Analyst Conflict of Interest and Earnings Conference Call Informativeness

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Abstract

We examine the informativeness of dialogues between managers and analysts during earnings conference calls. We distinguish between favored and disfavored analysts who face different conflict of interest levels when dealing with management. Favored analysts curry favor with management by providing favorable recommendations and achievable earnings forecasts. While market participants may dismiss dialogues with favored analysts as biased and uninformative, it is also possible that favored analysts enjoy more private access to management leading to more informative dialogues. Using intra-day absolute stock price reactions around specific analyst-manager dialogues to proxy for informativeness, we find that manager dialogues with disfavored analysts are more informative. Analysis of dialogue characteristics reveals that disfavored analysts elicit information from management by engaging in longer dialogues with more back-and-forth iterations relative to favored analysts. Stock prices directionally respond to both the analyst's linguistic tone and the manager's voice pitch. While favored analysts exhibit a more positive tone compared to disfavored analysts, managers reduce their voice pitch to signal dominance regardless of how favored the analyst is. We find no evidence that disfavored (favored) analysts systematically drive stock prices down (up). Overall, the capital market effects of earnings conference calls are far more nuanced than previously documented.

Key words: Conference Calls, Financial Analysts, Favored Analysts, Price Formation, Market Microstructure, Conflict of Interest

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1. Introduction

Academics and regulators have long been interested in how conflicts of interest impact sell side analysts (Mehran and Stulz 2007). In this paper, we focus on the informativeness of publicly broadcasted earnings conference call interactions between analysts and managers. We specifically examine whether the capital market responds differently to analyst-manager dialogues based on whether an analyst is favored or disfavored by management. Our investigation is motivated by research showing that sell side analysts overall are responsible for much of the informativeness of earnings conference calls (Matsumoto, Pronk, and Roelofsen 2011) and by SEC concerns about analyst conflicts of interest in the conference call setting (Cox 2005; Smith, Alfonso, and Hogan 2018). How informative the capital market finds conference call dialogues of favored and disfavored analysts is unclear as there are three possibilities.

First, one might expect a weaker response to favored analyst dialogues relative to disfavored analysts. This prediction follows from research documenting that the capital market is adept at identifying analyst conflicts of interest as evidenced by investors discounting favorable stock recommendations issued by analysts facing institutional investor (Gu, Li, and Yang 2013) or investment banking (Agrawal and Chen 2008) pressure.

In contrast, one might expect precisely the opposite, whereby investors respond more strongly to dialogues from favored analysts. This opposing prediction stems from the source of the conflict of interest. When facing institutional investor (investment banking) conflicts, analysts inject bias into their work product in exchange for trading commissions (investment banking fees). When managers serve as the source of the conflict, analysts curry favor in exchange for access to management's information. Research documents that favored analysts obtain more *private* access to management (Soltes 2014), and such private access results in both more accurate earnings forecasts and stronger price responses to analyst outputs (Chen and Matsumoto 2006; Green, Jame, Markov, and Subasi 2014). These findings imply that the bias analysts might inject into their work product to curry favor and obtain managerial access is outweighed by the informational benefits they receive from the access itself (Ke and Yu 2006). During a conference call, both favored and disfavored analysts obtain *public* access to management. However, if favored analysts have developed a deeper understanding of the firm through their private access to management, they may ask questions that are more informative and elicit answers that are more informative to market participants during the conference call.

The third possibility is that there may be no observable differences in capital market responses to dialogues with favored and disfavored analysts. Examining conference call dialogue differences is conditional on managers already allowing the analyst through the question queue. Prior research (Mayew 2008) has established that managers are more (less) likely to engage in public conference call dialogues with more favorable (unfavorable) analysts. Given this preferential treatment, whether meaningful heterogeneity remains among the analysts who are allowed to publicly speak with managers is unclear.

To empirically assess these competing predictions, we hand-collect a sample of 19,605 analyst-manager dialogues, which contain more than 215,000 turns-at-talk, from 2,455 earnings calls.[1] Our sample requires the manual identification of the point in time where one manager-analyst interaction ends and the next one begins, by restreaming, recording, and listening to the audio broadcast of each conference call.[2] Using intra-day stock price data at each manager-analyst changeover, we assess how stock prices change as managers speak with individuals in the conference call question and answer session. Following prior research, we classify how favored a given sell-side analyst is likely to be in the eyes of management based on both the stock recommendation of the analyst immediately prior to the call (Chen and Matsumoto 2006) and whether the analyst provided an achievable quarterly earnings forecast (Ke and Yu 2006). Analysts with buy or strong buy (hold, sell, or strong sell) recommendations and whose earnings forecasts are met or beaten (missed) are classified as favored (disfavored) analysts. Analysts with favorable (unfavorable)

[1] A "turn-at-talk" is a continuous stream of words spoken by a single participant in the call (analyst or a manager).
[2] Inferring manager-analyst changeover times from conference call transcripts is problematic for conducting intraday analysis because transcripts purge operator instructions and do not provide information on speech rates or pauses during discourse. These issues make it difficult to precisely identify the point of changeover between speakers, and in turn the ability to identify the appropriate intra-day price for analysis. This necessitates the manual parsing of audio files.

stock recommendations but whose forecasts were missed (met or exceeded) are categorized as intermediate cases in terms of currying favor with management.

Using the absolute stock return observed during the manager-analyst dialogue as our measure of informativeness, we find that favored analysts elicit market reactions that are smaller in magnitude when compared to disfavored analysts. The two intermediate cases exhibit market responses that are similar in magnitude and fall in between the magnitudes observed for the favored and disfavored cases. These results suggest that informativeness is decreasing in how favorably the manager views the analyst, which is more consistent with market participants discounting the dialogues of conflicted analysts rather than conflicted analysts generating dialogues with more information.

That our evidence suggests disfavored analyst dialogues are more informative does not, however, tell us what factors drive the differential informativeness. We therefore consider whether disfavored analysts generate dialogues that contain a higher *quantity* of value relevant information or information of higher *credibility*, both of which could generate a heightened market response. Regarding the quantity of value relevant information, we acknowledge that identifying important topical issues for a given firm in a given quarter is very subjective, and so we choose four proxies that do not require researcher discretion. The first proxy is the length of the dialogue, which the extant literature uses to proxy for information content (Matsumoto et al. 2011; Frankel, Mayew, and Sun 2010). The second proxy is an indicator for whether or not the dialogue contains forward-looking guidance. Forward-looking information has been shown to be more value relevant in the sense that stock prices respond more to forward-looking than backward looking information (Li 2010). We are able to precisely ascertain whether a given dialogue contains guidance by cross-referencing dialogue content to Thomson Reuters Guidance Reports. The third proxy is the order in which the analyst appears on the call, given that investor relations best practices suggest taking the most important questions first (Stewart 2007) and research showing that analysts who ask questions early in the call are more accurate forecasters (Cen, Chen, Dasgupta, and Ragunathan 2016). Finally, our fourth proxy is the number of turns-at-talk between the analyst and management. Incremental to the overall length of the dialogue, turns-at-talk proxy for the range of topics a given analyst covers in a dialogue.

We find that dialogues are more informative when they are longer in duration and contain more turns-at-talk. These effects are incremental to one another and vary depending on whether the analyst is favored or disfavored. We find disfavored analysts have longer dialogues, with more turns-at-talk, relative to favored analysts. We also find that earlier dialogues are more informative than later dialogues, but guidance does not impact informativeness incrementally.

The lack of incremental information content in guidance dialogues is attributable to the fact that such dialogues tend to be longer, occur earlier in the call, and have more turns-at-talk. In other words, the guidance dialogue informativeness is subsumed by other related dialogue attributes. However, we find little systematic evidence that a discussion of guidance or the order of analyst appearance is associated with how favored the analyst is in the eyes of management. Regarding guidance, favored analysts are more likely to discuss guidance relative to *both* disfavored analysts and analysts with favorable stock recommendations whose forecasts have been missed. Moreover, analysts holding *unfavorable* recommendations whose forecasts have been met are as likely as favored analysts to discuss guidance with management. These findings imply that the meeting of individual analyst forecasts is a key factor responsible for whether an analyst will discuss guidance with management, corroborating the survey results in Graham et al. (2005). Regarding order of appearance, favored analysts are not ordered in a manner that statistically differs from disfavored analysts.

Turning to the credibility of dialogue information, prior research suggests disfavored analysts are less likely to inject or elicit optimistic sentiment that assists management hide bad news (Cohen, Lou, and Malloy 2017). This implies disfavored analyst dialogues should be relatively more negative than favored analyst dialogues. Because negative information is more credible than positive information (Jennings 1987; Rogers and Stocken 2005), one may in turn observe larger magnitude market responses to dialogues with disfavored analysts because stock prices decrease more in response to negative information than increase in response to positive information. To test this prediction, we use signed stock returns. We, however, find no evidence that disfavored analysts drive stock prices down relative to favored analysts.

We next examine whether the capital market responds to specific verbal and nonverbal signals contained within the dialogues. Specifically, we examine whether the words and sounds expressed during the analyst-manager dialogues influence stock price changes. Based on prior work, we expect linguistic cues to be positively related to stock returns. Our linguistic cues include the linguistic tone (i.e. positive minus negative tone), separately measured for both analysts and managers, as well as the proportion of analyst praise words (Milian and Smith 2017).

Regarding sounds, a series of experimental studies in evolutionary psychology finds that human voice pitch decreases (increases) when a speaker engages in conversations with a competitor who the speaker perceives to be less (more) dominant (Tusing and Dillard 2000; Puts, Gaulin, and Verdolini 2006; Cheng, Tracy, Ho, and Henrich 2016). Applying this literature to our setting, we take managers as the speaker and analysts as the competitor and predict that the capital market will view lower-pitched dialogues favorably, as credibility is enhanced through dominance (Mikkelson, Sloan, and Hesse 2017). We measure voice pitch changes of managers by comparing the average voice pitch during the dialogue with that in the presentation, given the presentation captures the normal speaking voice of the manager prior to confrontation by analysts in the conference call Q&A (Mayew, Parsons, and Venkatachalam 2013).

With respect to linguistic cues, we find that stock returns during the dialogue are increasing in the linguistic tone of analysts but not that of managers (Price, Doran, Peterson, and Bliss 2012; Chen, Nagar, and Schoenfeld 2017). Favored analysts exhibit more favorable tone than disfavored analysts do. We also find stock prices increase when managers exude dominance in the conversation, as captured through changes in voice pitch. However, voice pitch changes do not vary with how favored the analyst is. All categories of sell side analysts engage in dialogues that contain a statistically equivalent amount of managerial dominance as measured through changes in voice pitch.

As a collection, our evidence suggests that disfavored analysts engage in more informative conference call dialogues than favored analysts, as evidenced by larger absolute stock price reactions. These larger stock price reactions result from disfavored analyst dialogues being longer and containing more turns-at-talk, which captures the elicitation of more information and/or reduction of uncertainty about existing information. The larger absolute stock price changes for disfavored analysts do not occur due to stock prices systematically changing in a particular direction. The lack of a differential directional price response to disfavored analysts relative to favored analysts overall reflects the fact that manager-analyst dialogues contain multiple important market moving signals including linguistic sentiment of analysts, which vary between favored and disfavored analysts, and voice pitch changes of managers, which does not vary with how favored or disfavored an analyst is.

Our paper makes four primary contributions. First, we provide new evidence on conflicts of interest between managers and analysts in the conference call setting, which is of interest to regulators (Cox 2005). Our investigation of stock prices during conference call dialogues suggests the market is attuned to analyst conflicts as disfavored analyst dialogues are viewed as more informative. This finding implies that informational benefits of access to management (Chen and Matsumoto 2006; Ke and Yu 2006; Soltes 2014; Green et al. 2014) that favored analysts enjoy is counteracted by the discount the market applies to favored analyst dialogues. Second, our paper is the first to offer a comprehensive assessment of the anatomy of the Q&A portion of earnings conference at the conversation level. Prior research primarily focuses on the content of conference calls overall or by section (i.e. presentation vs Q&A) of the call (Price et al., 2012; Chen et al., 2017; Milian and Smith, 2017) without considering features of individual dialogues between managers and specific analysts. We are able to provide this dialogue level assessment by assembling a unique dataset derived from original audio recordings of conference calls. Third, Matsumoto et al. (2011) document that the informativeness of conference call Q&A portion is driven by analyst involvement. We build on this finding by demonstrating *which* analysts matter to the capital market and *why* they matter. Fourth, by studying both the text and the audio of manager-analyst dialogues, we provide new evidence on how different analysts shape what investors hear and react to during such calls. This responds to the call in Kothari, So, and Verdi (2016) for a better understanding of the analyst's role in price formation.

2. Sample Selection and Research Design

2.1 Sample Selection

Our sample consists of 2,455 earnings conference calls of S&P 1500 firms that occurred during the period 2008-2010 for which we are able to obtain digital audio recordings. We focus on S&P 1500 firms following Hollander, Pronk, and Roelofsen (2010), who note that S&P 1500 firms' are sufficiently liquid to facilitate detection of intra-day pricing effects during conference calls. Additionally, S&P 1500 firms represent important firms in the economy that are actively followed by financial analysts, which increases the relevance of the Q&A portion of conference calls. We restrict our sample to calls that occur during trading hours so that intra-call stock returns can be computed reliably using TAQ data.[3]

To obtain audio recordings, we manually restream and record conference calls posted on www.earnings.com, a website that previously served as Thomson Reuters' individual investor portal during our data collection period. Restreaming capability is typically available for one quarter to one year from the initial date of broadcast. We require audio files so we can precisely identify when one speaker finishes and another speaker begins speaking during the call. These time-stamps in turn allow for the precise calculation of stock returns within the call. Using transcripts instead of audio files to approximate when speakers transition is problematic because conference call transcripts from commercial providers do not take into account varying speech rates among speakers, pauses, or speech hesitations. Moreover, operator instructions spoken during the live broadcast are typically purged from commercial transcripts, making it very difficult to infer the true time of day a given analyst speaks during a call. Audio files also allow us to measure acoustic features of speech that investors would hear when listening to the call (Mayew and Venkatachalam 2012; Mayew, Sharp, and Venkatachalam 2013).

[3] See Appendix B for details related to procuring and preparing TAQ data for analysis. After-hours trading data is not available to assess whether our findings generalize to conference calls held after trading hours. As Matsumoto et al. (2011) note, it is possible that the results observed from an analysis of conference calls held during trading hours may not generalize to calls that occur after trading hours. Additionally, our sample period occurs during the financial crisis, which may additionally limit the extent to which our results generalize to other periods.

We manually parse the aggregate conference call audio into individual turns-at-talk audio files by relying on human listeners, as it is not feasible to automate this process reliably. Because managers and analysts take turns talking, we utilize conference call transcripts, obtained from the Thomson Reuters StreetEvents database, to assist the listener in identifying each unique turn-at-talk during the broadcast. Each identified turn-at-talk during the conference call is then isolated into an audio file for measuring acoustic features and a text file for measuring linguistic features. There are 250,476 unique turns-at-talk in the entire conference call corpus we examine, of which 238,546 occur in the Q&A portion of the call.[4]

To study how the capital market responds to specific manager-analyst interactions, we isolate the sequence of turns-at-talk that comprise each manager-analyst dialogue in the Q&A portion of the conference call. Each dialogue starts with a question posed by a unique analyst and contains the full conversation between that specific analyst and the management team, two examples of which are provided in Appendix E. Each dialogue can contain multiple questions by an individual analyst and corresponding responses from members of management. The dialogue ends when a different analyst asks a question. There are 19,605 manager-analyst dialogues in our sample that, on average, last 3.8 minutes.

We proxy for how favored an analyst is in the eyes of management using both whether the individual analyst provided favorable stock recommendation (Chen and Matsumoto 2006) and whether the analyst provided an achievable quarterly earnings forecast (Ke and Yu 2006). We obtain both proxies from I/B/E/S in a two-part process. First, we utilize the I/B/E/S recommendation file, which contains the name and brokerage of each sell-side analyst providing a stock recommendation on the firm. We manually match the I/B/E/S recommendation file information with the name and affiliation of the analyst from the transcript header. With this match, we then use the unique analyst identifier (per the I/B/E/S recommendation file) to identify the same analyst's earnings forecast per the I/B/E/S unadjusted detail file. Comparing the earnings forecast with the I/B/E/S actual earnings allows us to ascertain whether the analyst provided an achievable earnings forecast or not. While the majority of manager-analyst dialogues in our sample involve

[4] About 10% of the turns in a conference call correspond to operators that moderate the call.

analysts that are identifiable in I/B/E/S, some are not. While decomposing the Q&A portion of the call, we retain dialogues pertaining to conference call participants that we cannot match to I/B/E/S as a base reference group in our empirical analysis. We cannot objectively measure how favored an analyst in the base group might be as it contains a mix of sell-side analysts who do not yet follow the firm (Jung, Wong, and Zhang 2015) along with buy-side analysts, media personnel, and other unidentified participants (Call, Sharp, and Shohfi 2018).

We obtain other variables for our analysis regarding analysts, stock prices, and firm characteristics from I/B/E/S, CRSP/TAQ, and Compustat, respectively. We also obtain information on whether individual manager-analyst dialogues contain forward-looking guidance by referring to Thomson Reuters Guidance Reports. Guidance reports tabulate for each fiscal year all of the guidance provided by a firm, both quantitative and qualitative, as well as the source of the guidance. For example, if a firm issues guidance pertaining to bad debt expense during a conference call, the guidance report provides the supporting evidence for the forecast by excerpting the specific sentences from the conference call that underpin the forecast. In Appendix C, we outline the process for identifying whether a given dialogue contains any forward-looking information as per the guidance report.

2.2 Research Design

To examine the informativeness of managerial interactions with favored and disfavored analysts, we begin by estimating the following OLS regression with robust standard errors clustered at the call level for manager-analyst dialogue *d* on firm-quarter conference call *c* (subscripts suppressed):

$$\text{DL\_ABSRET} = a_0 + a_1\text{DL\_BUY\_MEET} + a_2\text{DL\_BUY\_MISS} + a_3\text{DL\_NBUY\_MEET} + a_4\text{DL\_NBUY\_MISS} + \Sigma\ \textit{Controls} + \varepsilon \qquad (1)$$

In equation (1), the variable prefix "DL" signifies the analysis is conducted at the dialogue level. DL_ABSRET is the absolute stock price return surrounding the manager-analyst dialogue. The coefficients a_1 through a_4 capture the effect of sell-side analysts currying favor through a combination of favorable stock recommendations (Chen and Matsumoto 2006) and achievable quarterly earnings targets (Ke and Yu 2006). DL_BUY_MEET is an indicator variable that equals one for *favored* analysts (i.e. analysts that issue a

Buy/Strong Buy stock recommendation and whose forecasts have been met or exceeded), and zero otherwise. DL_NBUY_MISS is an indicator variable that equals one for *disfavored* analysts (i.e. analysts that issue a *Sell/Strong Sell/Hold* stock recommendation and whose forecasts have been missed), and zero otherwise. DL_BUY_MISS and DL_NBUY_MEET are indicator variables that capture the intermediate cases. DL_BUY_MISS is an indicator variable set to one for analysts with *Buy/Strong Buy* recommendations whose forecasts have been missed, and zero otherwise. DL_NBUY_MEET is an indicator variable set to one for analysts with *Sell/Strong Sell/Hold* recommendations whose forecasts have been met or exceeded, and zero otherwise.

Controls is a vector of variables that captures the quality of the analyst speaking with management and the general information environment of the firm. High quality analysts elicit stronger market responses (Gleason and Lee 2003) and we proxy for analyst quality by including indicator variables for whether the analyst is an all-star (DL_ALLSTAR) and whether the analyst works for a prestigious brokerage (DL_BROKER). We also control for variables that capture a firm's information environment by including proxies such as firm size (LnSIZE), dispersion of the consensus earnings estimate (DISPERSION), and the magnitude of the consensus earnings surprise (|UE|).[5]

Our primary interest lies in the difference between coefficient a_1 and a_4. On the one hand, if market participants perceive favored analysts as conflicted and consequently discount their interactions with management, we would expect $a_1 < a_4$. On the other hand, if favored analysts possess better insights about the firm as a result of their relationship with management, their interactions with management may be particularly informative and result in $a_1 > a_4$. Finally, if managers do not allow sufficiently disfavored analysts onto the call (Mayew 2008) there may be little observable difference among (dialogues with) analysts that do participate on the call. In such a case we would observe $a_1 = a_4$.

[5] We conduct sensitivity checks on our variable choices and definitions in Appendix D. In particular, we consider analyst experience with the firm as another proxy for analyst quality. We also assess whether our results are sensitive to using the absolute stock recommendation level as a basis for categorizing analysts as favored or disfavored. Rather than using the favorableness of the analyst's stock recommendation level on an absolute basis, we consider stock recommendation favorableness on a basis relative to analysts participating on the call. Our conclusions are not sensitive to these research design choices.

3. Empirical Analysis

3.1 Sample Validation

Before proceeding to estimate equation (1) we first validate our sample by ensuring that the results in Matsumoto et al. (2011) hold in our sample. This is important because our tests are designed to investigate how analysts might differentially influence price responses during the Q&A under the assumption that analysts play a key role in shaping capital market perceptions of the firm. Given our sample is restricted to S&P 1500 firms for which we are able to obtain conference call audio recordings, our sample of 2,455 conference calls is much smaller than the 10,062 conference calls used in Matsumoto et al. (2011). This validation exercise also mitigates any concern regarding generalizability of our results, given our sample is much shorter and overlaps with the financial crises period. We estimate the following empirical specifications

$$ABS\_ABNRET_{PR} = \alpha_0 + \alpha_1\, ABSRET_{DAYB4} + \varepsilon \quad (2)$$

$$ABS\_ABNRET_{PR} = \delta_0 + \delta_1\, ABSRET_{DAYB4} + \delta_2\, NUM\_ANA + \delta_3\, NUM\_ANA^2 + \varepsilon \quad (3)$$

$$ABS\_ABNRET_{QA} = \beta_0 + \beta_1\, ABSRET_{DAYB4} + \beta_2\, ABS\_ABNRET_{PR} + \varepsilon \quad (4)$$

$$ABS\_ABNRET_{QA} = \gamma_0 + \gamma_1\, ABSRET_{DAYB4} + \gamma_2\, ABS\_ABNRET_{PR} + \gamma_3\, NUM\_ANA + \gamma_4\, NUM\_ANA^2 + \varepsilon \quad (5)$$

ABS_ABNRET_{PR} refers to the absolute abnormal return during the presentation section of the call, ABS_ABNRET_{QA} is the absolute abnormal return during the Q&A section of the call, and $ABSRET_{DAYB4}$ is the absolute return for the 24-hour period prior to the start of the conference call, which captures the market response to the earnings press release. When computing abnormal returns we use the same period on a non-conference call day (7 days prior to the call) as a benchmark.[6] *NUM_ANA* represents the number of analysts participating in the Q&A session, and *NUM_ANA*^{2} captures the diminishing marginal effect on information content as the number of analysts participating in the Q&A increases.[7]

[6] We use 14 or 21 days prior to the call as a benchmark in the event that return for 7 days prior to the call is unavailable due to a holiday.
[7] Matsumoto et al. (2011) use the number of analysts following the firm, not the number of analysts on the conference call. Our inferences are virtually identical if we use the number of analysts following the firm instead of the number of analysts participating on the call. Because we will be assessing the favorableness of these same individual analysts in our main analysis, using the number of analysts actually participating in the Q&A ensures internal consistency.

Matsumoto et al. (2011) find that conference call presentations are informative over and above press releases, which implies $\alpha_0 > 0$ in equation (2). Additionally, they find analysts play no informational role in the presentation, implying $\delta_2 = 0$ and $\delta_3 = 0$ in equation (3). Within the call, the Q&A session is incrementally informative over both the presentation and earnings press release, which implies $\beta_0 > 0$ in equation (4). Finally, they document analysts are a key driver of Q&A information content from equation (4), which implies $\gamma_3 > 0$ and $\gamma_4 < 0$ in equation (5) and $\beta_0 > \gamma_0$.

Panel A of Table 1 provides the descriptive statistics of the variables used to estimate equations (2) – (5), and Panel B presents the estimation results. Overall, each of the predictions observed above hold and the coefficient estimates are of magnitudes similar to those documented in Matsumoto et al. (2011). For example, in Column (1) of Table 1, Panel B, we observe absolute abnormal presentation returns of α_0 = 0.0021 ($p<0.01$), incremental to prior day returns (coefficient α_1 = 0.0487 ($p<0.01$)). Matsumoto et al. (2011) find effect sizes of 0.0023 ($p<0.01$) and 0.0481 ($p<0.01$), respectively. The only substantive difference between Matsumoto et al. (2011) and our results pertain to the effects of analysts in explaining absolute abnormal Q&A returns. We find that absent analyst effects, the Q&A has information content of β_0 = 0.0029 (Table 1, Panel B, Column 3, $p<0.01$) similar to that documented in Matsumoto et al. (2011) (coefficient = 0.0021, $p<0.01$). However, after controlling for number of analysts present, no further Q&A effects are observed, either statistically or economically (Table 1, Panel B, Column 4, γ_0 = 0.0002, $p=0.90$), whereas Matsumoto et al. (2011) find that some Q&A effects exist even after accounting for the presence of analysts (coefficient = 0.0015, $p<0.01$). We take this difference to mean that in our sample, the role of analysts completely drives Q&A information content. Given we have documented that analysts play a role in the Q&A overall in our sample, we proceed with our dialogue level analysis.

3.2 Descriptive Statistics

Given prior literature commonly studies market responses to conference calls at the call level (Price et al. 2012; Milian and Smith 2017) or the presentation versus Q&A level (Matsumoto et al. 2011; Brockman et al. 2015; Chen et al. 2017) we first provide call level, presentation level, and Q&A level descriptive statistics for our sample in Table 2. We provide all variable definitions in Appendix A. The average duration (MINS) of earnings calls is about 54 minutes, with an absolute raw return (ABSRET) of 1.71%. Average signed return (RET) is close to zero, suggesting an equal mix of both positive and negative returns during calls in our sample. On average, a firm has about $12 billion in total assets (SIZE), 9 outstanding sell-side analyst recommendations (NUM_REC), and beats the consensus earnings estimate by about 2 cents (UE).

We present descriptive statistics for the presentation and Q&A sections separately in Panels B and C of Table 2, respectively. The average absolute return during the presentation section (PR_ABSRET) is 1.12%, similar to that for the Q&A section (QA_ABSRET), while the average value of signed returns is close to zero for both sections of the call (PR_RET and QA_RET). Consistent with Li et al. (2014) CEOs speak more than CFOs overall. During the presentation, the CEO gets only slightly more time at 9.6 minutes (PR_CEO_MINS) relative to the CFO, who speaks for 8.6 minutes (PR_CFO_MINS). This gap widens during the Q&A portion, where the CEO speaks almost twice as much as the CFO (QA_CEO_MINS = 12 minutes versus QA_CFO_MINS = 5.3 minutes). The presentation section has about 5 turns-at-talk (PR_TURNS), compared with 97 for the Q&A (QA_TURNS). Of these 97 Q&A turns, on average, the CEO speaks in 23 turns (QA_CEO_TURNS), the CFO speaks in 14 turns (QA_CFO_TURNS), and analysts speak in 41 turns (QA_ANA_TURNS). The remaining turns correspond to other firm executives and the operator. Q&A sessions last about 7 minutes longer than presentations (QA_MINS = 31 minutes versus PR_MINS = 24 minutes) with analysts speaking for about 9 minutes during the Q&A (QA_ANA_MINS). A Q&A session comprises of about 8 dialogues (QA_NUM_DIALOGUE).

Consistent with Mayew (2008), we find about 8 analysts asking questions during the Q&A (QA_NUM_ANA), 4 of whom provide explicit stock recommendations (QA_NUM_RECIN). The remaining analysts asking questions are primarily comprised of sell-side analysts without recommendations, buy-side analysts, the media or unidentified participants (Jung et al. 2015; Call et al. 2018). The 5 sell-side analysts with outstanding recommendations that do not participate (QA_NUM_RECOUT) have an average recommendation of 3.42 (QA_MEAN_RECOUT), which is less favorable than the average recommendation of participating analysts (QA_MEAN_RECIN = 3.57).[8] This is consistent with other findings in larger samples that managers prefer to speak with relatively more favorable analysts publicly during conference calls (Mayew 2008; Cohen et al. 2017).

Turning to the dialogue level, Table 3 Panel A reveals that the average dialogue of 3.8 minutes (DL_MINS) is comprised of 1.5 minutes of talk by the CEO (DL_CEO_MINS), 0.6 minutes by the CFO (DL_CFO_MINS) and 1.1 minutes by analysts (DL_ANA_MINS). The total dialogue talk time represents approximately 12 unique turns-at-talk (DL_TURNS), 3 from the CEO (DL_CEO_TURNS), 2 from the CFO (DL_CFO_TURNS) and 5 from analysts (DL_ANA_TURNS). The remaining talk time of 0.6 minutes and 2 remaining turns-at-talk pertain to other members of management and the operator. The absolute value of returns during the average dialogue (DL_ABSRET) is 40 basis points, with a standard deviation of 54 basis points. The signed return (DL_RET) is zero on average, and exhibits substantial variation with a standard deviation of 67 basis points. Panel B reveals that 35% of our sample dialogues are with analysts holding buy or strong buy recommendations (DL_BUY), while 31% are with analysts holding hold, sell or strong sell recommendations (DL_NBUY), with the remainder comprised of dialogues with analysts who have not issued recommendations for the firm publicly. To the best of our knowledge, our study is the first to provide granular analyst-manager dialogue-level descriptive statistics on earnings conference calls, and hence we do not have comparison benchmarks from prior research for many of these dialogue-level measures.

3.3 Results

The correlation matrix presented in Panel D of Table 3 reveals that dialogues with analysts that issue favorable stock recommendations (DL_BUY) are not robustly correlated with absolute stock price responses (DL_ABSRET) at statistically significant levels ($p=0.77$ and $p=0.06$ for Spearman and Pearson correlations, respectively). However, dialogues with analysts issuing unfavorable stock recommendations (DL_NBUY) are significantly positively correlated with absolute stock price responses ($p<0.01$ for both

[8] Recommendations are measured on the following scale: 1-Strong Sell, 2-Sell, 3-Hold, 4-Buy, 5-Strong Buy

Spearman and Pearson correlations). Similarly, we find that dialogues with analysts whose forecasts have been met or exceeded (DL_MEET) are not significantly correlated with absolute stock response ($p=0.30$ and $p=0.13$ for Spearman and Pearson correlations, respectively). Whereas, dialogues with analysts whose forecasts have been missed (DL_MISS) are positively correlated with absolute stock price response ($p<0.01$ for both Spearman and Pearson correlations). At first blush, this univariate evidence is suggestive that market participants react more to disfavored analysts.

To assess this more formally, we present estimation of equation (1) in Table 4, Panel A. Prior to estimation we standardize all continuous variables to allow for comparison of magnitudes between coefficients in the model and for comparison across specifications that will follow.[9] We find that dialogues with disfavored analysts (DL_NBUY_MISS) elicit stronger absolute price responses ($a_4 = 0.043$, $p <0.01$) than the base case condition. The base case condition, captured by the regression intercept, is comprised of both conference call participants for whom favored status cannot be determined as well as analysts without all-star status. Dialogues with the base case analysts elicit market responses in their own right, as captured by the statistically significant intercept ($a_0 = 1.588$, $p <0.01$).

Turning to our comparison of interest, an F-Test reveals that the market response of disfavored analysts exceeds favored analysts ($a_4=0.043$ vs. $a_1=0.004$; $p<0.01$). We also observe that the favored analyst effect does not statistically differ from the base case condition ($a_1=0.004$, $p=0.67$). The intermediate cases do not differ statistically from one another ($p= 0.50$) but fall between the favored and disfavored conditions with effect sizes that are larger than base case analysts ($a_2 = 0.017$, $p <0.05$; $a_3 = 0.015$, $p <0.10$). As a collection, these results suggest that the informativeness of manager-analyst dialogues is decreasing in how favored the analyst is viewed by management, consistent with market participants identifying analyst conflicts of interest and in turn discounting managerial interactions with favored analysts.

[9] Standardized coefficients are obtained by transforming both dependent and independent variables into standardized scores before estimating the regression. A standardized coefficient, β, obtained when regressing Y on X, is interpreted as the standard-deviation change in Y corresponding to a one standard-deviation change in X.

These effects hold incrementally to proxies for analyst quality and the firm's information environment. We find that dialogues with all-star analysts elicit heightened market responses (coefficient = 0.022, $p<0.01$), consistent with Gleason and Lee (2003). The magnitude of the all-star effect (0.022) falls roughly in between the effects of favored (0.004) and disfavored analysts (0.043). Manager-analyst dialogues are more informative for smaller firms (coefficient = -0.163, $p<0.01$) and firms with high earnings forecast dispersion (coefficient = 0.064, $p<0.01$), consistent with firm disclosures mattering more in poorer information environments (Atiase 1985).

While the evidence is consistent with market participants discounting favored analyst dialogues as relatively uninformative, we have no evidence regarding how the dialogue content, which contain the signals the market responds to, differs because of analyst favor. For example, do favored analysts simply draw out a lower *quantity* of value relevant information from management? Is the information elicited by favored analysts simply less *credible* because it is unduly optimistic? We consider each of these possibilities in sections 3.3.1 and 3.3.2, respectively.

3.3.1 Assessment of Dialogue Information Quantity

Identifying the quantity of value relevant topics for a given firm in a given quarter is highly subjective. As a result, we forward four proxies that require little researcher discretion. Our first quantity proxy is the length of the dialogue (DL_PCT_LEN), which has been used in the extant literature to capture the amount of information provided (Matsumoto et al. 2011; Frankel et al. 2010). Our second proxy considers whether the manager-analyst dialogue contains forward-looking guidance (DL_GUIDE) per Thomson Reuters Guidance Reports as outlined in Appendix C, under the assumption that forward-looking information is more value relevant than backward looking information (Li 2010; Muslu, Radhakrishnan, Subramanyam, and Lim 2014). Our third proxy is the sequential order in which analysts speak (DL_ORDER), where analysts are assigned a numeric value of 1 if they are the first speaker, 2 if second, and so on. We expect earlier manager-analyst dialogues to have a larger amount of value relevant information because analysts compete to provide insights to investors in the timeliest manner possible (Mayew, Sharp, and Venkatachalam, 2013), investor relations personnel suggest taking the most important questions first as a best practice (Stewart 2007), and analysts asking earlier questions tend to be of higher quality in the sense that they generate more accurate earnings forecasts and have more favorable career outcomes (Cen et al. 2016). Our fourth proxy is the number of turns-at-talk within the dialogue (DL_TURNS) under the notion that the more turns between managers and analysts, the more likely the analyst is covering a wider topical span.[10]

If variation in the quantity of value relevant information is responsible for the association we document between absolute stock price responses and analyst favor, we would empirically observe analyst favor to drive dialogue information quantity, and in turn, price responses. That is, the quantity of value relevant information in the dialogue serves as the mediating construct through which analyst favor influences stock prices. To assess the relation between analyst favor, dialogue information quantity, and market responses, we execute the following structural equation model as illustrated in Figure 1:

DL_ABSRET = *f* (*Information Quantity, Analyst Favor, Controls*) (1.1)
DL_PCT_LEN= *f* (*Analyst Favor, Analyst Quality*) (1.1.1)
DL_GUIDE = *f* (*Analyst Favor, Analyst Quality*) (1.1.2)
DL_ORDER = *f* (*Analyst Favor, Analyst Quality*) (1.1.3)
DL_TURNS = *f* (*Analyst Favor, Analyst Quality*) (1.1.4)

Where, *Information Quantity* is the set of variables just described (DL_PCT_LEN, DL_GUIDE, DL_ORDER, DL_TURNS); *Analyst Favor* are indicators that capture actions analyst take to curry favor with management (DL_BUY_MEET, DL_BUY_MISS, DL_NBUY_MEET, DL_NBUY_MISS); *Controls* are identical to that in equation (1); and *Analyst Quality* denotes the two variables DL_BROKER and DL_ALLSTAR. In equation (1.1), we expect a positive (negative) coefficient on the information quantity proxies DL_PCT_LEN, DL_GUIDE, DL_TURNS (DL_ORDER).

Table 4 Panel B presents the results from estimating the structural equation models. Column 5 presents the direct effects and the specification is identical to that reported in Table 4 Panel A, and in

[10] More turns-at-talk could also capture analysts asking follow up clarifying questions on a single topic so as to increase the precision of the information. To the extent this occurs, turns-at-talk would operationalize a quality of information notion rather than the quantity of information. In either case, more turns-at-talk would increase stock price. See Appendix E for examples of manager-analyst dialogues with multiple turns.

addition includes the four proxies for dialogue information quantity. We find longer dialogues (DL_PCT_LEN coefficient = 0.074, $p<0.01$) dialogues earlier in the Q&A (DL_ORDER coefficient = -0.047, $p< 0.01$) and dialogues with more turns (DL_TURNS coefficient = 0.083, $p<0.01$) each incrementally elicit more market responses. We find no evidence that dialogues containing guidance elicit an incremental price response (DL_GUIDE coefficient 0.007, $p=0.38$), although unconditionally we do find a positive association between guidance and absolute stock returns (Spearman $\rho=0.04$, $p<0.01$, Table 3, Panel D). Dialogues containing guidance have more turns, are longer, and occur earlier in the Q&A session (Table 3, Panel D), and so controlling for DL_TURNS, DL_PCT_LEN and DL_ORDER may ultimately subsume the effect of DL_GUIDE.

Regarding the direct effects of analyst favor, relative to Panel A, we now observe insignificant coefficients on DL_BUY_MISS and DL_NBUY_MEET. Additionally, DL_NBUY_MISS now has a coefficient magnitude of 0.032 ($p<0.01$), which is lower than the 0.043 observed when we estimated equation (1) in Table 4 Panel A. The attenuation of these coefficients results from analyst favor operating indirectly through its influence on dialogue information quantity, as shown in columns (1) through (4).

In column (1) we find that the coefficients on all four analyst categories are statistically significant ($p<0.01$), implying managers spend more time talking with sell-side analysts who have outstanding forecasts and recommendations on the firm than other base case participants. However, managers spend almost twice the amount of time responding to disfavored (DL_NBUY_MISS) analysts (coefficient = 0.051) relative to the three other analyst favor conditions (coefficient ranges from 0.029 to 0.033; p-value of difference in coefficients ranges from <0.01 to 0.09). This finding suggests that when managers are willing to allow disfavored analysts on the call, they do so to engage with these analysts rather than attempting to minimize their role in the call.

In column (2) regarding whether the dialogue contains guidance, favored (DL_BUY_MEET) analysts elicit more guidance than disfavored (DL_NBUY_MISS) analysts, but this effect is driven primarily by the analyst forecast error and not the analyst stock recommendation. Specifically, the coefficient on DL_BUY_MEET of 0.060 ($p<0.01$) is statistically indistinguishable from the coefficient on

DL_NBUY_MEET of 0.056 (p<0.01), and statistically greater in magnitude than the other analyst favor categories, which exhibit no statistically significant association with guidance issuance. This finding is consistent with the survey results in Graham et al. (2005) suggesting analysts probe for backward looking information when their forecasts are missed thereby preventing managers from speaking about the future.

In column (3) pertaining to the sequential order in which analysts get to ask questions, we find that all analyst favor categories have negative and statistically significant coefficients (p<0.01 in all cases). This signifies that sell side analysts following the firm receive order preference over base case analysts. However, the ordering of favored analysts does not statistically differ from disfavored analysts (DL_BUY_MEET coefficient = -0.077 vs DL_NBUY_MISS coefficient = -0.054, p=0.86).

In column (4) we observe that the number of turns at talk is decreasing in analyst favor. The statistically significant coefficient on DL_BUY_MEET of 0.019 (p=0.04) indicates that favored analysts iterate more with managers when compared to base case analysts. The intermediate analyst favor categories (DL_BUY_MISS and DL_NBUY_MEET) exhibit levels almost double that of favored analysts and nearly identical to each other (coefficient = 0.036, p< 0.01 and 0.037, p<0.01, respectively). Disfavored analysts (DL_NBUY_MISS) iterate the most with managers (coefficient = 0.065, p<0.01) and at magnitudes that statistically exceed all other analyst favor categories (p-value <0.02 in all cases). These findings imply that favored (disfavored) analysts probe managers less (more) for information when engaging in public dialogue.

Table 4 Panel C presents the standardized coefficients corresponding to the indirect and direct effects for each analyst favor category based on the estimation results outlined in Panel B of Table 4. As discussed earlier, the direct effect is significant only for disfavored analysts and not for any other analyst favor category (column (5)). While dialogue length, order, and number of turns play a significant role in mediating the effect of analyst favor on absolute stock returns, the mediating effect due to guidance issuance is negligible (columns (1)-(4)).

As a collection, the evidence in Table 4 suggests that the market responds more to disfavored analysts at least partially due to disfavored analysts generating dialogues that contain more value relevant information, as proxied by dialogue length and number of turns-at-talk within the dialogue. However, the incremental direct effect on stock price reactions for disfavored analysts in column (5) of Panel B (DL_NBUY_MISS coefficient = 0.032, $p<0.01$) suggests disfavored analysts are able to elicit market responses through dialogue aspects that we have not empirically captured. Perhaps additional effects of disfavored analysts operate through the credibility of the dialogue information, which we turn to next.

3.3.2 Assessment of Dialogue Information Credibility

The observed informativeness of disfavored analyst dialogues may also occur because disfavored analysts are more likely to elicit negative news in their dialogues. This notion follows from Cohen et al. (2017), who suggest relatively favorable analysts are more likely to inject or elicit optimistic sentiment so as to assist management in hiding bad news (Cohen et al. 2017). Because negative information is more credible than positive information (Jennings 1987; Rogers and Stocken 2005), we may observe larger absolute magnitude market responses to disfavored analysts because stock prices decrease more in response to a unit of negative information than increase in response to a unit of positive information. We assess this issue by examining directional price response via the following specification:

$$DL\_RET = a_0 + a_1 DL\_BUY\_MEET + a_2 DL\_BUY\_MISS + a_3 DL\_NBUY\_MEET + a_4 DL\_NBUY\_MISS + \Sigma\, Controls + \varepsilon \quad (6)$$

All variables in equation (6) are identical to that in equation (1) with the exception that the dependent variable (DL_RET) is the signed stock return over the course of the manager-analyst dialogue and the consensus earnings surprise (control variable) is signed (UE) instead of unsigned. If disfavored analysts elicit larger magnitude stock price responses due to the presence of relatively more negative news than favored analysts, we would expect the directional response to be *both* more positive for favored relative to disfavored analysts ($a_1 > a_4$) and of smaller magnitude ($|a_1| < |a_4|$).

The results of estimating equation (6) are presented in Panel A of Table 5. On average, the market response to the base case analyst dialogues is positive (coefficient = 0.09, $p<0.01$), but there is no meaningful incremental effect for analyst favor. In each of the four analyst favor conditions, the coefficients are not significantly different from zero at the conventional levels, except in the case of analysts with favorable stock recommendations whose forecast has been missed, where the coefficient is marginally significant at the 10% level. Comparing the effects of favored and disfavored analysts, we observe an insignificant coefficient on favored analysts (DL_BUY_MEET coefficient = -0.000) and a weak *positive* coefficient for disfavored analysts (DL_NBUY_MISS coefficient = 0.011). The coefficient signs are inconsistent with the notion that disfavored (favored) analysts elicit larger (smaller) magnitude price responses through larger (smaller) negative (positive) directional price changes.

That the directional dialogue level price response is not increasing in analyst favor is somewhat puzzling given analysts with favorable recommendations tend to provide outputs with positive sentiment (Twedt and Rees 2012) and that analyst linguistic tone in conference calls overall is increasing in the stock return *surrounding* the call (Brockman et al. 2015; Chen et al. 2017). Perhaps the dialogue level analysis that requires assessment of stock returns within the call is too granular to empirically detect sentiment effects. Alternatively, perhaps dialogues contain numerous competing signals from both the words used in the dialogue and the sound of managers and only when considering the signals separately can directional stock price effects be observed. For example, recent work by Chen et al. (2017) highlights the importance of separating analyst linguistic tone from that of managers as only analyst tone is associated with stock price changes, while managerial tone is not. Given we observe in Panel A of Table 3 that managers speak much more than analysts during the average dialogue in our sample, analyst linguistic effects may be masked by management sentiment. Additionally, Mayew and Venkatachalam (2012) document that the voice of managers can carry information beyond linguistic tone. To assess competing signals directly and incrementally, we forward four measures derived from both words and sounds from the dialogue and assess whether the capital market responds directly to these signals and whether these signals, in turn, vary with analyst favor as illustrated in Figure 2.

Our first measure is the linguistic tone of analyst questions (DL_ANA_TONE) during the manager-analyst dialogue (Price et al. 2012; Brockman et al. 2015; Chen et al. 2017). DL_ANA_TONE captures the relative proportion of positive and negative words (i.e. net positive tone) in the analyst statements to management (Loughran and McDonald, 2011). The second measure captures the extent to which analysts praise (DL_PRAISE) management, as captured by the proportion of praise words in analyst questions (Milian and Smith 2017; Milian, Smith, and Alfonso 2017). The third measure is the linguistic tone of managerial responses to analyst questions (DL_MGR_TONE), which is identical to analyst tone but measured solely from the text of manager responses. Higher values of each of these three linguistic measures imply more favorable manager-analyst dialogues.

Our final measure moves beyond word-based linguistic sentiment and instead assesses how managers sound. We focus on changes in managerial voice pitch, as captured by the speaker's fundamental frequency (F_0), and measure the average drop or increase in voice pitch of the manager during a manager-analyst dialogue, relative to the baseline voice pitch as approximated from the presentation portion of the conference call (DL_ABN_PITCH). We do not consider voice pitch changes for analysts because we do not have a baseline vocal pitch for them. We focus on voice pitch as our vocal signal of interest for three reasons. First, measuring vocal affect, which is the vocal analog to linguistic sentiment, via commercial emotion analysis software as in Mayew and Venkatachalam (2012) is not feasible because the manager-analyst dialogues are not of sufficient length.[11] Voice pitch, on the other hand, can be reliably measured from audio samples that are only a few seconds in length. Second, Mayew, Parsons, and Venkatachalam (2013) show that, on average, a manager's voice pitch drops relative to the presentation when answering questions in the Q&A. This implies the possibility that voice pitch changes may contain sufficient statistical power to detect voice effects on stock prices. Third, voice pitch is an evolution-based signal of dominance (Puts et al. 2006; Puts et al. 2007; Wolff and Puts 2010) and the signaling of dominance is especially important during competition and threatening confrontations. Experimental research finds that human voice pitch decreases (increases) when a speaker engages in conversations with a competitor who is

[11] The average length of speech per turn-at-talk is 19 seconds, and the average talk time for a CEO (CFO) in a dialogue is 1.45 (0.65) minutes. These durations are too short to robustly analyze vocal sentiment using the vocal emotion analyzer utilized by Mayew and Venkatachalam (2012). Mayew and Venkatachalam (2012) manually create audio files that contain the first five minutes of CEO speech. Creating audio files of sufficient length would require manual fusing of the 215,000 individual turns-at-talk audio files, and the resulting audio would span more than one manager-analyst dialogue. Additionally, as the authors note, the use of commercial emotion measurement tools can be limiting because the source acoustic features that underpin the software are proprietary. By using a primitive acoustic feature like voice pitch as measured from the acoustic software PRAAT, we can better isolate the specific acoustic feature that the capital market may be reacting to.

perceived to be less (more) dominant by the speaker (Tusing and Dillard 2000; Puts et al. 2006; Than 2006; Cheng et al. 2016).[12] We therefore take situations where a manager's voice pitch decreases (increases) as a condition where the manager exhibits dominance (inferiority) over the analyst asking the question. Displaying dominance (inferiority) in the face of analyst questioning should be viewed favorably (unfavorably) by the capital market given dominance facilitates credibility (Mikkelson et al 2017). We therefore expect stock prices to increase (decrease) when the manager's voice pitch drops (increases).

We estimate the following structural equation model to assess the model depicted in Figure 2:

DL_RET = *f* (*Information Credibility, Analyst Favor, Controls*) (6.1)
DL_ANA_TONE = *f* (*Analyst Favor, Analyst Quality*) (6.1.1)
DL_PRAISE = *f* (*Analyst Favor, Analyst Quality*) (6.1.2)
DL_MGR_TONE = *f* (*Analyst Favor, Analyst Quality*) (6.1.3)
DL_ABN_PITCH = *f* (*Analyst Favor, Analyst Quality*) (6.1.4)

Information Credibility is the set of variables just described (DL_ANA_TONE, DL_PRAISE, DL_MGR_TONE, DL_ABN_PITCH), and *Analyst Favor*, *Controls* and *Analyst Quality* are the same as in equation (1.1). In the full sample of 19,605 manager-analyst dialogues, Panel B of Table 3 reveals that the average number of positively (negatively) toned words in the analyst portion of a dialogue is 1.50% (1.51%), implying just over 1 word is positive (negative) per 100 words. When estimating the structural equation model, we therefore condition into a subsample of 10,375 manager-analyst dialogues where the analyst speaks at least 100 words to ensure sufficient power for the linguistic variables in our tests (Tetlock at el. 2008; Feldman et al. 2010).

Panel B of Table 5 presents the estimation. Beginning with direct effects in Column 5, among the three linguistic tone proxies, we only find a positive association between analyst tone and market responses (coefficient = 0.015, p=0.03). That we observe stock prices increasing in the linguistic tone of what analysts say but not what managers say is consistent with Chen et al. (2017), who study stock price responses to the entire Q&A session. That we find no incremental evidence on analyst praise is possibly a result of the

[12] We caveat that such voice pitch effects, demonstrated in prior experimental studies use male participants (Puts et al. 2006). The vast majority of the executives in our study are male.

analyst tone controlling away the effects of praise in our sample, given praise and analyst tone are positively correlated (Table 3, Panel D). Regarding the vocal signal of credibility, we find that a drop in voice pitch is viewed favorably by the stock market and is of similar magnitude as linguistic sentiment (coefficient = -0.017, p<0.01). This evidence is consistent with the capital market rewarding (punishing) managers who exhibit (lack) credibility through vocal dominance.[13]

We next assess how analyst favorableness shapes both the linguistic and vocal dialogue signals in Columns (1) - (4) in Panel B of Table 5. Regarding analyst tone, in Column (1) we find that favored analysts exhibit a positive tone (DL_BUY_MEET coefficient = 0.059, p<0.01) compared to base case analysts while disfavored analysts exhibit a negative tone (DL_NBUY_MISS coefficient = -0.029, p=0.01). While initially consistent with favored (disfavored) analysts driving stock prices up (down) through linguistic sentiment, such a conclusion would be premature because analyst tone is not increasing in analyst favor throughout the favor distribution. Analysts with favorable stock recommendations sometimes exhibit favorable tone relative to base case analysts and sometimes exhibit negative tone. The difference depends on whether the analyst forecast was met or not. Similarly, analysts with negative stock recommendations do not always exhibit negative tone. Analysts with unfavorable stock recommendations who have had their forecast met exhibit positive tone (DL_NBUY_MEET coefficient = 0.025, p=0.03), but their tone turns negative when the forecast is missed (DL_NBUY_MISS coefficient = -0.029, p=0.01).[14]

The relationship between analyst incentives and analyst tone in column (1) is similar to what we observe for analyst praise and the tone of management responses to analysts in columns (2) and (3) respectively. Favored analysts praise management more and elicit a more favorable management response

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[13] Voice pitch of managers during dialogues with analysts is lower by about 4 Hz, on average, when compared to voice pitch during the presentation session (Table 3 Panel C, DL_ABN_PITCH). The standard deviation of abnormal pitch in our sample is about 13 Hz. Human listeners can detect voice pitch changes of approximately 10Hz, and listeners perceive decreases (increases) in voice pitch as indicating the speaker is more (less) dominant (Fraccaro et al. 2013). Changes in voice pitch by less than 10 Hz, while not audible, proxy for dominance and inferiority displays observable in the conversation.

[14] To illustrate the importance of including analyst forecasts in defining analyst favor, we estimate the structural models represented in equations 1.1 and 6.1 by defining analyst favor solely based on stock recommendation. We find that the R-squared of the estimations drop from 0.07 (0.03) to 0.06 (0.01) for equation 1.1 (6.1). Hence, the contribution to the model explanatory power by adding the partitions based on analyst forecasts is non-trivial.

(DL_BUY_MEET coefficients = 0.070, $p<0.01$; 0.054, $p<0.01$ respectively). Disfavored analysts give less praise and elicit more negatively toned management responses (DL_NBUY_MISS coefficients = -0.056, $p<0.01$; -0.063; $p<0.01$ respectively). Interestingly, analysts with favorable stock recommendation whose forecasts have been missed (DL_BUY_MISS) exhibit less praise (coefficient: -0.042, $p<0.01$) and the resulting management response is more negative (coefficient: -0.029, $p<0.05$). Whereas, analysts with unfavorable stock recommendation whose forecasts have not been missed (DL_NBUY_MEET) exhibit praise and elicit managerial tone that is not significantly different from base case analysts. Despite the differential praise of sell-side analysts and the related differences in managerial tone, these effects do not ultimately affect stock prices incremental to other factors as shown in column (5).

Regarding credibility from voice pitch changes, column (4) reveals that, on average, base case analysts elicit a voice pitch drop (coefficient -0.587, $p<0.01$) and the sell-side analysts we examine elicit incremental managerial voice pitch drops relative to base case analysts (except in the case of analysts with favorable stock recommendation and missed forecasts where the effect is weaker). That all analysts – both base case analysts and those with recommendations and forecasts - elicit drops in managerial voice pitch is consistent with Mayew et al. (2013). However, we find that the managerial drop in voice pitch does not meaningfully vary across the four classes of analysts we study, with point estimates ranging from -0.018 to -0.026. Why managers exhibit more dominance when interacting with sell-side analysts is not clear and a potentially promising area for future research. One possibility is managers are relatively more familiar with, and have a better understanding of, the information needs of analysts who produce both recommendations and forecasts for their firm relative to other analysts. Another conjecture is that managers are aware that sell-side analysts with recommendations and forecasts likely provide important insights to institutional investors, and hence explicitly display dominance in order to build credibility with institutional investors (Brown et al. 2014).

Table 5 Panel C presents the standardized coefficients corresponding to the indirect and direct effects for each analyst favor category based on the estimation results outlined in Panel B of Table 5. The indirect effect of analyst favor on stock price changes due to analyst tone is statistically significant for all analyst categories (column (1)). Manager voice pitch plays a mediation role for all categories except in the case of analysts with favorable recommendations and missed forecasts (DL_BUY_MISS) where the effect is not significant at conventional levels (column (4)). Mediation tests also reveal that the indirect effects due to analyst praise and manager tone are almost non-existent (columns (2) and (3). The direct effects are also negligible for most categories of analysts with the exception of one of the intermediate cases (DL_NBUY_MISS) where the effect is significant at conventional levels (column (5)).

As a collection, the evidence in Table 5 supports the notion that directional stock response to analyst-manager interactions crucially depends on the signals contained in the dialogue. While we find some evidence that favored analysts drive stock prices upward by assuming a positive tone, market participants appear to discount the use of praise words by such analysts and the positive tone in managerial responses. Moreover, while managerial voice pitch drops do elicit more favorable market responses, there is no systematic differences among favored and disfavored analysts in eliciting vocal sentiment through voice pitch. Overall, directional stock price response to analyst-manager interactions is far more nuanced than what can be inferred from the extant literature. We caveat that the set of dialogue signals we analyze in this study is by no means comprehensive and future research can perhaps expand on the findings from our study. However, it is important to conduct such analysis at a dialogue level as illustrated in our paper for accurate inference as individual analyst incentives and relationship with management matter.

4. Conclusion

In this study, we provide evidence on how analyst conflicts of interest affect the informativeness of conference call dialogues between managers and analysts. Our investigation is motivated by the results in prior research on analyst conflict of interest which suggests that favored analysts curry favor with management by issuing favorable stock recommendations and biasing forecasts in exchange for private information. Whether rational market participants respond to managerial conversations with favored analysts differently than those with disfavored analysts is ultimately an empirical question. We find that market participants view managerial interactions with *disfavored* analysts as relatively more informative, consistent with market participants discounting dialogues of conflicted, i.e., favored analysts.

To better appreciate the factors that drive the informativeness of dialogues with disfavored analysts, we analyze dialogue characteristics, particularly those that relate to the quantity and credibility of information contained in dialogues. We find that disfavored analysts tend to have dialogues that are longer and exhibit more back-and-forth iterations compared to favored analysts, which market participants appear to price. While negative information is inherently more credible than positive information to market participants, our signed stock return analysis does not support the notion that disfavored analysts systematically drive stock prices downward by eliciting negative information. We find that disfavored analysts, on average, exhibit a more negative linguistic tone relative to favored analysts. However, we find no differences between favored and disfavored analysts in terms of managerial displays of dominance as captured by voice pitch changes. In other words, dialogues with disfavored analysts tend to generate multiple signals that, while independently informative to market participants, collectively display no systematic directional stock price effects.

Overall, we document that the capital market effects of managerial interactions with analysts is lot more nuanced than what we know from prior research. Individual attributes that capture analyst conflict of interest, particularly the stock recommendation and individual analyst forecast error, influence both the structure and sentiment of analyst-manager interactions and capital market participants pay attention to such dialogue characteristics. While our study attempts to capture some of the linguistic and acoustic signals conveyed through manager-analyst interactions in a conference call setting, the set of signals we analyze is by no means comprehensive.

Our study extends the literature on the informational role of conference calls by offering some of the first insights on the market response to information communicated during earnings conference calls at the more granular dialogue level. By examining calls at the dialogue level, we are able to describe the frictions and incentives that drive analyst and managerial behavior and in turn price responses. While the benefits to favored analysts in the form of more accurate and timely forecasts has been documented previously (Chen and Matsumoto 2006; Milian et al. 2016; Mayew et al. 2013), our study characterizes some of the incentives that drive individual analysts and the specific information signals that arise from their interactions with managers to which markets respond. In this way, we add new insights on how analysts facilitate price formation as called for by Kothari et al. (2016). However, a limitation of our analysis is that our sample focuses solely on calls of S&P 1500 firms occurring during trading hours over the short period 2008-2010. Whether our results generalize to conference calls held after trading hours or in a different sample period remains unclear. However, our ability to replicate key findings of conference call studies that use larger samples (Matsumoto et al. 2011) at least partially mitigates the generalizability concern. Given the cost and complexity of conducting market microstructure studies using very large samples, we leave a formal investigation of this issue and other extensions to future research.

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Appendix A (Description of Variables)

Variables in the text without a prefix pertain to the call level. We also compute the variables, if applicable, at the Presentation, Q&A, or Dialogue level using the same methodology and distinguish them using specific prefixes when presenting descriptive statistics. The prefix PR pertains to the presentation portion of the call, QA pertains to the question and answer portion of the call, and DL pertains to a manager-analyst dialogue within the question and answer portion of the call.

Variable	Description
MINS	*Length in minutes measured by computing the difference between starting and ending timestamps for the entire conference call*
CEO_MINS	*CEO talk time in minutes computed by identifying timestamps corresponding to CEO turns in the call*
CFO_MINS	*CFO talk time in minutes computed by identifying timestamps corresponding to CFO turns in the call*
ANA_MINS	*Analyst talk time in minutes computed by identifying timestamps corresponding to Analyst turns in the call*
RET	*Signed Return (buy-and-hold return) computed using mid-point of bid and ask prices from TAQ data corresponding to the starting and ending timestamps for the call.*
ABSRET	*Absolute value of signed return (RET)*
SIZE	*Total assets of the firm at the end of the quarter corresponding to the conference call (Compustat: ATQ)*
LnSIZE	*Natural logarithm of SIZE*
GUIDE	*Indicator Variable for whether a guidance was issued, and equals 1 if any sentence in the turn-at-talk was identified in a Thomson Reuters Guidance Report, and 0 otherwise. See Appendix C for further description of this data.*
DISPERSION	*Analyst Forecast Dispersion reported as the standard deviation of forecasts in IBES Summary Statistics*
UE	*Abnormal Earnings (actual earnings – analyst consensus estimate). Actual earnings and Analyst consensus estimate are obtained from IBES*
NUM_REC	*Number of Analysts providing Recommendations for the firm (IBES)*
MEAN_REC	*Mean Recommendation of Analysts (IBES)*
NUM_RECIN	*Number of Analysts providing Recommendations that participate in the call*
MEAN_RECIN	*Mean Recommendation of Analysts participating in the call*
DISP_RECIN	*Dispersion of Recommendation of Analysts participating in the call*
NUM_RECOUT	*Number of Analysts providing Recommendations but not participating in the call*
MEAN_RECOUT	*Mean Recommendation of Analysts not participating in the call*
DISP_RECOUT	*Dispersion of Recommendation of Analysts not participating in the call*
TURNS	*Number of Turns (Turn refers to contiguous speech by a single participant)*
CEO_TURNS	*Number of CEO Turns*
CFO_TURNS	*Number of CFO Turns*
ANA_TURNS	*Number of Analyst Turns*
NUM_ANA	*Number of Analysts in Q&A*
NUM_ALLSTAR	*Number of All Star Analysts in Q&A*
NUM_DIALOGUE	*Number of Dialogues in Q&A*
PCT_LEN	*Length of a dialogue expressed as a percentage of the Q&A Section Length*
ALLSTAR	*Indicator variable to denote ALL STAR analyst*

BUY	*Indicator variable to denote analyst with an outstanding Buy or Strong Buy recommendation. In the rare instances where data errors in IBES indicate an analyst has an earnings forecast but no recommendation, we take the consensus mean recommendation of all analysts following the firm.*
NBUY	*Indicator variable to denote analysts with an outstanding Sell, Strong Sell, or Hold recommendation. In the rare instances where data errors in IBES indicate an analyst has an earnings forecast but no recommendation, we take the consensus mean recommendation of all analysts following the firm*
MEET	*Indicator variable to denote analyst whose forecast was met or beat. In the rare instances where data errors in IBES indicate an analyst has a recommendation but no earnings forecast, we take the consensus mean forecast of all analysts following the firm to determine whether the forecast was met, beat or missed.*
MISS	*Indicator variable to denote analyst whose forecast was missed. In the rare instances where data errors in IBES indicate an analyst has a recommendation but no earnings forecast, we take the consensus mean forecast of all analysts following the firm to determine whether the forecast was met, beat or missed.*
BUY_MEET	*Indicator variable to denote analyst with Buy/Strong Buy recommendation and whose forecast was met or beat.*
BUY_MISS	*Indicator variable to denote analyst with Buy/Strong Buy recommendation whose forecast was missed*
NBUY_MEET	*Indicator variable to denote analyst with Sell/Strong Sell/Hold recommendation whose forecast was met or beat.*
NBUY_MISS	*Indicator variable to denote analyst with Sell/Strong Sell/Hold recommendation whose forecast was missed*
NUM_BUY	*Number of Analysts in Q&A with Buy or Strong Buy recommendation (BUY = 1).*
NUM_NBUY	*Number of Analysts in Q&A with Sell, Strong Sell, or Hold recommendation (NBUY = 1).*
NUM_MEET	*Number of Analysts in Q&A whose forecasts were met or beat (MEET = 1)*
NUM_MISS	*Number of Analysts in Q&A whose forecasts were missed (MISS = 1)*
PITCH	*Average Vocal Pitch of Manager (CEO or CFO) across all manager turns-at-talk in a given manager-analyst dialogue. To measure voice pitch for each turn-at-talk, we digitally analyze each of the 238,546 turn-at-talk .wav files using PRAAT acoustics software version 5.2.05 (http://www.fon.hum.uva.n./praat), via the GSU PRAAT add-on tool (Owren, 2008). Voice pitch is constructed using the autocorrelation method using default system settings and pitch floor (ceiling) values set to 75 (300) Hz, for adult males and 100 (600) for adult females, as appropriate given the speaker gender.*
BENCH_PITCH	*PITCH measured from the first 20 seconds of the Presentation portion of the conference call.*
ABN_PITCH	*Abnormal Vocal Pitch of Manager in Dialogue (PITCH – BENCH_PITCH)*
POSTONE	*Percentage of Positive Words (computed using Loughran and McDonald (2011) dictionary)*
NEGTONE	*Percentage of Negative Words (computed using Loughran and McDonald (2011) dictionary)*
ANA_POSTONE	*Percentage of Positive Words in Analyst Speech*
ANA_NEGTONE	*Percentage of Negative Words in Analyst Speech*
PRAISE	*Percentage of Praise Words in Analyst Speech (computed using Milian and Smith (2017) dictionary)*
ANA_TONE	*Analyst Net Tone (ANA_POSTONE – ANA_NEGTONE) / (ANA_POSTONE + ANA_NEGTONE)*
BROKER	*Carter-Manaster Broker Ranking (Scale:0-9)*
MGR_POSTONE	*Percentage of Positive Words in Management Speech*
MGR_NEGTONE	*Percentage of Negative Words in Management Speech*
MGR_TONE	*Manager Net Tone (MGR_POSTONE – MGR_NEGTONE) / (MGR_POSTONE + MGR_NEGTONE)*
ORDER	*ID number for the dialogue in ascending order of appearance by the analyst where the first analyst is coded 1, the second as 2, etc. Smaller values indicate the analyst speaks earlier in the call Q&A.*

Appendix B (Preparing TAQ Data)

We use trade and quote data from the NYSE Trade and Quote (TAQ) database for our empirical analysis. We follow the steps outlined below to prepare the TAQ high frequency data (Barndorff-Nielsen et al. 2009) for use in our analysis:

1. Delete entries with a time stamp outside the 9:30 am–4 pm window when the exchange is open.
2. Delete entries with a bid, ask, or transaction price equal to zero.
3. Delete zero volume quotes and quotes with abnormal sale conditions.
4. When multiple quotes have the same time stamp, replace all these with a single entry with the median bid and median ask price.
5. Delete entries for which the spread is negative.
6. Delete entries for which the spread is more than 500 times the median spread on that day (outliers)

Appendix C (Guidance Reports)

We use Thomson Reuters Guidance Reports to identify whether a given turn-at-talk contains forward-looking guidance by following the steps outlined below:

1. Manually download each guidance report, which are in .pdf format, for all fiscal years that contain the earnings conference calls in our sample. We are able to identify reports spanning the conference call date for 91% of our sample firms. For firms without a guidance report we set guidance equal to zero.
2. Convert .pdf files and assemble in machine-readable textual format. For example, the guidance report for Mohawk Industries, Inc. for FY 2009 identifies the following excerpt regarding guidance related to provision for bad debt expense:

Provision for Bad Debts

Latest Guidance issued on Feb 24, 2009 / 04:00PM GMT

Non-Numeric Guidance ($ mlns)	Q4 2008 Mohawk Industries, Inc. Earnings Conference Call — Transcript
	Ivy Zelman, Zelman & Associates - Analyst: **"Are you hearing from any of them any pressure from having working capital advancements to them by banks not being afforded to them?"**

Frank Boykin, Mohawk Industries, Inc. - CFO: **"If I can just go back to your question on bad debt expense, it's 23 basis points for the quarter."**
Ivy Zelman, Zelman & Associates - Analyst: **"I'm sorry, how much for the quarter?"**
Frank Boykin, Mohawk Industries, Inc. - CFO: **"23 basis points."**

3. Match the textual information extracted from guidance report to specific turns-at-talk in conference call transcripts. Set the indicator variable *DL_Guide=1* for the specific dialogue in the transcript that comprises of the matched turns-at-talk. The following excerpt identifies the matched turns-at-talk (turns 108-110) in the Q4 conference call transcript of Mohawk Industries, Inc. that corresponds to the guidance information in guidance reports:

Frank Boykin, Mohawk Industries, Inc. - CFO [108]

If I can just go back to your question on bad debt expense, it's 23 basis points for the quarter.

Ivy Zelman, Zelman & Associates - Analyst [109]

I'm sorry, how much for the quarter?

Frank Boykin, Mohawk Industries, Inc. - CFO [110]
----
23 basis points

Appendix D (Robustness Checks)

D.1 Alternative Control for Analyst Quality

Our main analyses control for analyst quality by including indicator variables for whether the analyst is an all-star (ALLSTAR) and whether the analyst works for a prestigious brokerage firm (BROKER). Another potential proxy for analyst quality is analyst experience, i.e. the number of years the analyst has been active in the industry. We avoid including analyst experience (ANAEXP) as an additional control variable in our main analyses, as more experienced analysts are more likely to be all-star analysts and/or employed by prestigious brokerage firms, and the resulting multi-collinearity can potentially affect statistical inference. As a robustness check, we control for analyst experience (ANAEXP) instead of all-star status. As expected, ANAEXP is significantly correlated with ALLSTAR (pearson 0.44; spearman 0.46) at the 1% level. We find that ANAEXP is also positively correlated with brokerage rank (BROKER), albeit relatively lower in magnitude (pearson 0.11; spearman 0.16; $p<0.01$). Analysts participating in Q&A section of the call in our sample have an average experience of 7 years. Results from re-estimating equation (1) using ANAEXP as a control variable reveal that analyst experience is not directly associated with unsigned returns in a dialogue. However, based on additional analysis (equation (1.1, 1.1.1-4)) we find that analyst experience is positively associated with number of turns in a dialogue (DL_TURNS), likelihood of guidance issuance (DL_GUIDE), and length of the dialogue (DL_PCT_LEN). Coefficients on our variables of interest corresponding to analyst favor (DL_BUY_MEET, DL_BUY_MISS, DL_NBUY_MEET, and DL_NBUY_MISS) are largely identical to that in Table 4 Panel B. We do observe that controlling for analyst experience attenuates the positive association between analysts whose forecasts were met or beat (DL_BUY_MEET, DL_NBUY_MEET) and dialogue length (DL_PCT_LEN, DL_TURNS). However, this does not affect our inferences.

Next, we proceed to re-estimating equation (6) and equations (6.1, 6.1.1-4) where we use signed returns as an outcome variable. While we find no association between analyst experience and signed returns based on the results of estimating equation (6), path analysis (i.e. equations 6.1, 6.1.1-4) reveals that experienced analysts praise management more and have a residual negative effect on returns after controlling for all indirect effects. However, our main inference based on the coefficients on variables corresponding to analyst favor conditions is unaltered. Overall, inclusion of analyst experience as an alternate control variable does not affect our inferences in this study.

D.2 Alternate definition of analyst favor

In our main analyses, we use the analysts' absolute stock recommendations to define BUY and NBUY. An alternate approach is to define analyst favor based on the recommendation of the participating analyst *relative* to the average recommendation of other analysts participating in a given firm's quarterly earnings call. Such a specification helps capture effects arising primarily from differences in analyst favor *within* a firm's quarterly conference call while being easily amenable to a path analysis estimation. Accordingly, we define BUY (NBUY) as an indicator variable that assumes a value of one if the analyst recommendation is more favorable (less or equally favorable) than the mean recommendation of all analysts participating in the call, and zero otherwise. We re-estimate all our empirical specifications using this alternate definition and our overall inferences are unaltered. The only results that change in statistical significance is the negative coefficient on abnormal voice pitch reported in Table 5, Panel B, Column 4 on DL_BUY_MISS (which becomes statistically significant) and DL_NBUY_MISS (which becomes statistically insignificant). As in Panel B of Table 5, there remains no statistical difference in voice pitch across analyst favor levels.

D.3 Autocorrelation in dialogue level stock returns

Matusmoto et al. (2011) document that there is autocorrelation in conference call returns whereby returns from the presentation portion of the call incrementally predict stock returns in the question and answer session. To ensure our inferences are not confounded by autocorrelation in dialogue level returns, we include the return from the previous dialogue as an additional control (untabulated). For the first dialogue in the question and answer session, we use the return from the final quartile of the presentation as the lagged return in our analysis. Our inferences remain unchanged to those reported in Tables 4 and 5.

Appendix E (Manager-Analyst Dialogue Examples)

Example #1

Q3 2009 Neenah Paper, Inc. Earnings Conference Call

DL_ABSRET = 217 basis points

Your next question comes from line of Mark Weintraub with Buckingham Research.

Mark Weintraub, Buckingham Research Group - Analyst [25]

Thank you, good morning Sean. Three questions, first, are there any pricing initiatives in any of your product lines?

Sean Erwin, Neenah Paper, Inc. - President, CEO and Chairman [26]

Yes, some are contractual. We have for a portion of our technical products business, it's embedded in there both in terms of pulp and latex. From just a market standpoint, we have, this quarter, taken some other actions, increasing prices in certain technical product segments. Fine Paper, where we took some heady increases at the end of 2008, we haven't adjusted our branded prices upwards. We have adjusted and will adjust our -- any non-branded products upwards as pulp moves. And, so not general price increases, but we are active both in non-branded Fine and in areas within tech products.

Mark Weintraub, Buckingham Research Group - Analyst [27]

And can you give us a sense on the tech products side how much of the pulp gets offset by contractual adjustments that get made on the pricing side?

Sean Erwin, Neenah Paper, Inc. - President, CEO and Chairman [28]

I would have to guess it's half. The other thing is in filtration business, the German business. A high percentage of that fiber was a mercerized pulp that is a contract price that had gone up actually quite a bit. This year on that we're seeing some relief on pricing so that we would expect to go against the market. And on the -- as I said in the other areas of tech, probably half are tied to pricing and contract.

Mark Weintraub, Buckingham Research Group - Analyst [29]

Right. Helpful. And is that a pretty much immediate pass through or does this tend to be a quarter lag or something to that effect?

Sean Erwin, Neenah Paper, Inc. - President, CEO and Chairman [30]

We lag a quarter both ways but it's typically -- we lag a quarter to a risking price.

Mark Weintraub, Buckingham Research Group - Analyst [31]

Okay. And then on the mill downtime, was there anything exceptional in the third quarter and/or to be expected in the fourth quarter?

Sean Erwin, Neenah Paper, Inc. - President, CEO and Chairman [32]

No. In the third quarter, I think the the first two quarters, Mark, they were averaging about $10 million a quarter. And the third quarter was a little over $2 million, so we had less of it. We do have some holiday downs in the fourth quarter. But those are normal. So year-on-year, that part will be less.

And we don't -- if you remember, especially in the month of December last year, we took tremendous downtime across the whole system and which was especially expensive in Germany before the short time work payment program of the government kicked in. We don't expect to experience any of that this year. So year-on-year, the operating rates will be substantially higher.

Mark Weintraub, Buckingham Research Group - Analyst [33]

Okay. So somewhat -- there will be some pickup in downtime costs seasonally related to third quarter but less than 4Q? Is that fair?

Sean Erwin, Neenah Paper, Inc. - President, CEO and Chairman [34]

Yeah. I think maybe a way to put it, Mark, is you are going to trade some holiday time for maintenance time. We'll take less maintenance and costly downtime but we will have some holiday downs.

Mark Weintraub, Buckingham Research Group - Analyst [35]

Okay. And then lastly, I think there have been some changes in Nova Scotia on the political scene. Are you seeing any -- are you closer to the end of the tunnel on the timber land side?

Sean Erwin, Neenah Paper, Inc. - President, CEO and Chairman [36]

You are as plugged in as I am. There have been some dramatic changes up there. And, saying things that are public, I think that the government has come out and said that they are interested in buying land, both for set-aside purposes, but also in ways that could support industry because it is an important part of the economic program up in Nova Scotia. And as I said in the prepared comments, we're active in the process, we're very plugged in to what's going on both politically there as well as through economic development and DNR, and hopefully that does not hurt the process. I think it helps; obviously, it helps us.

Mark Weintraub, Buckingham Research Group - Analyst [37]

Okay. Terrific. Thank you very much.

Example #2

Q2 2008 Dick's Sporting Goods, Inc. Earnings Conference Call

DL_ABSRET = 5 basis points

Operator: Sean McGowan, Needham & Co.

Sean McGowan, Needham & Co. - Analyst [138]

Most of my questions have been asked. I just wanted to know if you could comment on sort of the pace of business throughout the quarter and whether there were any meaningful spikes up or down relative to your expectations?

Ed Stack, Dick's Sporting Goods, Inc. - Chairman, CEO [139]

They were pretty much kind of within our expectations, other than -- the camping business was a little softer in the quarter at the beginning than we had anticipated. But other than that, it kind of played out the way we thought it would in our guidance.

Sean McGowan, Needham & Co. - Analyst [140]

Was July better than the rest of the quarter?

Ed Stack, Dick's Sporting Goods, Inc. - Chairman, CEO [141]

We have never commented on a month by month basis, and for competitive reasons we're not going to do that. But the month -- the quarter laid out pretty much as we had anticipated.

Sean McGowan, Needham & Co. - Analyst [142]

Thank you.

Figure 1

Assessing the Direct and Indirect Effects of Conflicts of Interest: Dialogue Information Quantity

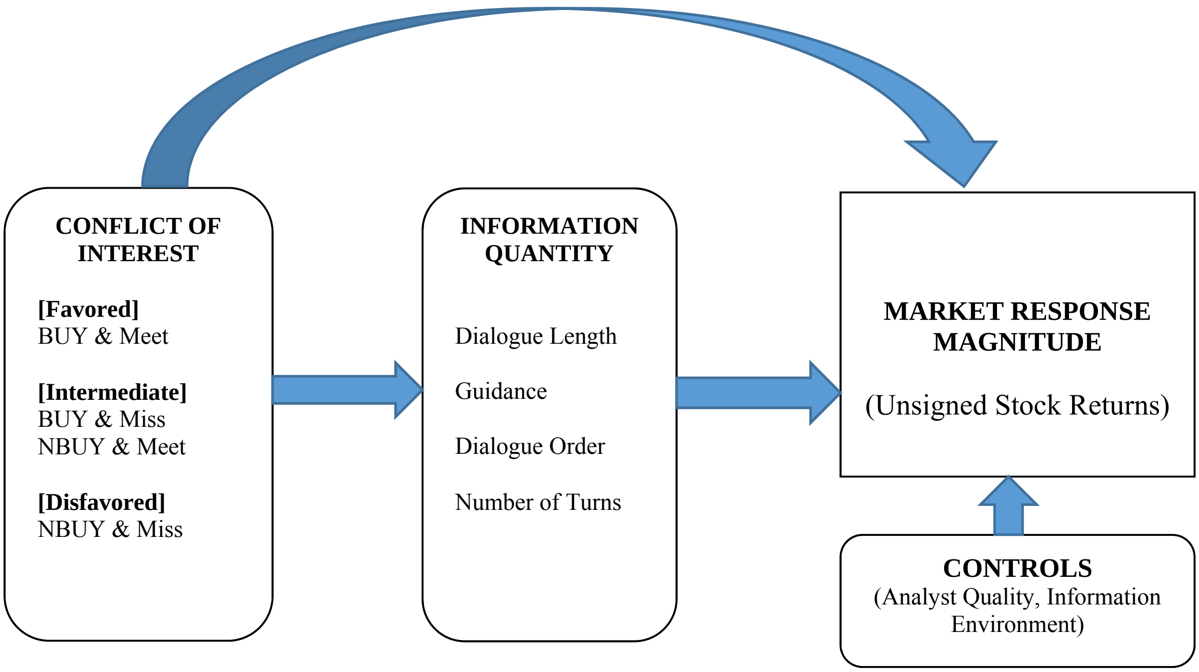

Figure 2

Assessing the Direct and Indirect Effects of Conflicts of Interest: Dialogue Information Credibility

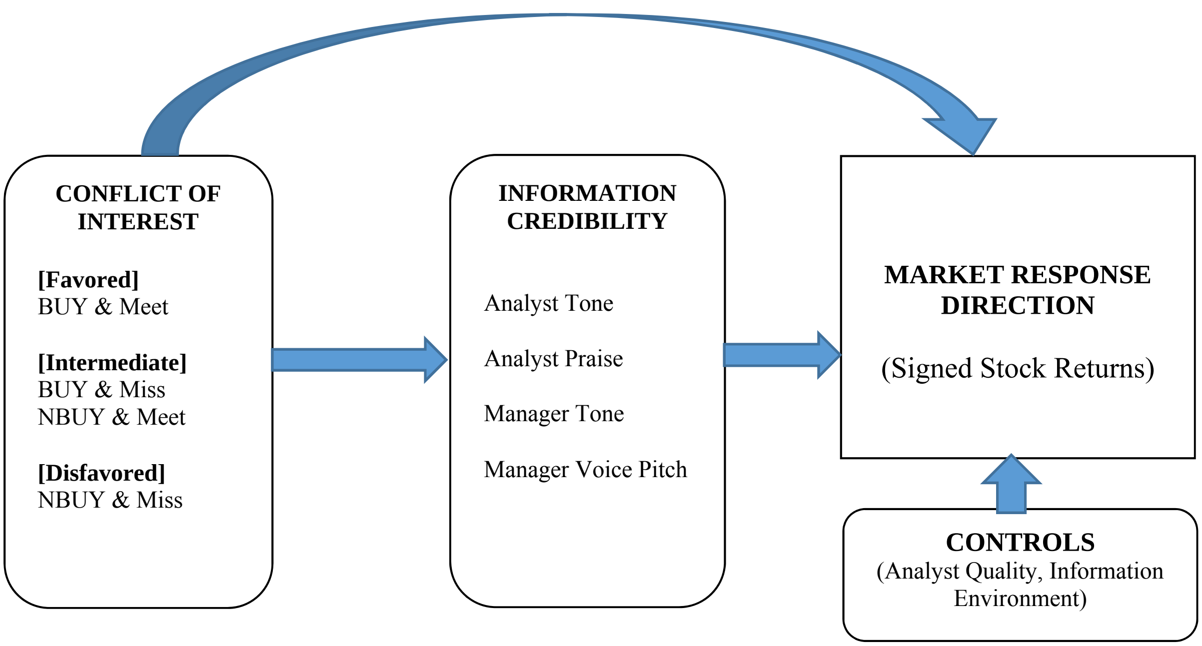

Table 1

Information Content of Earnings Conference Calls – Replication of Matsumoto et al. (2011)

This table reports the results from replication of Matsumoto et al. (2011) using a sample of 2,455 conference call observations. Panel A reports the variable definitions and descriptive statistics. Panel B provides the OLS estimation results. The t-statistics included in brackets are computed using robust standard errors clustered at the firm level. Two-tailed p-values are reported: *** p<0.01, ** p<0.05, * p<0.10.

Panel A: Variable Definitions and Descriptive Statistics

$ABSRET_{DAYB4}$: Absolute value of the return for the 24-hour period prior to the start of the conference call

ABS_ABNRET_{PR}: Absolute abnormal return during the presentation section computed using the same window on a non-conference call day (7, 14, or 21 days prior to the call) as a benchmark

ABS_ABNRET_{QA}: Absolute abnormal return during the Q&A section computed using the same window on a non-conference call day (7, 14, 0r 21 days prior to the call) as a benchmark

NUM_ANA: Number of analysts participating in the Q&A section of the call

Variables	N	Mean	Median	Std. Dev.
$ABSRET_{DAYB4}$	2,455	0.0533	0.0378	0.0496
ABS_ABNRET_{PR}	2,455	0.0047	0.0020	0.0141
ABS_ABNRET_{QA}	2,455	0.0052	0.0024	0.0146
NUM_ANA	2,455	7.5613	7.0000	3.3892

Panel B: Information Content of Presentation and Q&A sessions in the Presence of Analysts

Dependent Variable:		*ABS_ABNRET_{PR}*	*ABS_ABNRET_{PR}*	*ABS_ABNRET_{QA}*	*ABS_ABNRET_{QA}*
	Predicted Sign	*(1)*	*(2)*	*(3)*	*(4)*
$ABSRET_{DAYB4}$	+	**0.0487*** **	**0.0487*** **	**0.0281*** **	**0.0281*** **
		[5.05]	[5.05]	[3.74]	[3.77]
ABS_ABNRET_{PR}	+			**0.1802*** **	**0.1811*** **
				[5.08]	[5.13]
NUM_ANA	+		-0.0002		**0.0006** **
			[-0.54]		[2.12]
NUM_ANA^2	-		0.0000		**-0.0000* **
			[0.22]		[-1.87]
CONS	+	**0.0021*** **	**0.0033** **	**0.0029*** **	0.0002
		[4.68]	[2.08]	[7.10]	[0.12]
N		2,455	2,455	2,455	2,455
R-squared		0.03	0.03	0.05	0.05

Table 2

Descriptive Statistics

This table reports descriptive statistics for the variables at the Call, Presentation, and Q&A level. All variables are described in Appendix A. All continuous variables are winsorized at 1% and 99%. The prefixes PR and QA denote that the variables are measured at the presentation level and the Q&A level, respectively.

Panel A: Call Level

Variables	N=2,455				
	Mean	**Median**	**SD**	**Min**	**Max**
RET	0.000	0.000	0.025	-0.084	0.083
ABSRET	0.017	0.011	0.018	0.000	0.084
MINS	54.408	55.050	14.457	14.317	142.267
SIZE ($Bn)	12.103	3.199	33.293	0.125	287.583
LnSIZE	8.146	8.070	1.486	4.831	12.569
DISPERSION	0.065	0.030	0.121	0.000	2.740
NUM_REC	8.704	8.000	5.313	1.000	33.000
MEAN_REC	3.514	3.500	0.532	1.000	5.000
UE	0.023	0.020	0.124	-0.280	0.280

Panel B: Presentation Level

Variables	N=2,455				
	Mean	**Median**	**SD**	**Min**	**Max**
PR_RET	0.000	0.000	0.017	-0.058	0.056
PR_ABSRET	0.011	0.007	0.012	0.000	0.058
PR_MINS	23.515	22.733	8.190	4.267	77.000
PR_CEO_MINS	9.631	8.767	6.196	0.000	60.017
PR_CFO_MINS	8.591	8.200	5.840	0.000	42.650
PR_TURNS	4.860	5.000	1.588	2.000	21.000
PR_CEO_TURNS	1.502	1.000	0.829	0.000	8.000
PR_CFO_TURNS	0.994	1.000	0.544	0.000	6.000
PR_GUIDE	0.826	1.000	0.379	0.000	1.000

Panel C: Question and Answer (Q&A) Level

Variables	N=2,455				
	Mean	Median	SD	Min	Max
QA_RET	0.000	0.000	0.018	-0.060	0.067
QA_ABSRET	0.012	0.007	0.013	0.000	0.067
QA_MINS	30.892	30.783	11.809	1.650	90.400
QA_CEO_MINS	11.996	10.850	8.077	0.000	58.967
QA_CFO_MINS	5.274	4.083	4.950	0.000	39.167
QA_ANA_MINS	9.007	8.600	3.905	0.183	40.000
QA_TURNS	97.167	91.000	40.839	7.000	279.000
QA_CEO_TURNS	23.499	22.000	15.489	0.000	102.000
QA_CFO_TURNS	13.754	11.000	12.154	0.000	104.000
QA_ANA_TURNS	41.280	39.000	18.301	2.000	119.000
QA_NUM_ANA	7.561	7.000	3.389	1.000	22.000
QA_NUM_ALLSTAR	1.709	1.000	1.936	0.000	9.000
QA_NUM_BUY	2.592	2.000	2.175	0.000	14.000
QA_NUM_NBUY	2.296	2.000	1.993	0.000	14.000
QA_NUM_MEET	3.462	3.000	2.998	0.000	17.000
QA_NUM_MISS	1.425	0.000	2.126	0.000	19.000
QA_NUM_RECIN	4.028	4.000	2.503	0.000	17.000
QA_MEAN_RECIN	3.574	3.571	0.674	1.000	5.000
QA_DISP_RECIN	0.660	0.707	0.452	0.000	2.828
QA_NUM_RECOUT	4.676	4.000	3.864	0.000	23.000
QA_MEAN_RECOUT	3.424	3.385	0.619	1.000	5.000
QA_DISP_RECOUT	0.689	0.726	0.490	0.000	2.828
QA_NUM_DIALOGUE	8.202	8.000	3.669	1.000	25.000
QA_PRAISE	0.159	0.103	0.196	0.000	1.780
QA_GUIDE	0.784	1.000	0.412	0.000	1.000

Table 3
Analyst-Manager Dialogue Descriptive Statistics

This table reports descriptive statistics for the variables at the manager-analyst dialogue (prefix DL) level. All variables are described in Appendix A. All continuous variables are winsorized at 1% and 99%.

Panel A: Characteristics of Manager-Analyst Dialogues

Variables	N=19,605				
	Mean	**Median**	**SD**	**Min**	**Max**
DL_ORDER	5.384	5.000	3.587	1.000	25.000
DL_MINS	3.774	3.433	1.973	0.500	11.983
DL_CEO_MINS	1.454	1.133	1.451	0.000	9.983
DL_CFO_MINS	0.646	0.267	0.893	0.000	9.567
DL_ANA_MINS	1.105	0.967	0.649	0.017	9.650
DL_TURNS	11.757	11.000	6.165	2.000	62.000
DL_CEO_TURNS	2.862	2.000	2.572	0.000	28.000
DL_CFO_TURNS	1.687	1.000	2.1578	0.000	19.000
DL_ANA_TURNS	5.067	5.000	2.809	1.000	31.000
DL_PCT_LEN	0.125	0.105	0.084	0.008	0.523
DL_RET	0.000	0.000	0.007	-0.028	0.027
DL_ABSRET	0.004	0.002	0.005	0.000	0.028
DL_TONE	0.006	0.000	0.419	-1.000	1.000
DL_POSTONE	1.347	1.250	0.777	0.000	3.846
DL_NEGTONE	1.297	1.171	0.737	0.000	4.513
DL_GUIDE	0.337	0.000	0.473	0.000	1.000

Panel B: Characteristics of Analysts Asking Questions

Variables	N=19,605				
	Mean	**Median**	**SD**	**Min**	**Max**
DL_ALLSTAR	0.228	0.000	0.420	0.000	1.000
DL_BUY	0.348	0.000	0.476	0.000	1.000
DL_NBUY	0.307	0.000	0.461	0.000	1.000
DL_MEET	0.463	0.000	0.499	0.000	1.000
DL_MISS	0.192	0.000	0.394	0.000	1.000
DL_BUY_MEET	0.253	0.000	0.435	0.000	1.000
DL_BUY_MISS	0.095	0.000	0.293	0.000	1.000
DL_NBUY_MEET	0.210	0.000	0.407	0.000	1.000
DL_NBUY_MISS	0.097	0.000	0.296	0.000	1.000
DL_ANA_TONE	0.001	0.000	0.599	-1.000	1.000
DL_ANA_POSTONE	1.500	1.299	1.209	0.000	5.883
DL_ANA_NEGTONE	1.509	1.316	1.243	0.000	7.143
DL_PRAISE	0.158	0.000	0.435	0.000	7.692
DL_BROKER	5.487	6.709	3.317	0.000	9.000

Panel C: Characteristics of Management Responses to Analyst Questions

Variables	N=19,605				
	Mean	**Median**	**SD**	**Min**	**Max**
DL_ABN_PITCH	-4.477	-4.950	12.914	-36.567	34.400
DL_PITCH	125.145	122.025	20.986	91.600	207.500
DL_BENCH_PITCH	129.325	126.350	20.285	94.900	207.150
DL_MGR_TONE	0.143	0.200	0.551	-1.000	1.000
DL_MGR_POSTONE	1.332	1.205	0.954	0.000	4.455
DL_MGR_NEGTONE	0.965	0.836	0.774	0.000	3.615

Panel D: Correlation Matrix (*See Next Page)*

This table presents the correlation matrix for key dialogue-level regression variables. Spearman correlation is shown above diagonal and Pearson below (N=19,605). All variables are described in Appendix A. All continuous variables are winsorized at 1% and 99%.

VARS	*DL_ABSRET*	*DL_RET*	*DL_ORDER*	*DL_GUIDE*	*DL_TURNS*	*DL_PCT_LEN*	*DL_BUY*	*DL_NBUY*	*DL_MEET*	*DL_MISS*	*DL_ABN_PITCH*	*DL_MGR_TONE*	*DL_ANA_TONE*	*DL_PRAISE*	*DL_BROKER*	*DL_ALLSTAR*
DL_ABSRET	1.00	0.00	-0.12	0.04	0.17	0.21	0.00	0.03	0.01	0.04	-0.02	-0.01	-0.01	0.04	-0.02	0.01
	.	0.49	0.00	0.00	0.00	0.00	0.77	0.00	0.30	0.00	0.01	0.06	0.10	0.00	0.02	0.20
DL_RET	0.05	1.00	0.00	0.00	0.00	0.00	-0.01	0.00	-0.02	0.01	-0.01	0.00	0.01	-0.01	-0.01	0.00
	0.00	.	0.94	0.75	0.72	0.56	0.09	0.60	0.01	0.23	0.30	0.91	0.40	0.08	0.31	0.72
DL_ORDER	-0.10	0.00	1.00	-0.13	-0.14	-0.41	-0.08	-0.02	-0.04	-0.04	0.03	-0.02	-0.07	-0.11	-0.12	-0.06
	0.00	0.84	.	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DL_GUIDE	0.03	0.01	-0.13	1.00	0.15	0.16	0.03	0.02	0.06	-0.01	-0.03	0.01	0.03	0.06	0.02	0.03
	0.00	0.05	0.00	.	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.06	0.00	0.00	0.00	0.00
DL_TURNS	0.14	0.01	-0.13	0.15	1.00	0.50	0.00	0.04	0.00	0.03	0.02	-0.02	0.00	0.13	-0.08	-0.02
	0.00	0.07	0.00	0.00	.	0.00	0.99	0.00	0.61	0.00	0.00	0.00	0.91	0.00	0.00	0.01
DL_PCT_LEN	0.15	0.00	-0.36	0.12	0.41	1.00	0.03	0.03	0.01	0.04	-0.05	0.02	0.01	0.14	-0.03	0.00
	0.00	0.74	0.00	0.00	0.00	.	0.00	0.00	0.39	0.00	0.00	0.00	0.06	0.00	0.00	0.79
DL_BUY	-0.01	0.01	-0.07	0.03	-0.01	0.01	1.00	-0.49	0.35	0.14	-0.01	0.04	0.03	0.04	0.06	0.13
	0.06	0.30	0.00	0.00	0.34	0.42	.	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00
DL_NBUY	0.03	-0.01	-0.02	0.02	0.03	0.02	-0.49	1.00	0.24	0.19	-0.02	-0.03	-0.01	-0.03	0.12	0.10
	0.00	0.41	0.00	0.00	0.00	0.01	0.00	.	0.00	0.00	0.00	0.00	0.47	0.00	0.00	0.00
DL_MEET	-0.01	-0.01	-0.04	0.06	-0.02	-0.02	0.35	0.24	1.00	-0.36	-0.03	0.04	0.05	0.07	0.12	0.17
	0.13	0.06	0.00	0.00	0.04	0.02	0.00	0.00	.	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DL_MISS	0.05	0.02	-0.05	-0.01	0.04	0.03	0.14	0.19	-0.36	1.00	-0.01	-0.04	-0.05	-0.06	0.06	0.06
	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	.	0.42	0.00	0.00	0.00	0.00	0.00
DL_ABN_PITCH	-0.02	-0.01	0.04	-0.03	0.01	-0.04	-0.02	-0.01	-0.03	0.00	1.00	0.00	0.02	0.00	-0.02	0.00
	0.01	0.15	0.00	0.00	0.21	0.00	0.04	0.05	0.00	0.73	.	0.75	0.00	0.73	0.02	0.52
DL_MGR_TONE	-0.03	0.01	-0.03	0.02	-0.02	0.02	0.04	-0.03	0.04	-0.04	0.00	1.00	0.22	0.08	0.01	0.01
	0.00	0.38	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.85	.	0.00	0.00	0.11	0.11
DL_ANA_TONE	-0.02	0.01	-0.07	0.03	-0.01	0.02	0.02	0.00	0.05	-0.05	0.02	0.21	1.00	0.13	0.01	-0.01
	0.01	0.29	0.00	0.00	0.19	0.02	0.00	0.54	0.00	0.00	0.01	0.00	.	0.00	0.19	0.20
DL_PRAISE	0.03	-0.01	-0.11	0.05	0.12	0.10	0.04	-0.03	0.07	-0.06	-0.01	0.07	0.12	1.00	-0.03	0.00
	0.00	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.28	0.00	0.00	.	0.00	0.84
DL_BROKER	-0.02	-0.01	-0.13	0.02	-0.09	-0.05	0.09	0.13	0.14	0.07	-0.02	0.02	0.02	-0.03	1.00	0.37
	0.01	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.02	0.00	.	0.00
DL_ALLSTAR	-0.01	0.00	-0.05	0.03	-0.02	-0.05	0.13	0.10	0.17	0.06	0.00	0.01	-0.01	0.00	0.30	1.00
	0.17	0.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.53	0.08	0.16	0.51	0.00	.

Table 4

Conflict of Interest and Absolute Stock Price Responses

Panel A of this table reports OLS estimation of equation (1) using a sample of 19,605 analyst-manager dialogues. Panel B reports estimation of the structural equation model in equation (1.1) using a sample of 19,605 analyst-manager dialogues. Panel C presents standardized coefficients corresponding to direct and indirect effects. The t-statistics included in brackets are computed using robust standard errors clustered at the firm-call level. Standardized path coefficients with two-tailed p-values are reported: *** p<0.01, ** p<0.05, * p<0.10. See Appendix A for definitions of all variables.

Panel A: OLS Regression

Explanatory Variables	*(Conflict of Interest Level)*	*Absolute Return* (DL_ABSRET)
DL_BUY_MEET	**(Favored)**	0.004
		(0.42)
DL_BUY_MISS	**(Intermediate Favor)**	**0.017****
		(1.96)
DL_NBUY_MEET	**(Intermediate Favor)**	**0.015***
		(1.65)
DL_NBUY_MISS	**(Disfavored)**	**0.043*****
		(4.20)
DL_BROKER		-0.002
		(-0.27)
DL_ALLSTAR		**0.022*****
		(2.79)
LnSIZE		**-0.163*****
		(-13.85)
DISPERSION		**0.064*****
		(3.60)
|UE|		0.022
		(1.08)
CONSTANT		**1.588*****
		(23.03)
R-Squared		0.03
F-Tests (p-values; two-tail):		
DL_BUY_MEET = DL_NBUY_MISS		<0.01
DL_BUY_MEET= DL_BUY_MISS		0.12
DL_BUY_MISS = DL_NBUY_MEET		0.50
DL_NBUY_MEET = DL_NBUY_MISS		<0.01
DL_BUY_MEET = DL_NBUY_MEET		0.23
DL_BUY_MISS = DL_NBUY_MISS		0.03

Panel B: Structural Equation Models

	Mediating Variable				Outcome Variable
Variables (Column #)	*DL_PCT_LEN (1)*	*DL_GUIDE (2)*	*DL_ORDER (3)*	*DL_TURNS (4)*	*DL_ABSRET (5)*
DL_PCT_LEN					**0.074*** **
					(6.55)
DL_GUIDE					0.007
					(0.85)
DL_ORDER					**-0.047*** **
					(-5.57)
DL_TURNS					**0.083*** **
					(7.58)
DL_BUY_MEET	**0.030*** **	**0.060*** **	**-0.077*** **	**0.019** **	-0.002
	(3.10)	(6.41)	(-8.32)	(2.10)	(-0.33)
DL_BUY_MISS	**0.033*** **	0.013	**-0.058*** **	**0.036*** **	0.009
	(3.71)	(1.40)	(-6.27)	(3.99)	(1.05)
DL_NBUY_MEET	**0.029*** **	**0.056*** **	**-0.029*** **	**0.037*** **	0.010
	(3.24)	(6.27)	(-3.22)	(4.11)	(1.08)
DL_NBUY_MISS	**0.051*** **	0.010	**-0.054*** **	**0.065*** **	**0.032*** **
	(5.36)	(1.11)	(-6.17)	(6.86)	(3.13)
DL_BROKER	**-0.046*** **	0.007	**-0.114*** **	**-0.100*** **	0.001
	(-5.48)	(0.88)	(-14.48)	(-12.50)	(0.08)
DL_ALLSTAR	**-0.042*** **	0.011	-0.002	0.001	**0.018** **
	(-6.36)	(1.34)	(-0.36)	(0.09)	(2.31)
LnSIZE					**-0.131*** **
					(-10.68)
DISPERSION					**0.073*** **
					(3.98)
|UE|					0.022
					(1.06)
CONSTANT	**1.394*** **	**0.625*** **	**1.784*** **	**2.006*** **	**1.222*** **
	(59.24)	(36.91)	(87.33)	(93.63)	(15.52)
Overall R-squared	0.07				
F-Tests (p-values; two-tail):					
DL_BUY_MEET = DL_NBUY_MISS	<0.01	<0.01	0.86	<0.01	<0.01
DL_BUY_MEET= DL_BUY_MISS	0.19	<0.01	0.55	0.02	0.24
DL_BUY_MISS= DL_NBUY_MEET	0.22	<0.01	<0.01	0.36	0.81
DL_NBUY_MEET= DL_NBUY_MISS	<0.01	<0.01	<0.01	<0.01	0.02
DL_BUY_MEET= DL_NBUY_MEET	0.91	0.99	<0.01	0.04	0.19
DL_BUY_MISS= DL_NBUY_MISS	0.09	0.81	0.65	0.01	0.05

Panel C: Mediation Tests

Standardized coefficients corresponding to indirect and direct effects for each mediating variable are presented below. The standardized coefficient corresponding to the indirect effect is computed as the product of standardized coefficients in the indirect paths. The statistical significance of the indirect effect is assessed using the Sobel (1982) test (delta method). Standardized coefficients with two-tailed p-values are reported: *** p<0.01, ** p<0.05, * p<0.10.

	INDIRECT EFFECTS *(Mediating Variables)*				**DIRECT EFFECT**
Analyst Favor	**DL_PCT_LEN (1)**	**DL_GUIDE (2)**	**DL_ORDER (3)**	**DL_TURNS (4)**	**DL_ABSRET (5)**
DL_BUY_MEET	**0.0022*** **	0.0004	**0.0036*** **	**0.0015** **	-0.0028
DL_BUY_MISS	**0.0024*** **	0.0001	**0.0027*** **	**0.0030*** **	0.0092
DL_NBUY_MEET	**0.0022*** **	0.0004	**0.0014*** **	**0.0030*** **	0.0095
DL_NBUY_MISS	**0.0038*** **	0.0001	**0.0026*** **	**0.0053*** **	**0.0318*** **

Table 5

Conflict of Interest and Directional Stock Price Responses

Panel A of this table reports OLS estimation of equation (6) using a sample of 19,605 analyst-manager dialogues. Panel B reports estimation of the structural equation model in equation (6.1) using a reduced sample of 10,375 dialogues. Panel C presents standardized coefficients corresponding to direct and indirect effects. The t-statistics included in brackets are computed using robust standard errors clustered at the firm-call level. Standardized path coefficients with two-tailed p-values are reported: *** p<0.01, ** p<0.05, * p<0.10. See Appendix A for definitions of all variables.

Panel A: OLS Regression

Explanatory Variables	*(Conflict of Interest Level)*	*Signed Return (DL_RET)*
DL_BUY_MEET	**(Favored)**	-0.000
		(-0.05)
DL_BUY_MISS	**(Intermediate Favor)**	**0.015***
		(1.78)
DL_NBUY_MEET	**(Intermediate Favor)**	-0.010
		(-1.58)
DL_NBUY_MISS	**(Disfavored)**	0.011
		(1.25)
DL_BROKER		-0.008
		(-1.07)
DL_ALLSTAR		0.006
		(0.83)
LnSIZE		**-0.012*****
		(-3.04)
DISPERSION		-0.002
		(-0.39)
UE		0.002
		(0.38)
CONSTANT		**0.090*****
		(3.35)
R-Squared		0.001
F-Tests (p-values; two-tailed):		
DL_BUY_MEET = DL_ NBUY_MISS		0.24
DL_BUY_MEET= DL_BUY_MISS		0.12
DL_BUY_MISS= DL_NBUY_MEET		0.02
DL_NBUY_MEET= DL_NBUY_MISS		0.05
DL_BUY_MEET= DL_NBUY_MEET		0.12
DL_BUY_MISS= DL_NBUY_MISS		0.75

Panel B: Structural Equation Models

	Mediating Variables				Outcome Variable
Variables (Column #)	*DL_ANA_TONE (1)*	*DL_PRAISE (2)*	*DL_MGR_TONE (3)*	*DL_ABN_PITCH (4)*	*RET (5)*
DL_ANA_TONE					**0.015****
					(2.14)
DL_PRAISE					-0.009
					(-0.90)
DL_MGR_TONE					-0.007
					(-0.61)
DL_ABN_PITCH					**-0.017*****
					(-2.75)
DL_BUY_MEET	**0.059*****	**0.070*****	**0.054*****	**-0.026***	-0.007
	(5.06)	(5.42)	(4.46)	(-1.91)	(-0.76)
DL_BUY_MISS	**-0.022***	**-0.042*****	**-0.029****	-0.018	0.006
	(-1.89)	(-4.80)	(-2.47)	(-1.51)	(0.63)
DL_NBUY_MEET	**0.025****	0.006	0.009	**-0.025***	-0.016
	(2.11)	(0.50)	(0.69)	(-1.91)	(-1.59)
DL_NBUY_MISS	**-0.029*****	**-0.056*****	**-0.063*****	**-0.026****	0.017
	(-2.59)	(-6.31)	(-5.28)	(-2.08)	(1.08)
DL_BROKER	**0.028*****	**-0.048*****	**0.019***	-0.014	-0.003
	(2.68)	(-4.47)	(1.72)	(-1.32)	(-0.32)
DL_ALLSTAR	**-0.025****	-0.003	-0.007	**0.024****	-0.000
	(-2.29)	(-0.32)	(-0.64)	(2.02)	(-0.05)
LnSIZE					-0.011
					(-1.32)
DISPERSION					-0.004
					(-0.61)
UE					0.007
					(0.82)
CONSTANT	**-0.088*****	**0.534*****	**0.299*****	**-0.587*****	0.078
	(-3.66)	(23.74)	(11.58)	(-19.97)	(1.24)
Overall R-squared	0.03				
F-Tests (p-values; two-tail):					
DL_BUY_MEET = DL_NBUY_MISS	<0.01	<0.01	<0.01	0.62	0.19
DL_BUY_MEET= DL_BUY_MISS	<0.01	<0.01	<0.01	0.99	0.19
DL_BUY_MISS= DL_NBUY_MEET	<0.01	<0.01	<0.01	0.98	0.07
DL_NBUY_MEET= DL_NBUY_MISS	<0.01	<0.01	<0.01	0.63	0.09
DL_BUY_MEET= DL_NBUY_MEET	0.01	<0.01	<0.01	0.99	0.27
DL_BUY_MISS= DL_NBUY_MISS	0.64	0.21	0.02	0.60	0.53

Panel C: Mediation Tests

Standardized coefficients corresponding to indirect and direct effects for each mediating variable are presented below. The standardized coefficient corresponding to the indirect effect is computed as the product of standardized coefficients in the indirect paths. The statistical significance of the indirect effect is assessed using the Sobel (1982) test (delta method). Standardized coefficients with one-tailed p-values are reported: *** p<0.01, ** p<0.05, * p<0.10.

	INDIRECT EFFECTS ***(Mediating Variables)***				**DIRECT EFFECT**
Analyst Favor	**DL_ANA_TONE** (1)	**DL_PRAISE** (2)	**DL_MGR_TONE** (3)	**DL_ABN_PITCH** (4)	**DL_RET** (5)
DL_BUY_MEET	**0.0009****	-0.0006	-0.0004	**0.0004***	-0.0069
DL_BUY_MISS	**-0.0003***	0.0004	0.0002	0.0003	0.0059
DL_NBUY_MEET	**0.0004***	-0.0001	-0.0001	**0.0004***	**-0.0156***
DL_NBUY_MISS	**-0.0004***	0.0005	0.0004	**0.0004***	0.0170