Do Analysts and Investors Efficiently Respond to Managerial Linguistic Complexity during Conference Calls?

ABSTRACT

This paper examines whether analysts and investors efficiently incorporate the informational signals from managerial linguistic complexity (e.g. Fog) into their forecasts and trading decisions. We predict that managerial linguistic complexity on a conference call provides a signal of the manager's private information through their willingness to engage with analyst questions. Consistent with this engagement mechanism, we show that linguistic complexity evolves over the course of the call, with informative (uninformative) calls exhibiting more (less) informative technical disclosure as the call progress. We find that informative (obfuscatory) managerial Fog provides a positive (negative) signal of future earnings growth. We also find that analysts efficiently revise their forecasts to both positive and negative signals, whereas investors only correctly interpret obfuscation during the call; there is a delayed price reaction to informative Fog. However, when buy-side investors ask questions during a call, we find an efficient price reaction to informative Fog. Our findings highlight an important benefit of two-way interactive disclosures and underline the importance of call participation for efficiently incorporating linguistic signals of managers' private information.

Keywords: conference call; linguistic complexity; two-way engagement; informative technical disclosure; analyst forecasts; market reaction.

I. INTRODUCTION

This paper examines whether analysts and investors efficiently incorporate the informational signals from managerial linguistic complexity (e.g. Fog) during conference calls into their forecasts and trading decisions. Prior work finds that managers signal their expectations about future performance through linguistic features such as tone, scripting, and euphemisms, and that investors and analysts react to these signals (Davis, Piger, and Sedor 2012; Lee 2016; Suslava 2021). Unlike these signals, which are fairly direct and unambiguous to process (e.g., managers are unlikely to use negative tone, scripting, or euphemisms when they expect good future news), managerial linguistic complexity on a conference call could reflect either obfuscation or greater informative technical disclosure (Bushee, Gow, and Taylor 2018). We propose that managerial linguistic complexity provides a signal of the manager's private information through their willingness to engage with analyst questions on a conference call.

Unlike "one-way" disclosures such as SEC filings or press releases, conference calls provide "two-way" interactions that allow call participants to adjust their disclosure strategy dynamically based on cues from the other parties. For example, Rennekamp, Sethuraman, and Steenhoven (2022) provide experimental evidence that greater engagement between analysts and managers during conference calls leads to more informative calls. Managers with positive private information about future earnings have incentives to actively engage with analysts on the call, encouraging them to ask complex questions to improve their understanding of the state of the company.[1] Similarly, managers have incentives to use obfuscatory linguistic complexity and to discourage complex questions when they have negative future earnings news (Li 2008). Thus, we

[1] While informative technical disclosure could be a mix of good news and bad news, we expect that it will be net positive about future earnings; otherwise, the manager would have had incentives to obfuscate. We find that both positive and negative tone words increase significantly during calls with informative technical disclosure (Table 2), showing that information linguistic complexity is a potentially ambiguous signal.

predict that managers use informative (obfuscatory) linguistic complexity before good (poor) future earnings growth.

We examine this two-way engagement mechanism by conducting a within-call dialogue analysis to show how linguistic complexity evolves during the call. We partition each call into the first-five dialogues—where the manager's willingness to provide information should become apparent—and the subsequent dialogues.[2] For calls with high informative linguistic complexity (based on the Bushee, et al. 2018 measure), we find that analysts ask increasingly technical questions as the calls progress. Managers also increase their number of sentences and complex words—as well as positive tone, negative tone, and forward-looking words—consistent with managers providing more technical disclosure as analysts ask more complex questions. For calls with low informative linguistic complexity, we find the opposite: analysts ask simpler questions, and managers tend to give shorter answers with fewer complex words, as the calls progress.

Given the dynamic nature of this two-way interaction, we examine whether the ability of analysts and investors to efficiently process the signal in managerial linguistic complexity depends on their ability to actively participate in the call. We define "efficient processing" of the linguistic signal as a contemporaneous reaction to the signal with no drift in processing. For analysts, an efficient reaction would be a forecast revision in the same direction as the linguistic signal, with the subsequent forecast not exhibiting systematic under- or overreaction to the information. For investors, an efficient reaction would be stock returns in the same direction as the signal with no systematic drift in returns post-call. We predict that analysts will be more efficient in processing the signal in linguistic complexity than investors. As active participants in the call, analysts can

[2] We define a dialogue as an analyst question and manager answer (Jung et al. 2018).

better assess whether linguistic complexity in response to their specific questions represents informative technical disclosure or obfuscation.

We analyze a sample of almost 30,000 conference calls between 2006 and 2016. We measure the complexity of the language on the call using the Gunning (1952) Fog index. Following Bushee et al. (2018), we use the Fog of analysts' questions during the call and a number of business complexity variables to decompose the Fog of the manager's language into an "information component" of Fog and an "obfuscation component" of Fog. The information component reflects the managers' disclosure responses to business complexity in the absence of obfuscation (e.g., informative technical disclosure), whereas the obfuscation component reflects linguistic complexity intended to reduce the informativeness of the call. Our main tests examine whether the information (obfuscation) component of Fog is positively (negatively) associated with future earnings growth, analysts' forecast revisions, and stock return reactions during and after calls. In each test, we control for the earnings surprise, other linguistic attributes of the manager's language (e.g., tone, forward-looking statements), the issuance of guidance, and firm fixed-effects.

First, we find that the information component of Fog is positively associated with next year's earnings growth, suggesting that managers are more willing to engage in informative technical discussions with analysts when managers expect higher earnings growth. We also find that the obfuscation component of Fog is negatively associated with future earnings growth, confirming prior work on managerial incentives to obfuscate bad news (e.g., Li 2008). Thus, both informative technical disclosure and obfuscatory linguistic complexity provide signals of managers' private information about future earnings.

Next, we find that the information component of Fog is positively associated with analyst forecast revisions around the call, suggesting that analysts recognize the positive signal in managers' willingness to provide informative technical disclosure. Similarly, the obfuscation component of Fog is negatively associated with forecast revisions around the call. We also test for a relation between the Fog components and analyst inefficiency, defined as the difference between actual earnings and the post-call consensus analyst forecast. We do not find any significant evidence that analysts systemically underreact or overreact to the linguistic signals on the conference calls. Thus, analysts efficiently use the informational signals in managerial Fog when revising their forecasts of earnings during the call window.

Unlike analysts, investors are often passive participants on the call. The inability to ask questions potentially makes it more difficult for investors to react efficiently to the positive signal in informative Fog because managers are responding to analysts' questions that may reflect analysts' private information. Consistent with this idea, we do not find a significant association between the information component of Fog and the three-day cumulative abnormal stock returns (*CAR*) during the call window. Instead, we find a significant positive relation between the information component and post-call stock returns, indicating delayed investor processing of the positive signal. In contrast, the obfuscation component of Fog is significantly negatively related to *CAR*, but not significantly associated with post-call returns, suggesting an efficient investor response to the negative signal during the call window. These findings differ from Lee (2016) and Suslava (2021), which both find delayed negative price reactions to scripting and euphemisms, respectively. Overall, the results suggest that, while obfuscation through linguistic complexity is a clearer negative signal for investors than scripting and euphemisms, the positive signal in informative Fog is more difficult for investors to detect.

In some cases, buy-side analysts do participate in asking questions during a call. We examine these calls to provide further evidence on whether the ability to ask questions during the call is associated with efficient processing of linguistic signals. When buy-side analysts ask questions, stock returns respond to the information component of Fog on the call immediately;

when there is no participation of buy-side analysts, there is no immediate stock return reaction to the information component. Thus, when investors are also provided the opportunity to ask questions, they are better able to detect the signal value of informative technical disclosure.

We perform a number of additional analyses. First, we find a stronger relation between the managerial linguistic signals and future earnings growth when earnings quality is uncertain, which we measure using income-increasing discretionary accruals. Analysts recognize these stronger signals in their forecasts and revise them in an efficient manner; however, investors continue to have a delayed reaction to the information component of managerial Fog. Second, we find that, among managers who provide earnings guidance, managers act consistently across their guidance and call disclosure decisions in signaling future earnings; i.e., they provide more precise guidance with informative Fog and less precise guidance with obfuscatory Fog. Finally, we find that a higher information (obfuscation) component of Fog is associated with an improvement (reduction) in forecast accuracy and a reduction (improvement) in forecast dispersion. Thus, while analysts correctly interpret obfuscation as bad news, the lack of informative disclosure reduces the accuracy of the consensus forecast and leads to more disagreement among analysts.

Our paper contributes to the literature by providing new evidence on the interactive "two-way" nature of linguistic complexity on a conference call, which allows analysts to detect positive and negative signals in managerial Fog. Much of prior research relies on "one-way" corporate disclosures to test for private information signaling (e.g., Loughran and McDonald 2011, Davis et al. 2012). We show how the complexity and informativeness of analyst questions and managerial responses evolve during a call based on a manager's initial willingness to engage with analysts. In showing how analysts acquire and use information through this interactive signaling dynamic, our paper answers the call for more research on the analysts' "black box" information generating process (Bradshaw 2011, Brown et al. 2015).

Second, we provide evidence on the importance of call participation in facilitating efficient information processing. Mayew, Sharp, and Venkatachalam (2013) find that analysts participating in a call issue more accurate earnings forecasts, but they find limited evidence that such superior forecasting ability is due to information received during the call. Our results suggest that call participants are better able to interpret linguistic complexity as informative technical disclosure in response to their questions, compared to passive listeners. This finding suggests that there is a clear advantage to call participation when trying to interpret the linguistic signals of managers.

II. EMPIRICAL PREDICTIONS AND RELATED RESEARCH

Linguistic Complexity as a Signal of Future Earnings

We first examine whether managerial linguistic complexity provides a signal of a manager's private information about future earnings. Prior work finds that managers use linguistic complexity to obfuscate the true nature of the firm's current and expected performance (see Loughran and McDonald 2016 for a review). However, Bushee et al. (2018) suggest that linguistic complexity could be associated with more informative disclosure. Based on the assumption that analysts are unlikely to have obfuscation incentives when speaking during a conference call, Bushee et al. (2018) use analyst linguistic complexity on the call to benchmark for the amount of linguistic complexity needed to understand the business. After decomposing managerial Fog on a conference call into a component that represents obfuscation and a component that represents informative technical disclosure, they find that the obfuscation (information) component of Fog is positively (negatively) associated with information asymmetry around the call.

We extend Bushee et al. (2018) by examining whether a manager's decision to use linguistic complexity to obfuscate or to inform during a conference call provides a signal of the manager's private information about future earnings. Given that managers tend to obfuscate in the

10-K when they report good earnings news that is transitory or bad earnings news that is persistent (Li 2008), we expect that managerial obfuscation during a conference call predicts lower earnings growth in the future. In contrast, Bushee et al. (2018) find that managers of some loss firms use linguistic complexity (i.e., informative technical disclosure) to provide more information concerning the prospects of the business. We expect that managers are likely to provide more informative technical disclosure when they expect bad earnings news to be transitory. Managers also have incentives to be more informative about good earnings news that they expect to be persistent. Thus, we predict that future earnings growth following conference calls is positively (negatively) associated with informative (obfuscatory) managerial linguistic complexity on the call.

Linguistic Complexity and Analyst Forecast Revisions

We next examine whether analysts respond to managerial linguistic complexity efficiently. Prior research finds that linguistic complexity in a firm's disclosures affects the quality of analysts' forecast outputs. Lehavy et al. (2011) show that higher Fog in 10-Ks is associated with greater dispersion, lower accuracy, and greater overall uncertainty in analyst earnings forecasts. Using earnings press releases, Bozanic and Thevenot (2015) find that higher readability in the form of shorter sentences, textual similarity, and lexical diversity is associated with decreases in analysts' uncertainty. Filzen and Peterson (2015) find that analysts rely more on management guidance and are more likely to exclude items from non-GAAP earnings forecasts for firms with more complex financial statements. Thus, greater linguistic complexity in written disclosures tends to have a detrimental impact on analysts' ability to process information.

Prior work also suggests that conference calls, in general, increase analysts' ability to forecast earnings accurately (Bowen, Davis, and Matsumoto 2002, Kimbrough 2005). Analysts also have incentives to acquire value-relevant information during conference calls (e.g., Mayew 2008; Matsumoto, Pronk, and Roelofsen 2011; Twedt and Rees 2012). Mayew, et al. (2013) find that analysts participating in a call issue more accurate earnings forecasts after the call than nonparticipating analysts. However, they find limited evidence that the superior forecasting ability is due to new information received during the call, suggesting that the participating analysts' superior pre-call private information explains their results. Huang, Zang, and Rong (2014) find that analyst reports after conference calls are associated with a larger investor reaction when managers have incentives to withhold disclosure, but they do not look at whether the analysts' forecasts efficiently process the information in the call. Finally, consistent with analysts detecting managerial incentives to hide information during calls, Lee (2016) finds that the amount of "scripting" in managerial responses to questions during conference calls is negatively associated with future earnings performance and with analyst forecast revisions.

The difference between these two streams is that research showing that analysts have difficulty processing linguistic complexity mainly examines one-way communications. In contrast, conference calls are interactive, and this two-way dialog likely explains the findings that analysts issue more accurate forecasts after conference calls.

In our setting, we expect that the interactive format will allow analysts to efficiently process the informational signals in a manager's linguistic complexity on the call. Specifically, we assume that managers' initial responses to analysts' questions will signal to the analysts whether the manager is willing to be forthcoming with information (allowing the analysts to continue to ask complex, technical questions) or whether the manager is trying to obfuscate (encouraging the analysts to switch to simple questions).[3] Through this engagement mechanism, analysts can assess whether linguistic complexity in response to their specific questions represents a positive signal because of managers' willingness to engage in informative technical disclosure or a negative signal

[3] Our assumption is supported by Rennekamp et al. (2022), which use Linguistic Style Matching and an experiment to measure the level of engagement between analysts and managers on the calls. They find that greater engagement is associated with greater information content on the calls.

due to managers' obfuscation. Thus, we predict that analyst forecast revisions following conference calls are positively (negatively) associated with informative (obfuscatory) managerial linguistic complexity on the call.[4]

Linguistic Complexity and Investor Reactions

Finally, we examine whether investors respond to managerial linguistic complexity efficiently. Prior work finds that investors immediately react to any new information released during conference calls, especially during the Q&A portion (Bushee, Matsumoto, and Miller 2004; Matsumoto, et al. 2011). Investors also react to linguistic cues during calls. Price et al. (2012) find that the tone of the Q&A part of the call is positively associated with the stock return reaction to the call, both during the three-day window and over the next two months. Hollander, Pronk, and Roelofsen (2010) show a negative stock return reaction to the call when managers avoid answering specific questions during a call. Lee (2016) finds that calls with more "scripted" managerial responses to questions have negative stock returns during the call window and over the subsequent quarter. Similarly, Suslava (2021) finds that the greater use of "euphemisms" to soften bad news is associated with negative stock returns during the call and over the next quarter. These findings suggest that investors will react negatively to obfuscatory linguistic complexity during the call.

While Bushee et al. (2018) find that the information component of linguistic complexity reduces information asymmetry, they do not test whether there is a positive return reaction to greater information. In general, more information could lead to either a greater positive or a greater negative return reaction depending on the nature of the information. However, if managers strategically provide more information when they expect higher earnings growth, then we expect such informative linguistic complexity to lead to a positive market reaction to the conference call.

[4] Note that, with more informative disclosure, it is possible that analysts would learn bad news about the future and revise their forecasts downward. However, if we assume that, on average, managers with bad news have incentives to obfuscate, then informative disclosure should be more likely to be observed for good news

Thus, we predict that stock returns in the three-day window around conference calls are positively (negatively) associated with informative (obfuscatory) managerial linguistic complexity on the call.

However, unlike analysts, investors are often passive participants on the call. The inability to ask questions potentially makes it more difficult for investors to react efficiently to any signals in linguistic complexity because the managers are responding to analysts' questions that may reflect analysts' private information. Both the Lee (2016) and Suslava (2021) results suggest that, while investors do detect efforts to obfuscate during the call, they do not fully incorporate the information as there is a drift in negative returns after the call. Thus, we also examine whether investors efficiently react to the signals in linguistic complexity by testing whether the information or obfuscation components of linguistic complexity are associated with stock returns subsequent to the call. If investors have more difficulty in processing linguistic signals due to their passive role during calls, we expect that they would underreact to the linguistic signals, and subsequent returns would be positively (negatively) associated with informative (obfuscatory) managerial linguistic complexity on the call.

III. RESEARCH DESIGN

Regressions for the Main Tests

We examine whether the components of managerial linguistic complexity provide a signal of manager's private information about expected future earnings using the following regression:

$$DV = \beta_0 + \beta_1 Info(Both) + \beta_2 Obfu(Present) + \beta_3 Obfu(Response) + \beta_i CONTROLS + Firm\ Fixed\ Effects + \varepsilon \tag{1}$$

where $DV = GROWTH_{t+1}$, *AF_Revision, AF_Inefficiency, CAR, POST_CAR, CAR_AnalystReport*

We measure managerial linguistic complexity during conference calls using the Gunning Fog index and derive the information and obfuscation components of Fog following the approach of Bushee et al. (2018), which we explain further below. The "information component" of Fog (*Info(Both)*) is a proxy for the amount of informative technical disclosure provided by managers on the conference call. The "obfuscation component" (*Obfu(Present)* and *Obfu(Response)*) is a proxy for complex language that is likely intended to reduce the understandability of disclosure.

We measure our dependent variables as follows (see Appendix for full definitions). Next year's earnings growth, $GROWTH_{t+1}$, is operating income from year t+1 minus operating income in year t, scaled by total assets in year t and then multiplied by 100 (Lev and Nissim 2004; Huang et al. 2014). An analyst forecast revision, *AF_Revision*, is defined as the median analyst EPS forecast for year t+1 for all forecasts made within 30 days following the conference call (AFC*post*) less the median consensus forecast of year t+1 directly before the conference call (AFC*pre*), divided by beginning-of-quarter price.[5] We measure the cumulative abnormal stock return (*CAR*) for the three-day window [-1, 1] around the call as the raw daily return from the CRSP minus the return on the portfolio of firms in the same size and book-to-market deciles. For each of these *DV*s, we expect β_1 to be positive due to the predicted positive relation between informative Fog and expected future performance, analysts' responses, and investors' responses. We expect β_2 and β_3 to be negative due to the predicted negative relation between obfuscation and expected future performance, analysts' revisions, and investors' responses.

We also examine post-call *DV*s to assess the efficiency of analysts' and investors' initial responses to the managerial linguistic signals in the call. We measure analyst inefficiency, *AF_Inefficiency,* as the difference between actual earnings and the post-call consensus forecast (AFC*post*). If analysts systematically underreact (overreact) to positive information in the linguistic signals, *AF_Inefficiency* will be positive (negative). The opposite relations would hold

[5] If there is more than one median consensus analyst forecast during the specified periods, AFC*pre* is the latest median consensus analyst forecast before the conference call date and AFC*post* is the earliest median consensus analyst forecast after the conference call date.

for analyst inefficiency with respect to negative linguistic signals. We measure the post-conference call stock return, *POST_CAR*, as the cumulative abnormal return over the period beginning on Day +2 after quarter *t*'s earnings announcement and ending on Day +1 after the earnings announcement date for quarter *t*+1. Finally, we define *CAR_AnalystReport* as the three-day [-1,1] cumulative market-adjusted abnormal return around the first analyst report issued subsequent to the conference call window. For each of these variables, we would interpret a positive (negative) sign as indicating that analysts and investors underreacted (overreacted) to the information in the linguistic signals.

We control for a variety of firm and call characteristics throughout our analyses. First, we include an indicator variable (*DA*) to capture income-increasing discretionary accruals, which is a proxy for potential earnings management. Lo, Ramos, and Rogo (2017) find that obfuscation incentives for linguistic complexity are especially high in earnings management years. Second, we include the unexpected earnings surprise (*UESURP*) to measure the earnings news revealed in the earnings announcement. We define *UESURP* as the difference between actual EPS and the most recent median consensus analyst forecast prior to the call, scaled by beginning-of-quarter price (Kross, Ro, and Suk 2011; Kross and Suk 2012). We also include controls for firm size, growth, and stock performance, such as the market value of equity (*SIZE*), book-to-market ratio (*BM*), and stock returns for the prior 12 months (*RET*). We control for analyst following (*AFN*) and the level of institutional ownership (*INST_OWN*) as proxies for firms' external monitoring environment (Lang and Lundholm 1996; Kross et al. 2011; Lehavy et al. 2011).

Further, we include controls for a number of other textual attributes of the conference calls to ensure that our results are not merely capturing a previously-documented linguistic measure. We measure the proportion of sentences containing forward-looking statements in the presentation and response parts of the call as *FWDLOOK(Present)* and *FWDLOOK(Response)*, respectively

(Li 2010 and Bozanic et al. 2018). We capture the tone of the call with the number of positive and negative words in the presentation and response parts of the call—*POSTONE(Present)*, *POSTONE(Response)*, *NEGTONE(Present)*, *NEGTONE(Response)*—using the Loughran and McDonald (2011) dictionary. We also include an indicator variable that equals one if management guidance (*GUIDANCE*) is provided on the same day as the conference call; Billings, Jennings, and Lev (2015) report that over 80% of management forecasts are bundled with the earnings announcement in the post-Reg FD period. Finally, we include a number of controls that are specific to certain regressions, such as the standard deviation of analyst forecasts prior to the conference call (*AFSTD*) (Ajinkya, Bhojraj, and Sengupta 2005), the cumulative abnormal return for the three-day window [-1, 1] around the conference call (*CAR*), and the lagged quarterly change in EPS from the prior year ($\Delta LEPS$) (Kross et al. 2011).

Measures for the Information and Obfuscation Components of Fog

We construct our sample using all available observations from the overlap of the conference call transcripts from SeekingAlpha.com; analyst and management forecasts from I/B/E/S; and stock returns and financial statement data from CRSP and Compustat. We begin the sample in 2006 when conference call transcripts become well-populated on SeekingAlpha.com and conclude in 2016. The sample consists of 71,648 firm-quarters with conference call transcripts that have at least one analyst question and have the necessary CRSP, Compustat, and I/B/E/S data.

We measure linguistic complexity using the Gunning (1952) Fog index for the managerial presentation and the question and answer (Q&A) portions of the call separately. The Fog index measures linguistic complexity as a function of the number of words per sentence and the percent of complex words, where complex words are those words with more than two syllables:

$$Fog(.) = 0.4 \times (\text{average number of words per sentence} + \text{percent of complex words}) \quad (2)$$

To provide a benchmark for the expected amount of linguistic complexity needed to understand the business, we estimate the following regression following Bushee et al. (2018):

$$Fog(Manager) = \beta_0 + \beta_1 Fog(Analyst) + \sum \beta_i Business\ Complexity\ Variables + e \qquad (3)$$

where *Fog(Manager)* is one of the two managerial Fog indexes, *Fog(Present)* or *Fog(Response)*. *Fog(Present)* is the Fog of managers' language during the presentation portion of the call and *Fog (Response)* is Fog of the managers' responses in the Q&A. *Fog(Analyst)* is the Fog of analysts' language during the Q&A. The business complexity variables include market value of equity (*Size*); debt-to-assets ratio (*Leverage*); book-to-market ratio (*BM*); quarterly buy-and-hold stock returns (*Returns*); total acquisitions during the quarter (*Acquisitions*); PP&E-to-assets ratio (*CapIntensity*); capital expenditures (*Capex*); research and development (*R&D*); debt and equity issuance (*Financing*); cash flow volatility (*σCFO*); goodwill impairments (*Goodwill*); and restructuring charges (*Restructuring*) (Bushee et al. 2018).

The regression results for Equation (2) are reported in Panel A of Table 1. We rank all of the variables into deciles and scale them to range from 0 to 1. Using these coefficients, we decompose managerial linguistic complexity into information and obfuscation components. The information components of Fog, *Info(Present)* and *Info(Response)*, are measured as the fitted value from these coefficients in columns (1) and (2), respectively. These components capture managerial linguistic complexity that is driven by analyst linguistic complexity and business complexity. The obfuscation components of Fog, *Obfu(Present)* and *Obfu(Response),* are measured as the residual value from the model in columns (1) and (2), respectively. These components capture managerial linguistic complexity uncorrelated with analyst complexity and business complexity. The magnitude and significance of our coefficients are comparable with Bushee et al. (2018).

Panel B of Table 1 reports descriptive statistics for our estimates of these components. The means of *Obfu(Present)* and *Obfu(Response)* are zero by construction because they are regression residuals. The standard deviation of *Obfu(Present)* (*Obfu(Response)*) is 1.455 (1.499). The mean *Info(Present)* is 16.116 and the mean *Info(Response)* is 12.708; the magnitude of these components is large because they include the intercept. Because *Info(Present)* and *Info(Response)* are highly correlated, we combine them into a single variable, *Info(Both)*, using the first principle component of the two variables (Bushee et al. 2018). As this analysis standardizes the variables, the mean of *Info(Both)* is zero.

Evidence on Managerial Engagement and the Evolution of Linguistic Complexity during Conference Calls

Our key assumption is that managers' initial responses to analysts' questions will signal to the analysts whether the manager is willing to be forthcoming with information (due to positive private information) or whether the manager is trying to obfuscate (due to negative private information). Through this mechanism, we argue that the Bushee et al. (2018) information component measures the manager's choice to engage with analysts and provide more information on the calls; thereby signaling positive private information to the analysts.[6]

We test the validity of this engagement mechanism by conducting a within-call analysis at the dialogue level to provide descriptive evidence on how linguistic complexity evolves during the call. We partition each call into the first-five dialogues between managers and analysts—where the manager's willingness to provide information should become apparent—and the post-fifth-question dialogues. We define a dialogue as an analyst question and manager answer (Jung et al. 2018). We measure changes in the number of sentences and number of complex words per dialog between the post-fifth and first-five dialogues to capture the evolution of the technical discussion on the call. We also examine the number of positive and negative tone words per dialogue (using

[6] As the fitted value in the Bushee et al. (2018) decomposition model, the information component largely varies based on variation in the linguistic complexity of the analysts' questions during the call.

the Loughran and McDonald (2011) dictionary) and the number of forward-looking words per dialogue (Bozanic et al. 2018).

Table 2 provides evidence on how linguistic attributes evolve over the course of a conference call. To show how this evolution differs based on high and low information components of Fog, Panel A compares the calls in the top-third of the information component (*High-info*) to those in the bottom third (*Low-info*) group. The first two rows show results for analyst questions. For the *High-info* group, we find that analysts ask more complex questions (column 1) with more sentences (column 2) as the calls progress, suggesting that analysts ask increasingly technical questions for *High-info* calls. We find the opposite pattern for *Low-info* calls: analysts ask simpler questions as the calls go on. The next two rows show the same patterns for managers' responses. In the *High-info* group, managers increase their sentences and complex words, consistent with providing more technical disclosure as analysts ask more complex questions. In contrast, in the *Low-info* group, managers tend to give simpler answers and fewer complex words as the calls progress, consistent with managers' providing low information content.

In the next three columns, we examine other linguistic characteristics. We find that in *High-info* calls, managers increase positive tone words (column 3), negative tone words (column 4), and forward-looking words (column 5) per dialogue. In contrast, in *Low-info* calls, there is a reduction in all the three measures after the initial five dialogues. These results are further evidence suggesting that managers provide more information as the call progresses in the *High-info* calls.[7]

While our focus in this section is showing that the information component of Fog reflects managers' decisions to provide more information, we show the same analysis for the obfuscation

[7] Although we predict that managers provide more information when they have positive news about the future, we find a significant increase in negative tone words as *High-info* calls progress. There are two possibilities for the finding. First, managers are discussing historical information with a negative tone to highlight the expected future improvement in performance. Second, a manager could be mixing negative and positive tone but using contrastive words to emphasize the positive tone disclosure is more important (Palmon, Xu, and Yezegel 2016).

component for completeness. Panel B of Table 2 provides the same comparisons for high obfuscation component calls (*High-obfu*) versus low obfuscation calls (*Low-obfu*) group. We find that analysts reduce their sentences and use of complex words in the *High-obfu* calls, consistent with the notion that analysts realize managers are obfuscating and simplify their questions. We also find the same results in the *Low-obfu* group, but the magnitude of the changes is significantly higher in the *High-* versus *Low-obfu* calls (p-value <0.001). For managers, we find that they increase their complex words, consistent with managers obfuscating in the *High-obfu* calls. However, we find a similar but weaker pattern in the *Low-obfu* group. One possible explanation is that the *Low-obfu* group includes some high information component calls. Lastly, we find both analysts and managers reduce their uses of positive- and negative-tone words when they are in the *High-obfu* group, consistent with analysts asking simpler questions and managers obfuscating as the call continues.

In Panel C, we estimate regression models to control for the potential overlap between *High-info* and *Low-obfu* groups. We include indicator variables for the questions after the initial five (*POST*), for the *High-info* group, and for the *High-Obfu* group, as well as interactions of *POST* × *High-info* and *POST* × *High-obfu*. Consistent with Panel A, the coefficients on *POST* × *High-info* are positive and significant in all of the columns, suggesting that both analysts and managers increase their linguistic complexity and use of tone and forward-looking words after the initial questions for calls with a high information component of Fog. The coefficients on *POST* × *High-obfu* are largely insignificant, indicating *High-obfu* calls tend to have high managerial obfuscation throughout the call. Overall, this section supports our assumption that managers' decisions to engage with analysts and provide more informative calls are captured by the information component of Fog.

IV. EMPIRICAL RESULTS

Summary Statistics

Table 3 presents summary statistics for the sample used in the main tests. From our sample of 71,648 conference calls with the necessary data to estimate the Fog decomposition model, we merge with the I/B/E/S, Compustat, and CRSP databases and require necessary data to compute the control variables. We also require our sample to have at least three analysts issuing forecasts and the institutional data from Thomson Reuters. These data requirements result in a sample of 29,664 firm-quarter observations for our main tests.

Table 3 shows that the mean (median) *Info(Both)* is 0.0118 (-0.0698). The mean (median) *Obfu(Present)* is -0.0638 (-0.0590) and the mean (median) *Obfu(Response)* is -0.0709 (-0.2368). Those descriptive statistics are comparable with prior literature (Bushee et al. 2018). The mean (median) analyst forecast revision (*AF_Revison*) from before to after the conference call is 0.0003 (0.0002), suggesting that, in general, analysts revise their forecasts upward following the calls.

Analyst Responses to Managerial Linguistic Complexity during Conference Calls

We first predict that a manager's linguistic complexity on a conference call provides a signal about the firm's future earnings growth. Table 4 reports results based on equation (1) with next year's earnings growth ($GROWWTH_{t+1}$), analyst forecast revision (*AF_Revision*), and analyst forecast inefficiency (*AF_Inefficiency*) as the dependent variables. All regressions are estimated with firm fixed effects and all continuous variables are winsorized at 1% in either tail of the distribution to remove the effects of outliers. We adjust the standard errors by clustering observations by firm and by date of conference calls.

Column (1) shows that the coefficient on *Info(Both)* is positive and significant at the 1% level, indicating that the information component of linguistic complexity is positively associated with future earnings growth. This finding suggests that managers are more willing to engage in informative technical discussions with analysts when managers expect higher earnings growth. *Obfu(Present)* and *Obfu(Response)* are both significantly negatively associated with future earnings growth, indicating that managers obfuscate more when they expect lower earnings growth in the future. These results confirm our first prediction that the linguistic signals in managerial Fog provide a signal of future earnings growth.

In Column (2) of Table 4, we test whether analysts recognize the linguistic signals in managerial Fog and revise their annual earnings forecasts accordingly. We find that the coefficient on *Info(Both)* is positive and significant, indicating that analysts revise upward their forecasts of future earnings when managerial Fog has a larger information component. Thus, analysts recognize the incremental good-news signal of managers' willingness to engage in more technical disclosure. The coefficients on *Obfu(Present)* and *Obfu(Response)* are negative and significant, suggesting that analysts revise downward their forecasts of future earnings following calls with a greater obfuscation component, which is a signal of future bad news. Thus, analysts appear to understand the signaling inherent in managerial linguistic signals to update their forecasts about future earnings growth.[8]

While the results in Columns (1) and (2) show that managerial linguistic signals are related to future earnings performance and that analysts incorporate the signal when they revise their forecasts, it is unclear whether analysts respond to managerial linguistic signals efficiently or not. Therefore, in Column (3), we estimate the association between *AF_Inefficiency* and the information and obfuscation components of managerial Fog. These results indicate that analysts

[8] We also examine whether analyst forecast revisions are related to general linguistic complexity of managers. We find that the coefficient on *Fog(Present)* is negative and marginally significant (p-value = 0.053), consistent with managerial obfuscation, on average, in the presentation part of the call. However, the coefficient on *Fog(Response)* is insignificant. These results suggest that analysts do not tend to react to the general level of linguistic complexity in revising their forecasts; rather, they differentiate between "good" and "bad" linguistic complexity.

do not systemically underreact or overreact to the linguistic signals on the conference calls, consistent with analysts responding to the information and obfuscation components efficiently.

Investor Responses to Managerial Linguistic Complexity during Conference Calls

Next, we examine whether investors correctly interpret the informational signals in managerial linguistic complexity when reacting to conference calls. We estimate equation (1) with the contemporaneous stock return reaction (*CAR*), post-call stock returns (*CAR_POST*), and stock returns around the first post-call analyst report (*CAR_AnalystReport*) as dependent variables. To be consistent with prior work, we replace *UESURP* with the scaled decile rank, *DSUE*. All regressions are estimated with firm fixed effects and all continuous variables are winsorized at 1% in either tail of the distribution to remove the effects of outliers. We adjust the standard errors by clustering observations by firm and by date of conference calls.

Column (1) of Table 5 presents the results of regressions with *CAR* as the dependent variable. We find that the coefficient on *Info(Both)* is insignificant, indicating that investors do not immediately react to the positive future earnings signal that is in high levels of the information component of managerial Fog. In contrast, the coefficients on *Obfu(Present)* and *Obfu(Response)* are both negative and significant, suggesting that investors correctly interpret the obfuscation component of Fog as a negative signal about future earnings. This latter finding is consistent with Lee (2016), which finds that managers use scripting to obfuscate future bad performance.

In Column (2) of Table 5, we test for a delayed price reaction with the dependent variable *POST_CAR*. We find that the coefficient on *Info(Both)* is positive and significant at the 1% level, indicating that investors have a delayed price reaction to the positive signal in the information component of Fog. This result suggests that investors miss the linguistic signals initially and then update as more information, such as analyst forecast revisions, arrives after the call.

We also find that the coefficients on *Obfu(Present)* and *Obfu(Response)* are not significant, suggesting that investors efficiently impound the information in these signals in the conference call window. This finding differs from Lee (2016) and Suslava (2021), who both find delayed price reactions to scripting and euphemisms, respectively. Thus, these results suggest that investors appear to view managers' obfuscating with linguistic complexity during conference calls as clear negative signals about the firm future performance, unlike scripting and euphemisms, where the obfuscation signal is less immediately apparent to investors.[9]

Our finding that investors have a delayed price reaction to the positive signal in informative linguistic complexity raises the question of whether analysts play an information intermediary role in guiding investors following the conference calls. To explore this explanation, we estimate the regression in equation (1) using *CAR_AnalystReport* as the dependent variable and report the results in Column (3) of Table 5. We find that the coefficient on *Info(Both)* is positive and significant, indicating a price reaction to the information component of Fog when the first analyst reports are issued after the call window. We also find that the coefficients on *Obfu(Present)* and *Obfu(Response)* are both insignificant, consistent with investors fully incorporating the negative signal in obfuscation Fog during the call window. These results suggest that investors rely on the initial analyst report after the call to correctly interpret informative Fog as a positive signal about future earnings growth.[10]

[9] To ensure the results are not confounded by the Fog of the earnings release issued in the same [-1, +1] window as the conference call, we add a control for the Fog of concurrent earnings releases in our main models. The correlation between the Fog of conference call presentations and the Fog of the earnings releases is 0.595 (p-value <0.0001), suggesting that managers prepare earnings releases and conference call presentations in a consistent manner. When we include the control for the Fog of the earnings release, we find that our results are unchanged.

[10] We follow prior work in using a 30-day window for forecast revisions and a three-day window for stock returns. To ensure that the difference in window lengths is not driving the difference in observed efficiency between analysts and investors, we also estimate our forecast revision and stock return tests using the same nine-day window [-1, +7] centered on the conference call day. We find that both analysts and investors respond negatively to obfuscation Fog in the presentation and Q&As, but only analysts respond positively to the information component of Fog. These results mirror our main findings.

Taken together, our results suggest that the information and obfuscation components of managerial Fog provide an incremental signal of good and bad future earnings news, respectively. Analysts efficiently incorporate these linguistic signals into their forecasts, but investors only efficiently incorporate the obfuscation signal. Investors fail to immediately impound into price the positive signal in informative managerial Fog, and investors do not incorporate this positive signal until the first analyst report comes out after the call. While prior work has shown evidence consistent with the obfuscation role of linguistic complexity, our findings provide new evidence that managers' willingness to engage in informative technical disclosure with analysts during conference calls provides a signal of positive news that analysts efficiently process, while investors have a delayed reaction that is partially driven by their reaction to the first post-call analyst report.

Participation of Buy-side Analysts on the Conference Call

One possible explanation for the delayed reaction of investors to the positive signal in informative linguistic complexity is that, unlike sell-side analysts, most investors do not have the opportunity to ask questions during the conference call. Sell-side analysts who ask questions based on their private information are better able to determine whether a complex managerial response is information technical disclosure or obfuscation of the underlying answer. Since investors listening to the call do not necessarily have the same private information, it is more challenging for them to determine whether the manager's linguistic complexity is informatively answering the question or not. Thus, as passive participants on the call, investors have less ability to discern the potential signal in the manager's linguistic complexity.

To explore this explanation, we partition our sample based on whether investors are able to ask questions of managers during the call through their buy-side analysts. We collect all the names and affiliations of the analysts that participate on the conference calls and we hand collect the information about their affiliations to classify whether they are sell-side or buy-side analysts, following Jung et al. (2018). If there is at least one buy-side analyst asking a question on the conference call, we set the indicator variable *Buy-sider* equal to one; if we cannot identify any buy-side analysts asking questions during the call, we set *Buy-sider* equal to zero.

In Table 6, we estimate the regression in equation (1) using three-day cumulative abnormal returns at the call window (*CAR*) and split our sample based on whether *Buy-sider* = 1 (Column (1)) or *Buy-sider* = 0 (Column (2)). We find that the coefficient on *Info(Both)* is positive and significant in the *Buy-sider* = 1 subsample and not significant in the *Buy-sider* = 0 subsample. These results suggest that, when buy-side analysts get to ask questions, investors respond to the information component of Fog on the call immediately. However, when there is no participation of buy-side analysts on the conference call, there are no immediate stock return reactions to the information components. We also find that investors significantly respond to managerial obfuscation, regardless of whether there are any buy-side analysts on the call or not, consistent with a high obfuscation component providing a clear negative signal even to passive participants. These results help to explain why analysts respond to the information component of Fog during conference calls more efficiently than investors; having the ability to ask questions provides analysts more insight into the informativeness of managers' technical disclosure. When investors are also provided the opportunity to ask questions, they are also better at detecting the signal value of informative technical disclosure.

V. ADDITIONAL ANALYSES

Interactive Effects of Linguistic Signals and Potential Earnings Management

We provide further evidence on the signaling role of managerial linguistic complexity by examining whether linguistic signals are more valuable when managers have potentially engaged in earnings management. Prior literature finds that analysts have mixed success in detecting earnings management (Bradshaw et al. 2001, Burghstahler and Eames 2003, Abarbanell and Lehavy 2003).[11] In a survey of sell-side analysts, Brown, et al. (2015) report that analysts tend to not look for misreporting in the SEC filings, but they do try to determine whether the earnings are sustainable and reflect economic reality. Thus, when the potential for earnings management is high, analysts and investors will have greater uncertainty about the quality of the earnings news. Due to this uncertainty, we predict that any signal about obfuscation or informative disclosure present in high linguistic complexity will carry more weight for firms with uncertain earnings quality. To test the interactive effects of linguistic complexity and potential earnings management, we estimate the following regression:

$$\begin{aligned} DV = {} & \beta_0 + \beta_1 Info(Both) + \beta_2 Obfu(Present) + \beta_3 Obfu(Response) + \\ & \beta_4 Info(Both) \times DA + \beta_5 Obfu(Present) \times DA + \beta_6 Obfu(Response) \times DA + \\ & \beta_7 DA + \beta_i CONTROLS + Firm\ Fixed\ Effects + \varepsilon \end{aligned} \tag{4}$$

The *DV*s in this regression are the same as in Tables 4 and 5. The variables of interest in this regression are the interactions *Info(Both)×DA, Obfu(Present)×DA,* and *Obfu(Response)×DA*, where *DA* is our proxy for potential earnings management. We set *DA* equal to one if the firm reported income-increasing discretionary accruals during the year, and zero otherwise.[12] Discretionary accruals are estimated using an annual cross-sectional model for each industry defined at the two-digit SIC level, calculated based on the Ball and Shivakumar (2006) model with controls for earnings performance (Kothari, Leone, and Wasley 2005).[13]

[11] Coles, Hertzel, and Kalpathy (2006) find that, when earnings management is fairly transparent (e.g., abnormally low discretionary accruals between cancellations and reissuances of stock options), analysts are able to see through earnings management.

[12] We also use another proxy for potential earnings management: whether the firm just meet-or-beat its earnings target during the quarter (Burgstahler and Dichev 1997). We define the variable MBE = 1 if ΔEPS falls in the neighborhood from zero to three cents; otherwise MBE =0 (Lo et al. 2017). We find our results are essentially the same.

[13] The annual period includes the quarter of the conference call, but we do not attempt to measure the amount of income-increasing discretionary accruals in that specific quarter's earnings. Quarterly discretionary accruals can be noisier than annual models (Jeter and Shivakumar 1999), so we are trading off measuring the exact timing of the income-increasing accruals during the year to get a more precise measurement of income-increasing accruals.

Table 7 reports our results from estimating Equation (4). Panel A provides results with $GROWTH_{t+1}$, *AF_Revision*, and *AF_Inefficiency* as the dependent variables. The results show that, when there is potential earnings management, the linguistic signals in managerial Fog provide a stronger signal for future earnings growth and that analysts efficiently place a larger weight on these Fog components. Panel B reports results with *CAR*, *CAR_POST*, and *CAR_AnalystReport* as the dependent variables. We find that investors react even more inefficiently to the stronger implications of the linguistic signals when there is earnings management. Overall, the results suggest that the relation between managerial linguistic signals and future earnings growth is stronger when earnings quality is uncertain, consistent with managers having greater incentives to provide information (obfuscate) when they expect higher (lower) earnings growth in a period with income-increasing accruals. Analysts recognize this greater signal value of managerial linguistic complexity in their forecasts and revise them in an efficient manner. Meanwhile, investors continue to have a delayed reaction to the information component of managerial Fog, even when the signal has greater predictive value in the presence of potential earnings management.

Managerial Linguistic Complexity and Management Guidance Precision

Our maintained assumption is that managers intentionally provide greater technical disclosure during conference calls when they expect future good news and intentionally obfuscate when they expect bad news. To provide more support for this assumption, we test whether managers' guidance decisions are consistent with the signal in their linguistic complexity. Managers can signal their private information about future performance by providing more frequent guidance or by providing more precise guidance (Baginski and Hassell 1997; Cheng, Luo, and Yue 2013; Ettredge, Huang, and Zhang 2013). We predict that managers will act consistently in their disclosures during conference calls; i.e., managers will provide more precise guidance when the information component of Fog is high and they will provide less precise guidance when the obfuscation component is high.[14]

In Column (1) of Table 8, we report results of estimating equation (1) using managerial guidance precision as the dependent variable. We collect annual earnings forecasts issued within 30 days after the conference calls. Following Choi et al. (2010) and Ettredge et al. (2013), we define managerial guidance precision (*MG_Precision*) as the absolute value of the upper limit of the range forecast minus the lower limit, deflated by the share price at day –2 days. We then multiply the value by negative one so that more precise forecasts have a larger value. For point forecasts, precision is set to zero to code these forecasts as the most precise. Consistent with our prediction, we find that *Info(Both)* is positively associated with management guidance precision, indicating that managers that provide more informative technical disclosure on the call also issue more precise management forecasts subsequent to the calls. We also find that the coefficients on both *Obfu(Present)* and *Obfu(Response)* are negative and significant, indicating that managers who obfuscate more in their calls tend to issue less precise guidance as well. These findings support the assumption that managers are using linguistic complexity to signal future earnings as they provide a similar signal through their managerial guidance precision.[15]

Managerial Linguistic Complexity and Analyst Forecast Accuracy and Dispersion

While our main focus is on the signaling role of managerial linguistic complexity, we also provide descriptive evidence on whether managerial linguistic signals on the calls improve the

[14] Prior research shows that managers have incentives to "guide through the Fog;" i.e., provide more information when it is more difficult for investors to capture the signal of future earnings growth in complex 10-Ks (Guay, Samuels, Taylor 2016). In Guay et al. (2016), Fog is determined exogenously by accounting standard setters, and the managers respond by choosing the guidance precision. In our setting, managers choose both the precision of guidance and whether to inform or obfuscate during the conference call. Thus, this test provides evidence of whether managers are acting consistently across disclosures as they are making both voluntary disclosure decisions.

[15] We also examine the association between a manager's linguistic complexity on the conference call and their forecast horizons and we find a similar, but statistically weaker inference.

accuracy and reduce the dispersion for analysts in their subsequent forecasts. We define the change in analyst forecast accuracy ((ΔAF_ACCR) as [|Actual EPS – AFC*post*|/beginning-of-quarter price] – [|Actual EPS – AFC*pre*|/beginning-of-quarter price], multiplied by negative one, where Actual EPS is the IBES actual and the analyst forecast variables (Kross and Suk 2012). The change in analyst forecast dispersion (ΔAF_DISP) is (STD(AFC*post*) – STD(AFC*pre*))/beginning-of-quarter price, where analyst forecast dispersion before (after) the call is the standard deviation of individual analysts' annual EPS forecasts for year t+1. Similar to Kross and Suk (2012), we use pre- and post-call forecasts that are within 30 days of the call and exclude observations if there are fewer than three analysts following a company for the 60-day period.

Table 8 reports the results from regressions of changes in analyst forecast accuracy (Column (2)) and dispersion (Column (3)) on the information and obfuscation components of Fog (equation (1)). In Column (2), the coefficient on *Info(Both)* is positive and significant, indicating analyst forecast accuracy improves with a higher information component of linguistic complexity. The coefficient on *Obfu(Response)* is negative and significant, suggesting that obfuscatory linguistic complexity is associated with a decrease in the accuracy of the consensus analyst forecast. In Column (3), the coefficient on *Info(Both)* is negative and significant, indicating that analyst forecast dispersion declines following the calls with greater information components of linguistic complexity. The coefficients on *Obfu(Response)* are positive and significant, suggesting that analyst forecast dispersion increases following the conference calls when there is more obfuscation in managers' responses in the Q&As. Overall, these results suggest that analysts issue more accurate and less dispersed forecasts when they receive more informative technical disclosure from managers on the conference calls. However, analyst forecasts become less accurate and more dispersed when managers obfuscate on the calls. Thus, while analysts do not systematically underor over-react to the negative signal in managerial obfuscation, the lack of precise information due to the obfuscation leads to less accuracy and more disagreement among analysts.

VI. CONCLUSION

This paper shows that managerial linguistic complexity on a conference call provides a signal of a manager's private information about future earnings, and that the efficiency with which market participants react to this signal depends on their ability to actively participate in the call. The mechanism underlying these findings is that managers with positive private information about future earnings have incentives to actively engage with call participants, providing them the technical disclosure needed to fully understand managers' positive future expectations. We show that this informative linguistic complexity evolves over the call, with call participants increasing the complexity of their questions based on managers' initial willingness to engage with the questions. This engagement mechanism shows a benefit of two-way interactive disclosures, compared to one-way disclosures like SEC filings or press releases, and underlines the importance of call participation for efficiently incorporating linguistic signals.

A caveat to our results is that it is difficult to conclusively establish causality between managers' linguistic choices and analysts' and investors' information processing in a conference call setting. However, the advantage of the conference call setting is that we can control for the economic nature of the news (e.g., the earnings surprise) and other linguistic attributes to better isolate the role of linguistic complexity. There is also a low probability of reverse causality in our setting. It is unlikely that analysts intending to revise their forecasts downward would (or could) intentionally try to elicit obfuscatory linguistic complexity from managers.

Despite this caveat, our results provide new evidence on the signaling role of linguistic complexity, and on analyst and investor responses to such complexity, through exploiting the

Bushee et al. (2018) decomposition of Fog into its information and obfuscation components. These results suggest future research can increase the power of their tests by using a similar decomposition. Our findings also show how analysts and managers dynamically adapt their disclosure strategy based on initial cues in a two-way disclosure, suggesting that a dialog-level analysis in conference calls or conference presentations can yield new insights into how the evolution of an interactive disclosure signals the information sets and incentives of the parties involved in the disclosure.

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APPENDIX
Variable Definitions

Variable		Definition
Measures of linguistic complexity		
Fog(.)	=	Fog index of the respective portion of the conference call. *Fog(Analyst)* refers to the Fog index of analysts during the call. *Fog(Present)* refers to the Fog index of managers during the presentation portion of the call. *Fog(Response)* refers to the Fog index of managers during the response portion of the call.
Obfu(.)	=	Estimated latent obfuscation component following Bushee et al. (2018). *Obfu(Present)* refers to the presentation portion of the call, and *Obfu(Response)* refers to the response portion of the call.
Info(.)	=	Estimated latent information component following Bushee et al. (2018). *Info(Present)* refers to the presentation portion of the call, and *Info(Response)* refers to the response portion of the call. *Info(Both)* refers to the first principal component of *Info(Present)* and *Info(Response)*.
Firm characteristics to estimate linguistic complexity		
Acquisitions	=	Total acquisitions during the quarter, scaled by total assets at the beginning of the quarter.
BM	=	Book value of equity scaled by market value of equity at the beginning of the quarter.
Capex	=	Amount of capital expenditures scaled by total assets at the beginning of the quarter.
CapIntensity	=	Net plant, property, and equipment scaled, scaled by total assets at the beginning of the quarter.
Financing	=	Amount raised from stock and debt issuances during the quarter scaled by total assets at the beginning of the quarter.
Goodwill	=	Indicator variable for whether the firm had a goodwill impairment charge that quarter
Leverage	=	Long-term debt plus short-term debt, scaled by total assets at the beginning of the quarter.
R&D	=	Ratio of research and development expense to sales.
Restructuring	=	Indicator variable for whether the firm had a restructuring charge that quarter
Returns	=	Buy-and-hold return over the quarter, in percent.
Size	=	Natural log of market value of equity at the beginning of the quarter.
σCFO	=	Standard deviation of cash flows from operations scaled by total assets over the prior five years.
Dependent Variables		
$\boldsymbol{GROWTH_{t+1}}$	=	Future earnings growth, measured as operating income from year t+1 minus operating income in year t, scaled by total assets in year t and then multiply by 100, following Huang et al. (2014).

AF_Revision	=	Analyst forecast revision, computed as (AFC*post* - AFC*pre*)/beginning-of quarter price. It is measured as the difference between the median of analyst forecasts for year *t*+1 earnings, issued within 30 days post to the conference call (AFC*post*), and the median of analyst forecasts for year *t*+1 earnings, issued within 30 days prior to the conference call (AFC*pre*), and then the difference is scaled by price at the beginning of the fiscal quarter. If analysts made more than one median consensus analyst forecast during the specified period above, we use the one closest to the conference call date in calculating AFC*post* and AFC*pre*.
AF_Inefficiency	=	Analyst forecast inefficiency, measured as the actual reported earnings minus the consensus analyst forecasts issued within 30 days post to the conference call (AFC*post*), and then the difference is scaled by price at the beginning of the fiscal quarter.
CAR	=	The size-adjusted cumulative daily abnormal return over the three-day [-1,1] window. The daily abnormal returns are measured as the raw daily return from the CRSP minus the daily return on the portfolio of firms with approximately the same size (the market value of equity as of December) and book-to-market (BM) ratio (as of the prior June).
CAR_POST	=	The size-adjusted cumulative daily abnormal return over the period beginning on Day +2 after quarter *t*'s earnings announcement and ending on Day +1 after the earnings announcement date for quarter *t*+1. The daily abnormal returns are measured as the raw daily return from the CRSP minus the daily return on the portfolio of firms with approximately the same size (the market value of equity as of December) and book-to-market (BM) ratio (as of the prior June).
CAR_AnalystReport	=	The three-day [-1, 1] cumulative market-adjusted abnormal return around the first analyst report issued subsequent to the conference call window. Day 0 is the day when the first analyst forecast following the conference call is issued.

Independent and Additional Variables of Interest

DA	=	An indicator variable that equals one if the annual discretionary accruals are income increasing. Discretionary accruals are estimated using the cross-sectional (Ball and Shivakumar 2006) model and controlling for firm performance following (Kothari et al. 2005), estimated by industry and year. Specifically, discretionary accruals are estimated as the residual from the regression: $AC = \alpha + \beta_1 \Delta R + \beta_2 PPE + \beta_3 CFO + \beta_4 DCFO + \beta_5 CFO \times DCFO + \beta_6 ROA + \varepsilon$. AC is (cash flow from operations – income before extraordinary items)/average total assets; ΔR is ($revenue_t$ – $revenue_{t-1}$)/average total assets; PPE is gross property, plant, and equipment/average total assets; CFO is cash flow from operations/average total assets; DCFO is an indicator variable equal to one if CFO is negative, and zero otherwise; and ROA is (net income before extraordinary items)/average total assets.
UESURP	=	The difference between actual earnings and the most recent median consensus analyst forecast prior to the conference call date, scaled by the price at the beginning of the fiscal quarter.
RET	=	Market-adjusted (value-weighted) buy-and-hold returns for the previous 12 months prior to the conference call disclosure.

SIZE	=	Natural log of market value of equity at the beginning of the fiscal quarter, prior to the conference call disclosure.
BM	=	Natural log of book-to-market ratio at beginning of the fiscal quarter, prior to the conference call disclosure.
AFN	=	The number of analysts following at the end of the fiscal quarter, prior to the conference call disclosure.
INST_OWN	=	The percentage of institutional ownership at the beginning of the fiscal year end, prior to the conference call disclosure.
AFSTD	=	The standard deviation of analyst forecasts in the fiscal quarter prior to the conference call disclosure, scaled by price at the beginning of the fiscal quarter.
ΔLEPS	=	The change in earnings per share at the beginning of the quarter (EPS_{q-1} – EPS_{q-5}) prior to the conference call disclosure, scaled by q-5 quarter price.
DSUE	=	The decile of earnings surprise, which is defined as the actual EPS minus the most recent consensus analyst forecast, scaled by the price at the beginning of the fiscal quarter. The coefficient of DSUE can be interpreted as the abnormal return earned on a zero-investment portfolio that takes a long position in the highest DSUE decile (DSUE=1) and a short position in the lowest DSUE decile (DSUE=0).
SPECIAL	=	An indicator variable that equals one if firm *i* reports negative special items in quarter *t*; 0 otherwise.
4thQTR	=	An indicator variable that equals one if the earnings announcement is for the fourth fiscal quarter; 0 otherwise.
RESPONSIVE	=	An indicator variable that equals one if there is at least one analyst revising the forecast of next year's earnings within two trading days after the current quarter earnings announcement; 0 otherwise.
BNEWS	=	An indicator variable that equals one if the unexpected earnings are negative; 0 otherwise.
RET VOL	=	Stock return volatility, measured as the standard deviation of daily stock returns over the period [-127, -2] relative to the conference call date, following Mayew and Venkatachalam (2012).
RET MOM	=	The buy-and-hold return over the window [-127, -2] before the conference call date, following Mayew and Venkatachalam (2012).
FWDLOOK(Present)	=	The proportion of sentences containing forward-looking statements in the presentation of the call. We classify sentences in the call as forward-looking sentences if they include at least one forward-looking term, following Li (2010) and Bozanic et al. (2018).
FWDLOOK(Response)	=	The proportion of sentences containing forward-looking statements in the response of the call.
POSTONE(Present)	=	The number of positive tone words in the presentation of the call.
POSTONE(Response)	=	The number of positive tone words in the response of the call.
NEGTONE(Present)	=	The number of negative tone words in the presentation of the call.
NEGTONE(Response)	=	The number of negative tone words in the response of the call.
GUIDANCE	=	An indicator variable that equals one if at least one quantitative guidance is provided on the same day as the conference call, based on the IBES Guidance database.

Table 1
Estimating the Latent Components of Managers' Linguistic Complexity

Panel A: Estimation Model

Dependent Variable	*Fog (Present)*		*Fog (Response)*	
Variable	(1)		(2)	
Fog(Analyst)	**0.085**	***	**0.341**	***
	(21.89)		**(62.35)**	
Size	-0.974	***	-0.010	
	(-13.24)		(-0.45)	
Leverage	0.349	***	0.148	***
	(4.93)		(4.77)	
BM	-0.092		-0.287	***
	(-1.21)		(-6.65)	
Returns	-0.163	***	-0.037	***
	(-7.59)		(-3.82)	
Acquisitions	-0.305	***	-0.059	*
	(-5.69)		(-2.09)	
CapIntensity	-0.490	***	-0.619	***
	(-5.67)		(-18.32)	
Capex	0.001		0.132	**
	(0.02)		(2.36)	
R&D	0.369	***	0.420	***
	(4.46)		(8.44)	
Financing	0.133	*	0.030	
	(1.72)		(1.15)	
σCFO	-0.295	***	-0.354	***
	(-6.48)		(-7.6)	
Goodwill	0.232	***	0.076	**
	(2.97)		(2.55)	
Restructuring	-0.066		0.062	***
	(-0.99)		(4.56)	
No. Obs.	71,648		71,648	
Adj R2	7.324%		20.51%	

Table 1
Estimating the Latent Components of Managers' Linguistic Complexity

Panel B: Descriptive Statistics of Estimated Latent Components of Linguistic Complexity

Variable	Mean	Std	P25	Median	P75
Obfu(Present)	0.000	1.455	-0.925	0.009	0.959
Obfu(Response)	0.000	1.499	-1.047	-0.146	0.907
Info(Present)	16.116	0.409	15.821	16.095	16.397
Info(Response)	12.708	0.761	12.190	12.628	13.125
Info(Both)	0.000	0.800	-0.546	-0.083	0.440

Notes: Table 1 presents the regression results and descriptive statistics of the latent components of the linguistic complexity. Panel A reports results from estimating the linguistic complexity of managers during the respective portion of the conference call, *Fog(Present)* and *Fog(Response)*, as a function of the linguistic complexity of analysts, *Fog(Analyst)*, and variables related to business complexity. We use the following variables to measure business complexity: firm size (*Size*); firm leverage (*Leverage*); book-to-market ratio (*BM*); historical stock performance (*Returns*); acquisitions (*Acquisitions*), capital intensity (*CapIntensity*), capital expenditures (*Capex*), research and development (*R&D*); debt and equity issuance (*Financing*); cash flow volatility (*σCFO*); goodwill impairments (*Goodwill*) and restructuring charges (*Restructuring*). See Appendix for variable definitions. For ease of interpretation, each of the variables is ranked into deciles and scaled to range from 0 to 1. *t*-statistics appear in parentheses and are based on standard errors clustered by firm and disclosure date of the conference call. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively. Panel B reports the distribution of our empirical estimates of the latent components of managers' linguistic complexity. *Obfu(.)* is the latent obfuscation component during the respective section of the call and *Info(.)* is the latent information component during the respective section of the call. *Info(Both)* is the first principal component of *Info(Present)* and *Info(Response)*.

Table 2
Evolution of Linguistic Complexity over the Conference Call

Panel A: High versus Low Information Component Groups

	Number of Dialogues	Length -Sentence per dialogue		Complex words per dialogue		Tone - positive words per dialogue		Tone - negative words per dialogue		Fwdlook - word per dialogue	
		(1)		(2)		(3)		(4)		(5)	
High- Info group (top 1/3)	Mean	Mean	Change	Mean	Change	Mean	Change	Mean	Change	Mean	Change
First 5Qs - Analysts	5	5.112		9.148		1.399		1.089		0.741	
Post 5Qs - Analysts	27	5.445	0.333***	9.413	0.265***	1.339	-0.059***	1.120	0.031***	0.724	-0.017
Low-Info group (bottom 1/3)											
First 5Qs - Analysts	5	4.733		10.751		1.420		1.228		0.818	
Post 5Qs - Analysts	26	3.794	-0.939***	8.619	-2.131***	1.088	-0.332***	0.990	-0.238***	0.623	-0.195***
High- Info group (top 1/3)											
First 5As - Managers	5	7.153		15.268		2.331		1.375		1.472	
Post 5As - Managers	27	9.694	2.541***	21.032	5.764***	2.912	0.581***	1.909	0.534***	1.862	0.391***
Low-Info group (bottom 1/3)											
First 5As - Managers	5	7.407		18.397		2.633		1.654		1.698	
Post 5As - Managers	26	6.893	-0.515***	16.969	-1.428***	2.293	-0.340***	1.537	-0.118***	1.465	-0.233***

Table 2 (Continued)
Evolution of Linguistic Complexity over the Conference Call

Panel B: High versus Low Obfuscation Component Groups

	Number of Dialogues	**Length -Sentence per dialogue**		**Complex words per dialogue**		**Tone - positive words per dialogue**		**Tone - negative words per dialogue**		**Fwdlook - word per dialogue**	
		(1)		**(2)**		**(3)**		**(4)**		**(5)**	
High-Obfu group (top 1/3)	Mean	Mean	Change	Mean	Change	Mean	Change	Mean	Change	Mean	Change
First 5Qs - Analysts	5	4.616		10.758		1.486		1.202		0.828	
Post 5Qs - Analysts	26	4.188	-0.428***	9.631	-1.127***	1.261	-0.225***	1.069	-0.133***	0.711	-0.117***
Low-Obfu group (bottom 1/3)											
First 5Qs - Analysts	5	5.252		9.078		1.341		1.111		0.715	
Post 5Qs - Analysts	27	5.046	-0.206***	8.434	-0.644***	1.159	-0.181***	1.052	-0.059***	0.640	-0.075***
High-Obfu group (top 1/3)											
First 5As - Managers	5	6.830		19.959		2.747		1.639		1.804	
Post 5As - Managers	26	7.278	0.449***	21.477	1.519***	2.720	-0.027***	1.757	0.118***	1.784	-0.020
Low-Obfu group (bottom 1/3)											
First 5As - Managers	5	7.794		14.069		2.256		1.413		1.395	
Post 5As - Managers	27	9.692	1.898***	17.660	3.591***	2.617	0.361***	1.785	0.372***	1.644	0.249***

Table 2 (Continued)
Evolution of Linguistic Complexity over the Conference Call

Panel C: Across Groups Comparisons

	Length -Sentence per dialogue		**Complex words per dialogue**		**Tone - positive words per dialogue**		**Tone - negative words per dialogue**		**Fwdlook - words per dialogue**	
	(1) Analyst	**(2)** Manager	**(3)** Analyst	**(4)** Manager	**(5)** Analyst	**(6)** Manager	**(7)** Analyst	**(8)** Manager	**(9)** Analyst	**(10)** Manager
Intercept	4.992 ***	7.601 ***	9.915 ***	16.234 ***	1.381 ***	2.445 ***	1.170 ***	1.534 ***	0.767 ***	1.547 ***
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
POST	-0.5725 ***	0.6910 ***	-1.3883 ***	1.0802 ***	-0.2568 ***	0.0103	-0.1488 ***	0.1270 ***	-0.1347 ***	0.0080
	<.0001	<.0001	<.0001	<.0001	<.0001	0.7416	<.0001	<.0001	<.0001	0.7134
HI_INFO	0.1200 ***	-0.4480 ***	-0.7669 ***	-0.9658 ***	0.0182	-0.1138 ***	-0.0808 ***	-0.1587 ***	-0.0257 **	-0.0750 ***
	0.0087	<.0001	<.0001	0.0001	0.2761	0.0029	<.0001	<.0001	0.0209	0.005
HI_OBFU	-0.3761 ***	-0.7708 ***	0.8429 ***	3.7246 ***	0.1058 ***	0.3025 ***	0.0321 ***	0.1049 ***	0.0615 ***	0.2575 ***
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0087	<.0001	<.0001	<.0001
POST*HI_INFO	**0.9053** ***	**1.8505** ***	**1.6532** ***	**4.6834** ***	**0.1973** ***	**0.5707** ***	**0.1798** ***	**0.4070** ***	**0.1176** ***	**0.3828** ***
	<.0001	**<.0001**	**<.0001**	**<.0001**	**<.0001**	**<.0001**	**<.0001**	**<.0001**	**<.0001**	**<.0001**
POST*HI_OBFU	0.1448 **	-0.2424	0.2614 *	0.4384	0.0317	-0.0374	0.0158	-0.0088	0.0176	-0.0280
	0.0251	0.1028	0.0808	0.2196	0.1788	0.4887	0.3605	0.8061	0.2619	0.4576
No. Obs.	77,454	77,454	77,454	77,454	77,454	77,454	77,454	77,454	77,454	77,454
Adj. R2	1.170%	1.000%	0.680%	1.190%	0.840%	0.380%	0.430%	0.530%	0.500%	0.430%

Notes: Table 2 provides descriptive evidence on how Fog components, tone words, and forward-looking words evolve over the course of a conference call. Panel A compares the calls in the top third of the information component (High-info) to those in the bottom third (Low-info) group. Panel B compares the calls in the high obfuscation group (High-obfu) versus in the low obfuscation (Low-obfu) group. Panel C uses the regression models to control for the potential overlap between High-info and Low-obfu groups.

Table 3
Descriptive Statistics

Variables	N	Mean	Std	P25	Median	P75
Info(Both)	29,664	0.0118	0.7390	-0.4879	-0.0698	0.4198
Obfu(Present)	29,664	-0.0638	1.4335	-0.9781	-0.0590	0.8822
Obfu(Response)	29,664	-0.0709	1.4373	-1.0897	-0.2368	0.7876
$GROWTH_{t+1}$	27,807	0.4555	5.7454	-1.1522	0.5065	2.2279
AF_Revision	29,664	0.0003	0.0147	-0.0014	0.0002	0.0031
AF_Inefficiency	29,656	-0.0010	0.0382	-0.0051	0.0000	0.0027
CAR	28,859	0.0015	0.0734	-0.0332	0.0008	0.0374
CAR_POST	29,225	0.0031	0.1487	-0.0780	0.0053	0.0861
DA	29,664	0.3863	0.4869	0.0000	0.0000	1.0000
UESURP	29,664	-0.0026	0.0296	-0.0037	0.0003	0.0035
AFSTD	29,664	0.0076	0.0165	0.0012	0.0030	0.0071
ΔLEPS	29,664	0.0013	0.0159	-0.0021	0.0012	0.0041
RET	29,664	0.0496	0.3646	-0.1581	0.0062	0.1903
SIZE	29,664	8.1858	1.6298	7.0426	8.1700	9.2831
BM	29,664	0.4680	0.2582	0.2500	0.4500	0.6800
AFN	29,664	21.019	16.271	9.0000	17.000	28.000
INST_OWN	29,664	0.7628	0.2080	0.6623	0.7992	0.9003
RET_VOL	29,565	0.0198	0.0112	0.0117	0.0169	0.0248
RET_MOM	29,565	0.0083	0.1959	-0.1024	-0.0002	0.1057
4thQTR	29,225	0.2215	0.4152	0.0000	0.0000	0.0000
SPECIAL	29,225	0.5097	0.4999	0.0000	1.0000	1.0000
RESPONSIVE	29,225	0.8159	0.3876	1.0000	1.0000	1.0000
BNEWS	29,225	0.4332	0.4955	0.0000	0.0000	1.0000
FWDLOOK(Present)	29,664	4.4982	2.8706	2.0000	4.0000	7.0000
FWDLOOK(Response)	29,664	4.3127	2.7561	2.0000	2.0000	7.0000
POSTONE(Present)	29,664	4.4991	2.8730	2.0000	5.0000	7.0000
POSTONE(Response)	29,664	4.2655	2.7685	2.0000	2.0000	7.0000
NEGTONE(Present)	29,664	4.4992	2.8722	2.0000	4.0000	7.0000
NEGTONE(Response)	29,664	4.3651	2.7388	2.0000	2.0000	7.0000
GUIDANCE	29,664	0.4002	0.4900	0.0000	0.0000	1.0000

Notes: Table 3 presents descriptive statistics for the full sample. Our sample is constructed from the intersection of SeekingAlpha.com, I/B/E/S, and CRSP/Compustat. All variables are defined in Appendix and winsorized at the 1st and 99th percentiles.

Table 4
Linguistic Complexity, Future Earnings Growth, and Analysts' Efficiency

Dependent Variable =		***GROWTH$_{t+1}$***		***AF_Revision***		***AF_Inefficiency***	
		(1)		(2)		(3)	
Variable	Exp.Sign	Coeff.		Coeff.		Coeff.	
Info(Both)	+	**0.1703**	***	**0.0004**	***	**-0.0002**	
		(3.26)		**(3.38)**		**(-0.72)**	
Obfu(Present)	−	**-0.0667**	**	**-0.0001**	**	**0.0000**	
		(-2.33)		**(-2.17)**		**(-0.02)**	
Obfu(Response)	−	**-0.0715**	**	**-0.0001**	**	**0.0001**	
		(-2.37)		**(-2.18)**		**(0.73)**	
DA		-0.3081	***	0.0001		-0.0001	
		(-3.36)		(0.43)		(-0.14)	
UESURP		5.1361	**	0.1726	***	0.6804	***
		(2.03)		(18.18)		(16.24)	
RET		0.4976	***	0.0024	***	0.4871	***
		(2.83)		(7.36)		(4.10)	
SIZE		-0.0435		0.0002	*	-0.0196	***
		(-1.25)		(1.85)		(-5.78)	
BM		-0.1599		0.0008	*	-0.1054	**
		(-0.90)		(1.67)		(-2.13)	
AFN		0.0007		0.0000		-0.0022	***
		(0.16)		(-1.02)		(-3.16)	
INST_OWN		0.4994	**	-0.0009	*	0.0002	
		(2.13)		(-1.67)		(0.84)	
FWDLOOK(Present)		-0.0030		0.0000		-0.0034	**
		(-0.16)		(-0.51)		(-1.98)	
FWDLOOK(Response)		-0.0032		0.0000		0.0000	**
		(-0.09)		(0.28)		(-2.37)	
POSTONE(Present)		-0.0039		0.0000		0.0001	
		(-0.23)		(0.68)		(0.07)	
POSTONE(Response)		0.0285		0.0000		0.0002	**
		(1.07)		(-0.10)		(2.48)	
NEGTONE(Present)		0.0090		0.0000		0.0002	
		(0.42)		(0.23)		(1.61)	
NEGTONE(Response)		-0.0679	**	0.0001		-0.0001	
		(-2.31)		(0.92)		(-1.27)	
GUIDANCE		0.2595	***	0.0000		-0.0001	
		(2.91)		(0.23)		(-0.60)	
AFSTD		34.433	***	-0.0313	*	0.0000	
		(8.68)		(-1.93)		(0.07)	
CAR		2.3351	***	0.0318	***	-0.0001	
		(2.85)		(17.75)		(-1.15)	
ΔLEPS		16.245	***	0.1164	***	0.0003	
		(3.82)		(8.54)		(1.24)	
Firm FE		YES		YES		YES	
No. Obs.		27,807		29,664		29,656	
Adj R2		17.33%		22.17%		25.96%	

Notes: Table 4 presents results from estimating the relation between the latent components of linguistic complexity and the future earnings growth, analyst forecast revisions, and analyst forecast efficiency. All the variables are as defined in Appendix. *t*-statistics appear in parentheses and are based on standard errors clustered by firm and disclosure date of the conference call. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 5
Linguistic Complexity and Investors' Efficiency

Dependent Variable		*CAR*			*CAR_POST*		*CAR_AnalystReport*	
		(1)			(2)		(3)	
Variable	Exp.Sign	Coeff.		Exp.Sign	Coeff.		Coeff.	
Info(Both)	+	**-0.0005**		**?**	**0.0053**	***	**0.0013**	***
		(-0.73)			**(3.86)**		**(3.57)**	
Obfu(Present)	−	**-0.0012**	***	**?**	**-0.0012**		**-0.0001**	
		(-3.07)			**(-1.44)**		**(-0.58)**	
Obfu(Response)	−	**-0.0011**	***	**?**	**0.0000**		**-0.0002**	
		(-2.68)			**(-0.03)**		**(-1.19)**	
DA		-0.0028	**		-0.0009		-0.0002	
		(-2.17)			(-0.40)		(-0.31)	
DSUE		0.0444	***		0.098	***	0.004	**
		(13.13)			(14.42)		(2.02)	
ΔLEPS		0.289	***		0.021		0.048	*
		(7.90)			(0.18)		(1.93)	
SIZE		0.0002			0.0037	***	-0.0001	
		(0.27)			(3.42)		(-0.21)	
BM		0.002			0.0108	***	-0.0002	
		(1.10)			(2.60)		(-0.20)	
RET_VOL		0.265	***		1.384	***	0.086	*
		(3.33)			(9.00)		(1.74)	
RET_MOM		-0.0213	***		-0.0177	**	-0.0031	
		(-6.05)			(-1.99)		(-1.46)	
AFN		-0.0001	*		-0.0005	***	0.0000	*
		(-1.71)			(-3.85)		(-1.94)	
INST_OWN		0.007	**		0.0038		-0.0012	
		(2.40)			(0.55)		(-0.73)	
AFSTD		-0.0594			-0.4209	***	-0.0542	
		(-1.39)			(-3.85)		(-1.57)	
SPECIAL		-0.0027	**		-0.005	**	0.000	
		(-2.47)			(-2.42)		(-0.62)	
4thQTR		0.0020	*		0.0046	*	0.0004	
		(1.82)			(1.95)		(0.70)	
RESPONSIVE		0.0020			0.0029		-0.0009	
		(1.52)			(1.07)		(-1.16)	
BNEWS		-0.0065	***		0.0022		-0.0008	
		(-4.12)			(0.58)		(-0.87)	
FWDLOOK(Present)		-0.0004			-0.0001		0.0000	
		(-1.41)			(-0.23)		(-0.14)	
FWDLOOK(Response)		-0.0006			-0.0008		-0.0003	
		(-1.44)			(-0.99)		(-1.38)	
POSTONE(Present)		-0.0003			0.0005		0.0000	
		(-1.06)			(0.93)		(0.06)	
POSTONE(Response)		0.0005	*		-0.0006		0.0001	
		(1.76)			(-1.02)		(0.64)	
NEGTONE(Present)		0.0000			0.0006		0.0000	
		(0.14)			(1.12)		(0.33)	
NEGTONE(Response)		0.0002			-0.0004		0.0001	
		(0.74)			(-0.55)		(0.70)	
GUIDANCE		-0.0014			-0.0002		0.0002	
		(-1.07)			(-0.09)		(0.31)	
Firm FE		YES			YES		YES	
No. Obs.		28,737			29,225		21,344	
Adj R2		6.213%			5.278%		1.410%	

Notes: Table 5 presents results from estimating the relation between the latent components of linguistic complexity and investor market reactions. All the variables are as defined in Appendix. *t*-statistics appear in parentheses and are based on standard errors clustered by firm and disclosure date of the conference call. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 6
Participation of Buy-side Analysts on the Call

		Dependent Variable = *CAR*			
Interaction terms		***Buy-sider* =1**		***Buy-sider* =0**	
Variable	Exp.Sign	(1)		(2)	
Info(Both)	+	**0.0030**	***	**-0.0013**	
		(2.66)		**(-1.66)**	
Obfu(Present)	−	**-0.0018**	***	**-0.0010**	*
		(-3.03)		**(-2.52)**	
Obfu(Response)	−	**-0.0021**	***	**-0.0007**	**
		(-3.33)		**(-3.87)**	
DA		0.0002		-0.0038	***
		(0.16)		(-5.85)	
DSUE		0.045	***	0.044	**
		(8.69)		(4.78)	
ΔLEPS		0.3146	***	0.280	**
		(4.00)		(5.77)	
SIZE		-0.0009		0.0005	
		(-1.19)		(0.67)	
BM		0.0052		0.0022	
		(1.42)		(0.73)	
RET_VOL		0.3144	**	0.264	**
		(1.96)		(4.65)	
RET_MOM		-0.0139	**	-0.0234	**
		(-2.45)		(-3.24)	
AFN		0.0000		-0.0002	*
		(0.39)		(-2.52)	
INST_OWN		0.0027		0.0083	
		(0.56)		(1.57)	
AFSTD		-0.2312	***	-0.0234	
		(-2.89)		(-0.31)	
SPECIAL		-0.0025	*	-0.003	**
		(-1.68)		(-4.38)	
4thQTR		0.0011		0.0023	
		(0.65)		(2.21)	
RESPONSIVE		-0.0011		0.0028	
		(-0.47)		(1.41)	
BNEWS		-0.0055	**	-0.0068	
		(-2.22)		(-2.12)	
FWDLOOK(Present)		0.0002		-0.0005	
		(0.79)		(-1.92)	
FWDLOOK(Response)		-0.0006		-0.0006	
		(-0.82)		(-0.92)	
POSTONE(Present)		0.0003		-0.0005	
		(0.87)		(-1.09)	
POSTONE(Response)		-0.0008	*	0.0009	**
		(-1.72)		(3.53)	
NEGTONE(Present)		-0.0001		0.0001	
		(-0.26)		(0.51)	
NEGTONE(Response)		0.0010		0.0000	
		(1.55)		(0.00)	
GUIDANCE		0.0009		-0.0023	
		(0.55)		(-1.79)	
Firm FE		YES		YES	
No. Obs.		6,997		21,740	
Adj R2		9.770%		6.035%	

Notes: Table 6 presents results from estimating the relation between the latent components of linguistic complexity and the CAR at the call window for the subsamples of the participation of buy-side analysts. All the variables are as defined in Appendix. *t*-statistics appear in parentheses and are based on standard errors clustered by firm and disclosure date of the conference call. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 7
Interactions with Potential Earnings Management

Panel A: Future Earnings Growth and Analysts' Efficiency

Dependent Variable		***GROWTH$_{t+1}$***		***AF_Revision***		***AF_Inefficiency***	
		(1)		(2)		(3)	
Variable	Exp.Sign	Coeff.		Coeff.		Coeff.	
Info(Both) * DA	+	**0.2191**	*	**0.0004**	*	0.0001	
		(1.70)		**(1.81)**		(0.28)	
Obfu(Present) * DA	−	**-0.1228**	*	**0.0000**		0.0000	
		(-1.87)		**(-0.24)**		(0.04)	
Obfu(Response) * DA	−	**-0.1131**	*	**-0.0003**	**	-0.0003	
		(-1.80)		**(-2.28)**		(-0.74)	
Info(Both)	+	**0.1500**	***	**0.0002**	*	-0.0001	
		(2.75)		**(1.65)**		(-0.22)	
Obfu(Present)	−	**-0.0548**	*	**-0.0001**	*	0.0000	
		(-1.85)		**(-1.67)**		(-0.13)	
Obfu(Response)	−	**-0.0610**	*	**0.0000**		0.0001	
		(-1.91)		**(-0.47)**		(0.54)	
DA		-0.3087	***	0.0001		0.0000	
		(-3.37)		(0.31)		(-0.12)	
UESURP		5.1502	**	0.1725	***	0.6804	***
		(2.04)		(18.15)		(16.23)	
RET		0.5038	***	0.0024	***	-0.0022	***
		(2.84)		(7.37)		(-3.16)	
SIZE		-0.0433		0.0002	*	0.0002	
		(-1.24)		(1.84)		(0.83)	
BM		-0.1549		0.0008	*	-0.0034	**
		(-0.87)		(1.68)		(-1.98)	
AFN		0.0007		0.0000		0.0000	**
		(0.16)		(-0.99)		(-2.38)	
INST_OWN		0.4973	**	-0.0009	*	0.0001	
		(2.12)		(-1.66)		(0.07)	
FWDLOOK(Present)		-0.0029		0.0000		0.0002	**
		(-0.15)		(-0.48)		(2.46)	
FWDLOOK(Response)		-0.0030		0.0000		0.0002	
		(-0.08)		(0.32)		(1.58)	
POSTONE(Present)		-0.0039		0.0000		-0.0001	
		(-0.23)		(0.69)		(-1.27)	
POSTONE(Response)		0.0290		0.0000		-0.0001	
		(1.08)		(-0.18)		(-0.58)	
NEGTONE(Present)		0.0091		0.0000		0.0000	
		(0.43)		(0.16)		(0.08)	
NEGTONE(Response)		-0.0693	**	0.0001		-0.0001	
		(-2.36)		(0.92)		(-1.14)	
GUIDANCE		0.2628	***	0.0001		0.0003	
		(2.95)		(0.26)		(1.25)	
AFSTD		34.469	***	-0.0315	*	0.4871	***
		(8.68)		(-1.94)		(4.10)	
CAR		2.3284	***	0.0318	***	-0.0196	***
		(2.85)		(17.73)		(-5.79)	
ΔLEPS		16.232	***	0.1166	***	-0.1054	**
		(3.81)		(8.55)		(-2.13)	
Firm FE		YES		YES		YES	
No. Obs.		27,807		29,664		29,656	
Adj R2		17.58%		22.19%		25.96%	

Notes: Table 7 presents results from estimating the relation between the latent components of linguistic complexity and analysts' and investors' response when earnings management is likely to have happened. All the variables are as defined in Appendix. *t*-statistics appear in parentheses and are based on standard errors clustered by firm and disclosure date of the conference call. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 7 (Continued)
Interactions with Potential Earnings Management

Panel B: Investors' Efficiency

Dependent Variable		***CAR***		***CAR_POST***		***CAR_AnalystReport***	
		(1)		(2)		(3)	
Variable	Exp.Sign	Coeff.		Coeff.		Coeff.	
Info(Both) * DA	+	**0.0000**		**0.0063**	**	**0.0013**	*
		(0.00)		**(2.26)**		**(1.81)**	
Obfu(Present) * DA	−	**0.0008**		**-0.0025**	*	**-0.0005**	
		(1.20)		**(-1.72)**		**(-1.47)**	
Obfu(Response) * DA	−	**-0.0011**		**0.0015**		**0.0002**	
		(-1.52)		**(1.03)**		**(0.39)**	
Info(Both)	+	**-0.0005**		**0.0031**	*	**0.0008**	*
		(-0.68)		**(1.85)**		**(1.76)**	
Obfu(Present)	−	**-0.0015**	***	**-0.0002**		**0.0001**	
		(-3.20)		**(-0.20)**		**(0.36)**	
Obfu(Response)	−	**-0.0007**		**-0.0006**		**-0.0003**	
		(-1.56)		**(-0.59)**		**(-1.15)**	
DA		-0.0028	**	-0.0009		-0.0002	
		(-2.17)		(-0.40)		(-0.28)	
DSUE		0.0444	***	0.098	***	0.004	**
		(13.19)		(14.00)		(1.99)	
ΔLEPS		0.289	***	0.020		0.048	**
		(7.91)		(0.19)		(2.00)	
SIZE		0.0001		0.0037	***	0.0000	
		(0.24)		(3.32)		(-0.16)	
BM		0.002		0.0107	**	-0.0002	
		(1.09)		(2.49)		(-0.20)	
RET_VOL		0.264	***	1.385	***	0.087	*
		(3.31)		(8.55)		(1.72)	
RET_MOM		-0.0213	***	-0.0177	**	-0.0031	
		(-6.07)		(-2.03)		(-1.56)	
AFN		-0.0001	*	-0.0005	***	0.0000	*
		(-1.70)		(-4.20)		(-1.90)	
INST_OWN		0.007	**	0.0038		-0.0012	
		(2.41)		(0.57)		(-0.70)	
AFSTD		-0.0595		-0.4213	***	-0.0544	
		(-1.39)		(-3.81)		(-1.52)	
SPECIAL		-0.0027	**	-0.005	**	0.000	
		(-2.46)		(-2.45)		(-0.64)	
4thQTR		0.0020	*	0.0046	**	0.0005	
		(1.83)		(1.99)		(0.75)	
RESPONSIVE		0.0020		0.0029		-0.0010	
		(1.53)		(1.08)		(-1.20)	
BNEWS		-0.0065	***	0.0022		-0.0008	
		(-4.11)		(0.59)		(-0.86)	
FWDLOOK(Present)		-0.0004		-0.0001		0.0000	
		(-1.41)		(-0.25)		(-0.11)	
FWDLOOK(Response)		-0.0006		-0.0008		-0.0003	
		(-1.44)		(-1.00)		(-1.33)	
POSTONE(Present)		-0.0003		0.0005		0.0000	
		(-1.06)		(0.97)		(0.05)	
POSTONE(Response)		0.0005	*	-0.0006		0.0001	
		(1.75)		(-1.00)		(0.66)	
NEGTONE(Present)		0.0000		0.0006		0.0000	
		(0.11)		(1.19)		(0.30)	
NEGTONE(Response)		0.0003		-0.0004		0.0001	
		(0.76)		(-0.56)		(0.66)	
GUIDANCE		-0.0014		-0.0002		0.0000	
		(-1.06)		(-0.10)		(0.30)	
Firm FE		YES		YES		YES	
No. Obs.		28,737		29,225		21,344	
Adj R2		6.181%		5.312%		1.435%	

Table 8
Management Forecast Precision and Analyst Forecast Accuracy and Dispersion

Dependent Variable		***MG_Precision***		***ΔAF_Accuracy***		***ΔAF_Dispersion***	
		(1)		(2)		(3)	
Variable	Exp.Sign	Coeff.		Coeff.		Coeff.	
Info(Both)	+/−	**0.0003**	***	**0.0002**	**	**-0.0061**	***
		(4.71)		**(1.96)**		**(-3.27)**	
Obfu(Present)	−/+	**-0.0001**	**	**-0.0001**		**0.0007**	
		(-2.12)		**(-1.45)**		**(0.60)**	
Obfu(Response)	−/+	**-0.0001**	***	**-0.0001**	***	**0.0041**	***
		(-2.71)		**(-2.60)**		**(3.09)**	
DA		-0.0001		-0.0001		0.0015	
		(-1.32)		(-0.53)		(0.78)	
UESURP		0.0033		-0.0499	***	-0.037	
		(0.48)		(-7.24)		(-0.58)	
RET		0.0017	***	0.0000		-0.0011	
		(14.32)		(-0.02)		(-0.35)	
SIZE		0.0003	***	0.0000		-0.0017	*
		(6.73)		(0.41)		(-1.77)	
BM		-0.0025	***	0.0002		0.0106	**
		(-7.47)		(0.46)		(2.21)	
AFN		0.0000		0.0000	***	0.0003	***
		(-0.02)		(-4.18)		(3.49)	
INST_OWN		0.0010	***	0.0000		-0.0004	
		(2.86)		(-0.08)		(-0.06)	
FWDLOOK(Present)		0.0000		0.0650	***	0.0001	
		(0.49)		(4.24)		(0.22)	
FWDLOOK(Response)		0.0000		-0.0044	***	0.0002	
		(-0.62)		(-2.95)		(0.23)	
POSTONE(Present)		0.0000		0.0184	*	0.0001	
		(0.52)		(1.69)		(0.15)	
POSTONE(Response)		0.0000	*	0.0000		-0.0007	
		(1.94)		(-0.28)		(-1.12)	
NEGTONE(Present)		0.0000		-0.0001		0.0012	**
		(-0.59)		(-1.05)		(2.44)	
NEGTONE(Response)		0.0000		0.0000		0.0004	
		(-0.24)		(-0.75)		(0.49)	
GUIDANCE		0.0003	**	0.0000		0.0102	***
		(2.51)		(0.49)		(4.38)	
AFSTD		-0.0845	***	-0.0001	***	-0.4292	***
		(-5.09)		(-2.88)		(-3.27)	
CAR		0.0000	*	0.0000		0.0045	
		(1.65)		(0.27)		(0.28)	
ΔLEPS		-0.0076		0.0003	**	0.2279	*
		(-0.95)		(2.10)		(1.84)	
Firm FE		YES		YES		YES	
No. Obs.		12,242		29,656		21,224	
Adj R2		27.87%		4.520%		1.26%	

Notes: Table 8 presents results from estimating the relation between the latent components of linguistic complexity and the management forecast precision and the changes in analyst forecast accuracy and dispersion. All the variables are as defined in Appendix. t-statistics appear in parentheses and are based on standard errors clustered by firm and disclosure date of the conference call. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.