Labor Union and Linguistic Attributes in Firm Disclosure

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Abstract

Prior accounting studies on labor unions show whether, when, and how frequently managers disclose in order to gain bargaining power. Yet, little research examines managers' language itself in the presence of labor unions, especially using a rich communication channel such as earnings conference calls. By disentangling the two latent components of linguistic complexity (i.e. obfuscation and information) using conference call transcripts, I find that firms with stronger labor unions tend to disclose less information and, surprisingly, less obfuscation at the same time. However, the negative association between obfuscation and union strength is driven by the negative tone subsample, indicating that the strategic obfuscation of negative news is more likely for firms with a weaker labor union since strong unionized firms tend to be forthcoming about negative information to gain bargaining power and reserve resources. I also directly show that unionized firms are more likely to use negative words in their disclosures, consistent with previous literature that argues unionized firms signal negative outlooks to discourage employees' demands. Overall, these results suggest that the high information asymmetry of unionized firms is contributed not only by the low information level in managerial narratives, but also by the more negative tone in their disclosures on conference calls. This study examines not only a specific disclosure channel, but also the nuanced linguistic elements via which information asymmetry of unionized firms becomes more severe.

Keywords: labor union; voluntary disclosure; conference calls; linguistic attributes; content analysis

1. Introduction

The effects of labor unions have been researched by academics over the past decades (e.g. Faleye et al. 2006; Hamm et al. 2018; Hilary 2006). Labor unions have more influence on corporate decisions and stronger negotiation power compared to their non-unionized counterparts, because of their ability to withdraw contribution through strikes and equity ownership (e.g. Faleye et al. 2006; Prevost et al. 2012). In 2018, there were at least 20 major strikes involving 485,000 workers in the United States.[1] Since 1986, this year has the most workers that engaged in work stoppages and other disputes. Organized labor has also notched some significant victories over the past years. They have prompted California, Massachusetts and cities such as Seattle to increase their minimum wage to or toward $15 an hour. Previous studies on labor unions show whether, when, and how frequently managers disclose information (e.g. Bova 2013; Bova et al. 2014; Chung et al. 2015). However, few studies examine how they disclose regarding the language itself, especially in a rich communication channel such as conference calls.

In this paper, I investigate a previously unexplored link between labor unions and subtle linguistic elements of managerial disclosure by addressing the question of how powerful stakeholders (e.g. employees) affect disclosure strategy and language in the conference call setting. Stated differently, I attempt to examine how managers adjust their linguistic attributes and intentions (i.e. information vs. obfuscation) to maximize their interests in the face of strong labor unions. Since recent literature suggests that unionized firms tend to signal negative outlooks to discourage employees' demand for wage increases (Bova 2013; Chung et al. 2015), I also analyze another important linguistic attribute on earnings conference calls – tone.

[1] For more details, see http://time.com/5525512/american-workers-strikes-bureau-labor-statistics/.

Collectively, this paper aims to fill the void on the positive association between labor union strength and information asymmetry by indicating not only a specific disclosure channel, but also the linguistic mechanisms via which information asymmetry of unionized firms becomes greater.

This paper is motivated by two studies – Hilary (2006) and Bushee et al. (2018). Hilary (2006) argues that firms facing stronger labor unions tend to preserve information asymmetry to gain bargaining power against labor unions. Consistent with his prediction, he finds that unionized firms are associated with higher information asymmetry. In another line of research, Bushee et al. (2018) examine linguistic complexity in firm disclosures. They illustrate that linguistic complexity commingles two latent components—obfuscation and information—that are related to information asymmetry in opposite directions. Specifically, they find that the information component of linguistic complexity is negatively associated with information asymmetry whereas the obfuscation component is positively associated with information asymmetry.

Many scholars interpret high disclosure complexity as an intentional strategy by managers to obfuscate (e.g. Bova et al. 2014; Li 2008). These studies often use the Fog measure to examine the complexity or readability[2] of annual reports (i.e. 10-K filings) (e.g. De Franco et al. 2012; Li 2008). The idea behind this measure is that corporate filings should be easy to understand in order to decrease information processing costs for users. Thus, high Fog measure suggests low reporting quality. Consistent with this assumption, Leuz and Wysocki (2016) show that managers strategically inform and obfuscate since they need to balance the benefits of enhanced disclosure with the costs of transferring information to competitors. Also, managers tend to hide information and intentionally obfuscate to engage in self-interested activities.

[2] Readability and complexity are often used interchangeably in this line of research.

However, complex language could also represent necessary information regarding firms' complex business environments (Bloomfield 2008; Bushee et al. 2018). Therefore, it is important to identify the underlying information element and obfuscation element out of the existing complexity measure (i.e. Fog index) in order to properly evaluate reporting quality and capture managerial intentions behind firm disclosures.

Using linguistic features of managerial disclosures on conference calls offers a great way to understand why and how managers disclose information in the presence of labor unions. Public earnings conference calls are one of the most important tools for conveying the company message (e.g. Brown et al. 2018). Over the past decades, researchers have employed this disclosure channel because of its unique characteristics. First, unlike mandatory disclosures, the language on conference calls reflects less boilerplate information, and is more likely to show managers' disclosure strategies or intentions (Bushee et al. 2018). Further, conference calls provide additional cues compared to other disclosure channels. In addition, existing literature suggests that conference calls contain more complex information (Kimrough and Louis 2011; Matsumoto et al. 2011; Skinner 2019).

Unions require information to act effectively since they do not possess firms' detailed information regarding production and financing (Leap 1991). Despite the benefits from voluntary disclosure of information (e.g. Dye 1985; Jovanovic 1982), managers have an incentive to disclosure less since they know that labor unions actively collect and use firms' information to enhance their negotiation ability and extract rents from companies (e.g. Chung et al. 2015; Hamm et al. 2018). Prior literature illustrates this theory empirically by showing that revealing information weakens firms' positions in gaining bargaining power (e.g. Chung et al. 2015) while possessing more information enables labor unions to receive more resources and benefits

(Kleiner and Bouillon 1988). Additionally, Reynolds et al. (1998) indicate that firms often hide or misrepresent their true positions in labor negotiations. Thus, as the influence of unions and their ability to extract profits increase, managers have stronger incentives to disclose less information.

While it is reasonable to extend the above arguments and predict that managers of firms with strong labor unions disclose more obfuscation in order to maintain information advantage, there could exist an opposite conjecture: firms with strong unions tend to present less obfuscation. The obfuscation hypothesis (Courtis 1998) suggests that management mainly uses confusing languages to obscure bad news (e.g. Li 2008; Smith and Taffler 1992; Subramanian et al. 1993). However, Chung et al. (2015) show that managers facing strong labor unions are motivated to disclose bad news in a timely manner in order to preserve their bargaining power in labor negotiations. Thus, firms with strong labor unions might have fewer incentives to obfuscate.

I find that managers of firms with stronger labor unions tend to present lower information level of linguistic complexity on earnings conference calls as well as lower obfuscation level of linguistic complexity. Furthermore, I show that the negative association between the obfuscation component and union measures is stronger in the negative tone subsample, whereas it is weaker in the positive tone subsample. These results are consistent with the obfuscation hypothesis and indicate that strategic obfuscation (mainly of negative news) is more likely for firms with a weaker labor union, since strong unionized firms use negative information to gain bargaining power and reserve resources.

Building on the prior findings that unionized firms are more likely to send out negative outlooks to discourage employees' demand (Bova 2013; Chung et al. 2015), I next examine whether managers of firms with stronger labor unions tend to use more negative tone on conference calls. The results show that these managers indeed deliberately use more negative words.

Overall, this paper shows that the high information asymmetry of unionized firms (e.g. Hilary 2006) is contributed by not only the low information level in managerial narratives, but also the more negative tone in their disclosures on conference calls. To validate my sample, I reconcile my results with Hilary (2006) which indicates that unionized firms have greater information asymmetry. I find similar results that show labor unions are positively related to the information asymmetry measures – negatively related to analyst coverage and trading volume while positively related to bid-ask spread.

I acknowledge that this research does not necessarily require that unions have a direct involvement in corporate disclosures, in this case, conference calls. Instead, this paper aims to show initial evidence that subtle linguistic attributes in managerial disclosures could reflect labor unions' presence and influence. Such findings will also suggest that managers respond rationally to unions' rent extraction, risk aversion, and monitoring behaviors.

Prior literature shows the effects of labor unions on firm disclosure and information environment (e.g. Chung et al. 2015; Hilary 2006). For example, using data from South Korea, Chung et al. (2015) find that disclosure frequency is lower in firms with stronger labor unions. Bova et al. (2014) indicate that such firms tend to provide poorer and less frequent management forecasts, fewer conference calls, and low quality annual reports. My study differs from these papers in that it takes a closer look at the disclosure language itself by using a less boilerplate and richer disclosure channel (i.e. conference call) which provides more complex information as well as more cues, making managers' intentional choices behind disclosure easier to observe. It aims to draw explicit conclusions regarding whether and how unionized firms preserve information asymmetry through analyzing nuanced linguistic elements (i.e. information components, obfuscation components, and tones), as opposed to measuring the quality of certain disclosure items in a broad way. In other words, this research complements Hilary's (2006) findings on the positive relation between labor union strength and information asymmetry by identifying specific linguistic mechanisms via which information asymmetry of unionized firms becomes greater.

This study extends the literature that shows firms react to unions' rent extraction by hiding information and resources. For example, firms with strong unions tend to hold less cash (Klasa et al. 2009) and withhold information (Chung et al. 2015; Hilary 2006). Therefore, this paper contributes to this line of research by fostering a better understanding of how managers make the most of disclosure language to maximize their interests in the presence of strong labor unions.

Finally, this paper advances the stream of literature regarding conference calls and managerial disclosures. Most research on information disclosures employs the presence of certain disclosure items or the quality of disclosures using indices (e.g., Kelton and Yang 2008; Robbins and Austin 1986). However, the present study adds to a growing stream of empirical research on using linguistic measures constructed from conference calls to explore managerial intentions.

The remainder of this paper proceeds as follows. Section 2 reviews the background and develops the hypotheses. Section 3 discusses the sample, key variables and descriptive statistics. Section 4 provides the research design and main results. Section 5 displays the additional analyses, and Section 6 concludes.

2. Background and hypothesis development

2.1. Conference call and linguistic attributes

There exists a long stream of literature on earnings conference calls which become increasingly popular in recent years. They are one of the most important tools firms employ to convey financial and non-financial messages (e.g. Brown et al. 2018).

Conference calls normally include two parts: managers' presentation and Q&A. This disclosure channel provides incremental information beyond that is presented in the corresponding quarterly report or press release for several reasons. First, conference calls offer additional cues (e.g. natural language, verbal cues, and interaction opportunity). Chafe and Tannen (1987) argue that spoken word presents tone, emotion, and greater language variety relative to written languages. Second, existing literature suggests that conference calls contain more complex information, (Kimrough and Louis 2011; Matsumoto et al. 2011; Skinner 2019). A recent study documents that managers place complex information in rich disclosure channels, such as conference calls, to achieve maximum communication efficiency (Skinner 2019). In addition, conference calls are subject to lower risk of legal liability (Frankel et al. 1999), making statements less formal. Consequently, managers are willing to provide incremental information, such as forward-looking statements and detailed segment data, during conference calls than to include them in the press release directly, especially when they are unsure of the market's informational demand (Frankel et al. 1999; Jung et al. 2018; Miller and Skinner 2015). Because of these unique features of conference calls, analysts and stakeholders are interested in conference call disclosures to acquire and monitor corporate news, strategic position, and other incremental information.

Recent literature examines topics (Gomez et al. 2018) and linguistic features during conference calls, such as tones (Chen et al. 2018), non-plain English (Brochet et al. 2016), contrastive words (Palmon et al. 2016), and spontaneity (Lee 2015). For example, using textual analysis, Matsumoto et al. (2011) find that managers provide less financial information and more forward-looking disclosures when firm performance is unsatisfactory. Brochet et al. (2018) show that managers from ethnic groups that have a more individualistic culture often talk optimistically, present greater self-reference, and offer fewer apologies in their disclosures. Moreover, Blau et al. (2015) and Price et al. (2012) document that linguistic tones can predict abnormal returns and trading volume.

A long-standing literature has examined financial reports to measure their complexity. These studies mainly focus on annual reports (i.e. 10-K) and use the Fog measure to proxy for narrative readability (e.g. De Franco et al. 2012; Li 2008). The idea behind this readability measure is that regulators argue that corporate reports should be easy to understand for users in order to decrease information processing costs. Building on this assumption, researchers have widely used the Fog measure to capture reporting quality and find that more complex disclosure is related to greater analyst forecast dispersion and lower accuracy (Lehavy et al. 2011) as well as less trading by retail investors (Loughran and McDonalds 2010).

However, this complexity measure has also caused controversy. On the one hand, high disclosure complexity has been perceived as intentional obfuscation (Li 2008). Li (2008) indicates that managers purposefully convey messages in a complex manner in order to hide bad news. Leuz and Wysocki (2016) also show that managers use discretion both to inform and to obfuscate since they need to strike a balance between the benefits of enhanced disclosure and the costs of sending information to competitors. In addition, they suggest that managers obfuscate to engage in self-interested activities. Prior studies show that the main strategy to legally obscure information is to bury the awkward revelation in an overwhelming amount of uninformative text and data (e.g. Leuz and Wysochi 2016; Loughran and McDonald 2016). On the other hand, complex language could represent necessary information regarding firms' complex business environments (Bloomfield 2008; Bushee et al. 2018). Firms with advanced technologies or sophisticated line of operations tend to involve more complex disclosures because of the fundamental nature. Therefore, it is important to identify the underlying information element and obfuscation element from the existing complexity measure (i.e. Fog) in order to properly evaluate reporting quality and capture managerial intentions behind firm disclosures.[3]

To solve this problem, Bushee et al. (2018) use conference call transcripts and take the linguistic complexity of analysts as a benchmark to identify the portion of managerial linguistic complexity caused by obfuscation and the portion caused by information. Unlike mandatory disclosures (e.g. 10-K) that have been identified as problematic because of the use of "boilerplate" (e.g. Hoogervorst 2013), the language on conference calls reflects less boilerplate language and presents managers' disclosure strategies more directly (e.g. Bushee et al. 2018). Using these unique features of conference calls, Bushee et al. (2018) show that the information element of managerial narratives is negatively related to information asymmetry, while the obfuscation element is positively related to information asymmetry.

2.2. Labor union and information disclosure

Labor union strength is widely used as a proxy for the influence of workers on firm decisions, since unions are better able to organize group actions (e.g. strikes) and exert pressure on management (e.g. Faleye et al. 2006; Freeman and Medoff 1984; Prevost et al. 2012). Ample

[3] Appendix B provides examples of intentional obfuscation and informative disclosure.

studies have examined the effects of labor unions (e.g. Bova et al. 2014; Faleye et al. 2006; Hamm et al. 2018; Hilary 2006). Because unions use the threat of a strike to extract quasi-rents from firms, labor unions are perceived as rent-seekers (Baldwin 1983; Grout 1984). As a result, managers facing a strong labor union employ various strategies to shelter firm resources to gain an advantage during collective bargaining. For example, Bronars and Deere (1991) suggest that firms improve their bargaining power over unions by issuing more debt. These firms also tend to hold less cash (Klasa et al. 2009), cut dividends (DeAngelo and DeAngelo 1991), and strategically choose accounting methods (Bowen et al. 1995). Relatedly, D'Souza et al. (2001) indicate that firms also engage in earnings management to gain bargaining advantages. In a similar vein, Hamm et al. (2018) find that managers smooth earnings to obtain a balance between sheltering resources from employees' profit-sharing demands and catering to employees' aversion to downside risks. They show that union strength is positively associated with earnings smoothing activities through both accruals and R&D expenditures.

Besides labor unions' impact on corporate strategic policies, another stream of research questions whether firms' information disclosures reflect unions' existence. In the absence of costs or uncertainty, firms should fully disclose their information to the public. However, managers face competing incentives to disclose or conceal information (Healy and Palepu 2001; Verrecchia 2001). Low information asymmetry can benefit a firm in various ways, such as increasing firm value (Diamond and Verrecchia 1991; Verrecchia 2001). Yet, such benefits from voluntary revelation of information come at a cost that arises from the proprietary nature of information, thus preventing full disclosure (Verrecchia 2001). One example of such costs that eventually lead to firms' incentive to preserve information asymmetry is that stakeholders (e.g. employees) use disclosures to gain bargaining power and extract rents from firms.

Unions can bargain more effectively if they are more informed (Kleiner and Bouillon 1988). However, they do not possess employers' all the information regarding production, personnel, and financial situations (Brown 2000; Leap 1991). Throughout the history, unions have been actively seeking firms' information and business records upon which corporate strategic decisions are based on. For example, during the 3-month strike at General Motors Corp., the United Auto Workers demanded to "see the books" to determine if the company was able to increase the wage. Furthermore, General Motors Corp. suspended its earnings guidance as a strategy to gain more leverage in its negotiation with the labor union in 2005. Thus, withholding or misrepresenting a firm's true position is an inevitable choice during labor negotiations (Reynolds et al. 1998). In sum, labor unions impose additional costs on firms' full disclosure, providing firms with an incentive to offer less information. As a result, firms with strong labor unions adopt various strategies when deciding whether, when, and how much information to disclose.

Corroborative findings have also been shown in academic research. Scott (1994) illustrates that firms with a high likelihood of work stoppages or high salaries tend to provide less pension-related disclosure. Relatedly, Hilary (2006) argues that unionized firms are more likely to increase information asymmetry to gain bargaining power. Specifically, he shows that strong organized labor is associated with greater information asymmetry, measured by higher bid-ask spread, higher probability of informed trading, lower trading volume, and lower analyst coverage. However, he does not investigate the direct linguistic mechanism or disclosure channel that brings about the greater information asymmetry of unionized firms. In a similar spirit, Chung et al. (2015) demonstrate that the management's disclosure frequency is negatively related to the firm's labor union strength using data from South Korea. Bova et al. (2014) also confirm that managers provide less disclosure when negotiating with employees and suggest that employee ownership mitigates this effect.

2.3. Hypotheses Development

Taken together, as the influence of unions and their ability to extract profits increase, managers are expected to have stronger incentives to hide information and obfuscate. Based on the preceding findings and arguments, I formulate the following two hypotheses:

> *H1: Managers of firms with stronger labor unions present lower information level of linguistic complexity on earnings conference calls.*

> *H2a: Managers of firms with stronger labor unions present higher obfuscation level of linguistic complexity on earnings conference calls.*

In hypothesizing about the relation between labor union strength and the obfuscation level in voluntary disclosure, I also consider another scenario that leads to an opposite prediction. The obfuscation hypothesis (e.g Courtis 1998) suggests that managers mainly use ambiguous language to obscure bad news (e.g. Bloomfield 2008; Brennan et al. 2009; Li 2008; Smith and Taffler 1992; Subramanian et al. 1993). However, Bova (2013) and Chung et al. (2015) find that managers facing strong labor unions are motivated to be forthcoming about negative news and tend to release such information in a timely manner in order to preserve their bargaining power in labor negotiations. These firms even deliberately create negative signals by not walking forecasts downward when estimates are too high and by managing earnings downward when estimates are too low (Bova 2013). Given these arguments, it is possible that firms with stronger labor unions have fewer incentives to obfuscate, leading to the hypothesis:

> *H2b: Managers of firms with stronger labor unions present lower obfuscation level of linguistic complexity on earnings conference calls.*

Jensen and Meckling (1976) emphasize that corporate decisions are the outcome of a bargaining process among all stakeholders. In this regard, this paper is an attempt to foster a deeper understanding on how powerful stakeholders (i.e. unionized workers) affect managerial language in voluntary disclosures. In terms of the association between labor unions and managers' linguistic attributes, little research exists that speaks directly to my line of inquiry. This study differs from prior literature (e.g. Bova et al. 2014; Chung et al. 2015) in that it uses a less boilerplate and richer communication channel which provides more complex information as well as cues, making managers' intentional choices more observable. Furthermore, this paper disentangles the underlying information and obfuscation components of reporting complexity so that it can properly evaluate the disclosure quality and capture managers' intentions behind disclosures in the presence of labor unions. In sum, this paper aims to analyze nuanced linguistic elements and shed light on how managers strategically use disclosure language to maximize their interests in the face of strong labor unions.

3. Sample, key variables and descriptive statistics

3.1. Sample selection

Table 1 provides details regarding sample selection. The linguistic data is constructed using conference call transcripts retrieved from Thomson Reuters StreetEvents. The first labor union measure (*Union*) utilizes the data from the Union Membership and Coverage Database. Another labor union proxy (*UnionDummy*) is based on DirectEdgar 10-K filings data.[4] I also construct my sample using the information on analysts from IBES, stock returns from CRSP, and accounting items from Compustat. The sample period runs from 2002 to 2017, consisting of 59,184 firm-quarters. I begin the sample in 2002 because it is the first year that conference call

[4] I gratefully acknowledge the conference call data and the labor union measure (*UnionDummy*) from Bushee et al. (2018) and Hamm et al. (2018), respectively.

transcripts became available in StreetEvents. All continuous variables are winsorized at their top and bottom 1% distributions.

3.2. Key variables

3.2.1 Linguistic measures

Gunning (1952) Fog index is used to estimate linguistic complexity. It involves two factors – the number of words and the percent of complex words[5].

Fog = 0.4 × (average number of words per sentence + percent of complex words)

Higher value of *Fog* indicates more complex text. This index refers to the hypothetical years of education needed to fully understand the text. Using this Fog index, managerial linguistic complexity (i.e. *Fog(Manager)*) is measured for the presentation and Q&A sessions of conference calls. *Fog(Analyst)* refers to the complexity of analysts' language during the Q&A session. Bushee et al. (2018) show that a manager's linguistic complexity is determined by two factors – the intrinsic amount of information and intentional obfuscation. Thus, managerial linguistic complexity (i.e. *Fog(Manager)*) is represented as follows:

$$Fog(Manager) = \beta_0 + \beta_1 Info + \beta_2 Obfu + \varepsilon \qquad (1)$$

Using the linguistic complexity of analysts on conference calls, I then estimate the latent variables of *Fog(Manager)* – information (*Info*) and obfuscation (*Obfu*). Underlying this methodology developed by Bushee et al. (2018) is the assumption that managers have incentives to obscure information while analysts do not have such incentives since they aim to uncover relevant and essential information on the calls (Matsumoto et al. 2011; Mayew 2008; Twedt and Rees 2012). Thus, the linguistic complexity of analysts serves as a complexity benchmark when there is no obfuscation force involved. This methodology is presented as follows:

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[5] Complex words refer to those with more than two syllables.

$$Fog(Manager) = \beta_0 + \beta_1 Fog(Analyst) + \varepsilon \tag{2}$$

The fitted value of model (2) is the estimated information component (*Info*) and the residual is the estimated obfuscation component (*Obfu*). Bushee et al. (2018) indicate that these two components affect information asymmetry in different directions. Stated differently, the latent information element is negatively related to information asymmetry whereas the latent obfuscation element is positively related to information asymmetry.

Following Bushee et al. (2018), I add control variables regarding firm complexity to model (2) and use the following empirical model to estimate the latent components (i.e. *Obfu* and *Info*) that will be used in my study. *Fog(Present)* and *Fog(QA)* refer to managers' linguistic complexity during the presentation session and Q&A session, respectively. I include variables regarding firm complexity such as firm size (*Size*) that is related to disclosure practices (e.g. Lang and Lundholm 1996), book-to-market ratio (*BM*) that captures firms' growth potentials (e.g. Brochet et al. 2016; Bushee et al. 2003), and leverage (*Leverage*) that controls for managerial incentives when firms have high levels of debt and agency costs (Frankel et al. 1999). I also include stock returns (*Returns*), capital intensity (*CapIntensity*), research and development (*R&D*), acquisitions (*Acquisitions*), capital expenditure (*Capex*), debt and equity issuance (*Financing*), cash flow volatility (*σCFO*), goodwill impairments (*Goodwill*), and restructuring charge (*Restructure*). In addition, I include number of analysts (*Analyst*) to capture the variations driven by informational demand. See Appendix A for detailed variable definitions.

$$\begin{aligned} Fog(Present)\ (\text{or } Fog(QA)) = {} & \beta_0 + \beta_1 Fog(Analyst) + \beta_2 Size + \beta_3 Leverage + \beta_4 BM \\ & + \beta_5 Returns + \beta_6 Acquisitions + \beta_7 CapIntensity + \beta_8 Capex \\ & + \beta_9 R\&D + \beta_{10} Financing + \beta_{11} \sigma CFO + \beta_{12} Goodwill \\ & + \beta_{13} Restructure + \varepsilon, \end{aligned} \tag{3}$$

The fitted values are used as the estimated values of the latent information components (i.e. *InfoPres* and *InfoQA*), and the residual values are the estimated values of the latent obfuscation components (i.e. *ObfuPres* and *ObfuQA*). The results are reported in Table 2. The table shows that analysts' linguistic complexity (*Fog(Analyst)*) is positively and significantly related to managers' linguistic complexity in both the presentation (*Fog(Present)*) and Q&A (*Fog(QA)*) sessions. The coefficient on *Fog(Analyst)* is smaller in the *Fog(Present)* regression compared to the coefficient in the *Fog(QA)* regression (0.18 vs. 0.53), supported by the fact that managerial presentation is prepared well in advance and offered at the beginning of the call while *Fog(Analyst)* is more important in determining managers' linguistic complexity in the response. The results are similar with Bushee et al. (2018).

In addition, Table 2 shows that managers tend to use more complex language during presentation in firms that are smaller and have higher leverage, lower returns, more acquisitions, lower capital intensity, more R&D investment, more financing activity, and greater cash flow volatility. Table 2 also indicates that managers use more complex language during Q&A sessions if their firms have lower capital intensity, higher capital expenditure, more R&D investment, more financing activity, and higher cash flow volatility. The sign differences between these two regressions suggest that the model captures managers' linguistic choices in different portions of the call, instead of presenting a consistent linear combination of variables.

The adjusted R-squared of the model for managers' response (19.87%) is larger than the one for presentation (10.60%), consistent with the fact that analyst language has more influence on managerial language in the Q&A session. Of note, the adjusted R-squareds are relatively low. However, these results are similar with prior studies on textual analysis. For example, Bushee et al. (2018) present adjusted R-squareds of 2.2% to 14.3%. Li (2008) shows adjusted R-squareds of 6% to 8%.

3.2.2. Labor union measures

I use two measures to capture a firm's labor strength. Following Hilary (2006), the first measure (*Union*) is the product of labor intensity (i.e. the number of employees scaled by total assets) and unionization rate (i.e. the percentage of unionized employees in the industry) that is retrieved from the Union Membership and Coverage Database. This database provides information on labor union membership and coverage by industry. Prior accounting and finance research has used this proxy extensively (e.g. Chen et al. 2011; Chung et al. 2015; Hamm et al. 2018; Hilary 2006; Klasa et al. 2009). Since the unionization rate can be used as a proxy for the degree of bargaining, such pressure from labor unions brings threats to not only the corresponding firms, but also all the other firms in the industry. Even though all firms in the same industry are under a comparable pressure from labor unions, the impact on a specific firm is determined by firm characteristics. Thus, I interact the industry-level unionization rate with the firm-level labor intensity which measures whether employees have significant effects on managers' decisions. This proxy of union strength is for every firm-year since the data is updated annually.

Following Hamm et al. (2018), I use another proxy for firm-level unionization (*UnionDummy*) that suggests the existence of labor unions based on textual analysis of 10-K filings. It is constructed using keywords and phrases regarding the existence or non-existence of a labor union, such as "union", "collective(ly) bargain", and "labor/employee/worker organization". First, all these keywords and phrases are collected by randomly reading items 1 and 1A. Then, these search terms are applied to the full sample. Specifically, *UnionDummy* equals zero for those firm-years with no keywords in 10-K filings. For those contain the search terms, further examination is conducted to identify expressions that explicitly indicate non-existence of a labor union. These firm-years are set to zero. Examples of those terms are as follows: 1) No current U.S.-based employees are unionized; 2) None of our labor force is covered by a collective bargaining agreement. If these non-existence expressions are accompanied by a specific location, they will not be counted as non-existence. The examples are as follows: 1) We have no unionized employees in Europe; 2) None of our employees in Mexico are unionized. For the remaining subsample, which contains union expressions but no non-existence indicators, *UnionDummy* is set to one.

3.3. Descriptive statistics

Panel A of Table 3 displays descriptive statistics of the variables that are used to test the two hypotheses. It shows that sample firms are large (mean *Size* = 7.26) and receive high analyst coverage (mean = 9.13). *Union* has a mean value of 0.04. *UnionDummy* has a mean of 0.39, suggesting that about 39 percent of the sample firms have labor unions. *Fog(Present)* has a mean of 15.53, which is higher than the mean of *Fog(QA)* (12.01). This difference means that managers use more sophisticated words in the presentation session of the call compared to the Q&A session. It can be explained by the fact that the presentation scripts on conference calls are carefully constructed and vetted by departments such as investor relations and legal counsel whereas the response by managers tends to be more spontaneous and casual (e.g. Brown et al. 2018). These statistics are generally consistent with prior studies (Bushee et al. 2018; Hamm et al. 2018; Hilary 2006).

Panel B of Table 3 reports correlations among variables. Pearson (Spearman) correlations appear below (above) the diagonal. These results are also similar with previous literature (Bushee et al. 2018; Hamm et al. 2018). Specifically, the Pearson correlation between *ObfuPres* and *ObfuQA* is 0.33, indicating that managers adopt different strategies to obfuscate in the presentation and the response. The Pearson correlation between *InfoPres* and *InfoQA* is 0.71, consistent with the fact that the information components are mainly determined by the fundamental nature of firm complexity. There are no significant correlations between *Info(.)* and *Obfu(.)*. Panel B also shows a significant and positive correlation between *Union* and *UnionDummy* (0.16 for the Pearson correlation), suggesting that these two union proxies represent similar but different constructs. As for the correlations between the linguistic measures (i.e. *Obfu(.)* and *Info(.)*) and union variables (i.e. *Union* and *UnionDummy*), the table shows that they are negatively and significantly correlated with each other. For example, the correlation between *ObfuPres* and *Union* is -0.08, whereas the correlation between *InfoPres* and *Union* is -0.13. The negative correlations between the latent linguistic components and union variables provide preliminary support for *H1* and *H2b*. In addition, the differences in these correlations suggest that labor union strength represents much of the variation in the information component, compared to the obfuscation component.

4. Research design and main results

4.1. Test of H1 (information component of linguistic complexity):

H1 predicts that managers of firms with stronger labor unions tend to present lower information level of linguistic complexity on conference calls. I regress *InfoPres* and *InfoQA* separately on the firm-level labor union variable (*Union* or *UnionDummy*), controlling for firm complexity: firm size (*Size*), leverage (*Leverage*), book-to-market ratio to capture growth potentials (*BM*), 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*), restructuring charges (*Restructuring*), analyst following (*Analyst*), sales growth (*SGROW*), and loss indicator (*Loss*). These control variables are commonly used in prior literature to control for firm complexity (e.g. Barth et al. 2001; Bushee et al. 2018). In addition, I include industry and fiscal quarter fixed effects and cluster standard errors at the firm level. I expect to find that firms with more acquisitions (*Acquisitions*), more R&D investment (*R&D*), and high cash flow volatility (σCFO) will disclose more information components. For the remaining control variables, I am uncertain of their signs of coefficients.

$$\begin{aligned} InfoPres \text{ (or } InfoQA) = {} & \beta_0 + \beta_1 Union \text{ (or } UnionDummy) + \beta_2 Size + \beta_3 Leverage + \beta_4 BM \\ & + \beta_5 Returns + \beta_6 Acquisitions + \beta_7 CapIntensity + \beta_8 Capex + \beta_9 R\&D \\ & + \beta_{10} Financing + \beta_{11} \sigma CFO + \beta_{12} Goodwill + \beta_{13} Restructure + \varepsilon, \quad (4) \end{aligned}$$

where all the variables are defined in Appendix A. If stronger labor unions are associated with lower information level in managerial disclosures (*H1*), then β_1 will be negative and significant.

Table 4 reports results from model (4). I estimate regressions separately for the presentation and Q&A sessions of conference calls. Both labor union strength measures (i.e. *Union* in Panel A and *UnionDummy* in Panel B) show negative and significant coefficients on the information component of linguistic complexity for the presentation sessions of the call (*InfoPres*), while present negative but not significant coefficients for the Q&A portions of the call (*InfoQA*). These results are consistent with the fact that the presentation scripts on conference calls are carefully constructed considering all stakeholders (Jensen and Meckling 1976), while the managers' response in the Q&A session is relatively more spontaneous and driven by analysts' language. To avoid the risks of accidentally revealing private information, managers strategically circumvent the interactive nature of conference calls through biasing the participant selection by only allowing favorable analysts to ask questions (Mayew 2008) or intentionally ignoring sensitive questions (Hollander et al. 2010). Overall, *H1* is supported by the findings, suggesting that firms with stronger labor unions tend to disclose lower information level of linguistic complexity. Bushee et al. (2018) indicate that information components contribute to better information environment. Thus, my results suggest that higher information asymmetry of unionized firms (e.g. Hilary 2006) is contributed by the lower information level in managerial narratives on conference calls.

4.2. Test of H2 (obfuscation component of linguistic complexity):

H2a (*H2b*) suggests that managers of unionized firms tend to present higher (lower) obfuscation level of linguistic complexity on earnings conference calls. OLS regression for *H2* is similar with model (4), with *ObfuPres* and *ObfuQA* in place of *InfoPres* and *InfoQA*, respectively. Following prior literature (e.g. Bushee et al. 2018; Lang and Stice-Lawrence 2015; Skinner 2019), the variables I use to control for reporting incentives are firm size (*Size*), firm leverage (*Leverage*), book-to-market ratio (*BM*), stock returns (*Returns*), research and development (*R&D*), goodwill impairments (*Goodwill*), negative earnings (*Loss*), industry concentration (*HHI*), special items (*SpecItems*), analyst coverage (*Analyst*), analyst dispersion (*Dispersion*), earnings surprise (*Surprise*), and an indicator for whether the firm meets or beats analyst forecasts by a penny or less (*SmallBeat*). *H2a* suggests that β_1 is positive and significant while *H2b* hypothesizes the opposite.

$$\begin{aligned} ObfuPres \text{ (or } ObfuQA) = {} & \beta_0 + \beta_1 Union \text{ (or } UnionDummy) + \beta_2 Size + \beta_3 Leverage + \beta_4 BM \\ & + \beta_5 Returns + \beta_6 R\&D + \beta_7 Goodwill + \beta_8 Loss + \beta_9 HHI \\ & + \beta_{10} SpecItems + \beta_{11} Analyst + \beta_{12} Dispersion + \beta_{13} Surprise \\ & + \beta_{14} SmallBeat + \varepsilon \end{aligned} \tag{5}$$

Table 5 reports the results of model (5). Panel A shows that *Union* is negatively related to the obfuscation level of linguistic complexity in both the presentation and Q&A portions of the call, while the coefficient is statistically significant for the presentation sessions. Panel B also presents that *UnionDummy* is negatively related to the obfuscation level in both the presentation and Q&A portions, while the coefficient is statistically significant for the Q&A portions. Overall, these results support *H2b* which indicates that firms with stronger labor unions tend to present lower obfuscation level of linguistic complexity.

5. Additional tests

5.1. Subsample tests

Based on the obfuscation hypothesis (Bloomfield 2008; Courtis 1998) which suggests that managers mainly use misleading or ambiguous language to diffuse bad news (e.g. Brennan et al. 2009; Li 2008), unionized firms should have fewer incentives to obfuscate because they are more upfront about bad news to preserve their bargaining power in labor negotiations (Bova 2013; Chung et al. 2015), presented as *H2b*. To confirm this argument, I conduct analysis to test whether labor unions influence the managers' obfuscation level in their narratives differently in the positive tone setting versus the negative tone setting. Specifically, in each conference call session (i.e. presentation and Q&A), I create a variable, *Tone(.)*. It is calculated as the difference between the number of positive tone words and negative tone words, scaled by the total number of these tone words in the corresponding session. Then, I create two subsamples: a positive tone group if *Tone(.)* is greater than the industry average tone of managers, and a negative tone group if *Tone(.)* is lower than the industry average tone of managers. I expect to observe that the negative association between *Obfu(.)* and union measures (i.e. *Union* and *UnionDummy*) is stronger in the negative tone subsample, whereas it is weaker in the positive tone subsample.

The results of the subsample tests are presented in Table 6. Tests of the differences in the coefficients on *Union* across Panel A (i.e. positive tone group) and Panel B (i.e. negative tone group) indicate that the negative relation between union strength and the obfuscation level is significantly stronger in the negative tone group regarding the presentation sessions, while no significant differences between the two subsamples regarding the Q&A sessions. I find similar results when using *UnionDummy* as an alternative measure for union strength (Panel C and Panel D). These results are still consistent with the fact that the presentation on conference calls are scripted considering all stakeholders and relevant parties (Jensen and Meckling 1976), while the managers' response in the Q&A session is more spontaneous and driven by analysts' questions. These findings provide evidence that strategic obfuscation of negative news is more likely for firms with a weaker labor union, since strong unionized firms tend to be forthcoming about negative information to gain bargaining power. Overall, the results in Table 6 are consistent with my expectation that the negative association between obfuscation and union strength is stronger in the negative tone subsample. These tests also offer a deeper understanding regarding the obfuscation hypothesis and suggest that firms could have different strategies when disclosing negative information, instead of simply obscuring bad news.

5.2. Tone and labor unions

Building on the arguments suggested by prior studies that firms with strong labor unions are more likely to send negative signals (e.g. Bova 2013), I next investigate whether managers of unionized firms tend to use negative tone on conference calls. Tone is a crucial component of language, especially because managers might exploit the tone in their narratives for various purposes, such as gaining negotiation advantage over labor unions. Research shows that firms actively project a negative picture to better cope with employees' demands. Bova (2013) documents that unionized firms tend to miss earnings forecasts deliberately to signal negative outlooks to their unions. They are also more willing to employ conservative accounting methods and deflate earnings intentionally (Bowen et al. 1995; Chyz et al. 2013; DeAngelo and DeAngelo 1991; D'Souza et al. 2001). In addition, Chung et al. (2015) demonstrate that managers facing stronger labor unions tend to withhold positive news but release bad news in a timely manner.

Following the established findings above, I investigate the relation between labor strength and linguistic tones in this section. *Positive(.)* (*Negative(.)*) refers to the number of positive (negative) tone words in the respective portion of the conference call (Loughran and McDonald 2011). The word lists developed by Loughran and McDonald (2011) are designed specifically for financial disclosures and have been extensively used in both accounting and finance research (e.g. Bushee et al. 2018; Davis et al. 2015). I analyze the effects of labor unions on managers' tones during conference calls using the following regression specifications. Each tone variable (i.e. *Positive (.)* and *Negative (.)*) is regressed on industry and fiscal quarter fixed effects as well as firm clustering, while adding control variables that have been widely used in prior literature (e.g. Davis et al. 2015; Skinner 2019). I predict that managers of strong unionized firms have incentives to use more negative tone in the narratives.

$$\begin{aligned} \textit{Positive (.)} \text{ (or } \textit{Negative (.)}\text{)} = {} & \beta_0 + \beta_1 \textit{Union} \text{ (or } \textit{UnionDummy}\text{)} + \beta_2 \textit{HHI} + \beta_3 \textit{Size} \\ & + \beta_4 \textit{BM} + \beta_5 \textit{Returns} + \beta_6 \textit{Earnings} + \beta_7 \textit{EARN\_sd} + \beta_8 \textit{Age} \\ & + \beta_9 \textit{Capex} + \beta_{10} \textit{R\&D} + \beta_{11} \textit{Loss} + \varepsilon, \end{aligned} \quad (6)$$

Panel A of Table 7 shows that *Union* has no statistically significant relation to *Positive (.)*, in both the presentation and Q&A sessions. Using the alternative union measure, Panel B presents similar results regarding the relation between *UnionDummy* and *Positive (.)*. These results suggest that union strength has no effects on strategically using positive words on conference calls. Panel C and Panel D present the relation between union strength and negative tone. The coefficients of union strength measures (i.e. *Union* and *UnionDummy*) on *Negative (.)* are all positive and significant, except the coefficient of *Union* in the presentation portions of the call. Overall, these results indicate that managers of strong unionized firms tend to deliberately use more negative words on conference calls. Prior literature shows that negative tone contributes to higher information asymmetry (e.g. Bushee et al. 2018). Thus, the higher information asymmetry of unionized firms (e.g. Hilary 2006) is not only contributed by the lower information level in managerial narratives, but also contributed by the more negative tone in their disclosures on conference calls.

5.3. Hilary (2006) replication

To prove the validity of my data, such as selection bias, I reconcile my results with Hilary (2006) which shows the positive relation between labor union strength and information asymmetry. I replicate his study by using three proxies of information asymmetry which he uses – bid-ask spread, analyst coverage, and trading volume. Using my sample, I follow the methodology of Hilary (2006) and employ various combination of control variables in the regression specifications: indicator variable that equals one if the stock is traded on the NASDAQ (*NASD*) since prior studies (e.g. Bessembinder and Kaufman 1997; Huang and Stoll 1996) show that these firms are associated with greater information asymmetry, firm size (*Size*), standard deviation of the daily returns to measure return volatility (*ReturnSD*), book-to-market ratio (*BM*), firm leverage (*Leverage*), a dummy variable that takes the value of one if there is a bond rating by Standard and Poor's in the Compustat database (*Rating*), return on assets (*ROA*), industry concentration (*HHI*), analyst coverage (*Analyst*), and bid-ask spread (*Spread*). Also, I account for industry and year fixed effects which capture the variations over time and across industries. Consistent with Hilary (2006), I expect to find that labor unions are positively related to these information asymmetry measures – positively related to bid-ask spread while negatively related to analyst coverage and trading volume.

$$Spread = \beta_0 + \beta_1 Union + \beta_2 Analyst + \beta_3 NASD + \beta_4 Size + \beta_5 ReturnSD + \beta_6 BM + \beta_7 Leverage + \beta_8 Rating + \beta_9 ROA + \beta_{10} HHI + \varepsilon \tag{7}$$

$$Analyst = \beta_0 + \beta_1 Union + \beta_2 Spread + \beta_3 NASD + \beta_4 Size + \beta_5 ReturnSD + \beta_6 BM + \beta_7 Leverage + \beta_8 Rating + \beta_9 ROA + \beta_{10} HHI + \varepsilon \tag{8}$$

$$Volume = \beta_0 + \beta_1 Union + \beta_2 Spread + \beta_3 NASD + \beta_4 Size + \beta_5 ReturnSD + \beta_6 BM + \beta_7 Leverage + \beta_8 Rating + \beta_9 ROA + \beta_{10} HHI + \varepsilon \quad (9)$$

The results of estimating these models are presented in Table 8. When the dependent variable is *Spread* (Panel A), the coefficient for *Union* is positive and significant. This result suggests that firms with stronger labor unions tend to have higher bid-ask spread, in other words, higher information asymmetry. When the dependent variable is *Analyst* (Panel B), the coefficient for *Union* is negative and significant, indicating lower analyst coverage when a firm has a stronger labor union. Similarly, Panel C shows a negative and significant coefficient of *Union* on *Volume*, suggesting that firms with stronger labor unions have lower trade volume which is a proxy for higher information asymmetry. Overall, using the dataset of firms with conference call transcripts available, the results in Table 8 are consistent with those found in Hilary (2006), confirming that unionized firms tend to have higher information asymmetry.

6. Conclusion

In this paper, I use the conference call setting to observe managers' linguistic attributes in relation to their labor union strength. By disentangling the two latent components of linguistic complexity (i.e. obfuscation and information), I examine how unionized firms organize their language to maximize their interests under the influence of strong labor unions. I find that managers of firms with stronger labor unions tend to present lower information level of linguistic complexity on earnings conference calls as well as lower obfuscation level of linguistic complexity. I also show that the negative association between the obfuscation component and union measures is driven by the negative tone subsample, offering a deeper understanding regarding the obfuscation hypothesis.

In addition, I find that unionized firms are more likely to use negative tone in their disclosures, consistent with previous literature that argues unionized firms tend to send negative outlooks to discourage employees' demands (Bova 2013; Chung et al. 2015). Overall, these results suggest that the high information asymmetry of unionized firms (e.g. Hilary 2006) is contributed by both the low information level in managerial narratives, and the more negative tone in their disclosures on conference calls. Finally, I validate my sample by replicating Hilary (2006) to make sure the data does not suffer from severe selection bias.

This study takes a closer look at the disclosure language itself and analyzes the nuanced linguistic elements using a rich communication channel – earnings conference calls. It contributes to the literature in several ways. First, this paper investigates disclosures from the linguistic perspective. Unlike previous studies (e.g. Bova 2013; Chung et al. 2015), this paper highlights the language itself as a reflection of the influence from labor unions by using a less boilerplate and richer disclosure channel (i.e. earnings conference call). By analyzing subtle linguistic elements and disentangling the latent components of reporting complexity, as opposed to measuring the disclosure quality in a broad and noisy way, this paper aims to properly evaluate the disclosure quality and capture managers' intentional disclosure strategies in the presence of labor unions. It also responds to a call for research in textual analysis of disclosures (e.g. Li 2008) and adds to a growing stream of research on using linguistic measures to explore managerial intentions.

Second, this paper extends the literature on how managers respond rationally to unions' rent extraction, risk aversion, and monitoring behaviors (e.g. Chyz et al. 2013; Faleye et al. 2006). It contributes to this line of research by fostering a better understanding of how managers formulate tactics and construct their disclosure language when facing strong labor unions. Lastly, this study offers fresh insights into how labor unions affect firms' information asymmetry. Despite prior literature that argues the positive association between labor strength and information asymmetry (e.g. Chung et al. 2015; Hilary 2006), it is still less understood how managers exploit their language to achieve high information asymmetry in the presence of strong labor unions. This study sheds light on the relation between labor union strength and information asymmetry by indicating not only a specific disclosure channel, but also the underlying linguistic mechanisms.

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Appendix A
Variable Definitions

Variable	Description
Union	Firm-level union membership measure based on the Current Population Survey, calculated as the industry-level percentage of union membership times the number of employees scaled by the beginning total assets.
UnionDummy	Firm-level union dummy variable that takes the value of one if a union exists at the firm level, zero otherwise.
Fog(.)	Fog index (i.e. linguistic complexity) of the respective portion of the earnings conference calls. Specifically, *Fog(Analyst)* is the Fog index of analysts during the Q&A session of the call. *Fog(Present)* refers to the Fog index of managers during the presentation session. *Fog(Response)* indicates the Fog index of managers during the Q&A session of the call.
Obfu(.)	*Obfu(.)* is the residual from model (3). Estimated latent obfuscation component, derived from *Fog(.)*. *ObfuPres* indicates the obfuscation level of managers during the presentation session of the call. *ObfuQA* refers to the obfuscation level of managers during the Q&A session of the call.
Info(.)	*Info(.)* is the fitted value from model (3). Estimated latent information component, derived from *Fog(.)*. *InfoPres* indicates the information level of managers during the presentation session of the call. *InfoQA* refers to the information level of managers during the Q&A session of the call.
Positive(.)	The number of positive tone words in the respective portion of the call (Loughran and McDonald 2011).
Negative(.)	The number of negative tone words in the respective portion of the call (Loughran and McDonald 2011).
Tone(.)	The difference between the number of positive tone words and negative tone words, scaled by the total number of positive tone words and negative tone words in the respective portion of the call.
Spread	Median of monthly bid-ask spread.
Analyst	Log of the number of analysts following.

Vol	Median of monthly trading volume.
Size	Log of market value of equity.
Leverage	The sum of long term and short term debts scaled by total assets of the prior quarter.
BM	Book value of equity scaled by market value of equity of the prior quarter.
Returns	Buy-and-hold return over the quarter, in percent.
Acquisitions	Total acquisitions over the quarter scaled by total assets of the prior quarter.
CapIntensity	Net plant, property, and equipment scaled by total assets of the prior quarter.
Capex	Capital expenditures scaled by total assets of the prior quarter.
R&D	Research and development expense scaled by sales.
Financing	Amount raised from stock and debt issuances during the quarter scaled by total assets of the prior quarter.
σCFO	Standard deviation of cash flows from operations scaled by total assets over the prior five years.
Goodwill	Indicator variable that takes the value of one if the firm has a goodwill impairment charge during the quarter, zero otherwise.
Restructure	Indicator variable that takes the value of one if the firm has a restructuring charge during the quarter, zero otherwise.
Loss	Indicator variable that takes the value of one if the firm reports a loss, zero otherwise.
HHI	Sales-based Herfindahl-Hirschman index within each SIC 2-digit industry. A higher value indicates a higher concentration, or less competition.
SpecItems	Special items scaled by market value of equity of the prior quarter.

Dispersion	Standard deviation of analyst forecasts for the current quarter, measured prior to the conference call and scaled by price at the beginning of the quarter.
Surprise	Consensus forecast error scaled by market value of equity at the beginning of the quarter. Consensus forecast is the median analyst forecast on IBES measured prior to the conference call.
SmallBeat	Indicator variable for whether earnings per share beat consensus forecasts by a penny or less.
Age	Log of one plus the number of years of data in Compustat.
Earnings	Earnings before extraordinary items scaled by total asset of the prior quarter.
EARN_sd	Standard deviation of earnings scaled by total assets over the prior five years.
NASD	Indicator variable that takes the value of one if the stock is traded on NASDAQ, zero otherwise.
ReturnSD	Standard deviation of the daily returns.
Rating	Indicator variable that takes the value of one if there is a bond rating by Standard and Poor's, zero otherwise.

Note: All continuous variables are winsorized at 1% and 99%.

Appendix B
Examples of Obfuscation and Information[6]

Obfuscation

Q: “So, Walter, just in terms of that $1.5 billion | all right, so you're not going to give me how much the plus is, but how much do you need to keep? Do you need to keep $500 million sitting there, do you need to keep $1 billion of it sitting there and never use it? How much do you need to keep?"

A: “Listen, it's a great question. It's about situation driven and you evaluate it. As a definitional issue, you would say that you technically use the excess but you will assess it as you evaluate situation review at that particular time. On this particular-the way we look at it today, the excess is getting, as we moved out of the OD, certainly that will put less pressure on having any sort of contingent element within it. So, we are { we evaluate it. At this stage I would say technically it's all usable. Then depending on when we go to use it, we will assess the environment and assess the best use of the shareholder and how quickly we can replenish. I think you know where the earnings are coming from, it's less capital intense. So that gives us capability and that all goes into the evaluation of it. That's why we talk about the plus, because you really do have-it changes the circumstances but certainly within our definitions, we have excess that is usable."

Information

Q: “Good morning. I just wanted to follow up in regards to some of the questions around capital. Your CET1 ratio obviously appears to have very healthy and plenty of excess capital to be deployed over time, but it seems like your TCE ratio is relatively low compared to the peer group. Are you comfortable bringing down the TCE ratio below 7% as long as you have the CET1 ratio well above an 8% ratio?"

A: “Kevin, it's Mac. So we are focused on CET1, and we do have an operating range of 9% to 10% for CET1. As you see, the 9.5% which is where we are today calibrates, translates to a 7.2% TCE. We do monitor the tangible common ratio. It is something that we pay close attention to. I'm not sure I see it going below 7%, but it certainly is calibrated to CET1 and that's the ratio that ratio that we're really focused on.”

[6] Examples are provided by Barth et al. (2019)

Table 1
Sample selection

Conference call data	169,008
After merge with:	
Compustat	138,499
CRSP	104,281
IBES	87,946
Labor union	87,942
Less: missing key controls	(28,758)
Final Sample	59,184

Table 2
Estimating the latent components of managers' linguistic complexity

	Fog (Present)		*Fog(QA)*	
Variable	**coeff.**	**t-value**	**coeff.**	**t-value**
Fog(Analyst)	0.179***	18.54	0.528***	30.64
Size	-0.118***	-7.29	-0.012	-0.97
Leverage	0.469***	4.39	0.079	0.89
BM	-0.092	-1.6	-0.067	-1.49
Returns	-0.002***	-4.09	0.000	-0.61
Acquisitions	1.031***	4.26	-0.118	-0.64
CapIntensity	-0.240*	-1.65	-0.603***	-6.18
Capex	-0.710	-0.99	0.868**	2.01
R&D	8.445***	8.94	5.059***	7.94
Financing	0.145*	1.93	0.105*	1.8
σCFO	1.215***	5.7	0.571***	3.52
Goodwill	0.034	0.65	-0.045	-1.09
Restructure	-0.060	-1.39	-0.030	-0.87
Firm & Time cluster	Yes		Yes	
Obs	59,184		59,184	
Adj R2 (%)	10.60%		19.87%	

Note: This table presents results from model (3) that estimates the latent components of managers' linguistic complexity during the respective session of the earnings conference call. *Fog(Present)* refers to the linguistic complexity of managers during the presentation portion of the call. *Fog(QA)* refers to the linguistic complexity of managers during the Q&A portion of the call. *Fog(Analyst)* refers to the linguistic complexity of analysts.

∗∗∗, ∗∗, and ∗ denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 3

Panel A: Summary statistics

Variable	N	Mean	Std. Dev	P25	P50	P75
Fog(Present)	59,184	15.525	1.517	14.530	15.526	16.518
Fog(QA)	59,184	12.008	1.605	10.898	11.885	12.977
Fog(Analyst)	59,184	9.333	1.239	8.489	9.218	10.051
ObfuPres	59,184	0.001	1.423	-0.931	0.014	0.941
ObfuQA	59,184	0.023	1.416	-0.959	-0.087	0.893
InfoPres	59,184	15.521	0.447	15.221	15.442	15.721
InfoQA	59,184	11.981	0.676	11.515	11.923	12.383
Union	59,184	0.036	0.055	0.007	0.017	0.041
UnionDummy	47,201	0.389	0.488	0.000	0.000	1.000
Size	59,184	7.256	1.628	6.102	7.132	8.301
Leverage	59,184	0.222	0.216	0.012	0.187	0.345
BM	59,184	0.453	0.370	0.223	0.387	0.615
Returns	59,184	2.854	22.931	-10.138	2.202	14.191
Acqusitions	59,184	0.018	0.052	0.000	0.000	0.006
CapIntensity	59,184	0.221	0.207	0.069	0.147	0.307
Capex	59,184	0.026	0.031	0.007	0.016	0.033
R&D	59,184	0.016	0.028	0.000	0.001	0.021
Financing	59,184	0.102	0.212	0.002	0.015	0.090
σCFO	59,184	0.071	0.093	0.023	0.041	0.075
Goodwill	59,184	0.023	0.150	0.000	0.000	0.000
Restructure	59,184	0.247	0.431	0.000	0.000	0.000
Loss	59,184	0.267	0.442	0.000	0.000	1.000
HHI	59,184	0.193	0.180	0.065	0.127	0.253
SpecItems	59,184	-0.004	0.019	-0.002	0.000	0.000
Analyst	59,184	9.132	6.336	4.000	7.000	12.000
Dispersion	59,184	0.008	0.033	0.000	0.001	0.003
Surprise	59,184	0.000	0.001	0.000	0.000	0.000
SmallBeat	59,184	0.498	0.500	0.000	0.000	1.000

Table 3 (continued)

Panel B: Pearson and Spearman correlations

		I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI	XVII	XVIII	XIX	XX	XXI	XXII	XXIII	XXIV	XXV	XXVI	XXVII	XXVIII
I	*Fog(Present)*		**0.38**	**0.13**	**0.95**	**0.33**	**0.29**	**0.20**	**-0.17**	**-0.16**	**-0.18**	**-0.07**	**-0.08**	**-0.04**	**-0.03**	**-0.16**	**-0.06**	**0.19**	**0.05**	**0.17**	-0.01	**-0.04**	**0.20**	**-0.22**	**-0.03**	**-0.08**	**0.13**	-0.01	**0.04**
II	*Fog(QA)*	**0.36**		**0.42**	**0.30**	**0.90**	**0.34**	**0.45**	**-0.10**	**-0.13**	0.00	**-0.06**	**-0.11**	**-0.02**	**-0.02**	**-0.15**	**-0.05**	**0.14**	**0.03**	**0.07**	**-0.01**	**0.02**	**0.09**	**-0.14**	**-0.03**	**0.05**	**0.02**	0.00	0.00
III	*Fog(Analyst)*	**0.15**	**0.41**		-0.01	**0.05**	**0.54**	**0.94**	**-0.06**	**-0.03**	**0.15**	**-0.01**	**-0.09**	-0.01	**0.03**	**-0.06**	**-0.02**	**0.06**	**0.03**	-0.01	0.00	**0.08**	0.00	**-0.04**	**-0.04**	**0.14**	**-0.05**	**-0.03**	0.00
IV	*ObfuPres*	**0.96**	**0.30**	0.00		**0.33**	**0.03**	0.01	**-0.10**	**-0.09**	**-0.05**	**-0.04**	**-0.03**	0.00	**-0.02**	**-0.06**	0.00	**0.03**	0.01	**0.04**	-0.01	**-0.02**	**0.08**	**-0.15**	**-0.03**	**-0.02**	**0.06**	**-0.02**	**0.03**
V	*ObfuQA*	**0.32**	**0.90**	0.01	**0.33**		**0.05**	**0.05**	**-0.03**	**-0.08**	**-0.02**	**-0.01**	**-0.03**	**-0.01**	**-0.03**	**-0.04**	0.00	**0.01**	0.00	0.01	-0.01	**-0.02**	**0.05**	**-0.08**	**-0.01**	0.00	**0.02**	**0.01**	0.00
VI	*InfoPres*	**0.29**	**0.31**	**0.53**	0.01	0.01		**0.72**	**-0.24**	**-0.27**	**-0.46**	**-0.11**	**-0.12**	**-0.14**	0.01	**-0.41**	**-0.20**	**0.53**	**0.13**	**0.45**	**0.01**	**-0.06**	**0.37**	**-0.24**	**-0.03**	**-0.22**	**0.24**	**0.03**	**0.06**
VII	*InfoQA*	**0.21**	**0.44**	**0.95**	0.00	0.01	**0.71**		**-0.17**	**-0.14**	**0.07**	**-0.11**	**-0.20**	**-0.02**	**0.02**	**-0.27**	**-0.12**	**0.30**	**0.07**	**0.15**	**-0.01**	**0.08**	**0.11**	**-0.15**	**-0.04**	**0.13**	**-0.02**	**-0.01**	0.00
VIII	*Union*	**-0.11**	**-0.05**	**-0.03**	**-0.08**	**-0.01**	**-0.13**	**-0.09**		**0.26**	0.00	**0.09**	**0.03**	**0.03**	**0.06**	**0.34**	**0.24**	**-0.34**	0.00	**-0.13**	**0.02**	0.01	**-0.15**	**0.35**	-0.01	**-0.09**	**-0.08**	**0.00**	0.00
IX	*UnionDummy*	**-0.09**	**-0.06**	-0.01	**-0.04**	**-0.04**	**-0.20**	**-0.09**	**0.16**		**0.20**	**0.29**	**0.18**	0.01	**0.05**	**0.33**	**0.08**	**-0.33**	0.00	**-0.27**	**0.04**	**0.10**	**-0.15**	**0.20**	**-0.06**	**0.03**	0.00	**-0.02**	**-0.04**
X	*Size*	**-0.13**	**0.05**	**0.14**	0.00	0.00	**-0.45**	**0.08**	**-0.06**	**0.16**		**0.23**	**-0.22**	**-0.01**	**0.18**	**0.18**	**0.11**	**-0.20**	**0.08**	**-0.44**	**0.01**	**0.18**	**-0.37**	**0.07**	**-0.06**	**0.68**	**-0.41**	**-0.11**	**-0.09**
XI	*Leverage*	**0.01**	**-0.02**	**0.01**	0.00	0.00	**0.05**	**-0.04**	**-0.01**	**0.15**	**0.11**		0.01	**0.02**	**0.08**	**0.38**	**0.12**	**-0.35**	**0.26**	**-0.29**	**0.04**	**0.12**	**-0.04**	**0.17**	**-0.13**	**0.08**	**0.09**	**-0.07**	**-0.01**
XII	*BM*	**-0.01**	**-0.06**	**-0.05**	0.00	0.00	**-0.04**	**-0.13**	**-0.01**	**0.03**	**-0.25**	**-0.09**		**0.09**	**0.04**	**0.15**	**-0.05**	**-0.27**	**-0.15**	**-0.16**	**0.08**	**0.08**	**-0.02**	**0.15**	**-0.09**	**-0.21**	**0.21**	**0.05**	**-0.02**
XIII	*Returns*	**-0.03**	**0.00**	**-0.01**	0.00	0.00	**-0.10**	**-0.01**	**0.01**	-0.01	**-0.04**	-0.01	**0.11**		0.00	**0.03**	-0.01	**-0.20**	**0.04**	**-0.03**	**-0.05**	0.01	**-0.08**	0.01	**0.02**	**0.02**	**-0.03**	**0.11**	**-0.08**
XIV	*Acquisitions*	**0.04**	**0.02**	**0.01**	0.00	0.00	**0.14**	**0.04**	**0.04**	**0.03**	**0.03**	**0.10**	**-0.05**	**-0.01**		**-0.08**	**0.07**	**-0.90**	**0.18**	**-0.19**	**0.04**	**0.07**	**-0.15**	**0.08**	**-0.12**	**0.13**	**-0.20**	**-0.03**	0.00
XV	*CapIntensity*	**-0.10**	**-0.12**	**-0.07**	0.00	0.00	**-0.36**	**-0.29**	**0.12**	**0.23**	**0.10**	**0.25**	**0.03**	0.00	**-0.01**		**0.55**	**-0.37**	**0.05**	**-0.23**	0.01	0.01	**-0.11**	**0.19**	0.00	0.00	**0.07**	**-0.06**	0.00
XVI	*Capex*	**-0.07**	**-0.07**	**-0.06**	0.00	0.00	**-0.23**	**-0.17**	**0.12**	**0.04**	**0.05**	**0.06**	**-0.09**	**-0.04**	**0.02**	**0.60**		**-0.12**	**0.27**	**-0.07**	**0.03**	**-0.04**	**-0.09**	**0.07**	-0.01	**0.07**	**-0.05**	**-0.04**	**0.02**
XVII	*R&D*	**0.19**	**0.13**	**0.05**	0.00	0.00	**0.67**	**0.30**	**-0.17**	**-0.19**	**-0.23**	**-0.19**	**-0.21**	**0.01**	**-0.02**	**-0.21**	**-0.07**		**0.03**	**0.35**	**-0.03**	**0.03**	**0.32**	**-0.43**	0.00	0.00	**0.10**	**0.04**	0.00
XVIII	*Financing*	**0.08**	**0.03**	**0.01**	0.00	0.00	**0.28**	**0.07**	**0.02**	**-0.02**	**-0.06**	**0.27**	**-0.08**	0.00	**0.21**	**0.05**	**0.15**	**0.14**		0.00	**0.02**	0.00	**0.04**	**-0.04**	**-0.07**	**0.06**	**-0.04**	**-0.03**	**0.01**
XIX	*σCFO*	**0.16**	**0.08**	**0.03**	0.00	0.00	**0.55**	**0.20**	**-0.07**	**-0.18**	**-0.34**	**-0.14**	**-0.13**	0.00	**-0.03**	**-0.16**	**-0.03**	**0.51**	**0.16**		**-0.05**	**-0.16**	**0.30**	**-0.19**	**0.10**	**-0.20**	**0.27**	**0.06**	**0.03**
XX	*Goodwill*	0.00	0.00	**0.01**	0.00	0.00	**0.01**	0.00	0.00	**0.04**	**0.01**	**0.01**	**0.05**	**-0.06**	**0.01**	**-0.01**	0.00	**-0.03**	0.00	**-0.03**		**0.11**	**0.13**	**0.07**	**-0.22**	**0.01**	**0.04**	**-0.03**	**0.01**
XXI	*Restructure*	**-0.01**	**0.03**	**0.06**	0.00	0.00	**-0.06**	**0.06**	**-0.01**	**0.10**	**0.14**	**0.02**	**-0.01**	0.00	**0.03**	**-0.04**	**-0.05**	0.00	**-0.05**	**-0.09**	**0.12**		**0.02**	**0.10**	**-0.43**	**0.11**	**0.01**	**-0.02**	**-0.04**
XXII	*Loss*	**0.17**	**0.06**	**0.01**	**0.06**	**0.03**	**0.38**	**0.09**	**-0.09**	**-0.11**	**-0.36**	**0.02**	**0.07**	**-0.08**	**-0.03**	**-0.03**	**-0.01**	**0.36**	**0.11**	**0.31**	**0.12**	**0.03**		**-0.17**	**-0.17**	**-0.17**	**0.40**	**-0.15**	**0.15**
XXIII	*HHI*	**-0.09**	**-0.04**	**-0.01**	**-0.07**	**-0.02**	**-0.12**	**-0.06**	**0.12**	**0.16**	**0.01**	**-0.01**	**-0.03**	0.00	**0.03**	**0.05**	**0.01**	**-0.16**	**-0.04**	**-0.10**	**0.04**	**0.11**	**-0.07**		**-0.05**	-0.01	**-0.08**	**-0.01**	0.00
XXIV	*SpecItems*	**-0.04**	**-0.01**	**-0.01**	**-0.02**	**-0.01**	**-0.07**	0.00	0.00	**-0.03**	**0.10**	**-0.05**	**-0.08**	**0.06**	**-0.03**	0.00	0.00	0.00	**-0.04**	0.00	**-0.41**	**-0.15**	**-0.29**	**-0.04**		**-0.05**	**-0.07**	**0.07**	**-0.03**
XXV	*Analyst*	**-0.09**	**0.03**	**0.11**	**-0.01**	**-0.01**	**-0.28**	**0.07**	**-0.09**	**0.04**	**0.69**	**-0.01**	**-0.15**	**-0.01**	**0.01**	**0.12**	**0.14**	**-0.08**	**-0.08**	**-0.16**	**0.02**	**0.10**	**-0.16**	0.00	**0.04**		**-0.25**	**-0.07**	**-0.06**
XXVI	*Dispersion*	**0.07**	**0.02**	**-0.01**	**0.01**	**0.01**	**0.22**	**0.03**	**-0.06**	**-0.04**	**-0.22**	**0.07**	**0.10**	**-0.04**	**-0.04**	**0.03**	**0.01**	**0.20**	**0.07**	**0.20**	**0.01**	**-0.02**	**0.23**	**-0.06**	**-0.08**	**-0.10**		**0.01**	0.00
XXVII	*Surprise*	**-0.01**	0.00	0.00	0.00	0.00	**0.04**	0.00	0.00	**0.01**	**0.06**	**-0.02**	**-0.02**	**0.04**	0.00	0.00	0.00	**-0.02**	**-0.02**	**-0.02**	**-0.04**	0.00	**-0.15**	0.00	**0.12**	**0.03**	**-0.13**		**-0.78**
XXVIII	*SmallBeat*	**0.02**	**-0.01**	**-0.01**	**0.01**	0.00	**0.05**	**-0.01**	**0.01**	**-0.04**	**-0.10**	**0.02**	0.00	**-0.08**	**0.01**	**0.02**	**0.02**	0.00	**0.03**	**0.02**	**0.01**	**-0.04**	**0.14**	**-0.01**	**-0.04**	**-0.08**	**0.01**	**-0.28**	

Note: Panel A presents descriptive statistics for the variables used to test the two hypotheses. Panel B shows the correlation coefficients. Pearson correlations are presented below the diagonal; Spearman correlations are presented above the diagonal. Boldface indicates significance at the 5% level. I winsorize all the continuous variables at the 1st and 99th percentiles. All variables are defined in Appendix A.

Table 4
Labor union and managerial information component (*H1*)

Panel A: Managerial information component and *Union*

	Presentation		Q&A	
	coeff.	**t-stats**	**coeff.**	**t-stats**
Union	-0.062*	-1.870	-0.119	-1.310
Size	-0.061***	-39.500	0.077***	18.110
Leverage	0.376***	40.460	0.044*	1.850
BM	0.073***	14.630	0.003	0.260
Returns	-0.002***	-49.020	0.000	-0.870
Acquisitions	1.167***	50.480	0.390***	6.270
CapIntensity	-0.342***	-24.440	-0.614***	-16.230
Capex	-0.660***	-12.430	0.265*	1.830
R&D	8.802***	115.840	6.630***	33.740
Financing2	0.182***	26.400	0.075***	4.350
CFO	0.943***	44.850	0.640***	12.560
Goodwill	0.057***	8.370	0.010	0.530
Restructure	-0.023***	-6.250	0.063***	6.340
Industry fquarter fixed effect	Yes		Yes	
Firm cluster	Yes		Yes	
Obs	59,182		59,182	
Adj R^2 (%)	76.44%		22.49%	

Panel B: Managerial information component and *UnionDummy*

	Presentation		Q&A	
	coeff.	**t-stats**	**coeff.**	**t-stats**
UnionDummy	-0.007*	-1.930	-0.013	-1.260
Size	-0.056***	-37.230	0.088***	21.160
Leverage	0.406***	43.410	0.108***	4.260
BM	0.081***	18.550	0.015	1.280
Returns	-0.002***	-43.150	0.000	0.340
Acquisitions	1.138***	42.750	0.355***	4.890
CapIntensity	-0.353***	-25.340	-0.656***	-17.070
Capex	-0.766***	-16.240	-0.053	-0.410
R&D	9.023***	101.030	7.045***	29.510
Financing2	0.189***	25.830	0.064***	3.430
CFO	0.979***	41.290	0.683***	11.000
Goodwill	0.070***	9.640	0.045**	2.230
Restructure	-0.017***	-4.170	0.078***	7.070
Industry fquarter fixed effect	Yes		Yes	
Firm cluster	Yes		Yes	
Obs	47,199		47,199	
Adj R^2 (%)	72.75%		23.64%	

Note: ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 5
Labor union and managerial obfuscation component (*H2*)

Panel A: Managerial obfuscation component and *Union*

	Presentation		Q&A	
	coeff.	**t-stats**	**coeff.**	**t-stats**
Union	-1.791***	-4.430	-0.380	-0.950
Size	-0.060***	-2.930	-0.010	-0.590
Leverage	-0.322***	-3.280	-0.066	-0.830
BM	-0.233***	-4.430	-0.017	-0.380
Returns	0.001***	3.940	0.000	0.180
R&D	-5.416***	-5.890	-1.423**	-1.990
Goodwill	-0.122**	-2.090	-0.086*	-1.780
Loss	0.158***	4.630	0.072**	2.500
HHI	-0.454***	-2.860	-0.118	-0.900
SpecItems	-1.675***	-3.580	-0.653	-1.470
Analyst	0.004	0.990	0.001	0.170
Dispersion	0.426	0.920	0.256	0.700
Surprise	18.524***	2.870	5.738	0.810
SmallBeat	0.045**	2.520	-0.020	-1.200
Industry fquarter fixed effect	Yes		Yes	
Firm cluster	Yes		Yes	
Obs	59,182		59,182	
Adj R^2 (%)	9.31%		3.31%	

Panel B: Managerial obfuscation component and *UnionDummy*

	Presentation		Q&A	
	coeff.	**t-stats**	**coeff.**	**t-stats**
UnionDummy	-0.061	-1.320	-0.119***	-3.200
Size	-0.035*	-1.720	-0.011	-0.700
Leverage	-0.272***	-2.660	0.044	0.530
BM	-0.090**	-2.030	0.017	0.460
Returns	0.001***	3.990	0.000	1.320
R&D	-3.420***	-3.070	-0.975	-1.120
Goodwill	-0.133**	-2.180	-0.060	-1.130
Loss	0.188***	5.470	0.120***	3.990
HHI	-0.524***	-2.870	-0.193	-1.230
SpecItems	-1.081**	-2.190	-0.169	-0.370
Analyst	0.003	0.720	0.004	0.930
Dispersion	-0.079	-0.180	0.285	0.780
Surprise	19.077***	2.860	14.028**	2.060
SmallBeat	0.036**	1.920	-0.022	-1.250
Industry fquarter fixed effect	Yes		Yes	
Firm cluster	Yes		Yes	
Obs	47,199		47,199	
Adj R^2 (%)	8.03%		3.86%	

Note: ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 6
Subsample tests

Panel A: Managerial obfuscation component and *Union* (positive tone group)

	Presentation		Q&A	
	coeff.	**t-stats**	**coeff.**	**t-stats**
Union	-1.899***	-12.920	-0.107	-0.710
Size	-0.012*	-1.670	-0.021***	-2.820
Leverage	-0.025	-0.670	-0.034	-0.870
BM	-0.213***	-8.580	-0.100***	-3.960
Returns	0.000	0.330	0.000	-0.280
R&D	-4.390***	-12.210	-2.001***	-5.480
Goodwill	-0.095	-1.420	-0.160**	-2.350
Loss	0.273***	11.970	0.120***	5.190
HHI	-0.609***	-13.460	-0.274***	-5.960
SpecItems	-0.859	-1.400	-0.980	-1.570
Analyst	-0.007***	-4.210	0.003*	1.930
Dispersion	0.915***	3.410	0.709***	2.600
Surprise	18.538**	1.990	6.832	0.720
SmallBeat	0.038**	2.400	-0.006	-0.360
Obs	32,942		32,942	
Adj R^2 (%)	2.04%		0.30%	

Panel B: Managerial obfuscation component and *Union* (negative tone group)

	Presentation		Q&A	
	coeff.	**t-stats**	**coeff.**	**t-stats**
Union	-2.307***	-14.150	-0.439***	-2.700
Size	0.018**	2.050	-0.033***	-3.790
Leverage	-0.082*	-1.910	-0.056	-1.310
BM	-0.234***	-9.330	-0.072***	-2.900
Returns	0.001***	2.700	0.000	-0.960
R&D	-3.765***	-9.290	-1.648***	-4.080
Goodwill	-0.161***	-2.880	-0.039	-0.700
Loss	0.247***	10.470	0.099***	4.200
HHI	-0.670***	-13.090	-0.294***	-5.760
SpecItems	-1.793***	-3.960	-0.206	-0.460
Analyst	-0.016***	-7.650	0.001	0.300
Dispersion	0.942***	3.610	0.482*	1.850
Surprise	21.010***	2.560	8.816	1.080
SmallBeat	0.027	1.460	-0.027	-1.460
Obs	26,164		26,164	
Adj R^2 (%)	2.68%		0.41%	

Panel C: Managerial obfuscation component and *UnionDummy* (positive tone group)

	Presentation		Q&A	
	coeff.	**t-stats**	**coeff.**	**t-stats**
UnionDummy	-0.076***	-4.010	-0.118***	-6.240
Size	-0.010	-1.200	-0.005	-0.620
Leverage	-0.170***	-3.930	-0.042	-0.970
BM	-0.048**	-2.010	-0.029	-1.220
Returns	0.000	0.910	0.000	0.930
R&D	-1.728***	-3.750	-1.104**	-2.410
Goodwill	-0.135*	-1.770	-0.243***	-3.200
Loss	0.236***	8.610	0.182***	6.650
HHI	-0.555***	-9.840	-0.196***	-3.490
SpecItems	-1.301*	-1.940	-1.245*	-1.870
Analyst	-0.004*	-1.890	0.001	0.280
Dispersion	0.236	0.780	-0.086	-0.280
Surprise	6.400	0.610	-3.328	-0.320
SmallBeat	0.016	0.870	-0.026	-1.440
Obs	25,711		25,711	
Adj R^2 (%)	1.05%		0.49%	

Panel D: Managerial obfuscation component and *UnionDummy* (negative tone group)

	Presentation		Q&A	
	coeff.	**t-stats**	**coeff.**	**t-stats**
UnionDummy	-0.125***	-5.870	-0.130***	-6.110
Size	0.016*	1.750	-0.006	-0.620
Leverage	-0.183***	-4.020	0.092**	2.020
BM	0.012	0.530	-0.005	-0.240
Returns	0.001*	1.760	0.000	-0.500
R&D	-1.802***	-3.640	-0.261	-0.530
Goodwill	-0.105*	-1.680	0.020	0.320
Loss	0.225***	8.720	0.089***	3.460
HHI	-0.615***	-10.120	-0.281***	-4.620
SpecItems	-0.604	-1.210	0.042	0.080
Analyst	-0.006***	-2.760	-0.002	-0.680
Dispersion	0.051	0.190	0.635**	2.310
Surprise	24.483***	2.970	30.624***	3.710
SmallBeat	0.040*	1.890	0.000	-0.010
Obs	21,446		21,446	
Adj R^2 (%)	1.35%		0.51%	

Note: ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 7
Labor union and tones

Panel A: Managerial positive tone and *Union*

	Presentation		Q&A	
	coeff.	**t-stats**	**coeff.**	**t-stats**
Union	-3.073	-0.300	7.526	1.590
HHI	9.942***	2.930	2.093	1.210
Size	5.107***	15.410	6.418***	34.840
BM	1.386	1.270	-0.169	-0.270
Returns	0.046***	8.670	0.045***	12.040
Earnings	0.675*	1.900	-0.455*	-1.930
EARN_sd	2.562	1.220	-1.558	-1.150
Age	-0.002	-0.090	0.016	1.200
Capex	-30.837***	-2.580	-8.908	-1.410
R&D	-54.275***	-3.450	-29.309***	-2.980
Loss	4.061***	6.590	0.644*	1.660
Industry fquarter fixed effect	Yes		Yes	
Firm cluster	Yes		Yes	
Obs	59,143		59,143	
Adj R^2 (%)	14.52%		27.34%	

Panel B: Managerial positive tone and *UnionDummy*

	Presentation		Q&A	
	coeff.	**t-stats**	**coeff.**	**t-stats**
UnionDummy	0.987	0.990	0.504	0.890
HHI	8.052**	2.130	2.560	1.290
Size	5.474***	15.060	5.768***	27.950
BM	1.787*	1.690	-0.191	-0.300
Returns	0.057***	9.460	0.042***	9.270
Earnings	0.651	1.510	-0.428*	-1.660
EARN_sd	7.869***	2.780	0.689	0.380
Age	-0.002	-0.060	0.019	1.270
Capex	-33.656***	-3.610	0.907	0.160
R&D	-47.673**	-2.490	-42.386***	-3.590
Loss	3.693***	5.420	0.238	0.570
Industry fquarter fixed effect	Yes		Yes	
Firm cluster	Yes		Yes	
Obs	38,706		38,706	
Adj R^2 (%)	17.75%		23.67%	

Panel C: Managerial negative tone and *Union*

	Presentation		Q&A	
	coeff.	**t-stats**	**coeff.**	**t-stats**
Union	5.828	0.990	6.791**	2.240
HHI	6.007***	3.900	1.232	1.090
Size	1.994***	12.830	3.687***	31.860
BM	4.695***	7.560	1.465***	3.950
Returns	-0.062***	-19.540	-0.016***	-6.070
Earnings	0.125	0.740	-0.404***	-2.730
EARN_sd	2.226*	1.910	1.066	1.220
Age	0.004	0.380	-0.005	-0.610
Capex	-17.673***	-3.260	3.311	0.850
R&D	-78.112***	-9.970	-32.921***	-5.340
Loss	8.273***	23.530	1.468***	6.360
Industry fquarter fixed effect	Yes		Yes	
Firm cluster	Yes		Yes	
Obs	59,143		59,143	
Adj R^2 (%)	17.10%		18.75%	

Panel D: Managerial negative tone and *UnionDummy*

	Presentation		Q&A	
	coeff.	**t-stats**	**coeff.**	**t-stats**
UnionDummy	1.951***	3.850	1.250***	3.240
HHI	5.832***	3.210	1.717	1.280
Size	1.994***	11.200	3.438***	25.160
BM	3.984***	6.670	0.980**	2.440
Returns	-0.054***	-14.690	-0.012***	-3.820
Earnings	0.233	1.270	-0.569***	-3.550
EARN_sd	3.596**	2.470	1.884	1.620
Age	-0.004	-0.290	0.006	0.590
Capex	-21.795***	-4.590	8.588**	2.240
R&D	-82.063***	-8.440	-46.366***	-6.060
Loss	8.683***	20.720	1.639***	5.700
Industry fquarter fixed effect	Yes		Yes	
Firm cluster	Yes		Yes	
Obs	38,706		38,706	
Adj R^2 (%)	19.63%		18.29%	

Note: ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.

Table 8
Hilary (2006) replication

Panel A: Information asymmetry-spread

	Presentation	
	coeff.	**t-stats**
Union	0.215***	2.620
Analyst	-0.006***	-10.920
NASD	-0.021**	-2.220
Size	-0.069***	-14.080
ReturnSD	2.733***	8.670
BM	0.013***	5.330
Leverage	0.002	0.880
Rating	0.010	1.260
ROA	-0.134***	-4.140
HHI	-0.055**	-2.220
Industry fyear fixed effect	Yes	
Firm cluster	Yes	
Obs	45,850	
Adj R^2 (%)	32.95%	

Panel B: Information asymmetry-analyst

	Presentation	
	coeff.	**t-stats**
Union	-8.952***	-4.800
Spread	-2.571***	-9.660
NASD	1.464***	6.390
Size	1.109***	11.290
ReturnSD	-42.177***	-6.550
BM	1.127***	17.840
Leverage	-0.026	-0.470
Rating	-0.241	-0.950
ROA	-0.862*	-1.730
HHI	-1.424***	-3.020
Industry fyear fixed effect	Yes	
Firm cluster	Yes	
Obs	45,850	
Adj R^2 (%)	51.43%	

Panel C: Information asymmetry-trading volume

	Presentation	
	coeff.	**t-stats**
Union	-0.669**	-2.310
Spread	-1.609***	-26.840
NASD	0.203***	6.050
Size	0.038**	2.440
ReturnSD	6.560***	5.740
BM	0.425***	46.110
Leverage	0.098***	11.750
Rating	0.044	1.260
ROA	-0.230***	-2.660
HHI	-0.053	-0.690
Industry fyear fixed effect	Yes	
Firm cluster	Yes	
Obs	45,850	
Adj R^2 (%)	77.83%	

Note: ∗∗∗, ∗∗, and ∗ denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively.