coefficients on each of *Freq* and *Bsize*. For *Differ_Self* in column 2, we observe a positive and significant coefficient on *Fexp* as well as a negative and significant coefficient on *Bsize*. For *Differ_MPN*, in column 3, we observe negative and significant coefficients on each of *Freq* and *Bsize*, and a positive and significant coefficient on *Nfirms*. Thus, it appears that experienced analysts ask more unique questions across the same firm's calls and relative to other analysts on the same call. The questions posed by analysts from bigger brokers and analysts who forecast more frequently are less unique. Finally, there is some evidence that analysts who follow more firms ask questions that differ more from the management-provided narrative and from questions posed by other analysts on the same conference call.

We offer the following interpretations for the results in Table 3. First, analysts from bigger brokers and analysts who forecast more frequently ask less unique questions potentially because they want to protect their private information. Analysts from bigger brokers have more channels to acquire information from management, such as broker-hosted conferences (Chapman and Green 2018). Analysts that are able to revise their forecasts more frequently likely also acquire new information more frequently. Both of these types of analysts are interested in protecting their informational advantage during conference calls, but they still want to ask a question in the Q&A to keep their places in future calls. Thus, they ask less unique questions. On the other hand, analysts that have more experience, provide more forecasts for the same firm, and forecasts for more other firms ask more unique questions because they have a broader experience to draw from to formulate their questions. These analysts are aware of what questions are typically asked in past calls for the same firm or on calls of related firms. Therefore, they are able to prepare more unique questions to complete their information mosaic on firms (without potentially revealing their own private information with respect to the firms' underlying performance).

Besides analysts' characteristics, the control variables in Table 3 also show what other factors determine the uniqueness of analysts' questions in conference calls. The coefficients on most of the firm-level variables are insignificant. Given that we include firm-fixed effects in the regression, this suggests that *changes* to firm-level characteristics do not appear to influence the uniqueness of analysts' questions in conference calls. Therefore, uniqueness appears to be driven more by the analysts themselves than by the nature (or the changing nature) of the firms they follow. On the other hand, all of the call characteristics show significant associations with the *Differ* variables. Some of these associations are partly mechanical, specifically those related to *Analyst_WC*, *AnTotalCount*, *RelSelfCount*, and *MPNWordCount*. As we previously mention, cosine similarity is influenced by the length of the strings of text being compared, which these variables are meant to capture. Analyst's net optimism on the call (*AnNetOpt*) is increasing with *Diff_Others* and *Diff_Self* but decreasing with *Diff_MPN*. The optimism of all analysts on the call is likely a proxy for the news surrounding the call. When the news is good, analysts can use similar questions as there are no pressing issues to address. The negative association with *Diff_MPN* is likely caused by management needing to speak less when the news is good, reducing the length of the MPN and thus the associated cosine similarity. Analyst's individual optimism on the call (*AdjAnNetOpt*) is increasing with *Diff_Others* but decreasing with *Diff_Self* and *Diff_MPN*. The positive association with *Diff_Others* makes sense because if an analyst feels differently about the firms relative to other analysts, their questions should also differ. On the other hand, an analyst bullish about a firm's prospects is unlikely to feel the need to change their approach or to disagree with management. Finally, *PositionPerc* is positively associated with all three *Differ* variables. The later an analyst is in the question queue, the more likely they are to ask a question that has already been asked, to resort to past questions, and to mention an issue that management has already addressed.

To examine our second research question, whether the uniqueness of an individual analyst's question(s) on a firm's earnings conference call is associated with the likelihood that the individual analyst revises their forecast, we estimate equation (2). The results from this estimation are presented in Table 4. We observe that the likelihood that an analyst revises their forecast following the earnings conference call is increasing in *Diff_Self* and in *Diff_MPN*. Thus, it appears that analysts who ask more unique questions are more likely to update their forecasts following the conference call. Furthermore, the interaction terms between these two variables and absolute earnings surprise are also positive and significant. Analysts who ask more unique questions are even more likely to revise their forecasts following the conference call if the magnitude of earnings surprise is greater.

To further examine the second research question, whether analysts' information gathering activities are associated with revisions, we estimate equation (3) which is focused on the signed magnitude of analysts' revisions. The results from this estimation are presented in Table 5. We observe that an analyst's forecast revisions following the earnings conference call are increasing in *Diff_Self* and *Diff_MPN* when interacted with the quarter's absolute earnings surprise. Thus, when the earnings surprise is greater, analysts whose questions are more unique also revise their forecasts to a greater extent. When there is no earnings surprise, we find a marginally negative coefficient on *Diff_Self*. This suggests that when analysts ask more unique questions relative to their prior questions, and there is no earnings surprise, they are likely to make smaller forecast revisions following the call. Overall, results in both Table 4 and Table 5 suggest that analysts who ask more unique questions in conference calls react more strongly to earnings surprise, by both being more likely to revise their forecasts and by revising to a greater extent. Our interpretation of the results is that when analysts ask more unique questions, they are able to update their information more efficiently, perhaps by receiving a more informative response or by observing management's hesitancy to answer. We note that most results are stronger when earnings surprise is greater. This suggests that uniqueness of questions matter more when there is potentially additional information to uncover.

Other than the *Differ* variables, several other variables in our model also show associations with *Revise* and *Revision* in Table 4 and Table 5, respectively. Analysts that provide more forecasts for the firm and are from bigger brokers are more likely to revise their forecasts after the conference calls. Larger firms have their forecasts revised less often, whereas firms with higher leverage and higher volatility are more likely to have their forecasts revised after the calls. The absolute magnitude of the earnings surprise is by far the biggest driver of the magnitude of analysts' post-call revision. Analysts from bigger brokers revise for greater amount, while analysts that follow more firms issue smaller revisions.

To examine our third research question, whether the uniqueness of an individual analyst's question(s) on a firm's earnings conference call is associated with the accuracy of the analyst's post-call earnings forecast, we estimate equation (4). The results from this estimation are presented in Table 6. The coefficients on the *Diff_Others* and *Diff_Self* main effects are both positive and significant, which provides evidence that forecast accuracy is greater for the analysts whose questions on the call differ more from other analysts on the same call as well as from themselves in prior calls, when there is no earnings surprise. Furthermore, *Diff_Self* and *Diff_MPN*, when interacted with absolute earnings surprise, have positive and significant coefficients. Thus, analysts who ask questions that differ more from their peers' appear to be more accurate regardless of the earnings surprise. Analysts that ask different questions from the questions they ask in prior calls are more accurate in general and even more accurate when earnings surprise is greater. Finally, analysts who ask questions that are different from the MPN are only more accurate when there is an earnings surprise. Overall, results in Table 6 suggest that analysts who ask more unique questions in conference calls generally provide more accurate forecasts after the calls, potentially because they can extract more useful information from management. The variation in the results of the main effects and the interaction terms between the three *Differ* variables suggest that each variable might capture a different aspect of an analyst's willingness to publicly gather information from managers.

Table 6 also shows that analysts who have followed the firms for longer and who issue forecasts more frequently for the firm are less accurate. These somewhat surprising results are consistent with theories of analyst complacency and empirical results of analyst busyness espoused in the prior literature (Driskill, Kirk, and Tucker 2020). In term of firm characteristics, greater earnings surprise is associated with lower post-call accuracy. Analysts are more accurate for larger and more profitable firms but less accurate for firms that are undervalued by the market, more leveraged, and more volatile. Greater analyst following also appears to improve analyst's accuracy, suggesting that analysts can learn from each other.

Finally, to examine our fourth and final research question, whether the extent to which analysts' questions on a firm's earnings conference call differ is associated with the market's reaction to the conference call, we estimate equation (5). The results from this estimation are presented in Table 7. Column 1 presents the results with the full sample. Columns 2 and 3 present the results with the subsample with positive and negative earnings surprise, respectively. Column 1 and 2 shows that none of the interaction terms between the *Differ* variables and absolute earnings surprise are significant. Investors do not appear to react to the uniqueness of analysts' questions in conference calls when the news is good or at least neutral. On the other hand, all three interaction terms are significant in the subsample with negative earnings surprise. When analysts ask questions that differ from their own questions in prior calls (*Diff_Self*) and from the MPN (*Diff_MPN*), cumulative abnormal returns are decreasing with the magnitude of earnings surprise.

When earnings surprise is negative (i.e., the news is bad), managers have incentives to withhold information. These results suggest that analysts who ask questions that differ from their own questions in prior calls and from the MPN are able to push managers to release some of this information. As more negative news are disclosed in the call, investors react accordingly.

A somewhat surprising result in Table 7 is that the interaction between *Diff_Other* and absolute earnings surprise is positive and significant. When analysts ask questions that differ from other questions in the same call, with a negative earnings surprise, cumulative abnormal returns are *increasing* with the magnitude of earnings surprise. Questions that are different from other questions on the same call appear to help mitigate the impact of bad news on the firms' stock price. This result might be related to the phenomenon of casting as documented by (Cohen et al. 2020). When the news is bad, managers cast the call with positive analysts who can assist in introducing more positive talking points. These analysts' questions are different because other analysts likely focus on the negative earnings surprise. Thus, among observations with negative earnings surprise, questions that are unique relative to other questions in the same call might be indicative of friendly analysts.

5. Additional analysis

In our main tests, we investigate how the uniqueness of analysts' questions influence events that occur after the calls. This design is forced because analysts' forecast activities, such as revision and accuracy, are only observable after the call, even if they make the decision during the call. Nevertheless, a test that can demonstrate the real-time consequences of analysts' questions in the Q&A could yield valuable insights because conference calls are meant to be a "real-time" disclosure. Following Matsumoto et al. (2011), we use data from the NYSE Trade and Quote (TAQ) database to track stock prices during conference calls. Our aim is to examine whether and how stock returns during different sections of the conference calls vary with the uniqueness of analysts' questions. We note, however, that few calls happen during trading hours and so this investigation is on a relatively small subsample of the calls examined in the earlier analyses. Panel C of Appendix B describes this sample.

We follow the methods in Matsumoto et al. (2011), with only minor modifications to estimate the following regression:

$$DIFF\_RET = \beta_0 + \beta_1 RET\_B4 + \beta_2 Diff\_Others + \beta_3 Diff\_Self + \beta_4 Diff\_MPN + \varepsilon \qquad (6)$$

First, we calculate *RET_MPN* (*RET_QA*) as the difference between the quote midpoint at the start of the presentation (Q&A) and the quote midpoint at the end of the presentation (Q&A), scaled by the quote midpoint at the start of the presentation (Q&A). Then, *ABRET_MPN* (*ABRET_QA*) is computed as *RET_MPN* (*RET_QA*) less the median value of all returns measured during the same time period on non-conference call days during the quarter. *ABRET_MPN* and *ABRET_QA* represent the abnormal returns during the MPN section and the Q&A section of a conference call, respectively. Finally, the dependent variable *DIFF_RET* is calculated as *ABRET_MPN* less *ABRET_QA*. *DIFF_RET* represents how much higher the abnormal returns in the MPN section is compared to the abnormal returns in the Q&A section.

The control variable, *RET_B4*, is calculated as the quote midpoint at the start of the conference call less the quote midpoint at the same time one trading day before the conference call, scaled by the quote midpoint one day prior. In addition, we include all three *Differ* variables in equation (6). The *Differ* variables in equation (6) are computed at the call-level, rather than the analyst-call level as in other regressions, because we can only capture stock returns over the entire Q&A. The approximation technique in Matsumoto et al. (2011) is not precise enough to capture how stock prices react to each question. The call-level versions of *Differ* are denoted by a *C* suffix. Following Matsumoto et al. (2011), we cluster the standard errors at the firm-level.

Results of estimating equation (6) are located in Table 8. Similar to Matsumoto et al. (2011), we also find that *RET_B4* has a positive and significant coefficient. We note again here that *DIFF_RET* is the dependent variable in the regression and represents, according to Matsumoto et al. (2011), how much more information is shared in the MPN section relative to the Q&A section. For our variables of interest, *Diff_Others* has a positive and significant coefficient, while *Diff_Self* and *Diff_MPN* have negative and significant coefficients. Thus, when analysts' questions on a call are different from each other, the firm's Q&A, relative to the MPN, is relatively *less* informative. On the other hand, when the questions in the Q&A are different from the MPN and from questions in prior calls, the firm has a more informative Q&A, relative to the MPN. Questions that differ from the MPN and from questions in prior calls likely push management to disclose information that they attempt to avoid disclosing in the MPN, which increases the information content of the Q&A section of the call. Analysts asking different questions from each other appears to, at least at the time the call is taking place, reduce the informativeness of the Q&A, potentially seeing that analysts are each doing their own individual information gathering and the complete mosaic is not immediately interpretable to the investors at the time. Overall, results in this additional analysis provide further evidence that the uniqueness of analysts' questions in conference calls has significant impact on investor's perception of the informativeness of the call and that analysts can alter that perception with their public data gathering activities.

6. Conclusion

We examine how analysts gather information based on their public interactions with firm managers. Specifically, we use measures of textual similarity to capture the uniqueness of an individual analyst's question(s) on a firm's quarterly earnings conference call relative to the questions of other analysts on the same call, relative to the same analyst's question in prior calls, and relative to the management-prepared narrative. We examine the associations between the uniqueness of analysts' questions and analysts' characteristics and observe that the uniqueness of individual analysts' questions varies systematically with analysts' experience, broker size, forecast frequency, and number of firms followed.

We then examine how differences across analysts' questions impact analysts' revisions and accuracy, and the market's reaction to the conference call, focusing particularly on the sign of the quarterly earnings surprise. We find that analysts' unique questions appear to be indicative of private information and data gathering activities as they are associated with their later behavior, that is, their revisions and the accuracy of those revisions. Finally, we find results consistent with analysts' differential questioning behavior leading to increased information in the market, particularly negative information when firms have negative earnings surprises, and with more informative Q&As during the earnings conference call.

Our paper contributes to the literature examining analysts' activity on firm conference calls and the quality of their reports. It also provides insights into the nuanced interactions between analysts, analysts' own behavior over time, and the interactions that analysts have with managers. We provide evidence that analysts' information gathering activities during earnings conference calls foreshadow analysts' forecasting behaviors after the call. Furthermore, our study documents a new and significant association between analyst characteristics and their public information gathering activities. Finally, our paper demonstrates that differential information gathering by analysts can influence the market's reaction to the earnings conference call.

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Appendix A: Variable Definitions

Differ Variables and Other Dependent Variables

Differ_MPN	One minus the cosine similarity calculated by comparing the analyst's words on the firm's conference call with the words spoken by management on the same call during the manager-provided narrative.
Differ_Others	One minus the cosine similarity calculated by comparing the analyst's words on the firm's conference call with the words of all other analysts on the same call.
Differ_Self	One minus the cosine similarity calculated by comparing the analyst's words on the firm's conference call with the same analyst's words said on the same firm's most recent conference call.
Revise	Indicator variable that equals one if *Revision* is greater than a penny (in either direction) and zero otherwise.
$Revision_{i,j,q,t}$	Analyst *i*'s signed revision of their forecast of the upcoming fiscal year's earnings for firm *j* made in a 14-day window following the earnings conference call for firm *j* that takes place during quarter *q* and year *t* and scaled by price.
Accuracy	The difference between actual earnings for the upcoming year and the analyst's forecast of those earnings, made in the same 14-day window following the conference call, scaled by price and multiplied by -1.
CAR	The three-day abnormal return for the days preceding, including, and following the firm's quarterly earnings conference call.

Analyst Characteristic Variables

$Bsize_{i,t}$	The number of analysts appearing in I/B/E/S during year *t* for analyst *i*'s brokerage house.
$Fexp_{i,t}$	The number of consecutive years for which analyst *i* appears in I/B/E/S following firm *j* as of year *t*.
$Freq_{i,j,t}$	The number of EPS forecasts that analyst *i* issues for firm *j* during year *t*.
$Nfirms_{i,t}$	The number of firms followed by analyst *i* in I/B/E/S during year *t*.

Call Characteristic Variables

$Analyst\_WC_i$	The natural log of the total word count for analyst *i* on the call.
$AdjAnNetOpt_i$	Analyst *i*'s optimism on the call, adjusted for net analyst optimism on the call.
AnNetOpt	The net analyst optimism on the call, calculated as the total number of positive words less negative words spoken by all analysts on the call, divided by total positive and negative words combined.
$AnTotalCount_{i,j}$	The natural log of the total number of words spoken by all other analysts, excluding analyst *i*, on firm *j*'s call.
$MPNWordCount_j$	The natural log of the total number of words spoken during the management-prepared narrative on the call for firm *j*

$PositionPerc_i$	Analyst i's position on the call (i.e., the order in which he/she asks a question) relative to and as a percentage of all analysts.
$RelSelfCount_{i,j}$	The natural log of the total number of words spoken by analyst i on the previous call for firm j.

Firm Characteristic Variables

$AF_{j,t}$	Analyst following, calculated as the natural log of the number of estimates provided for firm j in year t.
BtM	Book-to-market ratio, calculated as the book value of equity divided by the market value of the firm.
Lev	Leverage, calculated as total liability divided by total asset.
RoA	Return on assets, calculated as net income divided by average total asset of the previous two quarters.
Size	Firm size, calculated as the natural log of the market value of the firm.
STD	Standard deviation of analysts' earnings forecasts for the year.
SUE	Earnings surprise for the quarter, calculated as actual earnings minus the median forecasts by all analysts.

Appendix B: Sample Construction

Panel A – Earnings Calls Dataset

Number of conference call transcripts 2004-2017	99,902
Less: Webcast transcripts with no text	(532)
Less: Special conference calls	(2,675)
Less: No Q&A section	(1,879)
Less: Missing identifiers	(806)
Earnings Calls Dataset	94,010

Panel B – Analyst-Call Sample

Number of questions by analysts in all valid transcripts	785,125
Less: Questions from analysts whose names cannot be matched to I/B/E/S	(381,144)
Less: Questions without all three valid *Differ* measures	(160,969)
Less: No match in Compustat and CRSP	(78,727)
Less: Observations without all necessary independent variables	(98,858)
Analyst-Call Sample	65,427

Panel C – Call-Level Sample

Earnings Calls Dataset	94,010
Less: Calls that did not occur during trading hours	(72,152)
Less: No match in Compustat, I/B/E/S, CRSP, and TAQ	(4,213)
Less: Observations without all necessary independent variables	(5,510)
Call-Level Sample	12,135

Table 1 – Descriptive Statistics

Variable	N	Mean	Std. Dev	25th	Median	75th
Diff_Others	65,427	0.739	0.096	0.673	0.739	0.806
Diff_Self	65,427	0.767	0.107	0.696	0.772	0.845
Diff_MPN	65,427	0.808	0.084	0.755	0.816	0.869
Revise	65,427	0.472	0.499	0.000	0.000	1.000
Revision	65,427	-0.068	0.699	0.000	0.000	0.018
Accuracy	65,427	-1.269	2.255	-1.347	-0.434	-0.140
CAR	65,427	0.001	0.073	-0.036	0.001	0.039
Fexp	65,427	4.956	4.733	1.000	3.000	7.000
Freq	65,427	5.861	2.749	4.000	5.000	7.000
Bsize	65,427	75.040	61.688	26.000	59.000	112.000
Nfirms	65,427	17.989	7.424	14.000	17.000	22.000
SUE	65,427	0.001	0.007	0.000	0.000	0.002
|SUE|	65,427	0.004	0.009	0.000	0.001	0.003
Size	65,427	15.282	1.543	14.202	15.230	16.341
BtoM	65,427	0.489	0.410	0.228	0.389	0.652
Lev	65,427	0.566	0.232	0.407	0.564	0.727
ROA	65,427	0.012	0.029	0.003	0.012	0.024
STD	65,427	0.050	0.074	0.010	0.030	0.050
AF	65,427	2.462	0.606	2.079	2.565	2.890
Analyst_WC	65,427	4.238	0.635	3.932	4.304	4.644
AnTotalCount	65,427	5.658	0.789	5.142	5.778	6.258
RelSelfCount	65,427	4.355	0.562	4.025	4.382	4.718
MPN_WC	65,427	7.427	0.440	7.215	7.475	7.703
AnNetOpt	65,427	0.044	0.616	-0.360	0.000	0.430
AdjAnNetOpt	65,427	-0.120	1.772	-0.999	-0.128	0.712
PositionPerc	65,427	0.549	0.286	0.300	0.529	0.800

Table 1 provides the descriptive statistics for the regression variables.

Table 2
Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 - Diff_Others		0.34	0.34	-0.01	0.00	-0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.05	0.00	-0.01	0.00	0.02	0.03
2 - Diff_Self	0.33		0.22	-0.01	0.00	0.01	0.00	0.02	0.04	0.03	-0.01	0.02	-0.02	0.21	-0.05	0.03	0.04	0.00	0.25
3 - Diff_MPN	0.33	0.22		0.01	0.00	0.01	0.01	-0.02	0.00	0.00	0.02	0.01	-0.02	0.06	-0.02	-0.04	0.00	0.01	0.07
4 - Revise	-0.01	0.00	0.01		-0.04	0.01	-0.02	-0.03	0.04	-0.09	-0.03	0.00	0.03	-0.06	0.00	-0.06	-0.03	0.01	-0.02
5 - Revision	0.01	0.01	0.01	0.05		0.13	0.12	0.01	0.00	0.01	0.01	0.19	-0.03	0.04	-0.04	0.01	0.07	-0.02	0.03
6 - Accuracy	-0.02	0.02	0.01	0.03	0.06		0.02	0.03	-0.08	0.02	0.02	0.09	-0.36	0.19	-0.26	-0.03	0.14	-0.23	0.14
7 - CAR	0.00	-0.01	0.00	-0.02	0.27	0.01		0.00	-0.01	0.00	0.00	0.26	-0.02	0.01	-0.02	0.00	0.08	-0.04	0.01
8 - Fexp	0.01	0.02	-0.02	-0.04	0.02	0.05	0.00		0.02	0.03	0.10	0.00	-0.03	0.23	0.00	0.09	0.07	0.00	0.12
9 - Freq	0.01	0.04	0.00	0.05	-0.01	-0.13	-0.01	0.03		0.09	0.03	0.00	0.07	0.24	0.12	0.07	0.03	0.22	0.21
10 - Bsize	0.01	0.03	0.00	-0.09	0.01	0.03	0.00	0.02	0.11		0.12	0.00	-0.02	0.20	-0.01	0.11	0.04	0.03	0.13
11 - Nfirms	0.01	-0.02	0.02	-0.03	0.01	0.03	0.00	0.16	0.02	0.16		0.00	0.02	0.04	0.02	0.06	-0.04	0.05	0.03
12 - SUE	0.02	0.02	0.01	0.03	0.37	-0.04	0.36	0.00	0.00	-0.01	0.00		-0.13	0.03	-0.04	-0.02	0.12	-0.02	0.02
13 - |SUE|	0.02	-0.05	-0.03	0.09	0.06	-0.33	0.05	-0.05	0.09	-0.05	-0.01	0.36		-0.18	0.26	0.07	-0.17	0.49	-0.13
14 - Size	0.05	0.21	0.06	-0.06	0.06	0.23	0.01	0.21	0.23	0.23	0.04	-0.02	-0.28		-0.20	0.20	0.26	0.05	0.65
15 - BtoM	-0.01	-0.06	-0.03	0.01	-0.05	-0.26	-0.02	0.02	0.12	-0.03	0.03	0.04	0.31	-0.21		-0.04	-0.15	0.19	-0.14
16 - Lev	-0.01	0.02	-0.04	-0.06	0.01	0.02	0.00	0.08	0.08	0.13	0.07	0.00	0.05	0.20	-0.08		-0.08	0.10	0.09
17 - ROA	0.00	0.05	0.03	-0.03	0.10	0.19	0.10	0.06	0.01	0.03	-0.06	0.09	-0.24	0.27	-0.36	-0.23		-0.11	0.13
18 - STD	0.02	0.01	0.01	0.01	-0.04	-0.20	-0.05	0.01	0.27	0.04	0.04	0.02	0.35	0.11	0.21	0.21	-0.16		0.00
19 - AF	0.04	0.25	0.08	-0.02	0.04	0.18	0.01	0.13	0.22	0.15	0.04	0.00	-0.22	0.67	-0.16	0.08	0.18	0.03	
20 - Analyst_WC	-0.44	-0.38	-0.44	0.01	-0.02	-0.02	-0.01	0.04	0.01	0.02	0.02	-0.02	0.05	-0.10	0.08	0.03	-0.05	0.03	-0.16
21 - AnTotalCount	-0.41	0.04	0.12	0.01	0.00	0.05	-0.01	0.00	0.03	-0.02	-0.04	-0.02	-0.06	0.15	-0.03	0.03	0.05	0.01	0.18
22 - RelSelfCount	-0.20	-0.48	-0.17	0.01	-0.01	-0.05	0.00	0.04	0.00	-0.01	0.01	-0.01	0.07	-0.17	0.10	0.00	-0.05	0.03	-0.25
23 - MPN_WC	0.07	0.10	-0.09	0.01	-0.03	0.03	-0.02	0.03	0.06	0.06	-0.02	-0.02	-0.03	0.18	0.00	0.08	-0.05	0.02	0.14
24 - AnNetOpt	-0.11	-0.12	-0.02	-0.02	0.13	0.11	0.17	-0.01	-0.06	-0.02	0.05	0.11	-0.05	-0.03	-0.10	0.01	0.03	-0.07	-0.03
25 - AdjAnNetOpt	0.03	0.00	-0.01	0.00	0.00	0.00	-0.01	-0.01	0.00	0.00	-0.02	-0.01	0.00	0.01	0.00	0.00	-0.01	0.00	0.01
26 - PositionPerc	-0.31	0.00	0.09	0.02	-0.01	-0.02	0.00	-0.03	-0.06	-0.10	-0.05	0.00	0.03	-0.10	0.03	-0.02	-0.03	-0.01	-0.12

Table 2 (Continued)

	19	20	21	22	23	24	25
1 - Diff_Others	-0.45	-0.43	-0.20	0.06	-0.11	0.03	-0.30
2 - Diff_Self	-0.32	0.03	-0.49	0.09	-0.11	0.00	0.00
3 - Diff_MPN	-0.46	0.11	-0.17	-0.12	-0.02	-0.01	0.09
4 - Revise	0.00	0.01	0.01	0.01	-0.02	0.00	0.02
5 - Revision	0.01	0.00	0.00	-0.02	0.05	0.00	-0.01
6 - Accuracy	-0.23	0.14	-0.01	0.03	-0.04	0.00	0.11
7 - CAR	-0.01	-0.01	0.00	-0.02	0.17	0.00	-0.01
8 - Fexp	0.03	0.01	0.03	0.03	0.00	-0.01	-0.02
9 - Freq	0.01	0.02	0.01	0.02	-0.05	0.00	-0.06
10 - Bsize	0.02	-0.02	-0.01	0.04	-0.02	-0.01	-0.09
11 - Nfirms	0.02	-0.03	0.01	-0.02	0.06	-0.01	-0.04
12 - SUE	-0.01	-0.01	-0.01	-0.02	0.08	0.00	-0.01
13 - |SUE|	0.03	-0.03	0.04	0.00	-0.06	0.00	0.01
14 - Size	-0.08	0.14	-0.17	0.14	-0.03	0.01	-0.10
15 - BtoM	0.04	-0.03	0.08	0.03	-0.13	-0.01	0.02
16 - Lev	0.02	0.03	0.00	0.06	0.01	0.00	-0.02
17 - ROA	-0.02	0.04	-0.03	-0.02	0.03	0.00	-0.03
18 - STD	0.02	0.00	0.03	0.00	-0.08	0.00	0.00
19 - AF	-0.12	0.18	-0.25	0.11	-0.03	0.01	-0.13
20 - Analyst_WC		-0.09	0.37	0.00	0.04	0.00	-0.09
21 - AnTotalCount	-0.08		-0.02	-0.03	-0.01	-0.03	0.72
22 - RelSelfCount	0.45	-0.03		-0.05	0.03	0.00	0.00
23 - MPN_WC	-0.01	-0.03	-0.05		-0.05	0.01	-0.01
24 - AnNetOpt	0.05	-0.01	0.03	-0.06		-0.03	0.01
25 - AdjAnNetOpt	-0.01	-0.03	-0.01	0.01	-0.07		-0.03
26 - PositionPerc	-0.09	0.74	0.00	-0.02	0.01	-0.03	

Table 2 provides the correlations between the regression variables. Pearson correlations are above the diagonal. Spearman correlations are below.

Table 3
Determinants of Uniqueness of Analysts' Conference Call Questions

Variable	DV = *Diff_Others*	DV = *Diff_Self*	DV = *Diff_MPN*
	Coeff. (T-value)	**Coeff. (T-value)**	**Coeff. (T-value)**
Fexp	0.001***	0.001**	-0.001
	(3.471)	(2.308)	(-0.162)
Freq	-0.001***	-0.001	-0.001***
	(-3.530)	(-0.047)	(-3.548)
Bsize	-0.001***	-0.001**	-0.001**
	(-3.048)	(-2.299)	(-2.514)
Nfirms	0.001***	0.001	0.001***
	(3.486)	(0.077)	(5.978)
|*SUE*|	0.007	-0.015	-0.042
	(0.165)	(-0.25)	(-0.961)
Size	-0.002	-0.001	0.002
	(-1.308)	(-0.331)	(1.210)
BtoM	-0.003	-0.002	0.001
	(-1.250)	(-0.764)	(0.655)
Lev	0.001	-0.001	-0.002
	(0.096)	(-0.179)	(-0.401)
ROA	-0.012	-0.032	-0.030*
	(-0.686)	(-1.359)	(-1.729)
STD	-0.003	0.004	-0.003
	(-0.445)	(0.377)	(-0.412)
AF	0.003	0.012***	0.002
	(1.587)	(5.755)	(1.085)
Analyst_WC	-0.073***	-0.025***	-0.060***
	(-102.93)	(-27.855)	(-101.151)
AnTotalCount	-0.061***	-0.005***	0.003***
	(-74.96)	(-5.89)	(4.857)
RelSelfCount	-0.003***	-0.072***	0.001
	(-4.764)	(-78.326)	(1.453)
MPN_WC	0.005***	0.008***	-0.022***
	(3.087)	(4.707)	(-14.440)
AnNetOpt	-0.012***	-0.012***	0.001**
	(-19.125)	(-15.698)	(2.052)
AdjAnNetOpt	0.001***	-0.001***	-0.001*
	(3.332)	(-2.927)	(-1.776)
PositionPerc	0.009***	0.013***	0.009***
	(4.491)	(5.234)	(4.490)
Intercept	1.384***	1.118***	1.167***
	(52.441)	(35.858)	(45.328)
Fixed effects	Firm/Quarter/Year	Firm/Quarter/Year	Firm/Quarter/Year

N	65,427	65,427	65,427
Adjusted R^2	0.479	0.329	0.294

Note: The table above shows the following regressions:

$$Differ_{i,j,q,t} = \beta_0 + \Sigma\beta(AnalystCharacteristics)_{i,j,t} + \Sigma\beta(FirmCharacteristics)_{j,q,t} + \Sigma\beta(CallCharacteristics)_{q,t} + \Sigma\beta(Year_t) + \Sigma\beta(Quarter_q) + \Sigma\beta(Firm_j) + \varepsilon_{i,j,q,t}$$

We describe all variables in Appendix A. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 4
Probability of Revisions

Variable	DV = *Revise*	
	Coeff.	T-value
Diff_Others_I	-0.008	-1.573
Diff_Self_I	0.030***	6.738
Diff_MPN_I	0.020***	4.457
Diff_Others_I × |*SUE*|	-0.182	-0.425
Diff_Self_I × |*SUE*|	1.553***	3.862
Diff_MPN_I × |*SUE*|	2.314***	5.460
Fexp	0.000	-0.522
Freq	0.014***	13.857
Bsize	0.000***	-11.793
Nfirms	0.000	-0.721
|*SUE*|	0.147	0.366
Size	-0.027***	-3.021
BtoM	-0.005	-0.339
Lev	0.072**	2.236
ROA	0.006	0.052
STD	0.120**	2.150
AF	-0.006	-0.521
Analyst_WC	0.005	1.429
AnTotalCount	0.008	1.588
RelSelfCount	0.013***	3.010
MPN_WC	0.040***	4.329
AnNetOpt	-0.005	-1.418
AdjAnNetOpt	-0.002**	-2.051
PositionPerc	0.004	0.349
Intercept	0.240	1.474
Fixed effects	Firm/Quarter/Year	
N	65,427	
Adjusted R^2	0.136	

Note: The table above shows the following regressions:

$$Revise_{i,j,q,t} = \beta_0 + \beta_1 Differ_{i,j,q,t} + \beta_2 |SUE|_{j,q,t} + \Sigma\beta_3 Differ \times |SUE| + \Sigma\beta(AnalystCharacteristics)_{i,j,t} + \Sigma\beta(FirmCharacteristics)_{j,q,t} + \Sigma\beta(CallCharacteristics)_{q,t} + \Sigma\beta(Year_t) + \Sigma\beta(Quarter_q) + \Sigma\beta(Firm_j) + \varepsilon_{i,j,q,t}$$

We describe all variables in Appendix A. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 5
Analysts' Forecast Revisions

Variable	DV = *Revision*	
	Coeff.	**T-value**
Diff_Others_I	0.001	0.107
Diff_Self_I	-0.012*	-1.877
Diff_MPN_I	-0.002	-0.395
Diff_Others_I × |*SUE*|	-1.464	-0.816
Diff_Self_I × |*SUE*|	6.273***	3.821
Diff_MPN_I × |*SUE*|	5.246***	2.801
Fexp	0.000	0.348
Freq	-0.002	-1.031
Bsize	0.000***	3.183
Nfirms	-0.001**	-2.108
|*SUE*|	19.704***	10.001
Size	0.037**	2.011
BtoM	-0.093**	-2.263
Lev	-0.019	-0.342
ROA	1.303***	4.161
STD	-0.090	-0.546
AF	-0.014	-0.724
Analyst_WC	0.003	0.429
AnTotalCount	-0.014*	-1.829
RelSelfCount	-0.006	-0.900
MPN_WC	-0.076***	-4.962
AnNetOpt	0.098***	13.065
AdjAnNetOpt	0.002	1.316
PositionPerc	0.015	0.764
Intercept	0.001	0.365
Fixed effects	Firm/Quarter/Year	
N	65,427	
Adjusted R^2	0.182	

Note: The table above shows the following regressions:

$$Revision_{i,j,q,t} = \beta_0 + \beta_1 Differ_{i,j,q,t} + \beta_2|SUE|_{j,q,t} + \Sigma\beta_3 Differ\times|SUE| + \Sigma\beta(AnalystCharacteristics)_{i,j,t} + \Sigma\beta(FirmCharacteristics)_{j,q,t} + \Sigma\beta(CallCharacteristics)_{q,t} + \Sigma\beta(Year_t) + \Sigma\beta(Quarter_q) + \Sigma\beta(Firm_j) + \varepsilon_{i,j,q,t}$$

We describe all variables in Appendix A. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 6
Analysts' Forecast Accuracy

Variable	**DV = *Accuracy***	
	Coeff.	**T-value**
Diff_Others_I	0.040**	1.966
Diff_Self_I	0.038**	2.261
Diff_MPN_I	0.013	0.667
Diff_Others_I × |*SUE*|	1.121	0.311
Diff_Self_I × |*SUE*|	6.388*	1.713
Diff_MPN_I × |*SUE*|	13.297***	3.207
Fexp	-0.005***	-2.759
Freq	-0.023***	-5.490
Bsize	0.000	-1.629
Nfirms	-0.001	-0.899
|*SUE*|	-42.373***	-7.776
Size	0.746***	8.537
BtoM	-0.978***	-5.840
Lev	-1.102***	-3.750
ROA	2.240***	2.373
STD	-3.798***	-5.358
AF	0.151*	1.866
Analyst_WC	-0.002	-0.124
AnTotalCount	-0.010	-0.418
RelSelfCount	0.016	0.987
MPN_WC	-0.094	-1.359
AnNetOpt	0.090***	3.691
AdjAnNetOpt	0.003	0.805
PositionPerc	0.057	0.974
Intercept	-11.173***	7.469
Fixed effects	Firm/Quarter/Year	
N	65,427	
Adjusted R^2	0.492	

Note: The table above shows the following regressions:

$$Accuracy_{i,j,q,t} = \beta_0 + \beta_1 Differ_{i,j,q,t} + \beta_2|SUE|_{j,q,t} + \Sigma\beta_3 Differ \times |SUE| + \Sigma\beta(AnalystCharacteristics)_{i,j,t} + \Sigma\beta(FirmCharacteristics)_{j,q,t} + \Sigma\beta(CallCharacteristics)_{q,t} + \Sigma\beta(Year_t) + \Sigma\beta(Quarter_q) + \Sigma\beta(Firm_j) + \varepsilon_{i,j,q,t}$$

We describe all variables in Appendix A. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 7
Market Reactions Surrounding Quarterly Earnings Conference Calls

Variable	Full Sample	SUE >= 0	SUE < 0
	Coeff.	**Coeff.**	**Coeff.**
	(P-value)	**(P-value)**	**(P-value)**
Diff_Others_I	0.016***	0.002**	-0.002
	(0.001)	(0.012)	(0.160)
Diff_Self_I	0.002	-0.001	0.001
	(0.475)	(0.889)	(0.507)
Diff_MPN_I	0.001	-0.001	-0.001
	(0.840)	(0.588)	(0.477)
Diff_Others_I × |*SUE*|	0.088	-0.209	0.245**
	(0.853)	(0.125)	(0.012)
Diff_Self_I × |*SUE*|	0.038	0.064	-0.245**
	(0.936)	(0.586)	(0.012)
Diff_MPN_I × |*SUE*|	0.298	0.127	-0.375***
	(0.610)	(0.247)	(0.001)
Fexp	-0.001	0.001	-0.001
	(0.439)	(0.739)	(0.249)
Freq	-0.001	0.001	0.001**
	(0.293)	(0.389)	(0.013)
Bsize	-0.001	-0.001*	0.001
	(0.828)	(0.089)	(0.166)
Nfirms	-0.001	-0.001**	0.001
	(0.347)	(0.046)	(0.412)
|*SUE*|	-0.229	1.131***	-0.601***
	(0.676)	(0.000)	(0.000)
Size	-0.001	-0.004***	0.008***
	(0.318)	(0.000)	(0.000)
BtoM	0.003***	0.006***	0.007***
	(0.010)	(0.000)	(0.001)
Lev	0.005**	0.005**	0.012***
	(0.038)	(0.04)	(0.005)
ROA	0.199***	0.171***	-0.013
	(0.000)	(0.000)	(0.727)
STD	-0.029***	-0.060***	0.029**
	(0.000)	(0.000)	(0.017)
AF	0.002*	0.002	-0.004**
	(0.051)	(0.11)	(0.043)
Analyst_WC	0.001	-0.001	-0.001
	(0.721)	(0.46)	(0.317)
AnTotalCount	-0.001	-0.001	-0.003**
	(0.193)	(0.932)	(0.035)
RelSelfCount	0.001	0.001	0.001
	(0.34)	(0.26)	(0.415)
MPN_WC	-0.003**	-0.001	-0.006***
	(0.012)	(0.313)	(0.004)
AnNetOpt	0.021***	0.016***	0.018***
	(0.000)	(0.000)	(0.000)

AdjAnNetOpt	0.001	0.001	0.001*
	(0.417)	(0.608)	(0.071)
PositionPerc	0.003	-0.001	0.007**
	(0.177)	(0.624)	(0.037)
Intercept	-0.002	0.069***	-0.119***
	(0.891)	(0.000)	(0.000)
Fixed effects	Firm/Quarter/Year	Firm/Quarter/Year	Firm/Quarter/Year
N	65,427	45,225	20,202
Adjusted R^2	0.039	0.045	0.075

Note: The table above shows the following regressions:

$$CAR_{j,q,t} = \beta_0 + \beta_1 Differ_{i,j,q,t} + \beta_2 |SUE|_{j,q,t} + \Sigma \beta_3 Differ \times |SUE| + \Sigma \beta(AnalystCharacteristics)_{i,j,t} + \Sigma \beta(FirmCharacteristics)_{j,q,t} + \Sigma \beta(CallCharacteristics)_{q,t} + \Sigma \beta(Year_t) + \Sigma \beta(Quarter_q) + \Sigma \beta(Firm_j) + \varepsilon_{i,j,q,t}$$

We describe all variables in Appendix A. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 8
Real-time Stock Market Reactions

Variable	**DV = *DIFF_RET***
	Coeff. (P-value)
RET_B4	0.010**
	(0.045)
Diff_Others_C	0.009***
	(0.000)
Diff_Self_C	-0.005***
	(0.001)
Diff_MPN_C	-0.010***
	(0.000)
Intercept	0.003
	(0.103)
Fixed effects	None
N	12,135
Adjusted R^2	0.005

Note: The table above shows the following regressions:

$$DIFF\_RET = \beta_0 + \beta_1 RET\_B4 + \beta_2 Diff\_Others + \beta_3 Diff\_Self + \beta_4 Diff\_MPN + \varepsilon$$

We describe all variables in Appendix A. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.