Engagement in Earnings Conference Calls

Kristina M. Rennekamp†
Samuel Curtis Johnson Graduate School of Management
Cornell University
Ithaca, NY 14853
Email: kmr52@cornell.edu

Mani Sethuraman
Samuel Curtis Johnson Graduate School of Management
Cornell University
Ithaca, NY 14853
Email: mani.sethuraman@cornell.edu

Blake A. Steenhoven
Samuel Curtis Johnson Graduate School of Management
Cornell University
Ithaca, NY 14853
Email: bas362@cornell.edu

July 8, 2020

(Preliminary: Please do not cite or distribute without permission)

†Corresponding Author. We appreciate helpful comments and suggestions from Rob Bloomfield, Nicole Cade (Discussant), Dan Dai (Discussant), Mike Durney, Scott Emett (Discussant), Lindsey Gallo, Ryan Guggenmos, Erik Harvey, Jessen Hobson, Eunjee Kim, Bill Mayew, Greg Miller, Venky Nagar, Brian White, an anonymous FARS 2019 reviewer, two anonymous ABO 2019 reviewers, participants at the 2019 FARS Midyear Meeting, the 2019 Transatlantic Doctoral Conference, the 2019 ABO Section Research Conference, and workshop participants at Cornell University and the University of Michigan. We also thank James Pennebaker for allowing us to present terms from the LIWC2015 dictionary.

Engagement in Earnings Conference Calls

ABSTRACT

Research on earnings conference calls documents that the question and answer (Q&A) portion is informative to market participants. However, prior studies on earnings calls focus on the attributes of managers and analysts individually. In this study, we use the interaction itself as our unit of analysis, and examine whether conversational engagement between managers and analysts in earnings calls is informative to market participants. Using a controlled experiment, we first demonstrate that linguistic style matching (LSM), a form of verbal coordination, is a reasonable proxy for conversational engagement. We further demonstrate using an additional quasi-experiment that investors respond to differences in engagement. Finally, using a unique hand-collected archival dataset comprised of audio recordings and textual transcripts from over 2,400 earnings calls, we show that LSM in manager-analyst conversations during the Q&A portion of earnings calls is positively associated with absolute stock returns during the conversation, suggesting that interactions with greater engagement are more informative to capital market participants.

JEL Codes: M40, M41

Key words: Conference Calls, Linguistic Style Matching, Engagement, Price Formation, Market Microstructure.

1. Introduction

Research in accounting has examined the information content of earnings conference calls, documenting that the question and answer session (Q&A), which involves interactions between managers and analysts, is the most informative portion (Matsumoto, Pronk, and Roelofsen 2011). Prior research addresses how the attributes and behavior of either managers or analysts affect the nature and content of information produced during the Q&A portion of the call (Chen and Matsumoto 2006; Ke and Yu 2006; Mayew, Sethuraman, and Venkatachalam 2020). Whereas prior research on individuals assumes a static interaction partner, a broad literature in social psychology demonstrates that interactions are dynamic processes that reflect participants' underlying social dynamics and cognitive states (Cicourel 1974; Snyder and Stukas 1999; Cialdini and Goldstein 2004). We rely on this literature to examine how characteristics of interactions between managers and analysts contribute to the information content of the Q&A. We exploit the comparative advantages of experimental and archival methods to provide evidence that conversations with greater engagement between managers and analysts are more informative to market participants.

Using interactions between managers and individual analysts in earnings conference calls as our unit of analysis, we specifically examine conversational engagement as an indicator of the information content in interactions. Engagement is characterized by the extent to which interacting parties are focused on each other (Niederhoffer and Pennebaker 2002). Important discussions are likely to demand greater engagement, with participants more intensely focused on each other during the interaction. In contrast, conversations perceived as less important typically elicit lower levels of engagement, with participants paying less attention to each other and the focal topics. Thus, beyond the topical content of a conversation, engagement between the interacting parties can signal the importance of the discussion. Prior research suggests that, even when investors have already acquired decision-relevant information, integration costs can prevent them from fully and accurately incorporating this information into their judgments (Hogarth 1987; Maines and McDaniel 2000; Blankespoor, DeHaan, Wertz, and Zhu 2019). Given the information advantage of managers and analysts on the call (Mayew 2008), their beliefs about the relative importance of an issue, as revealed through conversational engagement, may assist investors in integrating the discussion into their valuation judgments and investment decisions.

In addition to the reasons mentioned above, the level of engagement in manager-analyst conversations may be informative about the manager, the analyst, or the nature of their relationship. Prior research in social psychology finds that characteristics of interactions reveal information about participants' underlying social dynamics and cognitive states (Cicourel 1974; Snyder and Stukas 1999; Cialdini and Goldstein 2004). Research in accounting and finance suggests that investors value signals conveying information about managerial ability, manager-analyst relationships, private information, and incentives of analysts and managers (Trueman 1986; Mayew 2008; Mayew and Venkatachalam 2012; Mayew, Sharp, and Venkatachalam 2013; Blankespoor, Hendricks, and Miller 2017; Mayew, Sethuraman, and Venkatachalam 2020). To the extent that engagement between managers and analysts serves as a signal reflecting such information, investors may derive value from observing engagement in earnings calls.

To empirically identify engagement between managers and analysts, we rely on theory in psychology and sociolinguistics, which asserts that greater engagement between interacting parties increases the extent to which these parties coordinate their behavior, formally stated as the *"coordination-engagement hypothesis"* (Niederhoffer and Pennebaker 2002). This hypothesis is derived from the perception-behavior link identified in the interpersonal coordination literature, which shows that simply observing the behavior of the other party automatically and unintentionally increases "the tendency to adopt the behaviors, postures, or mannerisms of interaction partners" (Lakin and Chartrand 2003). As engagement increases the extent to which interacting parties observe each other's behaviors, the coordination-engagement hypothesis asserts that coordinated behavior is a signal of the extent of conversational engagement (Niederhoffer and Pennebaker 2002). Thus, behavioral coordination during manager-analyst interactions may be a signal of engagement between managers and analysts in the Q&A portion of earnings conference calls.

To measure engagement between managers and analysts, we use linguistic style matching (LSM), a measure of *verbal coordination* in function (i.e., non-content) words (Niederhoffer and Pennebaker 2002). LSM captures relative usage of parts of speech (conjunctions, auxiliary verbs, articles, etc.) in a given conversation to establish and compare participants' speaking styles, resulting in a measure of the extent to which the two individuals coordinate their language style during the discussion (Ireland and Pennebaker 2010). LSM has several advantages as a measure of coordination in earnings calls. First, in contrast to coordination of physical behaviors, verbal coordination is observable in the audio-only setting of conference calls. Second, unlike content words, which vary across firms, industries, and other contextual factors, function words are context-independent and can thus be examined across conference calls and individual interactions. Finally, whereas individuals are typically aware of their usage of content words, function words are produced nonconsciously and are thus extremely difficult, if not impossible, to vary intentionally (Pennebaker and King 1999). As a result, LSM provides an unbiased measure of nonconscious behavioral coordination reflecting conversational engagement.

We first validate LSM as a proxy for conversational engagement in earnings calls using a lab experiment with MBA students acting as managers in a conference call setting.[1] Participants in our setting listen to a question asked by an analyst (held constant across conditions) and record a verbal response. We manipulate manager incentives for engagement by varying characteristics of the analyst, specifically the familiarity of the analyst's brokerage, the analyst's level of experience, and the analyst's professional achievements. Consistent with the coordination-engagement hypothesis, we find that responses of managers with greater incentives for engagement exhibit higher LSM with the analyst's language. Our

[1] In an unpublished dissertation, Tausczik (2012) finds that participants in online chatrooms exhibit greater style matching when instructed to pay attention to each other, providing support for the coordination-engagement hypothesis. Our experiment differs in several ways. First, our experiment examines LSM in oral communication, consistent with communication in earnings calls. Second, we examine LSM using a single-turn dyadic interaction to provide evidence that engagement causes language styles to converge relatively quickly. Finally, whereas participants in Tausczik (2012) are directly instructed to pay attention to each other to improve performance in a collaborative task, our study uses a conference call setting and manipulates incentives for engagement unique to earnings calls.

experimental findings provide causal evidence that conversational engagement increases verbal coordination, and validates the use of LSM as a proxy for engagement in earnings calls.

Having validated LSM as a proxy for conversational engagement in manager-analyst interactions, we use archival analysis to examine whether engagement is informative to capital market participants. We analyze a sample of over 18,000 interactions between managers and analysts occurring in 2,452 earnings calls of S&P 1500 firms. Our dataset represents a subset of the earnings conference call sample used in prior research examining the effect of individual analysts' stock recommendations and earnings forecasts on the informativeness of conference calls (Mayew, Sethuraman, and Venkatachalam 2020). Precise mapping of manager-analyst conversations to intra-day price movements is achieved by collecting, recording, and listening to audio broadcasts of each conference call. As highlighted in Mayew et al. (2020), inferring timestamps corresponding to manager-analyst interactions from textual transcripts is not feasible, as such transcripts often fail to include operator instructions. Further, speech rates may differ among speakers, necessitating the analysis of audio files to identify the exact times where one speaker finishes talking and another begins (i.e., turnover points). After identifying precise timestamps corresponding to manager-analyst turnover points, we then use Trade and Quote (TAQ) data to compute intra-call stock returns during each individual manager-analyst conversation. This approach allows us to analyze activity within the Q&A at a much more granular level than prior studies, which generally examine price responses over the entire earnings call (Frankel, Johnson, and Skinner 1999; Price, Doran, Peterson, and Bliss 2012) or the whole presentation and Q&A portions (Matsumoto et al. 2011). This granularity allows us to examine individual manager-analyst interactions and the informativeness of such interactions as measured by the magnitude of stock price movements.

We first estimate a determinant model to explore factors that elicit greater levels of LSM in manager-analyst conversations. We consider several conversational characteristics, analyst attributes, and firm fundamentals as potential determinants. Consistent with engagement driving verbal coordination, we find greater LSM in relatively longer conversations and those that contain more back-and-forth iterations between the manager and the analyst. We also find that LSM is higher in conversations that occur earlier in the call, consistent with these interactions representing discussion of relatively more important issues that warrant deeper levels of engagement. Consistent with managers' incentives for engaging with influential analysts, LSM is also greater in interactions with all-star and experienced analysts. Finally, we find that LSM is higher when managers converse with favorable analysts and when analysts converse with managers of larger firms. These results corroborate our experimental findings and validate that LSM varies in a manner consistent with theoretical predictions for engagement in an earnings conference call setting. Combined, our experimental and archival evidence provide us confidence that LSM is a reliable measure of verbal coordination reflecting conversational engagement.

We next examine whether engagement is informative to capital market participants, using the absolute stock return observed during the manager-analyst conversation as our measure of information content. We find that manager-analyst interactions exhibiting higher LSM elicit greater absolute stock price reactions, consistent with conversational engagement serving as an informative signal to capital market participants. We also note that our results are robust to alternate specifications that control for firm/call-level or analyst-level fixed effects. In further analyses, we identify the specific components of LSM that drive our findings, and find consistent evidence across our experimental and archival results. Specifically, our experimental results are driven by LSM in usage of prepositions, auxiliary verbs, and quantifiers. These specific components (in addition to negations, which are not included in the experiment) underlie our archival results as well. Our consistent results across methodologies provide further confidence that our experimental and archival results are examining the same constructs.

We then examine several alternative explanations for the association between LSM and absolute stock returns. We first conduct additional robustness tests using our archival sample to rule out the possibility that our LSM measure captures managerial scriptedness or textual tone, or that the observed market reaction reflects differences in information processing costs. A supplemental quasi-experiment using actual manager-analyst conversations from earnings calls provides more direct evidence that investors detect differences in engagement, as measured by LSM. As variation in function words is difficult to perceive in real-time (Pennebaker and King 1999), we interpret our results as consistent with the market reacting to conversational engagement (which could manifest in multiple cues) between managers and analysts, rather than to LSM per se. Finally, we show that engagement provides information incremental to the topic under discussion by implementing controls for the topical content of the conversation. Collectively, our results suggest that conversational engagement serves as an informative signal to market participants.

Our paper contributes to the literature on the information content of earnings conference calls. First, we extend the literature on the Q&A portion of conference calls by examining characteristics at the conversation level. Prior literature largely considers characteristics of conference calls at a higher level, such as the whole presentation portion, the whole Q&A portion, or the entire call. Using a more granular conversation-level analysis, we are able to consider characteristics of specific manager-analyst interactions within the Q&A and thereby more clearly identify sources of information in the call. Second, using the interaction itself as our unit of analysis, we provide evidence on a previously unexplored feature unique to the Q&A portion of earnings calls. While prior research has suggested that analyst involvement is responsible for the incremental information content of the Q&A (Matsumoto et al. 2011), we demonstrate that characteristics of the interactions per se are informative. Third, we add to the literature on the nature of information produced in the Q&A. Consistent with prior research on the usefulness of qualitative characteristics in conveying information, our results show that engagement in manager-analyst interactions reveals information to the market. Finally, we contribute to research in psychology and sociolinguistics by providing an experimental test of the coordination-engagement hypothesis. Whereas prior literature on LSM is largely associational, our experimental results provide causal evidence for verbal coordination reflecting engagement and our archival analysis demonstrates that the findings are generalizable to capital market settings.

The remainder of the paper is organized as follows. In Section 2, we review the literature and present our theory. Section 3 describes our experimental validation of our measure of engagement. Section 4 describes the sample, research design, and results for the archival analyses. Section 5 presents additional evidence on the information conveyed by engagement. Section 6 concludes.

2. Theory and Hypothesis Development

2.1 Information Content in Earnings Conference Calls

Literature in accounting examines earnings conference calls as a form of voluntary disclosure and the information conveyed by such calls to capital markets (Frankel et al. 1999; Bowen, Davis, and Matsumoto 2002; Kimbrough 2005). As earnings calls occur immediately following earnings announcements, prior studies have tried to identify the source and nature of the information in conference calls. Matsumoto et al. (2011) find that, within the conference call, both the presentation by management and the subsequent question and answer (Q&A) session with analysts have incremental information content over and above earnings press releases, though the Q&A portion is more informative than the presentation. They suggest that the informativeness of the Q&A portion of earnings calls stems from fewer constraints on management's communication, the result of analyst involvement, or both.

Research on management's communication in earnings conference calls has primarily focused on qualitative characteristics. Research on linguistic characteristics has examined whether information is conveyed by managers' tone (Price et al. 2012; Davis, Ge, Matsumoto, and Zhang 2015) and linguistic complexity (Bushee, Gow, and Taylor 2018). Transcripts of earnings calls have also been used to measure managers' knowledge (Li, Minnis, Nagar, and Rajan 2014), time horizon (Brochet, Loumioti, and Serafeim 2015), and spontaneity (Lee 2016). Studies analyzing audio from earnings calls suggest that managers' vocal cues in earnings calls contain value-relevant information (Mayew and Venkatachalam 2012; Mayew, Sethuraman, and Venkatachalam 2020).

Other research suggests that analyst involvement may be responsible, directly or indirectly, for some of the information content in earnings calls. Frankel, Mayew, and Sun (2010) find that earnings calls are longer for firms that miss analyst expectations and include more probing questions from analysts. However, in a survey of sell-side financial analysts, Brown, Call, Clement, and Sharp (2015) document a reluctance on the part of analysts to interrogate management publicly during conference calls due to concerns about revealing information to competitors and the risk of threatening relationships with management. Further, although Mayew, Sharp, and Venkatachalam (2013) find that analysts who participate in earnings calls issue timelier and more accurate forecasts, this advantage does not appear to be driven by information revealed in the call. Managers' preference for allowing more favorable analysts to participate in conference calls (Mayew 2008) is consistent with firms attempting to "manage the narrative" during such calls (Brown, Call, Clement, and Sharp 2019). Other studies have examined analysts' language in the Q&A, including favorableness (Milian, Smith, and Alfonso 2017) and praise of management (Milian and Smith 2017).

Research on earnings calls suggests that the behavior and attributes of individuals within the call are informative to market participants. We extend this literature by examining the *interaction* between managers and analysts as our unit of analysis. A broad literature in social psychology demonstrates that characteristics of interactions are informative about participants' cognitive states and social dynamics (Frith and Frith 2012). To the extent that these factors are relevant to market participants, useful information may be revealed by the way managers and analysts interact with each other, which is uniquely observable in earnings calls. We begin this examination by focusing on the level of conversational engagement as a signal of the importance managers and analysts place on the discussion. We discuss the information conveyed by conversational engagement to investors in Section 4.

2.2 Linguistic Style Matching in Social Interactions as an Indicator of Engagement

To empirically identify engagement in earnings calls, we rely on the literature in psychology and sociolinguistics describing the link between engagement and behavioral coordination. Initially proposed by Niederhoffer and Pennebaker (2002), the "coordination-engagement hypothesis" suggests that behavioral coordination signals active engagement by interacting parties. This hypothesis draws on literature in social psychology describing the "perception-behavior link," which refers to an automatic and unintentional process through which simply perceiving the behavior of others increases the likelihood of engaging in the same behavior (Chartrand and Bargh 1999). At a fundamental level, this link requires that the two interacting parties are (1) focused on (i.e., paying attention to) each other, such that (2) the behavior of the counterparty is accurately perceived (van Baaren et al. 2003). Thus, the coordination-engagement hypothesis asserts that because attention to others varies with the level of engagement, behavioral coordination reflects the degree to which participants are conversationally engaged.

We measure behavioral coordination in earnings calls using linguistic style matching (LSM), a measure of verbal coordination that captures the extent to which individuals' language styles co-vary during an interaction (Niederhoffer and Pennebaker 2002). Specifically, LSM quantifies the similarity in usage of categories of "function" words, including pronouns, articles, prepositions, auxiliary verbs, adverbs, conjunctions, negations, and quantifiers (Ireland and Pennebaker 2010). In Appendix A, we provide brief descriptions of these categories and examples of words from each category that commonly appear in our archival sample of earnings calls. In contrast to "content" words, which comprise what is said, "function" words have little meaning on their own and thus reflect how content is communicated (i.e., the communication style) (Pennebaker, Mehl, and Niederhoffer 2003). While individual styles differ, convergence in style has been shown to occur over the course of a conversation (albeit, nonconsciously) and on a turn-by-turn basis in a conversation, reflecting both the flexibility of style and the mutual influence of interaction partners (Niederhoffer and Pennebaker 2002) on each other's style. As such, LSM represents the coordination of communication style, similar to coordination of non-verbal behaviors, and thus reflects the extent of engagement in interactions.

We measure LSM following the methodology described in Ireland and Pennebaker (2010). We use the Linguistic Inquiry and Word Count (LIWC; Pennebaker, Boyd, Jordan. and Blackburn 2015) software to measure the frequency of nine categories of function words: personal pronouns (*ppron*), indefinite pronouns (*ipron*), articles (*article*), prepositions (*prep*), auxiliary verbs (*auxverb*), adverbs (*adverb*), conjunctions (*conj*), negations (*negate*), and quantifiers (*quant*). The output of LIWC (denoted 'c' below) is the number of words belonging to each function category as a percentage of the total words.[2]

[2] For example, the 4-word sentence "we expect revenue growth" contains one personal pronoun ("we") and would therefore result in a value of 25% (i.e., 0.25) for *ppron*. As the sentence contains no other function words, the values for all other categories would be zero.

This output is used to compute the similarity between the use of each function word category by each participant (denoted as "manager" and "analyst" below) using the following formula:

$$LSM_c = 1 - \frac{\left| c_{manager} - c_{analyst} \right|}{c_{manager} + c_{analyst} + .0001}$$

The resulting LSM measure ranges from zero (indicating no linguistic style matching) to one (indicating perfect linguistic style matching). Rather than representing the quantity of function words used, this measure captures the similarity in the rate at which two speakers use function words. Thus, LSM will be higher when both participants use similarly high, moderate, or low rates of specific function word categories. An *Average LSM* measure can then be calculated as the simple average of the LSM measures computed for the nine categories of function words.

Using LSM as a measure of behavioral (verbal) coordination in conferences calls has several advantages. First, the measure relies on function words, rather than content words. Whereas content words vary across firms, industries, and other contextual factors, function words are context-independent and can thus be examined across conference calls and individual interactions. Further, while content words may reflect intentional choices by communicators, function words are produced nonconsciously and thus are difficult, if not impossible, for speakers to change intentionally (Pennebaker and King 1999). Observed linguistic style matching (LSM) between managers and analysts is therefore more likely to reflect nonconscious behavioral coordination, rather than intentional verbal synchrony. Finally, most analysts ask questions over a phone line during conference calls and most market participants only listen to the audio. Although much of the work on coordinated behavior focuses on motor movements like posture (Tiedens and Fragale 2003) and face touching (Chartrand and Bargh 1999), which are unobservable in an audio-only setting, there is a broad literature on coordination of verbal characteristics, including rate of speech (Webb 1969), syntax (Levelt and Kelter 1982), and linguistic style (Niederhoffer and Pennebaker 2002). As a result, LSM is a verbal form of coordination that is observable to researchers, in contrast to coordination of motor movements, which are not observable in earnings call settings.

According to the coordination-engagement hypothesis, coordination requires attentional resources on interaction partners and thus LSM serves as a signal of the extent to which participants are conversationally engaged (Niederhoffer and Pennebaker 2002). Studies across a variety of fields, including political science (Romero, Swaab, Uzzi, and Galinsky 2015), law enforcement (Taylor and Thomas 2008; Richardson et al. 2014; Ireland and Henderson 2014), and other more general settings (Gonzales, Hancock, and Pennebaker 2010) have provided support for this hypothesis. Our first hypothesis is as follows:

> ***H1****: Interactions with greater engagement between managers and analysts in earnings calls exhibit more linguistic style matching (LSM).*

While the evidence from prior literature collectively suggests that LSM represents a form of verbal coordination indicative of conversational engagement, there are several reasons to experimentally test this hypothesis in an earnings call setting. First, although the coordination-engagement hypothesis has been studied in psychology and sociolinguistics, most of these studies are associational. Using an experiment allows us to abstract from other potential determinants of behavioral coordination to provide causal evidence on the coordination-engagement hypothesis and substantiate the construct validity of LSM as a proxy for conversational engagement (Libby, Bloomfield, and Nelson 2002). Second, prior research on the coordination-engagement hypothesis is conducted in settings which differ from earnings calls. Although our theory relies on general psychological processes, these contextual differences make it unclear whether managers and analysts will exhibit similar behaviors (Bonner 2008). An experiment allows us to provide evidence on the generalizability of the coordination-engagement hypothesis to our specific setting.

3. Experimental Validation of LSM as a Proxy for Engagement

To validate the use of LSM as a proxy for engagement in earnings calls, we conduct an experimental test of the coordination-engagement hypothesis, which asserts that increased conversational engagement leads to greater behavioral coordination. The use of an experiment allows us to provide causal evidence by controlling for influential factors that are confounded in natural settings and are difficult to disentangle through archival analyses (Libby, Bloomfield, and Nelson 2002). While coordination is a characteristic of the interaction and is therefore a product of both the manager and the analyst in a call, our experiment holds constant the language of one interaction partner (the analyst), and allows the language of the other interaction partner (the manager) to vary. This avoids the loss of degrees of freedom associated with a design that pairs participants assigned to different roles, and provides a cleaner and more powerful test of the theory. Specifically, our experiment examines the effect of manager incentives for engagement on linguistic style matching (LSM) in interactions with analysts.

In a recent survey of investor relations professionals, 83% indicated that interactions with sell-side analysts are important, and conveying the company's message to investors is considered the most important service provided by sell-side analysts (Brown et al. 2019). This suggests that relationships with experienced, knowledgeable, and influential analysts are especially important and managers have greater incentives for engagement during interactions with these analysts. Therefore, consistent with H1, interactions with these analysts should generate greater engagement by management, leading to greater LSM.

3.1 Participants

Participants are one hundred students from a top-ranked two-year residential MBA program in the United States. MBA students are good proxies for managers in our study, as they are sufficiently knowledgeable to understand the business setting. Further, because we are examining a nonconscious psychological effect that should not vary with experience, these participants are well-matched to the goals of the experiment (Libby, Bloomfield, and Nelson 2002).[3] Due to technical issues, voice recordings for two participants were lost. Because the voice recording is necessary for computing our dependent measures, we have a final sample size of ninety-eight participants. On average, participants are 28.92 years old and have 5.21 years of total work experience with 1.55 years in a managerial role. About one-third (33.67 percent) of participants are female.

[3] See Libby and Rennekamp (2012) for a similar example of MBA students as suitable proxies for managers due to the knowledge required for the task and the nature of the psychological effect.

3.2 Design

We use a 1 x 2 between-participants experiment in which participants assume the role of the CEO of a hypothetical company preparing for an upcoming earnings call. After reading background materials and preparing for the earnings call, participants listen to a question from a research analyst. To create the audio recording, we hired three professional voice actors to read a prepared script. One actor acts as the firm's investor relations officer (IRO) and introduces the analyst. The other two actors read the analyst question, generating two recordings of questioning by the analyst.[4]

Holding constant the language of the analyst's question, we use a compound manipulation of incentives for engagement by varying characteristics of the analyst, using the analyst's brokerage, position, and professional achievements (see Appendix B). The analyst in the *High* (*Low*) *Incentives for Engagement* condition works for J.P. Morgan (Graham Nelson & Associates, a fictional brokerage), is a Senior (Junior) Research Analyst, and has the following professional achievements: *Institutional Investor* All-Star, *WSJ* Best on the Street List, *Thomas Reuters* Analyst Award, and CFA Charterholder (CFA Charterholder only). While we cannot directly manipulate the level of engagement exerted by participants, and each component of our compound manipulation captures a distinct construct, the common factor underlying these components is that they represent incentives for engagement. An analyst from a more familiar brokerage is more likely to be influential in their recommendations and forecasts. An analyst in a more senior position will generally be more experienced, increasing their ability to scrutinize responses. Finally, analysts with more professional achievements may be perceived as both asking higher quality questions and being more influential in their responses. As such, the components of our compound manipulation collectively increase incentives for participants acting as managers to engage more strongly with the analyst by increasing perceptions of the importance of the interaction and highlighting the stakes for their response.

---

[4] We use recordings from two voice actors and randomly assign recordings within conditions to ensure responses are not affected by specific characteristics of an actor. No such differences are identified, and we therefore do not mention them further.

We derive our dependent variable, linguistic style matching (LSM), from participants' recorded verbal responses to the analyst's question. After transcribing the language from audio files, we use the Linguistic Inquiry and Word Count (LIWC; Pennebaker et al. 2015) software to measure the frequency of each category of function words in participants' responses. As in Ireland and Pennebaker (2010), we compute LSM, a measure of the similarity between language used by the analyst (held constant in our experiment) and each participant. The resulting measure ranges from zero (indicating no linguistic style matching) to one (indicating perfect linguistic style matching).

3.3 Procedure

Participants in our experiment assume the role of the CEO of UShirt, a fictional publicly-traded online retailer. Participants are informed that the company is preparing for an upcoming earnings call where analysts are likely to ask about a recent strategic initiative, and that the company's Investor Relations Officer (IRO) has provided a fact sheet about the initiative to help them prepare. Participants use the fact sheet to write their thoughts on the initiative in preparation for the earnings call.[5] After the writing task, participants are informed that their IRO has provided a description of an analyst who will be asking a question on the call. After viewing the analyst description (including our manipulation of incentives for engagement), participants listen to an audio recording of the analyst's question in the conference call. To allow participants to associate the manipulated characteristics of the analyst with the analyst's linguistic style (held constant across conditions), the analyst information is presented on the screen and the participants are informed that they can listen to the question as many times as they would like. Once they have listened to the question, participants use audio recorders to record responses to the analyst. To mitigate self-presentation concerns and ensure that participants are not influenced by the

[5] The purpose of this writing task was twofold. First, in actual conference calls, managers have broad knowledge about the firm and its strategic initiatives, which allows cognitive resources to be directed toward analysts and characteristics of their communication to be used in responses. The writing task helps participants remember the provided facts. Second, the writing task encourages participants to draft their thoughts on how the provided facts relate to the company's "current and future performance," which mirrors the content of the question to which participants are later asked to verbally respond. Because they had already generated a written response to this question, participants were able to allocate greater resources to *how* they responded in the verbal task. We do not allow participants to view the actual facts or their written response while responding to the analyst.

presence or responses of others, participants make these audio recordings while they are alone in a small conference room. Participants then respond to manipulation checks and provide demographic information.

3.4 Results

We assess the effectiveness of our manipulation of incentives for engagement using two manipulation checks. First, participants are asked whether the analyst's position is "Junior Research Analyst" or "Senior Research Analyst." Ninety-two percent (90 of 98) of participants correctly identify the analyst's position, indicating a successful manipulation of the analyst's position. Second, to test whether we successfully manipulated familiarity with the analyst's brokerage in the high (low) conditions, participants are asked "How familiar are you with Stephen Nichols' brokerage, J.P. Morgan (Graham Nelson & Associates)?" Participants respond on a 5-point scale from 1 ("Not familiar at all") to 5 ("Extremely familiar"). Consistent with a successful manipulation, we find that participants in the High Incentives for Engagement condition are significantly more familiar (mean rating of 2.80) with the analyst's brokerage than participants in the Low Incentives for Engagement condition (mean rating of 1.12) ($p < 0.001$, two-tailed).

Our hypothesis predicts that managers with greater incentives for engagement will exhibit higher LSM with the analyst's question. We compute LSM for eight categories of function words and use MANOVA to test for differences across conditions.[6] MANOVA results, presented in Table 1, Panel A support our hypothesis that incentives for engagement increase the extent to which managers exhibit LSM.[7] Participant responses had significantly higher LSM with the analyst's language when incentives

---

[6] As the analyst script contains no negations, LSM for this category equals zero if responses include any negations, or one if no negations are included. As in Ireland and Pennebaker (2010), we therefore exclude this category from our analysis.

[7] In testing assumptions for multivariate analysis, we examine correlation plots and conduct three tests (Mardia's, Henze-Zirkler's, and Royston's tests) to confirm multivariate normality (Korkmaz, Goksuluk, and Zararsiz 2014). Only the Mardia's test indicates multivariate normality, and one observation was identified as an outlier, with a Mahalanobis Distance of 5.81, which is above the upper confidence limit of 3.86. Upon further examination, this response was the shortest in the sample (37 words, compared to a mean length of 157) and was the only response with an LSM for *adverb* of zero. Given the sensitivity of LSM to response length, this observation was excluded from our analysis. Upon eliminating the outlier, both the Mardia's test and Henze-Zirkler's test indicate that our data are

for engagement were higher, as proxied by characteristics of the analyst, including brokerage familiarity, seniority, and professional achievements (p = 0.023, one-tailed).[8]

Insert Table 1 about here

We next examine the individual components of LSM to examine whether specific categories of function words underlie our results. Results of t-tests for each of the category level LSM measures are presented in Table 1, Panel B. We find significant differences between conditions, all in the predicted direction, for LSM in auxiliary verbs (p = 0.022, one-tailed), prepositions (p = 0.022, one-tailed), and quantifiers (p = 0.048, one-tailed). Responses do not significantly differ for LSM in personal pronouns (p = 0.419), indefinite pronouns (p = 0.387), articles (p = 0.224), adverbs (p = 0.172), or conjunctions (p = 0.408).[9] Results collectively provide evidence consistent with the coordination-engagement hypothesis and support the use of LSM as a proxy for engagement between managers and analysts in an earnings call setting.

4. Archival Analysis

Having provided evidence on the appropriateness of LSM as a measure of engagement in manager-analyst conversations using a controlled experimental setting, we next explore the determinants of engagement in an archival setting and also examine whether the extent of engagement is associated with the information conveyed by manager-analyst conversations to capital market participants.

multivariate normal. MANOVA results without excluding the observation are inferentially identical (p = 0.050, one-tailed).

[8] We also compare the simple average of LSM for each function word category between our two conditions. While results are directionally consistent with our predictions, we do not find a significant effect of incentives for engagement on this overall metric (p = 0.426, one-tailed; untabulated). We use MANOVA in our analyses to account for structural within-treatment correlations between category-level LSM measures and to control the experiment-wise error rate associated with testing each of these measures.

[9] Although prior research on LSM does not provide a theoretical basis for matching on specific function word categories, one potential reason for the lack of differences in LSM for these categories is that they are less malleable than others. For example, articles (“a,” “an,” and “the”) always accompany common nouns, and no more than one article can be used per noun. In contrast, a verb may be preceded by zero, one, or multiple auxiliary verbs (e.g., “be,” “have,” and “may”), depending on the tense and modality (e.g. none in “we considered” vs. two in “we had been considering”). The extent to which other factors can account for matching on individual categories is a potential avenue for future research.

There are several reasons why conversational engagement between managers and analysts may be informative to market participants. First, to the extent that engagement is driven by the perceived importance of the issue being discussed, this signal may help market participants determine the weight to place on interactions for valuation purposes. Prior research suggests that, even when investors have already acquired decision-relevant information, integration costs can prevent them from fully and accurately incorporating this information into their judgments (Hogarth 1987; Maines and McDaniel 2000; Blankespoor, DeHaan, Wertz, and Zhu 2019). Given the information advantage of managers and analysts on the call (Mayew 2008), their beliefs about the relative importance of an issue as revealed through conversational engagement may assist investors in integrating the discussion into their valuation judgments and investment decisions. Second, the level of engagement in manager-analyst conversations may be informative about the manager, the analyst, or the nature of their relationship. Research in accounting and finance suggests investors value signals conveying information about factors like managerial ability, manager-analyst relationships, private information, and incentives of analysts and managers (Trueman 1986; Mayew 2008; Mayew and Venkatachalam 2012; Mayew et al. 2013; Blankespoor et al. 2017; Mayew et al. 2020). A broad literature in social psychology demonstrates that characteristics of interactions reveal information about participants' underlying social dynamics and cognitive states (Cicourel 1974; Snyder and Stukas 1999; Cialdini and Goldstein 2004). To the extent that engagement between managers and analysts serves as a signal reflecting such information, investors will derive value from observing engagement in earnings calls.

Alternatively, it is possible that investors observe a variety of verbal and non-verbal signals to inform their judgements and decisions, and therefore do not gain any additional material value by observing engagement per se. Moreover, even if engagement is an informative signal, it is possible that investors are simply unable to perceive differences in engagement by listening to a conference call and hence cannot rely on such a signal for decision making. Therefore, we formally state our hypothesis in the alternative form as follows:

***H2**: Conversational engagement between managers and analysts in earnings conference calls is informative to capital market participants.*

4.1 Sample Selection

We use a sample of 2,452 earnings conference calls of S&P 1500 firms that occurred during the period 2008-2010 for which we are able to obtain both textual transcripts and audio recordings.[10] S&P 1500 firms are particularly suited for our analysis as these firms routinely hold conference calls with active analyst participation. Further, such firms' stocks are relatively more liquid, which helps with reliable detection of intra-day stock price movements (Hollander, Pronk, and Roelofsen 2010).

First, we parse the conference call transcripts to separate the presentation and Q&A portions. We further parse the Q&A portion to identify the turns-at-talk corresponding to management conversations with each individual analyst. Each conversation starts with an analyst question and includes all the back-and-forth turns-at-talk between that specific analyst and management (see Appendix E for an example). Conversations may include multiple questions posed by the same analyst and the responses from management. Following the procedure outlined in Section 2.2, we measure LSM scores for each conversation. We correlate the audio recording for each call with the transcript to precisely identify timestamps corresponding to the start and stop of each manager-analyst conversation. All conference calls included in our sample occur during trading hours. We compute intra-day stock returns corresponding to manager-analyst conversations using TAQ data.[11] We obtain firm characteristics from Compustat. We obtain consensus analyst forecast, earnings per share, and forecast dispersion from IBES. We obtain conference call transcripts from Thomson Reuters StreetEvents database. Our final sample comprises 18,395 manager-analyst conversations from 2,452 earnings conference calls.

[10] We start with the sample of earnings calls (transcripts and audio files) used in prior research (Mayew et al. 2020) but impose the additional restriction that in each manager-analyst conversation, the manager and the analyst each speak at least 50 words for reliable computation of LSM.
[11] Appendix D outlines the steps corresponding to procuring and preparing TAQ data for analysis.

4.2 Research Design

First, we estimate the following specification to explore determinant factors that elicit greater levels of engagement in manager-analyst conversations:

$$LSM\_AVG = a_0 + a_1 CONV\_CHAR + a_2 ANA\_CHAR + a_3 FIRM\_CHAR + \varepsilon \qquad (1)$$

LSM_AVG is the average of LSM for each function word category for the specific manager-analyst conversation. *CONV_CHAR*, *ANA_CHAR*, and *FIRM_CHAR* refer to conversation, analyst, and firm characteristics, respectively. *CONV_CHAR* refers to conversational characteristics such as the length of the conversation and the importance of the topic being discussed. It is conceivable that longer conversations and discussion of important issues elicit greater engagement. We measure length of a conversation using the following two variables: (i) number of turns-at-talk in the manager-analyst conversation (TURNS), and (ii) duration of the conversation in minutes as a percentage of total Q&A length (PCT_LEN).[12] We proxy for the importance of a conversation using the sequence number of the conversation within the Q&A (ORDER), as earlier questions in the Q&A are more likely to address more important issues. *ANA_CHAR* refers to analyst attributes such as quality, experience, and favorableness. In line with our arguments outlined in experimental analyses, we expect managerial conversations with more influential analysts to elicit greater levels of engagement. We measure analyst quality using the following two variables: (i) an indicator variable that denotes whether the analyst is an all-star analyst (ALLSTAR), and (ii) Carter-Manaster ranking reflecting the prestige of the brokerage to which the analyst belongs (BROKER). We expect that managers are likely to engage more when conversing with more experienced analysts. We measure analyst experience based on the number of years the analyst has been active in the industry corresponding to the firm (ANAEXP). Given findings in prior research that managers discriminate among analysts by granting more participation to favorable analysts (Mayew 2008), we include an additional indicator variable (BUY) that takes a value of one if the analyst provided

[12] Given conference calls tend to vary in total duration across firms, PCT_LEN captures the relative importance of a conversation within the call.

a *buy / strong buy* stock recommendation for the firm, and zero otherwise. *FIRM_CHAR* refers to firm fundamentals such as size, performance, and uncertainty that may influence the extent to which analysts engage with management in earnings calls (Mayew et al. 2020). We proxy for these firm characteristics using the logarithm of total assets (LnSIZE), absolute value of unexpected earnings (|UE|), and analyst forecast dispersion (DISPERSION), respectively.

Second, we estimate the following specification to explore whether manager-analyst engagement, as measured by LSM, is associated with the information relayed to capital market participants during conversations in the Q&A portion of earnings conference calls:

$$ABSRET = a_0 + a_1 LSM\_AVG + a_2 CONV\_CHAR + a_3 ANA\_CHAR + a_4 FIRM\_CHAR + \varepsilon \quad (2)$$

ABSRET is the absolute stock price reaction surrounding the manager-analyst conversation and serves as a proxy for the informativeness of the specific conversation. While much of the research in psychology and sociolinguistics has focused on positive determinants and consequences, engagement and the resulting coordinated behavior occurs in adversarial as well as prosocial interactions (Ireland and Henderson 2014). This suggests that we would expect to see greater behavioral coordination between managers and analysts in conversations of greater importance, regardless of whether they are discussing positive or negative information. As such, we use unsigned returns to proxy for information content. *LSM_AVG, CONV_CHAR*, *ANA_CHAR*, and *FIRM_CHAR* refer to average LSM measure, conversation characteristics, analyst attributes, and firm characteristics, respectively, as explained above.

4.3 Descriptive Statistics and Univariate Analysis

We provide descriptive statistics for all key variables in Table 2. Panel A provides the summary statistics for all variables. A firm in our sample, on average, has about $12 billion in total assets (SIZE) and beats the consensus earnings estimate (UE) by a mean (median) of 1 cent (2 cents). Conversations, on average, comprise about 12 turns-at-talk between the manager and the analyst. About one-quarter of the conversations in our sample occur with all-star analysts. The average absolute return (ABSRET) during a manager-analyst conversation is about 40 basis points. The average LSM score (LSM_AVG) for conversations in our sample is 0.79. The average LSM scores for individual function word categories range from about 0.39 to 0.91. The median net tone is zero suggesting that our sample is not biased with regard to conversation tone.

Insert Table 2 about here

Panel B presents the correlation table for all key conversation-level regression variables. At a univariate level using LSM_AVG, we find that earlier conversations in the Q&A exhibit higher LSM (Pearson -0.12; p<0.01), consistent with such conversations likely involving a discussion of more important issues that elicit greater levels of engagement. LSM is positively correlated with both the number of turns (TURNS; Pearson 0.32; p<0.01) as well as the length of the conversation (PCT_LEN; Pearson 0.25; p<0.01), suggesting that longer conversations within the Q&A exhibit higher LSM. The significant correlation between TURNS and LSM is also consistent with a greater number of back-and-forth iterations between the manager and analyst implying deeper discussion of important issues leading to greater levels of engagement. With regard to analyst quality measures, LSM is positively associated with analyst all-star status (ALLSTAR; Pearson 0.06; p<0.01), consistent with our earlier experimental evidence suggesting greater levels of engagement in conversations with influential analysts. In a similar vein, LSM is positively correlated with analyst experience (ANAEXP; Pearson 0.09; p<0.01). However, LSM is not significantly correlated with analyst brokerage rank (BROKER), potentially because brokerage rank is a relatively noisier measure of individual analyst quality. Finally, we also find a strong positive correlation between LSM_AVG and absolute returns (ABSRET; Pearson 0.10; p<0.01) during the conversation. Overall, our univariate evidence based on archival data is largely consistent with our experimental evidence suggesting that conversation and analyst characteristics influence LSM in a manner consistent with the coordination-engagement hypothesis, and engagement as measured by LSM is associated with the information content in conversations.

4.4 Determinant Model for LSM

We estimate the determinant model outlined in equation (1) and report the results in column 1 of Table 3. Consistent with the univariate evidence presented earlier, we find that earlier conversations that typically involve a discussion of more important issues tend to exhibit higher LSM as indicated by the negative coefficient (-0.036; p<0.01) on ORDER. The coefficients on PCT_LEN (0.144) and TURNS (0.263) are both positive and significant at the 1 percent level, suggesting that engagement is more pronounced in longer conversations and those characterized by a greater number of back-and-forth iterations between the manager and the analyst. The coefficients on our proxies for analyst status (BROKER, ALLSTAR) as well as analyst experience (ANAEXP) are significantly positive suggesting that greater engagement manifests in managerial dialogues with influential and experienced analysts. Interestingly, we also note that managers tend to engage more with analysts that provide a favorable stock recommendation (BUY) as indicated by the positive coefficient (0.022; p<0.01). Among firm characteristics, we find that firm size (SIZE) is positively associated with LSM. Columns 2 and 3 provide estimation results for equation (1) after controlling for call-level and analyst-level fixed effects.[13] In these estimations, as firm and analyst characteristics are largely subsumed by the inclusion of call and analyst fixed effects, respectively, we note that the previously observed associations between conversation characteristics and LSM continue to hold.

Insert Table 3 about here

Overall, conversations that occur earlier in the call and those characterized by longer discussions and more back-and-forth iterations between the manager and the analyst elicit greater levels of engagement. Engagement seems to manifest more prominently in managerial dialogues with analysts who are more influential, more experienced, and have more favorable outstanding recommendations.

[13] Controlling for call-level fixed effects captures intra-call variation stemming from managerial conversations with different analysts participating in a given call, whereas controlling for analyst fixed effects captures inter-call variation stemming from individual analyst conversations with different managers.

Similarly, analysts seem to engage more when talking to managers of larger firms. In the next section, we analyze whether conversations exhibiting greater levels of engagement are also more informative to capital market participants.

4.5 Main Results from Multivariate Analysis

We estimate equation (2) to ascertain the association between manager-analyst conversational engagement (as measured by LSM) and the information content perceived by investors (as measured by absolute stock returns). We present the results in column (1) of Table 4.[14] We find that the coefficient on LSM_AVG is positive (0.052) and significant at the 1% level.[15] The coefficient is significantly positive (0.031) even after including call-level fixed effects (see column (2))[16]. Column (3) presents the results after inclusion of analyst fixed effects (but without any call-level fixed effects) with the objective of capturing cross-sectional variance in engagement stemming from individual analyst's conversations with different managers across calls. We find that the coefficient on LSM_AVG (0.045) is positive and significant at the 1% level. Across all specifications, we include controls for conversation characteristics (i.e. order, length, turns), analyst attributes (status, experience, stock recommendation), and firm characteristics (size, uncertainty, performance) as appropriate.

Insert Table 4 about here

This evidence strongly supports the argument that engagement in manager-analyst conversations serves as a channel through which capital market participants elicit information from earnings calls. In

[14] For ease of interpretation and comparison across all specifications, we present the standardized coefficients from all estimations. 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.
[15] In other words, a one standard deviation increase in LSM results in an increase of about 3 basis points in the absolute return during the manager-analyst conversation after controlling for other known determinants of stock returns. This corresponds to more than a 7% increase in the information content during a conversation as compared to a mean conversation-level return (ABSRET) of 40 basis points, and is economically significant.
[16] Including call-level fixed effects controls for correlated omitted variables at the firm/call level that potentially influence stock price movement during earnings calls. As a result, the observed coefficient on LSM_AVG captures the effect of LSM on conversation-level stock returns arising from within-call variance in manager-analyst engagement (i.e. managerial conversations with different analysts participating in the call). Coefficients on control variables corresponding to firm-level characteristics are subsumed by inclusion of call-level fixed effects.

other words, greater levels of engagement between the manager and the analyst when discussing firm performance in the Q&A portion of earnings calls appears to provide incremental information to market participants.

4.6 LSM Component-Level Analysis

Having established that the average LSM measure is associated with the informativeness of manager-analyst conversations, we next examine the extent to which each individual component (i.e. function word category) of LSM drives our main results. We estimate equation (2) using the LSM component measure corresponding to each function word category separately:

$$ABSRET = a_0 + a_1LSM\_COMP + a_2CONV\_CHAR + a_3ANA\_CHAR + a_4FIRM\_CHAR + \varepsilon \quad (3)$$

where *LSM_COMP* refers to the LSM measure computed for each function word category (personal pronouns, indefinite pronouns, articles, prepositions, auxiliary verbs, adverbs, conjunctions, negations, and quantifiers) separately. All other variables are as defined earlier and described in Appendix C. We include all control variables as well as call-level fixed effects in all estimations, and tabulate results in Table 5.

We find that the LSM measure based on four function word categories – negations, auxiliary verbs, prepositions, and quantifiers – are associated with absolute returns (see columns (1), (3), (6), and (9)). We do not find a statistically significant coefficient on LSM measures based on articles, pronouns, adverbs, and conjunctions. Multivariate evidence presented in column (10) suggests that the matching of prepositions, quantifiers, auxiliary verbs, and negations are most potent in capturing information content in conversations. We again do not find a statistically significant coefficient on articles, pronouns, adverbs, and conjunctions.

Overall, these results are consistent with our earlier findings based on experimental analysis. With the exception of negations, which are excluded from the experimental analysis, LSM for prepositions, quantifiers, and auxiliary verbs underlie both the experimental and archival findings. This suggests that our archival results are driven by the same construct as our experimental results, and provides further support for the construct validity of LSM as a proxy for engagement.

4.7 Robustness Check

In this section, we conduct a robustness check for our main results by controlling for three additional factors that could potentially confound our inference: (i) managerial scriptedness, (ii) conversation tone, and (iii) information processing delay. Lee (2016) documents that stock market reactions to earnings conference calls are influenced by managerial scriptedness (i.e. lack of spontaneity) during interactions with analysts. Price et al. (2012) note that conference call linguistic tone is associated with abnormal returns surrounding a call. While these studies focus on the directional impact of scriptedness and tone on stock returns, the primary objective of our study is to measure the informativeness (i.e., magnitude of price impact) of manager-analyst engagement. Further, research on scriptedness and tone examines stock market reactions surrounding the day of the call, whereas we focus on market reactions to engagement at a more granular conversation level. However, given the granular nature of conversation-level analyses in our study, any delay in investor processing of information conveyed by an interaction could potentially confound our results.

To account for these confounding factors, we estimate equation (2) after including the following three additional control variables: (i) quintile ranking of manager scriptedness computed as the cosine similarity between manager's use of function words in the presentation portion and the specific conversation (SCRIPT), (ii) net tone of the manager-analyst conversation (TONE), and (iii) lagged absolute dialogue returns to account for drift or delay in information processing (ABSRET_LAG). We present the results in Table 6. While we find a significant positive coefficient on lagged absolute returns in all specifications, the coefficient on SCRIPT and TONE are not statistically significant at conventional levels. The coefficient on LSM_AVG is positive and statistically significant at the 1 percent level across all specifications (columns (1)-(3)). Overall, these results suggest that the effect of conversational engagement between managers and analysts on the informativeness of interactions is distinct from and robust to controlling for other factors such as managerial scriptedness, conversational tone, and information processing costs that impact stock prices directionally.

5. Examination of Information Conveyed by Engagement

Our previous analyses show that conversations with greater engagement between managers and analysts are more informative to capital market participants. While our results are consistent with engagement serving as an informative signal to investors, we note that this interpretation rests on two assumptions. First, for conversation engagement between managers and analysts to be used as a signal, investors must be able to detect differences in engagement. Second, for this signal to be useful to investors, it must be incrementally informative over other available information. In this section, we conduct additional analyses to shed light on these assumptions.

5.1 Detectability of Engagement

For engagement between managers and analysts to be used as a signal, market participants must be able to observe differences in engagement across conversations in earnings calls.[17] To provide further evidence that investors detect these differences, we conduct a quasi-experiment to examine investor perceptions of actual conversations between managers and analysts from our archival sample. Participants are 74 students enrolled in a business degree program. On average, participants have taken 2.5 accounting courses and 2.6 finance courses, and have an average of 2.3 years of personal investing experience.

To test whether investors detect differences in engagement, we select pairs of conversations which differ in LSM, our proxy for engagement. While a quasi-experiment necessarily sacrifices some of the control offered by a traditional lab experiment, we minimize differences in other conversation characteristics when selecting pairs. Starting with our full sample of 2,452 calls (18,395 dialogues), we ensure that conversations are of similar length by keeping only dialogues with a duration of 3-4 minutes (based on the median dialogue length of 3.5 minutes) and 5-9 turns. To ensure that no LSM component

[17] As noted previously, one of the advantages of LSM as a proxy for engagement is that function words are produced nonconsciously, making them difficult, if not impossible, for speakers to intentionally vary (Pennebaker and King 1999). As such, it is unlikely that our findings reflect a conscious response by capital market participants to LSM per se.

(i.e., function word category) is unduly influencing the average LSM measure, we keep only dialogues with non-zero LSM component measures.

To control for firm-specific or time-varying factors, we form within-call pairs of conversations. Although we cannot hold the analyst constant within a call, we ensure that analysts within a pair of conversations have similar all-star status. Among conversations that meet all of the above criteria, we keep pairs that have a difference in LSM of at least 0.05 to ensure a reasonable difference in our empirical proxy for engagement, leaving us with 90 within-call pairs. We manually examine these pairs to remove those with unusual content (e.g., politics, religion, profanity, etc.) or interruptions. To ensure that our results are not driven by a specific conversation pair, we present participants with three different conversation pairs for our materials.

Participants are asked to assume the role of an investor listening to conversations between managers and financial analysts. Participants listen to pairs of conversations and respond to the question, *"In which of the two conversations do both the CEO and the analyst sound more engaged with each other (i.e., more involved in the conversation)?"*. We randomly assign each participant to listen to two of the three pairs of conversations and randomize whether the high LSM conversation or the low LSM conversation is presented first. After evaluating the conversation pairs, participants are debriefed and respond to demographic questions.

We code participant responses as 1 if they indicate that the CEO and analyst were more engaged in the high LSM conversation and 0 if they chose the low LSM conversation. In a preliminary examination of participant responses, we find that 67% of responses (91 out of 136) indicate that engagement was higher in the high LSM conversation, which a binomial test confirms is significantly greater than chance ($p < 0.01$, untabulated).[18] To account for call, order, and participant-specific effects in our data, we estimate a generalized linear mixed model with order and call as fixed effects and

[18] We originally selected four pairs of conversations for our experimental materials. Due to a coding error, one of the conversation pairs was not presented to participants and 12 participants were assigned the same pair of conversations for their first and second judgments. Because of this, we keep only the first response from these participants, resulting in 136 total responses.

participant random effects. Accounting for call, order, and participant effects, the estimated grand marginal mean from this model is 0.70 (SE = 0.055), significantly greater than 0.50 ($p < 0.01$, untabulated). These results provide additional evidence both that LSM is a reasonable proxy for engagement, and that investors detect differences in engagement.

5.2 Incremental Informativeness over Topical Content

While LSM is entirely based on the occurrence of function words in manager-analyst conversations, which are theoretically unrelated to conversation subject matter and content, it is possible that engagement is correlated with discussion of specific topics. To provide further evidence that engagement is incrementally informative beyond the topic being discussed, we re-estimate equation (2) after explicitly controlling for conversation content. By controlling for topical content, we examine whether the level of conversational engagement is incrementally informative to market participants after accounting for the topical content of the conversation.

We identify the extent to which manager-analyst conversations include discussion of 14 key topics - *Regulation, Risk, Competition, Consumers, Economy, Sales, Products, Earnings, Operations, Investments, Outlook, Geography, Growth, Tax* – that prior research (Huang, Lehavy, Zang, and Zheng 2018; Gomez, Heflin, Lee, and Wang 2018) has identified as potential drivers of stock prices during conference calls. We construct an indicator variable for each of these topics, that is set to one if the conversation includes one or more words related to that specific topic, and zero otherwise. We re-estimate equation (2) after including the indicator variables as additional controls and present our results in Table 7. Panel A presents the dictionary of words that identify key topics. Panel B presents descriptive statistics for the topic indicator variables. We note that 99% of the conversations in our sample are related to one or more of the 14 topics defined in our analyses.

Insert Table 7 about here

In Panel C, we present the results from estimating equation (1) after including the topic indicator variables as additional controls. We find that the coefficient on LSM_AVG is positive and significant at the 1% level in all our specifications (columns (1)-(3)). This result is not surprising, given that our main specification controls for other conversation and analyst level characteristics (such as sequencing order, conversation length, analyst status, etc.) that are potentially correlated with the discussion of important topics. Overall, we find that our main results are robust to inclusion of additional controls that capture the topical content of the conversation, suggesting that the level of engagement is informative regardless of the topic being discussed.

6. Conclusion

Prior research examining interactions between managers and analysts has exclusively focused on attributes and behaviors of the specific individuals involved in the interaction. In contrast, our paper is the first to examine characteristics of the interaction itself as the unit of analysis. By exploiting the comparative advantages of experimental and archival methods, we provide evidence that conversational engagement between managers and analysts is informative to market participants.

Drawing on literature in psychology and sociolinguistics, we provide experimental and archival evidence that linguistic style matching (LSM), a form of verbal coordination, is a reasonable measure of the level of engagement between managers and analysts in earnings calls. In an experimental test of the coordination-engagement hypothesis, we find that managers' verbal responses exhibit greater LSM when attributes of the analyst increase incentives for engagement. We complement this causal evidence with archival tests using a unique dataset derived by carefully correlating textual transcripts and audio files from over 2,400 earnings calls of S&P 1500 firms. We find that conversations which occur earlier in the Q&A and those characterized by more back-and-forth iterations exhibit higher LSM, consistent with the idea that more important conversations and deeper levels of discussion result in greater levels of engagement. We also find that LSM is higher in interactions involving influential analysts or larger firms. These tests provide convergent evidence that LSM is a reliable measure of conversational engagement between managers and analysts in earnings calls.

Further analysis reveals that engagement in manager-analyst conversations is incrementally informative to capital market participants after controlling for conversation, analyst, and firm characteristics. We also find that our experimental and archival results are driven by LSM for similar categories of function words, providing additional evidence that our results are driven by a common mechanism. Results of a supplemental quasi-experiment suggest that investors detect differences in engagement, and additional analyses suggest that engagement provides information distinct from factors examined by prior research. Our study contributes to the broader literature in psychology and sociolinguistics on indicators of engagement, and provides new evidence that characteristics of manager-analyst interactions are informative to capital markets.

An alternative explanation for our results is that greater conversational engagement between managers and analysts reflects that more information (other than engagement itself) is being revealed in the conversation. For example, conversational engagement resulting from probing questions asked by analysts in the Q&A could lead to the release of new content (Frankel et al. 2010; Abraham and Bamber 2017). It is also possible that interactions that involve discussion of new content may be perceived as more important by managers and analysts, leading to greater conversational engagement. These explanations would predict a positive association between manager-analyst engagement and the informativeness of the conversation. Although prior research indicates analysts are reluctant to interrogate management during conference calls (Brown et al. 2015), and that firms go to great lengths to prevent unintentional disclosure (Mayew 2008; Brown et al. 2018; Bamber and Abraham 2019), we cannot definitively rule out the release of new content that is accompanied by greater conversational engagement. Future research can shed light on the extent to which conversational engagement signals the release of new value-relevant information to investors.

References

Abraham, S., & Bamber, M. (2017). The Q&A: Under surveillance. *Accounting, Organizations and Society*, *58*, 15-31.

Bamber, M., & Abraham, S. (2019). On the "Realities" of Investor-Manager Interactivity: Baudrillard, Hyperreality, and Management Q&A Sessions. *Contemporary Accounting Research*.

Barndorff-Nielsen, O.E., Hansen, P.R., Lunde, A., and Shephard, N. (2009). Realized Kernels in Practice: Trades and Quotes. *Econometrics Journal* 12:c1-c32

Blankespoor, E., Dehaan, E., Wertz, J., & Zhu, C. (2019). Why do individual investors disregard accounting information? The roles of information awareness and acquisition costs. *Journal of Accounting Research*, *57*(1), 53-84.

Blankespoor, E., B. Hendricks, and G. Miller (2017). Perceptions and Price: Evidence from CEO presentations at IPO roadshows. *Journal of Accounting Research,* 55(2), 275-327.

Bonner, S. E. (2008). *Judgment and decision making in accounting*. Prentice Hall.

Bowen, R. M., Davis, A. K., & Matsumoto, D. A. (2002). Do Conference Calls Affect Analysts' Forecasts? *The Accounting Review*, *77*(2), 285–316.

Brochet, F., Loumioti, M., & Serafeim, G. (2015). Speaking of the short-term: Disclosure horizon and managerial myopia. *Review of Accounting Studies*, *20*(3), 1122-1163.

Brown, L. D., Call, A. C., Clement, M. B., & Sharp, N. Y. (2015). Inside the "Black Box" of Sell-Side Financial Analysts. *Journal of Accounting Research*, *53*(1), 1–47.

Brown, L. D., Call, A. C., Clement, M. B., & Sharp, N. Y. (2019). Managing the narrative: Investor relations officers and corporate disclosure. *Journal of Accounting and Economics*, *67*(1), 58-79.

Bushee, B. J., Gow, I. D., & Taylor, D. J. (2018). Linguistic Complexity in Firm Disclosures: Obfuscation or Information? *Journal of Accounting Research*, *56*(1), 85–121.

Chartrand, T. L., & Bargh, J. A. (1999). The Chameleon Effect: The Perception-Behavior Link and Social Interaction. *Journal of Personality and Social Psychology*, *76*(6), 893–910.

Chen, S. and Matsumoto, D.A. (2006). Favorable vs Unfavorable Recommendations: The Impact on Analyst Access to Management-Provided Information. *Journal of Accounting Research* 44(4): 657-689

Cialdini, R. B., & Goldstein, N. J. (2004). Social Influence: Compliance and Conformity. *Annual Review of Psychology*, *55*(1), 591–621.

Cicourel, A. V. (1974). *Cognitive Sociology: Language and Meaning in Social Interaction*. New York, NY, US: Free Press.

Davis, A. K., Ge, W., Matsumoto, D., & Zhang, J. L. (2015). The effect of manager-specific optimism on the tone of earnings conference calls. *Review of Accounting Studies*, *20*(2), 639-673.

Frankel, R., Johnson, M., & Skinner, D. J. (1999). An Empirical Examination of Conference Calls as a Voluntary Disclosure Medium. *Journal of Accounting Research*, *37*(1), 133–150.

Frankel, R., Mayew, W. J., & Sun, Y. (2010). Do Pennies Matter? Investor Relations Consequences of Small Negative Earnings Surprises. *Review of Accounting Studies*, *15*(1), 220–242.

Frith, C. D., & Frith, U. (2012). Mechanisms of social cognition. *Annual review of psychology*, *63*, 287-313.

Gomez, E., F. Heflin, J. Lee, and J. Wang. (2018). Who and what drive the investor response to earnings conference calls? An analysis using sentence-level price movement. *Working Paper.*

Gonzales, A. L., Hancock, J. T., & Pennebaker, J. W. (2010). Language Style Matching as a Predictor of Social Dynamics in Small Groups. *Communication Research*, *37*(1), 3–19.

Hogarth, R. M. (1987). *Judgement and choice: The psychology of decision* (2nd ed.). John Wiley & Sons.

Hollander, S., Pronk, M., and Roelofsen, E. (2010). Does Silence Speak? An Empirical Analysis of Disclosure Choices during Conference Calls. *Journal of Accounting Research* 48(3):531-563

Huang, A. H., Lehavy, R., Zang, A. Y., & Zheng, R. (2018). Analyst Information Discovery and Interpretation Roles: A topic modeling approach. *Management Science*, *64*(6), 2833-2855.

Ireland, M. E., & Henderson, M. D. (2014). Language Style Matching, Engagement, and Impasse in Negotiations. *Negotiation and Conflict Management Research*, *7*(1), 1–16.

Ireland, M. E., & Pennebaker, J. W. (2010). Language Style Matching in Writing: Synchrony in Essays, Correspondence, and Poetry. *Journal of Personality and Social Psychology*, *99*(3), 549–571.

Ke, B., and Yu, Y. (2006). The Effect of Issuing Biased Earnings Forecasts on Analysts' Access to Management and Survival. *Journal of Accounting Research* 44(5):965-999

Kimbrough, M. D. (2005). The Effect of Conference Calls on Analyst and Market Underreaction to Earnings Announcements. *The Accounting Review*, *80*(1), 189–219.

Korkmaz, S., Goksuluk, D & Zararsiz, G. (2014) MVN: An R Package for Assessing Multivariate Normality. *The R Journal*, 6(2):151-162.

Lakin, J. L., & Chartrand, T. L. (2003). Using Nonconscious Behavioral Mimicry to Create Affiliation and Rapport. *Psychological Science*, *14*(4), 334–339.

Lee, J. (2016). Can Investors Detect Managers' Lack of Spontaneity? Adherence to Predetermined Scripts during Earnings Conference Calls. *The Accounting Review*, *91*(1), 229–250.

Levelt, W. J., & Kelter, S. (1982). Surface Form and Memory in Question Answering. *Cognitive Psychology*, *14*(1), 78–106.

Li, F., Minnis, M., Nagar, V., & Rajan, M. (2014). Knowledge, compensation, and firm value: An empirical analysis of firm communication. *Journal of Accounting and Economics*, *58*(1), 96-116.

Libby, R., Bloomfield, R., & Nelson, M. W. (2002). Experimental Research in Financial Accounting. *Accounting, Organizations and Society*, *27*(8), 775–810.

Libby, R., & Rennekamp, K. (2012). Self-Serving Attribution Bias, Overconfidence, and the Issuance of Management Forecasts. *Journal of Accounting Research*, *50*(1), 197–231.

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, *66*(1), 35-65.

Loughran, T., & Ritter, J. (2004). Why has IPO underpricing changed over time? *Financial Management*, 5-37.

Maines, L. A., & McDaniel, L. S. (2000). Effects of comprehensive-income characteristics on nonprofessional investors' judgments: The role of financial-statement presentation format. *The Accounting Review*, *75*(2), 179-207.

Matsumoto, D., Pronk, M., & Roelofsen, E. (2011). What Makes Conference Calls Useful? The Information Content of Managers' Presentations and Analysts' Discussion Sessions. *The Accounting Review*, *86*(4), 1383–1414.

Mayew, W. J. (2008). Evidence of Management Discrimination among Analysts during Earnings Conference Calls. *Journal of Accounting Research*, *46*(3), 627–659.

Mayew, W. J., Sethuraman, M., & Venkatachalam, M. (2020). Individual Analysts' Stock Recommendations, Earnings Forecasts, and the Informativeness of Conference Call Question and Answer Sessions. *The Accounting Review* In-Press.

Mayew, W. J., Sharp, N. Y., & Venkatachalam, M. (2013). Using Earnings Conference Calls to Identify Analysts with Superior Private Information. *Review of Accounting Studies*, *18*(2), 386–413.

Mayew, W. J., & Venkatachalam, M. (2012). The Power of Voice: Managerial Affective States and Future Firm Performance. *The Journal of Finance*, *67*(1), 1–43.

Milian, J. A., & Smith, A. L. (2017). An Investigation of Analysts' Praise of Management during Earnings Conference Calls. *Journal of Behavioral Finance*, *18*(1), 65–77.

Milian, J. A., Smith, A. L., & Alfonso, E. (2017). Does an Analyst's Access to Information Vary with the Favorableness of Their Language When Speaking to Management? *Accounting Horizons*, *31*(4), 13–31.

Niederhoffer, K. G., & Pennebaker, J. W. (2002). Linguistic Style Matching in Social Interaction. *Journal of Language and Social Psychology*, *21*(4), 337–360.

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). *The development and psychometric properties of LIWC2015*.

Pennebaker, J. W., & King, L. A. (1999). Linguistic Styles: Language Use as an Individual Difference. *Journal of Personality and Social Psychology*, *77*(6), 1296–1312.

Pennebaker, J. W., Mehl, M. R., & Niederhoffer, K. G. (2003). Psychological aspects of natural language use: Our words, our selves. *Annual review of psychology*, *54*(1), 547-577.

Price, S. M., Doran, J. S., Peterson, D. R., & Bliss, B. A. (2012). Earnings Conference Calls and Stock Returns: The Incremental Informativeness of Textual Tone. *Journal of Banking & Finance*, *36*(4), 992–1011.

Richardson, B. H., Taylor, P. J., Snook, B., Conchie, S. M., & Bennell, C. (2014). Language Style Matching and Police Interrogation Outcomes. *Law and Human Behavior*, *38*(4), 357–366.

Romero, D. M., Swaab, R. I., Uzzi, B., & Galinsky, A. D. (2015). Mimicry Is Presidential: Linguistic Style Matching in Presidential Debates and Improved Polling Numbers. *Personality and Social Psychology Bulletin*, *41*(10), 1311–1319.

Snyder, M., & Stukas, A. A. (1999). Interpersonal Processes: The Interplay of Cognitive, Motivational, and Behavioral Activities in Social Interaction. *Annual Review of Psychology*, *50*(1), 273–303.

Sobin, N. (2010). *Syntactic Analysis: The Basics*. John Wiley & Sons.

Tausczik, Y. R. (2012). *Changing Group Dynamics through Computerized Language Feedback*. Unpublished doctoral dissertation. University of Texas at Austin, Austin, TX.

Taylor, P. J., & Thomas, S. (2008). Linguistic Style Matching and Negotiation Outcome. *Negotiation and Conflict Management Research*, *1*(3), 263–281.

Tiedens, L. Z., & Fragale, A. R. (2003). Power Moves: Complementarity in Dominant and Submissive Nonverbal Behavior. *Journal of Personality & Social Psychology*, *84*(3), 558–568.

Trueman, B. (1986). Why do managers voluntarily release earnings forecasts? *Journal of Accounting and Economics*, *8*(1), 53-71.

van Baaren, R. B., Maddux, W. W., Chartrand, T. L., de Bouter, C., & van Knippenberg, A. (2003). It Takes Two to Mimic: Behavioral Consequences of Self-Construals. *Journal of Personality and Social Psychology*, *84*(5), 1093–1102.

Webb, J. T. (1969). Subject Speech Rates as a Function of Interviewer Behaviour. *Language and Speech*, *12*(1), 54–67.

Appendix A (Function Word Categories)

This appendix presents the nine categories of function words used for measuring LSM, and the corresponding variable names from LIWC2015. Definitions for terms are derived from Pennebaker et al. (2015) and Sobin (2010). We present examples of words from each function word category that occur most frequently in our full sample of earnings calls. To identify these words, we first count the number of times each word from each function word category appears in our sample. We then select the three most frequently occurring words from each category. To provide more representative examples, we exclude words that either (1) appear in other function word categories or (2) are variants of other words in the same category (e.g., because we present "is" as an auxiliary verb, we exclude the words "are" and "it's" from our examples).

Category	**LIWC2015 Category Label**	**Definition**	**Examples in Earnings Calls**
Adverb	*adverb*	modifies verbs, adjectives, and other parts of speech	there, just, very
Article	*article*	specifies definiteness of a noun	the, a, an
Auxiliary Verb	*auxverb*	specifies tense or mood of another verb	is, have, will
Conjunction	*conj*	joins words, sentences, and phrases	and, as, but
Impersonal Pronoun	*ipron*	substitutes for nouns not referring to a person	that, it, this
Negation	*negate*	converts affirmative phrases to negative phrases	not, no, nothing
Personal Pronoun	*ppron*	substitutes for nouns referring to a person	we, you, I
Preposition	*prep*	indicates relationships between words and phrases	to, of, in
Quantifier	*quant*	expresses quantities for nouns	some, more, all

Appendix B (Incentives for Engagement Stimuli in Experimental Materials)

This appendix presents the analyst descriptions provided to participants in our main experiment. Participants are randomly assigned to experimental conditions wherein characteristics of the analyst create *high incentives for engagement* (Panel A) or *low incentives for engagement* (Panel B). After viewing one of these descriptions, participants listen to an audio recording of the analyst's question and provide a verbal response. Descriptions presented below hold constant the name and image of the analyst. We manipulate incentives for engagement using the analyst's brokerage ("J.P. Morgan," a highly ranked brokerage with which participants are familiar, or "Graham Nelson & Associates," a fictional brokerage), the analyst's position ("Senior" or "Junior" Research Analyst), and the analyst's professional achievements (awards and certifications).

Panel A. High Incentives for Engagement Condition

Stephen Nichols

Brokerage:
J.P. Morgan

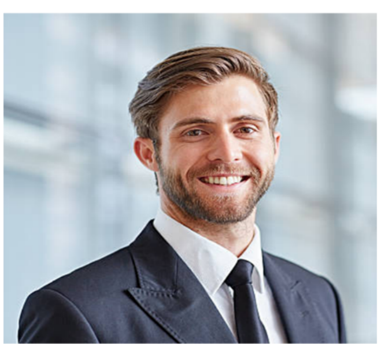
Position:
Senior Research Analyst

Professional Achievements:

	Yes	No
Institutional Investor All-Star	✓	
WSJ Best on the Street List	✓	
Thomas Reuters Analyst Award	✓	
CFA Charterholder	✓	

Panel B. Low Incentives for Engagement Condition

Stephen Nichols



Brokerage:
Graham Nelson & Associates

Position:
Junior Research Analyst

Professional Achievements:

	Yes	No
Institutional Investor All-Star		x
WSJ Best on the Street List		x
Thomas Reuters Analyst Award		x
CFA Charterholder	✓	

Appendix C (Description of Variables)

Variable	Description
ABSRET	*Absolute value of stock return during the manager-analyst conversation (dialogue)*
ABSRET_LAG	*Absolute value of stock return corresponding to the previous manager-analyst conversation (dialogue) that occurred within the same earnings call. For the first manager-analyst conversation in the Q&A section of an earnings call, we use the absolute stock return from the last quartile of the presentation portion as the lagged return. This variable controls for drift in stock returns.*
SIZE	*Total assets of the firm at the end of the quarter corresponding to the conference call (Compustat: ATQ)*
LnSIZE	*Natural logarithm of SIZE*
DISPERSION	*Analyst Forecast Dispersion reported as the standard deviation of forecasts in IBES Summary Statistics*
|UE|	*Absolute Abnormal Earnings (actual earnings – analyst consensus estimate). Actual earnings and Analyst consensus estimates are obtained from IBES.*
TURNS	*Number of Turns in the manager-analyst dialogue (Turn refers to contiguous speech by a single participant)*
PCT_LEN	*Length of a dialogue (in minutes) expressed as a percentage of the Q&A Section Length*
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.*
SCRIPT	*Quintile ranking of manager scriptedness in the dialogue. Scriptedness is computed by computing the cosine similarity between use of function words in the manager's speech in the dialogue and manager's speech in the presentation section of the call.*
TONE	*Overall tone of the manager-analyst conversation (i.e. net positive tone measured based on Loughran and McDonald (2011) dictionary of positive and negative words). Tone is set to zero when the number of positive and negative words is zero.*
ALLSTAR	*Indicator variable to denote ALL STAR analyst.*
BROKER	*Carter-Manaster Broker Ranking (Scale:0-9). Higher values reflect more prestigious brokers. Underwriter reputation rankings obtained from https://site.warrington.ufl.edu/ritter/ipo-data/. See Loughran and Ritter (2004).*
ANAEXP	*Analyst experience measured as the number of years the analyst has been active in the industry [IBES]*
BUY	*Indicator variable to denote analyst with an outstanding Buy or Strong Buy recommendation on the firm's stock. This variable captures the favorableness of the analyst's stock recommendation. [IBES]*
LSM_AVG	*Measure of linguistic style matching in the manager-analyst conversation (Scale:0-1), computed as the average of LSM scores corresponding to the following nine different categories of function words, as defined by LIWC 2015 software: personal pronouns (ppron), indefinite pronouns (ipron), articles (article), prepositions (prep), auxiliary verbs (auxverb), adverbs (adverb), conjunctions (conj), negations (negate), and quantifiers (quant).*
LSM_Ppron	*Measure of LSM based on personal pronouns*
LSM_Ipron	*Measure of LSM based on indefinite pronouns*
LSM_Article	*Measure of LSM based on articles*
LSM_Prep	*Measure of LSM based on prepositions*
LSM_Auxverb	*Measure of LSM based on auxiliary verbs*
LSM_Adverb	*Measure of LSM based on adverbs*
LSM_Conj	*Measure of LSM based on conjunctions*
LSM_Negate	*Measure of LSM based on negations*
LSM_Quant	*Measure of LSM based on quantifiers*

Appendix D (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 (Mayew et al. 2020) 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 E (Manager-Analyst Conversation Example)

Q4 2008 Philip Morris International Earnings Conference Call

Jonathan Fell, Deutsche Bank - Analyst [38]

Hi there. I have to say, actually in David's camp as well as far as getting the FX impact wrong, just wondering if you could give us a bit more help for the model. I mean, it looks like you are talking about an overall FX impact if we take the mid range of your underlying growth estimate and the actual guidance. Looks like FX impact is negative 20%. Can you give us - - is it going to be a similar negative 20% at both revenue and EBIT? And would I be right in thinking that in the EU and Asia that the impact is going to be quite a long way under the 20% and would be higher in the region?

Louis Camilleri, Philip Morris International - Chairman and CEO [39]

Yes, that would be a fair characterization, Jonathan. As I say, we're being dramatically hurt by principally the four markets I mentioned, which were Russia, Mexico, Turkey, and the Ukraine. There are others. The Kazakhstan [Tanguay] was devalued by 20% just today. That's a $35 million net income hit.
So there are a lot of other currencies that one has to build into the model, but I would say that the four key ones are the ones I mentioned, and they are $0.60 out of the $0.80, those four. I mean, the ruble alone, in the last month, has affected our guidance by $0.20. So 25% of our currency hit happened in one currency, in one month.

Jonathan Fell, Deutsche Bank - Analyst [40]

I guess on the EU, looks like we saw a little bit of a deterioration there in underlying shipments and profitability trends in the fourth quarter. Is there anything there which concerns you or is that something that would you expect to see disappear fairly rapidly in 2009 and merge into normal?

Louis Camilleri, Philip Morris International - Chairman and CEO [41]

No, I'm not overly concerned. In fact, quite to the contrary. I think we tried, to the best of our ability, to point out that distortions in the EU that were caused by events in both the Czech Republic and Poland. If you eliminate those, as our earnings release points out, the trends are actually okay, and, in fact, if I look at market shares, in most instances, the trend is actually pretty good, and we're looking towards a much better year next year, because we'll have the distortions of the Czech and Poland behind us.
Germany is doing well. I think with the pricing in a few places we've narrowed the gap with Marlboro, so we'll see what happens there. And I would say that EU looks today better than it certainly did at the beginning of last year. Let's forget also, as I mentioned, in an answer to a previous question that the total markets we don't see eroding the way they did in 2008, either. Because most of the public smoking restrictions that affected industry shipments and consumption are behind us.

Jonathan Fell, Deutsche Bank - Analyst [42]

Okay. Thanks very much.

Louis Camilleri, Philip Morris International - Chairman and CEO [43]

Thank you, Jonathan.

Table 1

Experimental Results

This table reports results of our 1 x 2 between-subjects experiment on the effect of *Incentives for Engagement* on linguistic style matching. Participants are ninety-eight MBA students who verbally respond to a question from either a high-influence or low-influence analyst. See Appendix B for images of the materials provided to participants in each condition. Dependent variables are measures of linguistic style matching between transcribed participant responses and the language of the analyst (held constant across conditions) for eight categories of function words: personal pronouns, indefinite pronouns, articles, prepositions, auxiliary verbs, adverbs, conjunctions, and quantifiers. Panel A presents results of a multivariate analysis of variance for these variables. Panel B presents descriptive statistics and results of t-tests for the category level LSM measures.

Panel A: Multivariate Analysis of Variance

	Numerator df	*Denominator df*	*F-stat*	*One-tailed p-value*
Incentives for Engagement	8	88	2.085	**0.023**

Panel B: Category LSM Mean, (Standard Deviation), and t-Tests

	Incentives for Engagement			
LSM Category	*Low*	*High*	*t-stat*	*One-tailed p-value*
Adverbs	0.82	0.83	-1.375	0.172
	(0.02)	(0.02)		
Articles	0.78	0.75	-1.223	0.224
	(0.02)	(0.02)		
Auxiliary Verbs	0.83	0.88	2.039	**0.022**
	(0.02)	(0.02)		
Conjunctions	0.84	0.82	-0.832	0.408
	(0.01)	(0.01)		
Indefinite Pronouns	0.84	0.82	-0.870	0.387
	(0.02)	(0.02)		
Personal Pronouns	0.88	0.87	-0.081	0.419
	(0.01)	(0.01)		
Prepositions	0.89	0.91	2.042	**0.022**
	(0.01)	(0.01)		
Quantifiers	0.72	0.77	1.677	**0.048**
	(0.02)	(0.02)		

Table 2

Descriptive Statistics

This table reports descriptive statistics for the variables. Panel A presents the summary statistics for all variables and Panel B presents the correlation matrix for key regression variables. Spearman correlation is shown above the diagonal and Pearson below. Two-tailed p-values are reported below the correlations. All variables are described in Appendix C. All continuous variables are winsorized at 1 percent and 99 percent.

Panel A: Summary Statistics

Variable	N	Mean	Median	SD
SIZE ($Bn)	2452	12.114	3.199	33.312
LnSIZE	2452	8.148	8.070	1.484
DISPERSION	2452	0.062	0.030	0.119
UE	2452	0.007	0.020	0.246
ORDER	18395	5.244	5.000	3.509
TURNS	18395	12.127	11.000	6.141
PCT_LEN	18395	0.131	0.109	0.093
SCRIPT	18395	3.000	3.000	1.414
TONE	18395	0.016	0.000	0.404
ALLSTAR	18395	0.235	0.000	0.424
BROKER	18395	5.481	6.709	3.330
BUY	18395	0.353	0.000	0.478
ANAEXP	18395	6.768	5.000	6.724
ABSRET	18395	0.004	0.002	0.005
LSM_AVG	18395	0.792	0.796	0.072
LSM_Negate	18395	0.390	0.398	0.383
LSM_Article	18395	0.858	0.885	0.117
LSM_Auxverb	18395	0.876	0.900	0.098
LSM_Ppron	18395	0.864	0.890	0.108
LSM_Ipron	18395	0.831	0.865	0.140
LSM_Prep	18395	0.911	0.928	0.072
LSM_Adverb	18395	0.820	0.853	0.143
LSM_Conj	18395	0.845	0.877	0.128
LSM_Quant	18395	0.740	0.794	0.222

Panel B: Correlation Table (N=18,395)

VARS	*ORDER*	*PCT_LEN*	*TURNS*	*SCRIPT*	*TONE*	*BROKER*	*ALLSTAR*	*ANAEXP*	*BUY*	*LSM_AVG*	*ABSRET*
ORDER	1.00	-0.39	-0.10	-0.10	-0.08	-0.12	-0.06	-0.08	-0.08	-0.10	-0.11
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PCT_LEN	-0.35	1.00	0.46	0.10	0.09	-0.05	-0.02	0.06	0.02	0.33	0.19
	0.00		0.00	0.00	0.00	0.00	0.03	0.00	0.01	0.00	0.00
TURNS	-0.11	0.39	1.00	-0.04	-0.01	-0.11	-0.04	0.03	-0.01	0.33	0.14
	0.00	0.00		0.00	0.12	0.00	0.00	0.00	0.17	0.00	0.00
SCRIPT	-0.09	0.06	-0.04	1.00	0.05	0.07	0.03	0.01	0.01	0.07	0.03
	0.00	0.00	0.00		0.00	0.00	0.00	0.23	0.22	0.00	0.00
TONE	-0.09	0.07	-0.01	0.05	1.00	0.02	0.02	0.04	0.06	0.01	0.01
	0.00	0.00	0.04	0.00		0.00	0.02	0.00	0.00	0.08	0.27
BROKER	-0.13	-0.06	-0.11	0.07	0.04	1.00	0.37	0.16	0.06	0.00	-0.02
	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.82	0.00
ALLSTAR	-0.05	-0.06	-0.04	0.03	0.02	0.31	1.00	0.46	0.13	0.06	0.00
	0.00	0.00	0.00	0.00	0.02	0.00		0.00	0.00	0.00	0.96
ANAEXP	-0.05	0.02	0.06	0.00	0.03	0.11	0.44	1.00	0.30	0.10	0.00
	0.00	0.01	0.00	0.90	0.00	0.00	0.00		0.00	0.00	0.54
BUY	-0.07	0.00	-0.02	0.01	0.06	0.08	0.13	0.24	1.00	0.03	-0.01
	0.00	0.92	0.04	0.22	0.00	0.00	0.00	0.00		0.00	0.29
LSM_AVG	-0.12	0.25	0.32	0.08	0.03	0.01	0.06	0.09	0.04	1.00	0.11
	0.00	0.00	0.00	0.00	0.00	0.21	0.00	0.00	0.00		0.00
ABSRET	-0.09	0.14	0.13	0.02	-0.01	-0.02	-0.02	-0.01	-0.02	0.10	1.00
	0.00	0.00	0.00	0.01	0.37	0.00	0.04	0.28	0.02	0.00	

Table 3

Determinants of Manager-Analyst Engagement

This table reports OLS estimation of equation (1) using a sample of 18,395 manager-analyst dialogues. The t-statistics included in brackets are computed using robust standard errors clustered at the firm-call level. Standardized coefficients with two-tailed p-values are reported: *** p<0.01, ** p<0.05, * p<0.10. See Appendix C for definitions of all variables.

Variables (Column #)	*LSM_AVG (1)*	*LSM_AVG (2)*	*LSM_AVG (3)*
ORDER	**-0.036*** **	**-0.069*** **	**-0.053*** **
	(-4.26)	(-7.48)	(-5.25)
PCT_LEN	**0.144*** **	**0.389*** **	**0.143*** **
	(13.42)	(24.49)	(11.94)
TURNS	**0.263*** **	**0.197*** **	**0.229*** **
	(32.52)	(19.44)	(23.20)
BROKER	**0.020** **	-0.010	-0.023
	(2.51)	(-1.20)	(-0.79)
ALLSTAR	**0.040*** **	**0.027*** **	0.219
	(4.84)	(2.89)	(0.86)
ANAEXP	**0.046*** **	**0.046*** **	0.135
	(5.47)	(5.10)	(1.37)
BUY	**0.022*** **	0.006	**0.023** **
	(2.94)	(0.66)	(2.45)
LnSIZE	**0.022*** **		0.018
	(2.59)		(1.18)
DISPERSION	0.016		0.012
	(1.53)		(0.79)
|UE|	-0.006		-0.003
	(-0.57)		(-0.19)
CONS	**0.000*** **	**0.000*** **	**0.000*** **
	(178.67)	(325.67)	(50.01)
FE	None	Call	Analyst
R-Squared	0.13	0.21	0.22

Table 4

Information Content in Manager-Analyst Engagement

This table reports OLS estimation of equation (2) using a sample of 18,395 manager-analyst dialogues. The t-statistics included in brackets are computed using robust standard errors clustered at the firm-call level. Standardized coefficients with two-tailed p-values are reported: *** p<0.01, ** p<0.05, * p<0.10. See Appendix C for definitions of all variables.

Variables (Column #)	*ABSRET (1)*	*ABSRET (2)*	*ABSRET (3)*
LSM_AVG	**0.052*** **	**0.031*** **	**0.045*** **
	(6.70)	(4.03)	(5.07)
ORDER	**-0.047*** **	**-0.061*** **	**-0.062*** **
	(-5.36)	(-5.99)	(-6.02)
PCT_LEN	**0.064*** **	**0.164*** **	**0.076*** **
	(5.55)	(11.94)	(5.77)
TURNS	**0.066*** **	**0.040*** **	**0.073*** **
	(5.97)	(3.91)	(6.04)
BROKER	0.002	-0.000	**-0.052* **
	(0.24)	(-0.02)	(-1.86)
ALLSTAR	**0.022** **	0.005	0.092
	(2.42)	(0.61)	(1.00)
ANAEXP	**-0.014* **	-0.000	**-0.526*** **
	(-1.73)	(-0.05)	(-4.18)
BUY	-0.011	-0.001	**-0.021** **
	(-1.41)	(-0.15)	(-1.97)
LnSIZE	**-0.130*** **		**-0.118*** **
	(-10.08)		(-6.30)
DISPERSION	**0.073*** **		**0.056** **
	(4.03)		(2.48)
|UE|	0.024		0.021
	(1.15)		(1.09)
CONS	**0.000*** **	**0.000** **	**0.000*** **
	(6.09)	(2.25)	(6.20)
FE	None	Call	Analyst
R-Squared	0.05	0.30	0.10

Table 5

Component Analyses

This table reports OLS estimation of equation (3) for each component of LSM using a sample of 18,395 manager-analyst dialogues. The t-statistics included in brackets are computed using robust standard errors clustered at the firm-call level. Standardized coefficients with two-tailed p-values are reported: *** p<0.01, ** p<0.05, * p<0.10. See Appendix C for definitions of all variables.

Variables (Column #)	*ABSRET (1)*	*ABSRET (2)*	*ABSRET (3)*	*ABSRET (4)*	*ABSRET (5)*	*ABSRET (6)*	*ABSRET (7)*	*ABSRET (8)*	*ABSRET (9)*	*ABSRET (10)*
LSM_Negate	**0.021*** **									**0.020*** **
	(2.88)									(2.80)
LSM_Article		0.005								0.003
		(0.74)								(0.47)
LSM_Auxverb			**0.016** **							**0.015** **
			(2.42)							(2.11)
LSM_Ppron				0.003						-0.000
				(0.35)						(-0.02)
LSM_Ipron					-0.004					-0.008
					(-0.61)					(-1.19)
LSM_Prep						**0.019*** **				**0.017** **
						(2.66)				(2.39)
LSM_Adverb							0.007			0.006
							(1.04)			(0.85)
LSM_Conj								0.003		0.000
								(0.48)		(0.07)
LSM_Quant									**0.015** **	**0.013* **
									(2.16)	(1.92)
Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Call FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
R-Squared	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30

Table 6

Robustness Check - Information Content in Manager-Analyst Engagement

This table reports OLS estimation of equation (2) using a sample of 18,395 manager-analyst dialogues, after controlling for manager scriptedness, dialogue net tone, and drift in dialogue stock returns. The t-statistics included in brackets are computed using robust standard errors clustered at the firm-call level. Standardized coefficients with two-tailed p-values are reported: *** p<0.01, ** p<0.05, * p<0.10. See Appendix C for definitions of all variables.

Variables (Column #)	*ABSRET (1)*	*ABSRET (2)*	*ABSRET (3)*
LSM_AVG	**0.049***** (6.63)	**0.030***** (3.93)	**0.043***** (4.93)
ORDER	**-0.025**** (-2.44)	**-0.053***** (-5.22)	**-0.041***** (-3.40)
PCT_LEN	**0.054***** (4.73)	**0.163***** (11.47)	**0.064***** (4.82)
TURNS	**0.062***** (6.11)	**0.040***** (3.84)	**0.067***** (5.52)
BROKER	0.002 (0.30)	-0.001 (-0.07)	**-0.049*** (-1.88)
ALLSTAR	**0.020**** (2.39)	0.005 (0.63)	0.071 (0.93)
ANAEXP	**-0.013*** (-1.79)	-0.002 (-0.23)	**-0.418***** (-3.68)
BUY	-0.007 (-0.98)	-0.001 (-0.08)	-0.015 (-1.50)
LnSIZE	**-0.100***** (-7.70)		**-0.098***** (-5.28)
DISPERSION	**0.060***** (4.20)		**0.045**** (2.38)
|UE|	0.015 (0.98)		0.013 (0.85)
SCRIPT	**0.014*** (1.76)	0.010 (1.10)	0.011 (1.24)
TONE	-0.007 (-1.01)	0.006 (0.78)	-0.013 (-1.64)
ABSRET_LAG	**0.289***** (3.48)	**0.095***** (2.86)	**0.247***** (2.88)
CONS	**0.000***** (2.99)	0.000 (1.29)	**0.000***** (4.33)
FE	None	Call	Analyst
R-Squared	0.13	0.31	0.16

Table 7

Additional Analysis – Controlling for conversation content

This table reports results based on content analysis. Panel A provides the dictionary of words used to identify topics in conversations (Huang et al. 2018; Gomez et al. 2018). Panel B provides descriptive statistics on the indicator variables denoting dialogue topic. Panel C presents OLS estimation of equation (2) using a sample of 18,395 analyst-manager dialogues after including the indicator variables denoting dialogue topic as additional controls. The t-statistics included in brackets are computed using robust standard errors clustered at the firm-call level. Standardized coefficients with two-tailed p-values are reported: *** p<0.01, ** p<0.05, * p<0.10. See Appendix C for definitions of all other variables.

Panel A: Topic Dictionary

REGULATION: regulate, regulates, regulating, regulation, regulations, regulator, regulators, regulatory
RISK: risk, risks, risky
COMPETITION: competition, competitions, competitive, competitively, competitiveness, competitor, competitors, rival, rivals
CONSUMER: advertise, advertised, advertisement, advertisements, advertiser, advertisers, advertising, brand, branded, branding, brands, consumer, consumers, customer, customers
ECONOMY: economies, economy, macroeconomic, macroeconomics, macroeconomy
SALES: revenue, revenues, sales, sale
PRODUCTS: product, production, productline, productlines, products
EARNINGS: earnings, ebitda, ebit, ebitdas, ebitdax, eps, income, profit
OPERATIONS: operate, operated, operating, operation, operational, operationally
INVESTMENTS: investment, investments
OUTLOOK: outlook, business, expansion, looking, forward, guidance, forecast, market, opportunity
GEOGRAPHY: geography, segments, markets, china, europe, global, emerging, america, region, asia, india, japan, country, west, european, central, international, foreign
GROWTH: growth, organic, strong, digit, acquisition, business, revenue-growth, eps-growth, strengthen, margin, solid
TAX: tax, taxes, carryforward, carryback, avoidance, haven, statutory, break, provision, IRS, NOL

Panel B: Descriptive Statistics

Topic Indicator Variable	Mean	Median	SD
REGULATION	0.03	0.00	0.17
RISK	0.09	0.00	0.29
COMPETITION	0.18	0.00	0.39
CONSUMER	0.37	0.00	0.48
ECONOMY	0.12	0.00	0.33
SALES	0.46	0.00	0.50
PRODUCTS	0.35	0.00	0.48
EARNINGS	0.28	0.00	0.45
OPERATIONS	0.28	0.00	0.45
INVESTMENTS	0.16	0.00	0.37
OUTLOOK	0.86	1.00	0.35
GEOGRAPHY	0.52	1.00	0.50
GROWTH	0.73	1.00	0.44
TAX	0.16	0.00	0.37

Panel C: Regression Results

Variables (Column #)	***ABSRET* *(1)***	***ABSRET* *(2)***	***ABSRET* *(3)***
LSM_AVG	**0.041***** (5.19)	**0.028***** (3.66)	**0.039***** (4.34)
Topic Indicators	Yes	Yes	Yes
Controls	Yes	Yes	Yes
FE	None	Call	Analyst
R-Squared	0.06	0.30	0.10