Linguistic Information Quality in Customers' Forward-Looking Disclosures and Suppliers' Investment Decisions*

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ABSTRACT

This study examines whether and how linguistic information quality (measured by readability) of customer firms' management earnings forecast reports (MEFRs) affects supplier firms' investment quality (measured by investment efficiency). Our analyses reveal that supplier investment efficiency is positively associated with the average linguistic information quality of customers' prior MEFRs, and the positive association between supplier investment efficiency and customer MEFRs' numerical information quality is stronger in supplier firms with more readable customer MEFRs. Our analyses also reveal that higher linguistic information quality of customer MEFRs improves the monitoring of supplier firms by their outside stakeholders, such as institutional investors and financial analysts, and ameliorates the negative impact of suppliers' customer-dependence on their investment efficiency. Our results suggest that greater linguistic information quality of a customer firm's forward-looking disclosures is associated with higher-quality investments made by its suppliers along the supply chain.

Qualité linguistique des informations prospectives communiquées par les clients et décisions des fournisseurs en matière d'investissement

RÉSUMÉ

Les auteurs se demandent si la qualité linguistique des informations — selon le critère de la lisibilité — que communiquent les sociétés clientes (les clients) dans les rapports de la direction sur les prévisions de résultats (RDPR) influe sur la qualité des investissements des sociétés fournisseurs (les fournisseurs) — selon le critère de l'efficience — et, le cas échéant, comment s'exerce cette influence. Leurs analyses révèlent que l'efficience de l'investissement du fournisseur est en relation positive avec la qualité linguistique moyenne des informations communiquées dans les RDPR précédents des clients, et que la relation positive entre l'efficience de l'investissement du fournisseur et la qualité des informations numériques des RDPR du client est plus marquée chez les fournisseurs dont les clients produisent des RDPR plus lisibles. Leurs analyses révèlent également que la qualité plus élevée des informations communiquées dans les RDPR des clients permet aux

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parties prenantes externes comme les investisseurs institutionnels et les analystes financiers d'effectuer un meilleur suivi des fournisseurs, et qu'elle atténue l'incidence négative de la dépendance des fournisseurs à l'égard des clients sur l'efficience de l'investissement. Les résultats obtenus semblent indiquer qu'une plus grande qualité linguistique des informations prospectives communiquées par un client est associée à une plus grande qualité des investissements des fournisseurs de la chaîne logistique.

1. Introduction

This study investigates whether and how the linguistic information quality of customer firms' management earnings forecast reports (MEFRs) is associated with supplier firms' investment quality. Our investigation is motivated by two streams of extant research. One stream of research documents problems of information asymmetry between strong customers and weak suppliers (Guan et al. 2015; Radhakrishnan et al. 2014; Patatouskas 2012; Ozer et al. 2011; Cachon and Lariviere 2001). While Guan et al. (2015) find that analysts who follow both a customer and its supplier tend to make better predictions, Radhakrishnan et al. (2014) indicate that better numerical disclosure quality of a customer improves the operating performance of its supplier. The implication is that the quality of information transfer from a strong customer to its weak suppliers is affected by the quality of public disclosure by the customer. The other stream documents evidence on how numerical disclosure quality (i.e., earnings quality and earnings forecast quality) impacts investment quality by reducing the information asymmetry between corporate insiders and outside stakeholders such as equity investors (Goodman et al. 2014; Chen et al. 2011; Biddle et al. 2009; McNichols and Stubben 2008; Hope and Thomas 2008; Biddle and Hilary 2006). These studies suggest that more transparent disclosures can mitigate the problem of information asymmetry between the two parties in general and thus improves external monitoring by outside investors in particular. This improved monitoring leads to better investment decisions. However, this line of existing research is limited in the following two aspects.

First, the literature has focused exclusively on the impact on investment quality of *numerical* disclosure quality (i.e., earnings quality in annual reports and earnings forecast quality in MEFRs). It has neglected the potential impacts of *linguistic* disclosure quality. A growing body of research shows, however, that linguistic aspects of corporate disclosure (i.e., readability, tone, narrative structure, topic, etc.) have incremental information value over and beyond the already known numerical aspects (e.g., Miller and Skinner 2015; Davis et al. 2012; Loughran and McDonald 2011; Li 2010; Feldman et al. 2010; Kothari et al. 2009; Henry 2008). In fact, Beyer et al. (2010) find that the numerical component of corporate disclosures (historical and forward-looking put together) explains only 28 percent of the changes in quarterly stock returns. The indication is that the linguistic (as opposed to numerical) component of corporate disclosure can be a potentially important and complementary source of relevant firm-specific information to outsiders. The impact of such linguistic component on investment quality, however, is likely to vary with linguistic disclosure quality.

Second and more importantly, the existing literature on the linguistic quality of corporate disclosure has focused on its impact on reducing the information asymmetry between firm insiders and outside equity investors or equity capital suppliers (e.g., Davis et al. 2012; Loughran and McDonald 2011; Li 2010) and has paid little attention to other outside stakeholders such as input suppliers along the supply chain. As a result, little is known about the impact of linguistic disclosure quality on decisions made by these outsiders. We argue that the impact is likely to be more relevant to input suppliers than capital suppliers. Unlike capital suppliers who can diversify the supply of their capital across firms, an input supplier is often dependent on one or two major customers, who are typically much larger in size than the supplier, for the majority of its products that are raw inputs or intermediate products supplied to its customers (e.g., Guan et al. 2015; Radhakrishnan et al. 2014; Patatouskas 2012). The asymmetric bargaining power of the strong customer is problematic to the weak supplier because it allows the customer (who knows more about its own future prospects) to be opportunistic with the communicated information both at the time of formal contracting and at the time of informal private discussions (Cachon and Lariviere 2001). This ongoing information asymmetry between strong customers and weak suppliers, resulting from the unequal relationship between the two parties, adversely affects the quality of supplier firms' investment decisions or simply investment quality. Consequently, high-quality public disclosure about customers' future prospects, whether linguistic or numerical, is relevant to supplier investment decisions not only in itself but also as a credibility signal for other forms of customer disclosure available to input suppliers.

We extend the existing literature on the customer-supplier relationship along the supply chain by investigating the impact of linguistic information quality of customer firms' forward-looking disclosures on supplier firms' investment efficiency. We construct a sample of 1,453 unique publicly listed suppliers (4,304 unique supplier-years in 8,679 supplier-customer-years) whose customers have issued at least one MEFR per year during the sample period of 1998–2011. We use only "unbundled" MEFRs in our study.[1] We use the *average* linguistic readability of the customer MEFRs issued in the three-year period prior to a supplier's investment quality measurement year (and an M&A announcement/completion year) as a measure of its average linguistic information quality for the supplier firm in that given year. Our main analyses on the investment efficiency of supplier firms' capital expenditure reveal the following.

First, we find (i) that supplier firms' investment efficiency (a proxy for investment quality) is positively associated with linguistic readability (a proxy for linguistic information quality) of prior MEFRs issued by their major customers and (ii) that the positive association between suppliers' investment efficiency and *numerical* information quality of MEFRs issued by their major customers is stronger in supplier firms with more readable customer MEFRs. These findings are consistent with our first hypothesis that the linguistic information quality of customer firms' forward-looking disclosures improves the investment efficiency of supplier firms directly and by complementing the impact of numerical information quality in customer MEFRs. Second, we find that supplier investment efficiency is positively associated with institutional ownership and analyst following of a supplier firm and that this positive association is stronger for supplier firms with more readable customer MEFRs. This result is consistent with our second hypothesis that linguistic information quality of customer MEFRs facilitates external monitoring of supplier firms by their outside stakeholders, such as institutional investors and financial analysts. Third, the negative association between suppliers' customer-dependence and their investment efficiency is attenuated in those suppliers with more readable customer MEFRs. This result is consistent with our third hypothesis that higher linguistic information quality of customer MEFRs ameliorates the negative impact of suppliers' customer-dependence on their investment efficiency. Our additional event-based analyses on the investment payoffs of supplier firms' M&A decisions (another proxy for investment quality) indicate that supplier firms with more readable customer MEFRs issued in the three years prior to M&A tend to make M&A decisions with greater payoffs.[2] The inferences from these findings are in line with the view that linguistic information quality of a customer firm's forward-looking disclosures matters to the investment decisions of its suppliers along the supply chain.

Our study contributes to the existing literature in two important ways. First, this study is, to the best of our knowledge, the first to examine the incremental effect of *linguistic* information quality (over and beyond the known effect of numerical information quality) in customer firms' *forward-looking* disclosures (i.e., MEFRs) on the investment efficiency of a supplier's capital expenditure as well as the investment payoffs of a supplier's M&A. Previous studies have largely focused on the effect of *numerical* information quality (i.e., earnings quality) in *historical* disclosures (i.e., annual reports) of a firm on the investment efficiency of its own capital expenditure (e.g., Chen et al. 2011; Biddle et al. 2009; McNicols and Stubben 2008; Acharya et al. 2007;

1. MEFRs "bundled" with quarterly or annual earnings announcements were taken out of our sample.
2. We thank an anonymous reviewer for encouraging us to conduct this line of analysis.

Whited 2006; Richardson 2006; Biddle and Hilary 2006; Wurgler 2000; Fazzari et al. 1988; Hubbard 1998). While Goodman et al. (2014) extend this well-established line of research by examining the effect of *numerical* information quality (i.e., earnings forecast quality) of a firm's forward-looking MEFRs on its *own* investment decisions, they omit the *linguistic* component of MEFRs altogether. Second, to our knowledge, our study is the first to extend this line of research to the supply chain by examining the incremental effects on suppliers' real investment decisions of linguistic information quality associated with customers' forward-looking disclosures. While previous studies (e.g., Guan et al. 2015; Radhakrishnan et al. 2014) have looked at the impact of numerical information quality of customer disclosure on suppliers, the impact of the *linguistic* component of customer disclosure has been unexplored. Finally, by looking at the effect of a customer firm's disclosure quality on the investment decisions of its supplier—that is, not the same firm—our results allow us to make stronger causal inferences on the link between the quality of forward-looking disclosures and the quality of real investment decisions.

2. Hypotheses

In the customer-supplier relationship along the supply chain, the regular channels through which customers directly disclose forward-looking firm-specific information to suppliers include formal contracts (e.g., purchase orders) and informal private communications. However, both channels are fraught with the information asymmetry problem. Customer firms are able to make decisions detrimental to suppliers because customers know more about their future prospects than outside suppliers. This information asymmetry problem cannot be easily rectified because of the unequal relationship between strong, dominant customers and weak, dependent suppliers. For example, changes in order quantities seldom result in contractual penalties, notwithstanding the fact that such changes constitute a formal breach of contract on the part of customers (Ozer et al. 2011). The legal recourse is of little use to suppliers, because suppliers, being typically smaller and dependent on the larger customers for survival, can ill afford to lose their customers through formal contractual enforcement. This asymmetric bargaining power of the customers allows them to be opportunistic with the information conveyed to suppliers at the time of formal contracting as well as at the time of informal private communications (Cachon and Lariviere 2001). Because this information asymmetry problem is ongoing in nature, it adversely affects the quality of information available to outsider suppliers and thus the quality of their investment decisions. An important function of corporate disclosure is to reduce the information asymmetry inherent between firm insiders and outsiders. Thus, customers' MEFRs, as a major source of forward-looking information, are expected to reduce the adverse impact of the information asymmetry between strong customers and weak suppliers and thus facilitate the efficiency of suppliers' investment decisions. However, we expect that the usefulness of customers' MEFRs to suppliers varies with the information quality of these reports.

Our first and main hypothesis concerns the impact of linguistic information quality (measured by readability) in customers' forward-looking MEFRs on suppliers' investment decisions. We argue that greater linguistic information quality in customers' forward-looking MEFRs enables suppliers to improve their investment efficiency by reducing the information asymmetry between them and their customers, particularly, for the following two reasons. First, greater linguistic information quality reduces the cost of processing the linguistic component of the information in MEFRs for all outside stakeholders. Greater linguistic readability in customers' MEFR can make the information content of these reports more easily understood by outside suppliers. Straightforward and easy-to-read MEFRs are more informative, compared with convoluted and difficult-to-understand ones, mainly because such reports translate the content of customers' information into suppliers' understanding in a less costly fashion.

Second, greater linguistic information quality in a major form of forward-looking corporate disclosure such as a customer's MEFRs *signals* that the customer firm has less to hide from outside stakeholders and less to mislead them. Since the signal of having less to hide is essentially a signal of greater overall transparency, it is likely to make *all* information disclosed by the customer firm—whether it is public (such as that contained in MEFRs) or private (such as that gleaned from purchase orders and private communications)—more credible to suppliers as well as other outsiders and more likely to be used by suppliers in making their investment decisions.[3]

We therefore predict that linguistically more readable MEFRs issued by customer firms can improve supplier firms' investment efficiency through the reduction in information asymmetry between strong customers and weak suppliers.[4] To provide large-sample, systematic evidence on this unexplored issue, we propose and test the following hypothesis in alternative form:

HYPOTHESIS 1. *The supplier's investment efficiency is positively associated with the linguistic readability of its major customers' management earnings forecast reports, all else being equal.*

While our first hypothesis concerns the linguistic information quality of customer MEFRs reducing the information asymmetry between customers and suppliers, our second hypothesis is concerned with whether quality linguistic information in customers' MEFRs reduces the information asymmetry between suppliers and their outside stakeholders, such as institutional investors and financial analysts. Higher-quality information in the form of MEFRs from the major customer firm should also improve a supplier's investment efficiency, indirectly, by enhancing the external monitoring of the supplier firm by outside stakeholders. The main reason is that, with better quality of customers' disclosure, a supplier's outside stakeholders are better able to distinguish problems arising from the customer firm from those specific to the supplier firm. This allows them to perform more effective external monitoring of the supplier and thus reduces the information asymmetry between the supplier firm and its outside stakeholders, such as institutional investors and financial analysts. Thus, we hypothesize that a reduction in this form of information asymmetry, in turn, induces *additional* efficiency in investment decisions made by the supplier firm. We therefore propose and test the following hypotheses in alternative form:

HYPOTHESIS 2a. *The positive association between suppliers' investment efficiency and suppliers' institutional ownership, if any, is stronger in supplier firms with more readable customer earnings forecast reports, all else being equal.*

HYPOTHESIS 2b. *The positive association between suppliers' investment efficiency and suppliers' analyst following, if any, is stronger in supplier firms with more readable customer earnings forecast reports, all else being equal.*

The unequal relationship between strong customers and weak suppliers is even more unequal for those suppliers who are more dependent on their customers. One implication is that the information asymmetry between customers and suppliers is greater for such suppliers and thus there is a negative association between suppliers' dependence on customers and their investment efficiency. The other implication is that linguistic information quality from customer disclosures is of greater relevance to investment decisions by suppliers who are more dependent on customers; the suppliers who depend more heavily on customers are likely to benefit to a greater degree from higher-quality linguistic information of customer MEFRs. This is because the impact of such reports on mitigating the information asymmetry problem and thus improving investment efficiency is greater for more dependent suppliers. Therefore, we predict that the negative association between suppliers' dependence on their major customers and suppliers' investment efficiency is attenuated for those suppliers with more readable customer MEFRs. We therefore propose and test the following hypothesis in alternative form:

3. One consequence of the signaling effect, for example, is to make the information content of the customer's MEFRs more credible to suppliers' outside stakeholders (e.g., suppliers' institutional investors and other market intermediaries) and thus more likely to be used by them to monitor the suppliers.
4. We measure a supplier firm's investment efficiency by its deviations from expected investment (Goodman et al. 2014; Chen et al. 2011; Biddle et al. 2009).

HYPOTHESIS 3. *The negative association between suppliers' investment efficiency and suppliers' dependence on their major customers, if any, is weaker in supplier firms with more readable customer earnings forecast reports, all else being equal.*

3. Research design

Measurement of key research variables

Identifying management forecast reports

Our empirical strategies require us to identify and read actual MEFRs and construct proxies for linguistic information quality—namely, measures of MEFR readability. Since no such report is readily archived in any database, we obtain these reports from public sources. To identify likely MEFRs issued by all companies in the period from 1998 through 2011, we use three different approaches suggested by Baginski et al. (2004), Chuk et al. (2013), and Hutton et al. (2003). These approaches involve three different sets of keywords to search the Dow Jones News Service, PR Newswire, the Business Wire, and the *Wall Street Journal.*[5] After deleting duplications, we obtain 199,707 unique possible reports. We then identify actual management forecast reports from these possible reports and extract the corresponding accounting information of companies for which these MEFR reports are issued, following the procedures described below.

First, we develop an algorithm to extract the company name and associated ticker symbol in each of the possible reports. This information identifies the company for which the report is written.[6] We screen out nonlisted companies by deleting all the reports without ticker symbols. Second, we use the resultant list of ticker symbols and names to locate their corresponding CUSIP numbers and PERMNO (permanent number) numbers in CRSP. We are able to match 152,999 reports with ticker symbols with corresponding CUSIP and PERMNO numbers. Third, we use the identified CUSIP numbers to locate in the CIG database the issuance dates of management forecasts. We classify the forecast reports that fall within the three-day window after known forecast issuance dates as *actual* management forecast reports.[7] We use the identified PERMNO numbers to extract the corresponding accounting information of such companies that issued management forecast reports from COMPUSTAT. Using the steps above, we identify 62,093 actual MEFRs issued by 4,359 firms in the period from 1998 through 2011. Of these MEFRs, 34,648 are "unbundled" with earnings announcements in the sense that these reports were not issued within any five-day period before and after actual earnings announcements. We use only "unbundled" MEFRs in this study.

Measurement of linguistic information quality

We use two linguistic readability measures to proxy for linguistic information quality. We use two approaches to obtain these two measures—that is, *IND-WORD* and *IND-LENGTH.* One approach to assess the readability of a document is based on the complexity of words in the document, focusing on:

5. The first set of keywords includes *expects earnings*, *expects net*, *expects income*, *expects losses*, *expects profits*, and *expects results*—in addition to three parallel lists in which "*expects*" is replaced alternatively by "*forecasts*," "*predicts*," and "*sees*" (Baginski et al. 2004). This search yields 22,842 possible reports. The second set of keywords includes *forecast*, *guidance*, *outlook*, *expectation*, *expect*, *guide*, *anticipate*, *expected*, and *anticipated*, each within the five words of *earnings*, *profit*, *loss*, *income*, *sales*, *EBITDA*, *revenue*, and *cash flow* (Chuk et al. 2013). This search yields 165,481 possible reports. The third set of keywords includes (*forecast* or *estimate* or *predict* or *anticipate* or *expect*) in the same paragraph as (*sale* or *sales* or *revenues* or *earnings* or *profits* or *loss* or *losses* or *margin* or *margins* or *cash flows* or *cash flows* or *income* or *EBIT* or *EBITDA* or *result* or *results*) in the same paragraph as (*manager* or *management* or *CEO* or *executive* or *president* or *official* or *officials* or *officer* or *spokesperson* or *spokesman* or *spokeswoman*) (Hutton et al. 2003). This search yields 64,071possible reports.

6. For reports with more than one company name, we use the one appearing in the title of the report. If the title contains no company name, we count the number of times each company name is mentioned in the report and attribute the report to the company whose name is mentioned the most often.

7. We perform a random check on 300 reports manually to see whether these reports are actual management forecast reports. The success rate from the random check is 100 percent.

(i) the average number of characters (i.e., letters) in each word, (ii) the average number of (sound-based) syllables in each word, and (iii) the average number of these words in a sentence.[8] There are, to our knowledge, six different readability indices based on this approach: (i) Gunning Fog Index (*Fog*), (ii) Flesch–Kincaid Index (*FK*), (iii) Flesch Reading East (*FRE*), (iv) SMOG Grading *(SMOG*), (v) Coleman-Liau Index (*CLI*), and (vi) Automated Readability Index (*ARI*). Each index captures a somewhat different dimension of readability, and researchers also have different opinions about the readability accuracy of characters per word versus that of syllables per word.

Following De Franco et al. (2015), we construct an aggregate readability measure based on all six readability measures in the following steps. First, we calculate the six measures for each MEFR.[9] Second, we calculate the *average* linguistic readability (for each of the six measures) of "unbundled" customer's MEFRs issued in the three years prior to a given measurement year for investment efficiency (see Figure 1 in Appendix 1) as the linguistic readability of a customer's MEFRs.[10] Third, we rank each of the six measures into percentile (0–99), and take the average of these six percentile rankings as the measure of *Readability-Word.*[11] We then construct an indicator variable, *IND-WORD*, that equals one if *Readability-Word* of the customer's MEFRs is greater than the sample median, and zero otherwise. Note here that *IND-WORD* captures the lack of MEFR readability or MEFR unreadability, given that the wordier MEFR is less readable.

Loughran and McDonald (2014) argue that readability measures based on characters and/or syllables may not suit the realm of business writing very well. The reason lies in the difficulty in identifying complex words for business. They suggest that the approach of using size-based measures can better proxy for financial document readability. There are three different size-based readability measures, all using larger size to indicate lower readability. The first is based on the file size, measured by megabytes, of the financial document (Loughran and McDonald 2014). The second and the third measures are based on the number of words and the number of characters, respectively, in financial documents (Li 2008; De Franco et al. 2015). As we did for the measure of *Readability-Word*, we construct the *Readability-Length* measure in four steps. First, we calculate all three size-based measures for each report. Second, we similarly calculate the *average* linguistic readability (for each of the three measures) of "unbundled" customer MEFRs issued in the three years prior to a given measurement year for investment efficiency (see Figure 1 in Appendix 1) as the linguistic readability of customer MEFRs. Third, we compute the percentile scores for each of the three measures. Fourth, we compute the *Readability-Length* measure as the average of the three percentile rankings. We then construct an indicator variable, *IND-LENGTH*, which equals one if *Readability-Length* of customer MEFRs is greater than the sample median, and zero otherwise. Given that, all else equal, the lengthier report has lower readability, *IND-LENGTH* captures the lack of MEFR readability or MEFR unreadability.

Measurement of linguistic information content

We adopt the approach by Feldman et al. (2010) and use the "tone surprise" measure as our proxy for firm-specific linguistic or tone information content of customers' MEFRs. See online Appendix A[12] for detailed steps of calculation.

8. A word with three or more syllables is considered a complex word.
9. With the exception of *FRE*, a larger measure indicates lower readability. To be consistent, we multiply all *FRE* measures by minus one (−1).
10. To the extent that the average measure of linguistic information quality of three prior years indicates the consistency over time of such information quality, it is more suitable to the longer-term nature of investment decisions (e.g., Goodman et al. 2014).
11. For example, customer A may have the rankings for the average of six measures of its MEFRs issued in the period from year $t-3$ to year $t-1$: 1 based on *Fog*, 10 based on *FK*, 6 based on *FRE*, 35 based on *SMOG*, 22 based on *CLI*, and 52 based on *ARI.* The *Readability-Word* measure for customer A is 21.
12. Please see supporting information, "Appendix A: Detailed description of four other key variable measurements," as an addition to the online article.

Measurement of numerical information quality[13]

Baginiski and Rakow (2012) propose a multiplicative measure to proxy for the quality of a firm's management earnings forecast policy. Since this measure captures the numerical (rather than linguistic) component of MEFRs, we adopt this measure to proxy for the numerical information quality of customers' MEFRs (*NumQUALITY*). See online Appendix A for detailed steps of calculation.

Measuring investment efficiency

Following voluminous prior research (e.g., Goodman et al. 2014; Chen et al. 2011; Biddle et al. 2009; McNicols and Stubben 2008; Acharya et al. 2007; Whited 2006; Richardson 2006; Biddle and Hilary 2006; Wurgler 2000; Fazzari et al. 1988; Hubbard 1998), we measure investment efficiency by the magnitude of deviations of actual investment from an expected level of investment given the firm's growth opportunities (measured by sales growth from previous year). See online Appendix A for a detailed description of the model used.

Measuring historical information quality

Following prior literature, we use earnings (i.e., accruals) quality to control for the quality of historical information in published financial statements. We estimate discretionary accruals using the Dechow and Dichev (2002) model, modified by McNichols (2002). Online Appendix A provides a detailed description of the model used.

Measuring corporate governance

We also control for supplier firms' governance efficacy using three corporate governance proxies—that is, *INSTITUTION, ANALYST*, and *IND-SAME. INSTITUTION* refers to the level of institutional ownership, measured by the percentage of a supplier firm's shares held by institutional investors. *ANALYST* refers to analyst coverage of a supplier firm, measured as the natural logarithm of one plus the number of analysts following the supplier firm. Guan et al. (2015) find that the same analyst following both a supplier and its customers can improve analyst earnings forecasts for the supplier firm. We therefore control for the presence of analysts following both suppliers and customers, measured by *IND-SAME.* This is an indicator variable that equals one if at least one analyst follows the supplier and its customers at the same time for a supplier, and zero otherwise.

Measuring suppliers' dependence on customers

Following Patatoukas (2012), we use customer-based concentration (*CC*) to proxy for a supplier's dependence on its major customers. *CC* is calculated as:

$$CC_{it} = \sum_{j=1}^{J} \left(CSALE_{ijt}/SALE_{it}\right)^2, \tag{1}$$

where $CSALE_{ijt}$ represents the sales of supplier i to customer j in year t and $SALE_{it}$ is supplier i's total sales in year t. A higher *CC* indicates more dependence of the supplier firm on its major customers.

Other controls

Our regression models include 14 supplier-based and 8 customer-based control variables. Appendix 2 provides the list of these variables, along with their detailed definitions.

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13. Note that the numerical information content of a disclosure is inseparable from its quality (i.e., both are in the form of a *numeral*, as in a *precise* earnings forecast or an *accurate* earnings forecast).

Model specification

Following Goodman et al. (2014), Chen et al. (2011), and Biddle et al. (2009), we test Hypothesis 1 using the following equation:

$$Inv\_ineff_{i,t} = a_1 + b_1\, C-Unreadability_{i,(t-3,t-1)} + \sum\nolimits_n c_n\, Controls_{i,t-1} + \varepsilon_{i,t}. \tag{2}$$

In equation (2), Inv_ineff_t is our proxy for the *lack* of investment efficiency or the extent of investment inefficiency, defined as the absolute value of deviations of actual investment from an expected level of investment. The key variable of our interest is $C\text{-}Unreadability_{(t-3,t-1)}$ which denotes the lack of readability or unreadability of unbundled customer MEFRs issued in the three years prior to the measurement period for investment inefficiency. It measures the average (lack of) linguistic information quality of these reports.[14] As explained above, $IND\text{-}WORD_{(t-3,t-1)}$ and $IND\text{-}LENGTH_{(t-3,t-1)}$ equal one to indicate that the unreadability of customers' MEFRs is relatively high. Thus, Hypothesis 1 is supported if we observe $b_1 > 0$, suggesting that less readable customers' MEFRs in the period from $t - 3$ to $t - 1$ (i.e., higher $C\text{-}Unreadability_{(t-3,t-1)}$) increases investment inefficiency in year t, after controlling for the linguistic information tone ($IND\text{-}CTONE_{t-1}$) and numerical information quality ($NumQUALITY_{(t-3,t-1)}$) of customer MEFRs, and suppliers' and customers' other characteristics in year $t - 1$.

Following prior studies (Guan et al. 2015; Radhakrishnan et al. 2014; Patatoukas 2012; Chen et al. 2011; Biddle et al. 2009), we control for suppliers' and customers' characteristics that can affect supplier investment inefficiency. Supplier characteristics include accruals quality (*AQ*), institutional ownership (*INSTITUTION*), analyst following (*ANALYST*), analysts who follow both suppliers and customers (*IND-SAME*), the supplier's dependence on its major customers (*CC*), firm size (*SIZE*), market-to-book ratio (*MTB*), bankruptcy risk (*ZScore*), leverage (*LEV*), business operating cycle (*OperatingCycle*), the frequency of loss (*LOSS*), investment volatility (*INVEST-VOL*), sales volatility (*SALESVOL*), and cash flow volatility (*CFOVOL*). Customers' characteristics include the duration of relation between the supplier and customer (*CLINK*), the customer's input dependence on suppliers (*CDEP*), customer firm size (*CSIZE*), customer sales volatility (*CSALESVOL*), customer cash flow volatility (*CCFOVOL*), and customer accruals quality (*CAQ*). Appendix 2 provides detailed definitions of the above control variables.

To test Hypotheses 2a, 2b, and 3, we add into our baseline regression in equation (2) the interaction term of linguistic information quality of customers' MEFRs (*C-Unreadability*) with each of three firm-specific characteristics—that is, institutional ownership (*INSTITUTION*), analyst following (*ANALYST*), and a supplier's dependence on customers (*CC*), respectively. Let *FSC* denote one of these firm-specific characteristics. Specifically, we estimate the following regression in equation (3) with the same control variables used in equation (2):

$$\begin{aligned} Inv\_ineff_{i,t} = a_1 &+ b_1\, C-Unreadability_{i,(t-3,t-1)} + b_2\, FSC_{i,t-1} + b_3\, C-Unreadability_{i,(t-3,t-1)} \\ &\times FSC_{i,t-1} + \sum\nolimits_n c_n\, Other\ Controls_{i,t-1} + \varepsilon_{i,t}. \end{aligned} \tag{3}$$

14. We note that there is a problem in the misalignment of time horizon between short-term earnings forecast information and longer-term investment decisions, just as there is a (bigger) problem in the misalignment of time horizon between zero-term realized earnings information and longer-term investment decisions. However, the misalignment problem introduces a conservative bias into our analysis as it works against our study discovering significant results. Given the amount of evidence that historical earnings information (which has a zero-term time horizon) significantly impacts investment decision quality, it can be argued that forward-looking earnings forecast information (albeit short-term) may be useful in contributing positively to making investment decisions. We argue further that the three-year measure is better than the one-year measure in addressing the misalignment problem because the three-year measure captures the *average* linguistic information quality over time rather than the linguistic information quality in a singular year. To the extent that average quality is indicative of consistency in quality over time, the three-year measure relieves the misalignment concern to a certain extent. We thank an anonymous reviewer who brought the above issues to our attention.

When *FSC* = *INSTITUTION*, we expect to observe $b_2 < 0$ in equation (3) to the extent that institutional monitoring reduces investment inefficiency. Hypothesis 2a is supported if we observe $b_3 > 0$, suggesting that less readable customer MEFRs would weaken the impact of institutional ownership on *reducing* suppliers' investment inefficiency. When *FSC* = *ANALYST*, we also expect to observe $b_2 < 0$ in equation (3) to the extent that analyst monitoring reduces investment inefficiency. Hypothesis 2b is supported if we observe $b_3 > 0$, suggesting that less readable customers' MEFRs would weaken the impact of analyst following on *reducing* suppliers' investment inefficiency.

When *FSC* = *CC*, we expect to observe $b_2 > 0$ in equation (3) because greater supplier dependence on customers is likely to exacerbate the information asymmetry between customers and suppliers and thus suppliers' investment inefficiency. Hypothesis 3 is supported if we observe $b_3 > 0$, suggesting that less readable customer MEFRs would strengthen the impact on increasing suppliers' investment inefficiency associated with suppliers' dependence on customers. We provide an extensive discussion in online Appendix C on how to address the selection-bias and endogeneity issues.[15]

4. Main analyses

Sample construction and descriptive statistics

We use the following steps to construct our sample of customer-supplier pairs. First, following Pandit et al. (2011) and Cohen and Frazzini (2008), we use an algorithm to match customers' names in the Segment File of COMPUSTAT (which provides the names of major customers of listed companies and the amount of revenue generated by each major customer) with *standard* company names and corresponding CUSIP and PERMNO numbers in CRSP as well as GVKEYS in COMPUSTAT. The objective is to exclude customers not covered by CRSP and COMPUSTAT. We manually check each supplier-customer pair for accuracy. Second, we match each supplier-customer pair, using CUSIP for its stock return information in CRSP, GVKEY for its accounting information in COMPUSTAT, and analyst coverage information in I/B/E/S. The resulting sample consists of 10,225 unique supplier-years with at least one customer identified in the annual report, which is used for the voluntary disclosure probit model in online Appendix D. Finally, we use PERMNO to match each supplier-customer pair with its corresponding customer management forecast report. Our final sample consists of 8,679 supplier-customer-year pairs, representing 4,304 unique supplier-years with at least one identified customer issuing at least one management earnings forecast in a year and 1,452 unique suppliers in the period of 1998–2011.[16]

In panel A of Table 1, the upper and lower halves provide descriptive statistics of the suppliers and their corresponding customers, respectively. With respect to the results in panel A, the following are noteworthy. First, the average size of the supplier (*SIZE*) is significantly smaller than that of its customer (*CSIZE*). Second, the average age of the supplier (*AGE*) is also significantly younger than that of its customer (*CAGE*). Third, the average number of major customers for a supplier (*NO_CUST*) is just 2.00 in our sample. Fourth, the average length of supplier-customer relationship in our sample (*CLINK*) is 4.26 years. The above findings are consistent with those reported in prior studies in both accounting (e.g., Patatoukas 2012) and supply chain literatures (Ozer et al. 2011), and suggest that the supplier is a weaker party than its major customers because the supplier is

15. Online Appendices D and E explain the actual procedures carried out.

16. For each supplier with more than one customer, we construct a *composite* customer with each variable of the composite customer taking on a sales-weighted average of the supplier's customers (Patatoukas 2012). Since only 5,328 (out of 8,679) customer-years issue at least one MEFR during a year and the rest (3,379) did not issue any MEFR, the readability measure for these 3,379 customer-year is set to zero when we calculate the sales-weighted aggregated readability measure for each supplier-year. Panel B of Table 1 reports the statistics of 5,328 customer-years solely because we want to show the descriptive statistics of customer-years *with* MEFRs.

TABLE 1
Descriptive statistics

Panel A: Descriptive statistics of suppliers' and customers' characteristic variables

Variables	N	Mean	SD	Min	Q1	Median	Q3	Max
Suppliers' characteristics								
Inv_ineff_t	4,304	10.53	8.55	0.78	3.98	8.07	14.76	31.92
INSTITUTION	4,304	0.47	0.31	0.01	0.18	0.48	0.75	0.96
ANALYST	4,304	1.64	1.07	0.00	0.69	1.79	2.48	3.33
IND-SAME	4,304	0.33	0.47	0.00	0.00	0.00	1.00	1.00
AQ	4,304	−0.06	0.04	−0.16	−0.08	−0.05	−0.03	−0.02
CC	4,304	0.09	0.10	0.00	0.02	0.04	0.12	0.36
SIZE	4,304	5.64	1.92	2.32	4.17	5.61	7.01	9.24
MTB	4,304	2.01	1.32	0.77	1.10	1.52	2.42	5.74
ZScore	4,304	0.97	1.27	−2.13	0.39	1.16	1.82	3.03
LEV	4,304	0.44	0.24	0.10	0.24	0.42	0.61	0.92
OperatingCycle	4,304	4.82	0.57	3.69	4.44	4.83	5.21	5.83
LOSS	4,304	0.41	0.49	0.00	0.00	0.00	1.00	1.00
INVESTVOL	4,304	13.74	14.56	1.12	3.92	8.37	17.11	56.72
SALESVOL	4,304	0.22	0.17	0.03	0.09	0.16	0.28	0.68
CFOVOL	4,304	0.09	0.07	0.02	0.04	0.07	0.11	0.27
AGE	4,304	13.55	10.79	1.13	5.06	10.48	19.21	38.61
NO_CUST	4,304	2.00	1.13	1.00	1.00	2.00	3.00	5.00
Customers' characteristics								
$IND\text{-}LENGTH_{(t-3,t-1)}$	4,304	0.5	0.5	0	0	1	1	1
$IND\text{-}WORD_{(t-3,t-1)}$	4,304	0.5	0.5	0	0	1	1	1
$CABSCG\_TONE_{t-1}$	4,304	41.36	23.78	6.090	21.53	38.50	60	87.75
$IND\text{-}CTONE_{t-1}$	4,304	0.5	0.5	0	0	1	1	1
$NumQUALITY_{(t-3,t-1)}$	4,304	1.79	0.87	0.41	1.04	1.79	2.48	3.33
CLINK	4,304	4.26	3.12	1.00	2.00	3.12	6.00	12.00
CDEP	4,304	0.02	0.04	0.00	0.00	0.00	0.01	0.15
CAGE	4,304	31.52	21.81	4.84	14.48	24.81	46.82	77.00
CSIZE	4,304	9.05	2.04	4.52	7.86	9.51	10.56	11.88
CSALESVOL	4,304	0.15	0.11	0.02	0.07	0.12	0.20	0.45
CCFOVOL	4,304	0.04	0.03	0.01	0.02	0.03	0.05	0.11
CAQ	4,304	−0.04	0.02	−0.09	−0.05	−0.03	−0.02	−0.01

Panel B: Descriptive statistics of qualitative information quality measures: $Readability_{(t-3,t-1)}$

Variables	N	Mean	SD	Min	Q1	Median	Q3	Max
CFOG	5,328	17.16	1.81	14.39	15.79	16.90	18.33	20.98
CFK	5,328	12.56	1.77	10.01	11.24	12.20	13.73	16.43
CFRE	5,328	−53.58	8.02	−66.25	−59.80	−54.58	−48.01	−37.61
CSMOG	5,328	14.20	1.18	12.35	13.26	14.15	15.01	16.68
CCLI	5,328	12.13	1.30	9.99	11.19	12.02	12.94	14.83
CARI	5,328	15.44	2.26	12.32	13.74	14.87	17.00	20.37
Readability-Word	5,328	39.80	22.58	8.50	20.67	37.00	57.33	81.83
CLFILE	5,328	−4.27	0.50	−5.14	−4.60	−4.29	−3.93	−3.27
CWORD	5,328	6.37	0.48	5.52	6.06	6.36	6.69	7.33
CCHARACTER	5,328	7.98	0.51	7.10	7.64	7.96	8.32	9.00
Readability-Length	5,328	48.14	23.04	10.00	28.33	49.33	67.33	86.33

Notes: Panel A reports the descriptive statistics for suppliers' characteristic variables and customers' characteristic variables. For each supplier with more than one customer, we construct a composite customer with each variable of the composite customer taking on a sales-weighted average of the supplier's customers (Patatoukas 2012). Panel B reports the descriptive statistics for the linguistic information quality measures of customers' MEFRs. All variables are defined in Appendix 2.

much smaller in size, less established, has relatively few major customers to choose from, and tends to depend heavily on existing customers.

Panel B of Table 1 shows the descriptive statistics for the raw indices that we use to calculate *Readability-Word* and *Readability-Length.* One of the indices is the popular Fog index (*CFOG*), which indicates the number of years of formal education required to understand a document. According to this index, the average number of years of formal education required to understand the management forecast report in our sample is 17.16 years, with the minimum at 14.39 years and the maximum going to 20.98 years. This finding suggests that (i) the MEFRs in general are not straightforward for financial professionals (and much less so for the layperson) to understand and (ii) the cost of processing the linguistic information into understanding is nontrivial. The implication is that greater readability of an MEFR can make its content more informative and more user-friendly. Please see the sample MEFR reports in online Appendix B.

Table 2 provides the Pearson correlation statistics of the key variables used in our study. As shown in Table 2, the following are apparent. First, *Inv_ineff*, which is measured by the absolute deviation of actual investment from an expected level of investment and captures the lack of investment efficiency, is positively and significantly correlated with unreadability of customer MEFRs captured by *Readability-Word* and *Readability-Length.* Though only indicative of the underlying relation, this finding is consistent with the prediction in Hypothesis 1, suggesting that more readable MEFRs issued by major customers help suppliers improve their investment efficiency. Second, *Inv_ineff* is negatively and significantly correlated with both *AQ* and *CAQ*, indicating that suppliers' investment inefficiency increases with not only lower earnings quality of suppliers themselves but also lower earnings quality of their major customers. Third, *Inv_ineff* is negatively and significantly correlated with whether a supplier has institutional investors (*INSTITUTION*). These findings are largely consistent with those of previous related studies (e.g., Chen et al. 2011; Biddle et al. 2009). Fourth, *Inv_ineff* is negatively correlated with *NumQUALITY* as expected, although the correlation is not significant at the conventional level. Fifth, *NumQUALITY* is negatively and significantly correlated with both *Readability-Length* and *Readability-Word*, suggesting that high numerical information quality tends to go hand in hand with high linguistic information quality in MEFRs. Sixth, the lack of suppliers' investment efficiency (*Inv_ineff*) is positively and significantly associated with *CC* (the extent to which a supplier is dependent on its major customers). This correlation indicates that investment efficiency is lower for suppliers who are more dependent on their major customers. Seventh, investment inefficiency (*Inv_ineff*) is negatively and significantly associated with *CDEP* (the extent to which major customers of a supplier firm depend on the input of this supplier firm). This negative correlation is in line with the view that investment efficiency is higher for suppliers whose major customers are more dependent on them.

Main results

Test of Hypothesis 1: Linguistic information quality

Table 3 provides results of regression in equation (2) using the lack of investment efficiency (*Inv_ineff*) as the dependent variable. As shown in columns (1) and (2) of Table 3, when unreadability of customer MEFRs (*C-Unreadability*) is measured by *IND-LENGTH* and *IND-WORD*, we find that the coefficients on *IND-LENGTH* and *IND-WORD* are both highly significant with an expected positive sign after both supplier and customer characteristics are controlled for. Less readable customer MEFR exacerbates the investment inefficiency of suppliers after controlling for factors including (i) the linguistic information tone (*IND-CTONE*) and (ii) the numerical information quality (*NumQUALITY*) in customers' MEFRs as well as the historical earnings quality of both suppliers and customers (i.e., *AQ* and *CAQ*, respectively). Moreover, the beta coefficient on unreadability of customer MEFRs, captured by *IND-LENGTH* or *IND-WORD*, is larger in magnitude than those of *NumQUALITY* and *CAQ*. This result suggests that the linguistic information quality of customer MEFRs is economically more significant than the numerical quality of these

TABLE 2

Pearson pairwise correlations among main regression variables

	Inv_ ineff$_t$	*Readability-Word*	*Readability-Length*	*CABSCG_TONE*	*INSTITUTION*	*ANALYST*	*IND-SAME*	*AQ*	*CC*	*CLINK*	*CDEP*	*NumQUALITY*
Readability-Word	0.073***											
Readability-Length	0.037**	0.588***										
CABSCG_TONE	0.003	0.032**	0.066***									
INSTITUTION	−0.033**	0.018	−0.089***	−0.016								
ANALYST	−0.015	0.035	−0.018	−0.021	0.644***							
IND-SAME	−0.060***	−0.071***	−0.041***	−0.086***	0.318***	0.478***						
AQ	−0.113***	−0.010	−0.073***	−0.030**	0.309***	0.285***	0.198***					
CC	0.098***	−0.060***	−0.052***	−0.104***	−0.045***	−0.061***	−0.038**	−0.077***				
CLINK	−0.049***	0.02	−0.084***	0.012	0.152***	0.017	0.025	0.104***	−0.008			
CDEP	−0.052***	0.122***	0.045***	0.001	0.157***	0.228***	0.187***	0.126***	0.085***	0.005		
NumQUALITY	−0.012	−0.072***	−0.202***	−0.202	0.075***	0.033**	0.099***	−0.012	−0.100***	0.062***	−0.045***	
CAQ	−0.083***	−0.220***	−0.254***	−0.118	0.033**	0.059***	0.024	0.069***	−0.027*	0.090***	−0.129***	0.096***

Notes: This table reports the Pearson pairwise correlations among main regression variables. ***, **, and * indicate significance levels at 1, 5, and 10 percent, respectively. All variables are defined in Appendix 2.

TABLE 3
Suppliers' investment inefficiency and customers' linguistic forward-looking information quality

Dependent variable = Inv_ineff_t	(1) *C-Unreadability* = $IND\text{-}LENGTH_{(t-3,t-1)}$	(2) *C-Unreadability* = $IND\text{-}WORD_{(t-3,t-1)}$
$C\text{-}Unreadability_{(t-3,t-1)}$	5.666***	3.694***
	(5.536)	(5.197)
Supplier-based controls		
INSTITUTION	0.174	0.101
	(0.271)	(0.154)
ANALYST	−0.193	−0.138
	(−0.706)	(−0.516)
IND-SAME	−0.191	−0.233
	(−0.579)	(−0.730)
AQ	−13.474***	−14.769***
	(−3.457)	(−3.714)
CC	5.668**	5.849**
	(2.177)	(2.232)
SIZE	−0.235	−0.221
	(−1.376)	(−1.284)
MTB	0.823***	0.849***
	(4.090)	(4.368)
ZScore	−0.585***	−0.598***
	(−3.278)	(−3.268)
LEV	−0.939	−1.155
	(−1.168)	(−1.450)
OperatingCycle	0.442	0.464
	(1.040)	(1.090)
LOSS	−0.745**	−0.682*
	(−2.161)	(−1.941)
INVESTVOL	0.043***	0.043***
	(2.743)	(2.793)
SALESVOL	−0.989	−0.867
	(−0.847)	(−0.726)
CFOVOL	1.555	1.567
	(0.758)	(0.762)
Customer-based controls		
$IND\text{-}CTONE_{t-1}$	−0.215	−0.241
	(−0.600)	(−0.690)
$NumQUALITY_{(t-3,t-1)}$	−0.756***	−0.663**
	(−2.673)	(−2.458)
CLINK	−0.004	−0.017
	(−0.077)	(−0.327)
CDEP	−1.864	−1.195
	(−0.388)	(−0.251)
CSIZE	0.010	0.210**
	(0.100)	(2.466)
CSALESVOL	9.583***	9.858***
	(4.506)	(4.457)
CCFOVOL	−22.545***	−26.711***
	(−2.782)	(−3.180)

(The table is continued on the next page.)

TABLE 3 (continued)

Dependent variable = Inv_ineff_t	(1) C-Unreadability = $IND\text{-}LENGTH_{(t-3,t-1)}$	(2) C-Unreadability = $IND\text{-}WORD_{(t-3,t-1)}$
CAQ	−14.271*	−17.890**
	(−1.739)	(−2.180)
Lambda_readability	−3.191***	−2.039***
	(−5.742)	(−5.090)
Constant	4.687	4.039
	(1.599)	(1.341)
Beta coefficients		
$C\text{-}Unreadability_{(t-3,t-1)}$	0.331	0.216
$NumQUALITY_{(t-3,t-1)}$)	−0.077	−0.067
CAQ	−0.033	−0.042
Observations	4,304	4,304
Adjusted R^2	0.121	0.119

Notes: This table reports the regression results of the effects of linguistic information quality of customers' MEFRs on suppliers' investment inefficiency. The dependent variable is Inv_ineff_t, the measure of investment inefficiency, defined as the absolute value of *Resid. Resid* is the deviations from expected investment level, measured by the residuals estimated from Biddle et al.'s (2009) model. In column (1), the variable of interest, *C-Unreadability*, is measured by *IND-LENGTH*, which is an indicator variable equal to one if the *Readability-Length* of the customer's MEFR is greater than the sample median, suggesting low linguistic information quality, and zero otherwise. In column (2), the variable of interest, *C-Unreadability,* is measured by *IND-WORD*, which is an indicator variable equal to one if the *Readability-Word* of the customer's MEFR is greater than the sample median, suggesting low linguistic information quality, and zero otherwise. Beta coefficients are the standardized coefficients, defined as estimates resulting from a regression analysis in which each variable is standardized by subtracting its mean from each of its values and then dividing these new values by the SD of the variable, with the variances of dependent and independent variables being one. Beta coefficients compare the strength of the effect of each individual independent variable to the dependent variable. The higher the absolute value of the beta coefficient, the stronger the effect. All regressions include the inverse Mills ratio of *Lambda_readability*, estimated from the probit model in online Appendix E. Standard errors are clustered by firm and year. *t*-statistics are presented in parentheses below the coefficient estimates. All variables are defined in Appendix 2. ***, **, and * indicate significance levels at 1, 5, and 10 percent, respectively.

MEFRs (captured by *NumQUALITY*) and the historical information quality of customers' published financial statements (reflected in *CAQ*). Our finding is in strong support of Hypothesis 1 and suggests that supplier investment efficiency increases with the linguistic information quality of major customers' MEFRs.[17]

With respect to the estimated coefficients on other control variables, the following are noteworthy. First, we find that the coefficient on *NumQUALITY* is negative and highly significant at less than the 1 percent level. The finding indicates that suppliers whose major customers issue MEFRs of higher numerical quality (*NumQUALITY*) tend to have higher investment efficiency. This finding is consistent with the notion that both the numerical quality and linguistic quality of

17. Note that for the supplier, the benefit from having a more transparent customer is to be traded off against the "cost" of having third parties (including the supplier's competitor) and the market in general becoming more informed about the customer and the supplier (i.e., the disappearance of opacity-generated rent, if any). The fact that we find significant results indicates the net benefit of transparency is economically material. We thank an anonymous reviewer for pointing this out.

customers' MEFRs can separately impact suppliers' investment efficiency. Second, suppliers with better historical earnings quality (*AQ*) as well as those whose major customers have better historical earnings quality (*CAQ*) tend to have lower investment inefficiency (or higher investment efficiency). Third, suppliers who are more dependent on their major customers (*CC*) tend to be more investment-inefficient.

The results in Table 3 suggest that poor linguistic information quality of customers' MEFRs exacerbates suppliers' investment inefficiency directly. To investigate whether linguistic information quality of customers' MEFRs can improve suppliers' investment efficiency indirectly by complementing the effects of numerical information quality of these MEFRs, we modify the baseline model in equation (2) by inserting the interaction variable *C-Unreadability*×*NumQUALITY*. Table 4 presents the estimated regression results for regressions with this interaction term. As shown in Table 4, the coefficient of *C-Unreadability* remains positive and highly significant in both columns (1) and (2), as in the baseline model in Table 3. The coefficient of *C-Unreadability*×*NumQUALITY* is positive and significant, and the coefficient of *NumQUALITY* is negative and significant in both columns. These results indicate that (i) better numerical information quality of customers' MEFRs reduces suppliers' investment inefficiency and (ii) this effect is significantly weakened by less readable MEFRs.

These results are consistent with our view that higher linguistic information quality in customer MEFRs enhances the credibility of numerical information of these reports and other

TABLE 4
The effects of customers' linguistic forward-looking information quality on the relation between suppliers' investment inefficiency and customers' numerical forward-looking information quality

Dependent variable = Inv_ineff_t	(1) $C\text{-}Unreadability$ = $IND\text{-}LENGTH_{(t-3,t-1)}$	(2) $C\text{-}Unreadability$ = $IND\text{-}WORD_{(t-3,t-1)}$
$C\text{-}Unreadability_{(t-3,t-1)}$	4.859***	2.835***
	(3.248)	(3.057)
$NumQUALITY_{(t-3,t-1)}$	−0.792***	−1.056***
	(−2.663)	(−3.179)
$C\text{-}Unreadability \times NumQUALITY_{(t-3,t-1)}$	0.711*	0.764**
	(1.762)	(1.969)
Controls	Yes	Yes
Observations	4,304	4,304
Adjusted R^2	0.107	0.106

Notes: This table reports the regression results of the effects of linguistic information quality of customers' MEFRs on suppliers' investment inefficiency. The dependent variable is Inv_ineff_t, the measure of investment inefficiency, defined as the absolute value of *Resid*. *Resid* is the deviations from expected investment level, measured by the residuals estimated from Biddle et al.'s (2009) model. The numerical information quality in customer MEFRs is measured by $NumQUALITY_{(t-3,t-1)}$, computed as the natural log of (1 + [*Issuance*×*Frequency*×*Precision*]). A higher value indicates better quality. In column (1), the variable of interest, *C-Unreadability*, is measured by *IND-LENGTH*, which is an indicator variable equal to one if the *Readability-Length* of the customer's MEFR is greater than the sample median, suggesting low linguistic information quality, and zero otherwise. In column (2), the variable of interest, *C-Unreadability*, is measured by *IND-WORD*, which is an indicator variable equal to one if the *Readability-Word* of the customer's MEFR is greater than the sample median, suggesting low linguistic information quality, and zero otherwise. All regressions include the same supplier-based control variables and customer-based controls as in Table 3. All regressions include the inverse Mills ratio of *Lambda_readability*, estimated from the probit model in online Appendix E. Standard errors are clustered by firm and year. *t*-statistics are presented in parentheses below the coefficient estimates. All variables are defined in Appendix 2. ***, **, and * indicate significance levels at 1, 5, and 10 percent, respectively.

disclosures (i.e., the signaling function of linguistic information quality) and thus their effects on reducing suppliers' investment inefficiency. The impact of other control variables on investment inefficiency (not tabulated) is not materially different from that of the same controls in Table 3.

Test of Hypothesis 2: Effects on suppliers' outsider stakeholders

Hypothesis 2 investigates whether higher-quality linguistic information provided by customers in their MEFRs can increase the investment efficiency of suppliers by enabling suppliers' outside stakeholders to monitor suppliers' investment decisions more effectively. In Hypothesis 2, outside stakeholders refer to institutional investors of the supplier firms (Hypothesis 2a) and financial analysts who follow the supplier firms (Hypothesis 2b).

Panel A of Table 5 presents the results of regression in equation (3) with *FSC* = *INSTITUTION*. The coefficient on *C-Unreadability* remains positive and statistically significant in both

TABLE 5

The effects of customers' linguistic forward-looking information quality on the relation between suppliers' investment inefficiency and suppliers' external monitoring strength

Panel A: Suppliers' institutional ownership: *INSTITUTION*

Dependent variable = Inv_ineff_t	(1) *C-Unreadability* = $IND\text{-}LENGTH_{(t-3,t-1)}$	(2) *C-Unreadability* = $IND\text{-}WORD_{(t-3,t-1)}$
$C\text{-}Unreadability_{(t-3,t-1)}$	6.176***	2.294***
	(5.493)	(2.663)
INSTITUTION	−1.165	−1.547*
	(−1.409)	(−1.861)
C-Unreadability×*INSTITUTION*	2.285**	2.667***
	(2.463)	(2.728)
Controls	Yes	Yes
Observations	4,304	4,304
Adjusted R^2	0.119	0.113

Panel B: Suppliers' analysts following: *ANALYST*

$C\text{-}Unreadability_{(t-3,t-1)}$	5.692***	2.616***
	(5.195)	(2.965)
ANALYST	−0.541*	−0.523*
	(−1.883)	(−1.820)
C-Unreadability×*ANALYST*	0.508**	0.770***
	(1.977)	(2.820)
Controls	Yes	Yes
Observations	4,304	4,304
Adjusted R^2	0.117	0.121

Panel C: Analysts following the supplier and its customer: *IND-SAME*

$C\text{-}Unreadability_{(t-3,t-1)}$	6.616***	3.855***
	(5.940)	(5.101)
IND-SAME	−0.346	−0.760**
	(−0.878)	(−2.075)
C-Unreadability×*IND-SAME*	0.158	0.933*
	(0.356)	(1.653)

(The table is continued on the next page.)

TABLE 5 (continued)

Panel C: Analysts following the supplier and its customer: *IND-SAME*

Controls	Yes	Yes
Observations	4,304	4,304
Adjusted R^2	0.124	0.121

Notes: This table reports the regression results for the effects of customers' linguistic forward-looking information quality on the relation between suppliers' investment inefficiency and suppliers' external monitoring strength. The dependent variable is Inv_ineff_t, the measure of suppliers' investment inefficiency. In panel A, we use the supplier's institutional ownership to proxy for the supplier's external monitoring strength, which is measured by *INSTITUTION*, the percentage of firm shares held by institutional investors. In panels B and C, we use the supplier's analyst following to proxy for the supplier's external monitoring strength. In panel B, the supplier's analyst following is measured by *ANALYST*, which is the natural logarithm of one plus the number of analysts following the supplier, as provided by I/B/E/S. In panel C, we test the effect of analysts that follow both the supplier and its customer at the same time, which is measured by *IND-SAME*, an indicator variable equal to one if at least one analyst follows the supplier and its customer at the same time, and zero otherwise. In column (1), *C-Unreadability* is measured by *IND-LENGTH*, which is an indicator variable equal to one if *Readability-Length* is greater than the sample median, suggesting low linguistic information quality, and zero otherwise. In column (2), *C-Unreadability* is measured by *IND-WORD*, which is an indicator variable equal to one if *Readability-Word* is greater than the sample median, suggesting low linguistic information quality, and zero otherwise. All regressions include the same supplier-based control variables and customer-based controls as in Table 3. All regressions include the inverse Mills ratio of *Lambda_readability*, estimated from the probit model in online Appendix E. Standard errors are clustered by firm and year. *t*-statistics are presented in parentheses below the coefficient estimates. All variables are defined in Appendix 2. ***, **, and * indicate significance levels at 1, 5, and 10 percent, respectively.

columns (1) and (2). The coefficient of *INSTITUTION* is negative in both columns and significant at less than the 10 percent level in column (2), indicating that a supplier's institutional ownership reduces its investment inefficiency. The coefficient of *C-Unreadability*×*INSTITUTION* is positive and significant at the 1 and 5 percent levels in columns (1) and (2), respectively. These results suggest that less readable customers' MEFRs weaken the impact of institutional investors on improving supplier investment efficiency. More readable customers' MEFRs makes external monitoring by institutional investors of supplier firms more effective, and more effective monitoring explains the additional reduction in investment inefficiency. The evidence is consistent with the prediction in Hypothesis 2a.

Panel B of Table 5 shows the results of regression in equation (3) with *FSC* = *ANALYST*. The coefficient on *C-Unreadability* remains positive and significant in both columns (1) and (2). The coefficient of *ANALYST* is negative and significant in both columns, indicating that a larger analyst following of a suppler firm tends to reduce its investment inefficiency. The coefficient of *C-Unreadability*×*ANALYST* is positive and significant in both columns. These results suggest that less readable customers' MEFRs weaken the impact of suppliers' analyst following on reducing suppliers' investment inefficiency. More readable customer MEFRs make external monitoring by financial analysts who follow supplier firms more effective, which, in turn, explains the improvement in investment efficiency. The evidence is consistent with the prediction in Hypothesis 2b.

Panel C of Table 5 shows the results of regression in equation (3) with *FSC* = *IND-SAME*. The coefficient on *C-Unreadability* remains positive and significant in both columns (1) and (2). The coefficient of *IND-SAME* is negative, as expected, in both columns and significant in column (2) (where *C-Unreadability* = *IND-WORD*), indicating that the supplier firms with analysts who follow them as well as their customers tend to be more efficient in their investment decisions. The coefficient of *C-Unreadability*×*IND-SAME* is positive in both columns (1) and (2), but it is significant only in column (2). This suggests that the effect of analysts following both suppliers and their customers on reducing suppliers' investment inefficiency is weakened by less readable customers' MEFRs. More readable customers' MEFRs make external monitoring by financial analysts who follow both supplier firms and their customers more effective. The change in the level of effective monitoring explains the change in investment inefficiency. This result is consistent with those in panel B of Table 5 and in support of Hypothesis 2b.

Collectively, the results of Table 5 suggest that linguistic information quality of customer MEFRs can affect the level of supplier investment efficiency via its impact on the efficacy of external monitoring of suppliers by their outsider stakeholders, such as institutional investors and analysts. These results are consistent with our hypothesis that linguistic information quality of customers' MEFRs increases suppliers' investment efficiency by reducing the information asymmetry between suppliers and their outside stakeholders.

Test of Hypothesis 3: More dependent suppliers

Our Hypothesis 3 investigates whether the effect of suppliers' dependence on their customers (measured by *CC*) on exacerbating suppliers' investment inefficiency is weaker in suppliers with more readable customers' MEFRs. To this end, we estimate the model in equation (3) with $FSC = CC$. The estimated results are presented in Table 6.

TABLE 6
The effects of customers' linguistic forward-looking information quality on the relation between suppliers' investment inefficiency and suppliers' dependence on their customers

Dependent variable = Inv_ineff_t	(1) *C-Unreadability* = $IND\text{-}LENGTH_{(t-3,t-1)}$	(2) *C-Unreadability* = $IND\text{-}WORD_{(t-3,t-1)}$
$C\text{-}Unreadability_{(t-3,t-1)}$	6.746***	3.962***
	(4.988)	(4.284)
CC	4.910*	5.148*
	(1.733)	(1.869)
C-Unreadability×*CC*	1.445**	1.280*
	(2.107)	(1.700)
Controls	Yes	Yes
Observations	4,304	4,304
Adjusted R^2	0.119	0.109

Notes: This table reports the regression results of the effects of linguistic information quality in customers' MEFRs on the relation between suppliers' investment inefficiency and suppliers' dependence on their customers. The dependent variable is Inv_ineff_t, the measure of suppliers' investment inefficiency. The supplier's dependence on its major customers is measured by *CC*, the level of customer-based concentration. A higher *CC* indicates more dependence. In column (1), *C-Unreadability* is measured by *IND-LENGTH*, which is an indicator variable equal to one if *Readability-Length* is greater than the sample median, suggesting low linguistic information quality, and zero otherwise. In column (2), *C-Unreadability* is measured by *IND-WORD*, which is an indicator variable equal to one if *Readability-Word* is greater than the sample median, suggesting low linguistic information quality, and zero otherwise. All regressions include the same supplier-based control variables and customer-based controls as in Table 3. All regressions include the inverse Mills ratio of *Lambda_readability*, estimated from the probit model in online Appendix E. Standard errors are clustered by firm and year. *t*-statistics are presented in parentheses below the coefficient estimates. All variables are defined in Appendix 2. ***, **, and * indicate significance levels at 1, 5, and 10 percent, respectively.

As shown in Table 6, the coefficient of *C-Unreadability* remains positive and significant in both columns (1) and (2). The coefficient of *CC* is positive and significant at the 10 percent level in both columns. The coefficient of *C-Unreadability*×*CC* is positive and significant in both columns, which is consistent with the prediction in Hypothesis 3. Together, these results indicate that (i) suppliers who are more dependent on their customers tend to be more investment-inefficient and (ii) the effect of suppliers' customer-dependence on exacerbating suppliers' investment inefficiency is further worsened by less readable customers' MEFRs.

Results from robustness checks

To provide robustness checks on our results, we conduct the following analyses.[18]

Analyses of supplier's investment response to customers' forecasts

One may be concerned with whether suppliers actually use customers' management earnings forecasts in their investment decisions. To address this concern, we test the supplier's contemporaneous investment response to management earnings forecasts news in customers' MEFRs and further test whether the linguistic information quality of customers' MEFRs will affect the supplier's reliance on such forecast news. The forecasts news reported in customers' MEFRs (if credible) will alter the supplier's expectations about customers' future demand, which leads to necessary adjustments in the supplier investment level. We use the following model to test the above conjecture:

$$cg\_INVEST_{i,t} = a_1 + b_1 C-Unreadability_{i,(t-3,t-1)} + b_2 CMFNEWS_{i,t} + b_3 C-Unreadability_{i,(t-3,t-1)} \times CMFNEWS_{i,t} + \sum\nolimits_n c_n \; Other\ Controls_{i,t-1} + \varepsilon_{i,t}, \tag{4}$$

where cg_INVEST_t is a proxy for the supplier's contemporaneous investment response to customers' forecasts news, calculated as the raw changes in the supplier's investment level from year $t - 1$ to year t (see Figure 2 in Appendix 1). $CMFNEWS_{i,t}$ is the measure of customers' forecasts news, calculated as management earnings forecasts in the customer's MEFR minus the most recent consensus analyst earnings forecast divided by the absolute value of the most recent consensus analyst earnings forecast.[19] Equation (4) includes the same supplier-based and customer-based controls as in equation (2). We also add the lagged sales growth (SG_{t-1}) to equation (4) as an additional control variable.

The results, as shown in Table 7, show that the coefficient on $CMFNEWS_{i,t}$ is significantly positive, suggesting that the supplier adjusts contemporaneously to its investment in response to customers' management earnings forecasts news. More importantly, we find that the coefficient of $C\text{-}Unreadability_{(t-3,t-1)}$ and the coefficient of the interaction term $C\text{-}Unreadability_{(t-3,t-1)} \times CMFNEWS_t$ are both significantly negative. The findings suggest that supplier investment level is sensitive to linguistic information quality of customers' MEFRs, and that good linguistic information of customer MEFRs enhances an impact of customers' forecasts news on suppliers' investment adjustments. This is because good-quality linguistic information in customers' MEFRs is viewed as more credible forward-looking information. To improve investment efficiency, it is necessary to adjust the level of investment. The evidence that linguistic information quality has an impact on supplier investment level adjustment establishes the necessary (though not sufficient) condition that good-quality linguistic information in customer MEFRs improves suppliers' investment efficiency.

18. We thank the reviewers and the editor for suggesting these analyses.
19. We use only range and point estimates when calculating *CMFNEWS*. In the case of range estimates, we follow Anilowski et al. (2007) and Schivakumar et al. (2011) and compute management earnings forecasts as the average of high and low estimates when First Call's CIGCODEQ equals "B," the lower estimate when CIGCODEQ equals "G," and the higher estimate when CIGCODEQ equals "H." We compute the aggregate value of *CMFNEWS* of all "unbundled" MEFRs issued in year t as our measure of customers' forecasts news.

TABLE 7
The effects of customers' linguistic forward-looking information quality on the supplier's contemporaneous investment response to customers' management earnings forecasts news

Dependent variable = cg_INVEST_t	(1) $IND\text{-}LENGTH_{(t-3,t-1)}$	(2) $IND\text{-}WORD_{(t-3,t-1)}$
$C\text{-}Unreadability_{(t-3,t-1)}$	−3.030**	−1.982*
	(−2.038)	(−1.838)
$CMFNEWS_t$	2.956**	2.811**
	(2.206)	(1.990)
$C\text{-}Unreadability_{(t-3,t-1)} \times CMFNEWS_t$	−3.858**	−4.311**
	(−2.357)	(−2.079)
Supplier-based controls		
INSTITUTION	−0.490	−0.573
	(−0.402)	(−0.479)
ANALYST	−0.223	−0.234
	(−0.699)	(−0.686)
IND-SAME	0.483	0.577
	(0.973)	(1.168)
AQ	10.253*	10.509*
	(1.691)	(1.692)
CC	−1.437	−1.302
	(−0.713)	(−0.610)
SG_{t-1}	9.506***	9.469***
	(7.818)	(8.172)
SIZE	−0.305	−0.329
	(−1.179)	(−1.224)
MTB	0.904***	0.932***
	(4.411)	(4.313)
ZScore	0.372	0.388
	(1.233)	(1.314)
LEV	−0.903	−0.898
	(−0.531)	(−0.524)
OperatingCycle	−2.049***	−2.020***
	(−4.976)	(−5.112)
LOSS	−1.729**	−1.717**
	(−2.356)	(−2.289)
INVESTVOL	0.052***	0.057***
	(3.579)	(3.849)
SALESVOL	1.218	1.091
	(0.230)	(0.210)
CFOVOL	−0.663	−0.522
	(−0.662)	(−0.538)
Customer-based controls		
$IND\text{-}CTONE_{t-1}$	0.126	0.120
	(0.233)	(0.198)
$NumQUALITY_{(t-3,t-1)}$	0.543*	0.399
	(1.755)	(1.162)
CLINK	0.145**	0.123*
	(2.055)	(1.702)
CDEP	0.253	1.004
	(0.134)	(0.500)
CSIZE	−0.077	−0.147
	(−0.661)	(−1.445)

(The table is continued on the next page.)

TABLE 7 (continued)

Dependent variable = cg_INVEST_t	(1) $IND\text{-}LENGTH_{(t-3,t-1)}$	(2) $IND\text{-}WORD_{(t-3,t-1)}$
CSALESVOL	−2.875	−3.152
	(−1.041)	(−1.104)
CCFOVOL	0.411	5.207
	(0.054)	(0.676)
CAQ	−16.239	−16.620
	(−1.269)	(−1.157)
Lambda_readability	1.432	0.841
	(1.490)	(1.187)
Constant	10.282***	12.651***
	(3.161)	(4.521)
Industry indicators	Yes	Yes
Year indicators	Yes	Yes
Observations	3,838	3,838
Adjusted R^2	0.085	0.088

Notes: This table reports the regression results of the effects of customers' linguistic forward-looking information quality on the supplier's contemporaneous investment response to customers' forecasts news. The dependent variable is cg_INVEST_t, proxy for the supplier's contemporaneous investment response, calculated as the raw changes in the supplier's investment level from year $t-1$ to year t. Customers' management earnings forecasts news is measured by $CMFNEWS_t$, calculated as management earnings forecast in the customer's MEFRs minus the most recent consensus analyst earnings forecast divided by the absolute value of the most recent consensus analyst earnings forecast. In column (1), *C-Unreadability* is measured by *IND-LENGTH*, which is an indicator variable equal to one if the *Readability-Length* of the customer's MEFR is greater than the sample median, suggesting low linguistic information quality. In column (2), *C-Unreadability* is measured by *IND-WORD*, which is an indicator variable equal to one if the *Readability-Word* of the customer's MEFR is greater than the sample median, suggesting low linguistic information quality. All regressions include year indicator, industry indicator, and the inverse Mills ratio of *Lambda_readability,* estimated from the probit model in online Appendix E. Standard errors are clustered by firm and year. *t*-statistics are presented in parentheses below the coefficient estimates. All variables are defined in Appendix 2. ***, **, and * indicate significance levels at 1, 5, and 10 percent, respectively.

Analyses of future sales growth anticipation

One indicator of investment quality improvement is the extent to which current investment level can anticipate future sales growth. We use the following model to conduct this analysis:

$$
\begin{aligned}
Investment_{i,t} = a_1 &+ b_1 C-Unreadability_{i,(t-3,t-1)} + b_2 SG_{i,t-1} + b_3 SG_{i,t} + b_4 SG_{i,(t+1,t+3)} \\
&+ b_3 C-Unreadability_{i,(t-3,t-1)} \times SG_{i,t-1} \\
&+ b_3 C-Unreadability_{i,(t-3,t-1)} \times SG_{i,t} \\
&+ b_3 C-Unreadability_{i,(t-3,t-1)} \times SG_{i,(t+1,t+3)} + \sum\nolimits_n c_n Other\ Controls_{i,t-1} \\
&+ \varepsilon_{i,t},
\end{aligned} \tag{5}
$$

where *Investment* is the measure of the supplier's investment level in year *t*. SG_t and SG_{t-1} are the percentage changes in the supplier's sales growth in year *t* and year $t-1$, respectively. $SG_{(t+1,t+3)}$ is used to proxy for the supplier's three-year future sales growths (see Figure 3 in Appendix 1). Equation (5) includes the same supplier-based and customer-based controls as in equation (2).

Table 8 results show that the supplier's three-year future sales growth—that is, $SG_{(t+1,t+3)}$—is significantly and positively associated with its investment level in year *t*, which suggests that the

TABLE 8
The effects of customers' linguistic forward-looking information quality on the ability of the supplier's investment level to anticipate future sales growth

Dependent variable = *Investment*$_t$	(1) $IND\text{-}LENGTH_{(t-3,t-1)}$	(2) $IND\text{-}WORD_{(t-3,t-1)}$
SG_{t-1}	0.843	0.427
	(0.949)	(0.444)
SG_t	9.423***	9.074***
	(4.730)	(4.529)
$SG_{(t+1,t+3)}$	1.557**	1.884***
	(2.083)	(2.878)
$C\text{-}Unreadability_{(t-3,t-1)}$	−1.338**	−1.111*
	(−1.971)	(−1.685)
$C\text{-}Unreadability_{(t-3,t-1)} \times SG_{t-1}$	−0.937	−0.197
	(−0.880)	(−0.193)
$C\text{-}Unreadability_{(t-3,t-1)} \times SG_t$	−0.909	−0.356
	(−0.380)	(−0.143)
$C\text{-}Unreadability_{(t-3,t-1)} \times SG_{(t+1,t+3)}$	−2.595**	−2.656**
	(−2.033)	(−2.062)
Supplier-based controls		
INSTITUTION	1.594	1.456
	(1.277)	(1.124)
ANALYST	1.160**	1.046**
	(2.456)	(2.206)
IND-SAME	−0.564	−0.353
	(−0.695)	(−0.466)
AQ	14.413	14.001
	(1.459)	(1.396)
CC	1.755*	1.537
	(1.764)	(1.602)
SIZE	−0.832***	−0.808***
	(−3.819)	(−3.544)
MTB	2.131***	2.136***
	(7.431)	(7.217)
ZScore	−2.156***	−2.208***
	(−5.672)	(−6.089)
LEV	−0.995	−1.222
	(−0.508)	(−0.624)
Operatingcycle	−4.199***	−4.271***
	(−4.999)	(−5.086)
LOSS	−3.552***	−3.450***
	(−4.898)	(−4.587)
INVESTVOL	−0.014	−0.011
	(−0.976)	(−0.794)
SALESVOL	2.579	1.443
	(1.054)	(1.124)
CFOVOL	6.879	6.494
	(1.091)	(1.007)

(The table is continued on the next page.)

TABLE 8 (continued)

Dependent variable = *Investment*$_t$	(1) $IND\text{-}LENGTH_{(t-3,t-1)}$	(2) $IND\text{-}WORD_{(t-3,t-1)}$
Customer-based controls		
$IND\text{-}CTONE_{t-1}$	0.081	0.540
	(0.165)	(1.076)
$NumQUALITY_{(t-3,t-1)}$	0.572	0.159
	(1.431)	(0.363)
CLINK	0.006	0.008
	(0.076)	(0.099)
CDEP	−1.425***	−1.326**
	(−2.579)	(−2.336)
CSIZE	0.177	0.110
	(1.424)	(0.881)
CSALESVOL	−11.505***	−12.100***
	(−3.666)	(−3.540)
CCFOVOL	42.105***	41.674***
	(3.751)	(3.545)
CAQ	21.986	30.702*
	(1.438)	(1.914)
Lambda_readability	0.663	0.588
	(1.347)	(1.367)
Constant	29.021***	31.012***
	(4.159)	(4.965)
Industry indicators	Yes	Yes
Year indicators	Yes	Yes
Observations	3,614	3,614
Adjusted R^2	0.305	0.309

Notes: This table reports the regression results of the effects of customers' linguistic forward-looking information quality on the ability of the supplier's investment level to anticipate future sales growth. The dependent variable is *Investment*$_t$, proxy for the supplier's current investment level, *SG* is the percentage changes in the supplier's sales growth. $SG_{(t+1,t+3)}$ proxy for the supplier's three-year future sales growth. In column (1), *C-Unreadability* is measured by *IND-LENGTH*, which is an indicator variable equal to one if the *Readability-Length* of the customer's MEFR is greater than the sample median, suggesting low linguistic information quality. In column (2), *C-Unreadability* is measured by *IND-WORD,* which is an indicator variable equal to one if the *Readability-Word* of the customer's MEFR is greater than the sample median, suggesting low linguistic information quality. All regressions include year indicator, industry indicator, and the inverse Mills ratio of *Lambda_readability*, estimated from the probit model in online Appendix E. Standard errors are clustered by firm and year. *t*-statistics are presented in parentheses below the coefficient estimates. All variables are defined in Appendix 2. ***, **, and * indicate significance levels at 1, 5, and 10 percent, respectively.

supplier's current investment decisions are able to anticipate future sales growth. More importantly, the coefficient of the interaction term $C\text{-}Unreadability \times SG_{(t+1,t+3)}$ is significantly negative, which suggests that the level of supplier investment is better able to anticipate future sales growth in supplier firms when their customer MEFRs are more readable or equivalently of higher linguistic quality. The greater ability of investment level to anticipate future sales growth, resulting from better linguistic information quality of customer MEFRs, indicates improved investment quality. This evidence corroborates our main results and is in support of our main hypothesis (Hypothesis 1).

Analyses of discretionary readability

The linguistic information quality of an MEFR is jointly determined by the underlying firm fundamentals (e.g., complexity, uncertainty, etc.) and managerial incentives. One way to control for firm complexity is to include complexity proxies when firm readability is estimated as we did in online Appendix E using the model by Li (2008). Alternatively, we can decompose the customer linguistic information quality into a nondiscretionary component reflecting customer firm fundamentals, and a discretionary component reflecting managerial incentives, managerial private information, managerial biased forecasts, and noise. Following Huang et al. (2014), we run annual cross-sectional regressions of readability (using the continuous variable *Readability-Length and Readability-Word*) on the readability determinants that are the same as those used in the model in online Appendix E. The residuals estimated from the regressions are used as a proxy for the customer discretionary linguistic quality, which solely reflects the managerial strategic choice of readability either to inform or mislead outside stakeholders. Then we redo the baseline analysis in Table 3 using this discretionary portion of readability, *Dis-Unreadability*, as our key independent variable. The results (untabulated) show that the coefficient on *Dis-Unreadability* is positive and significant at the 1 and 5 percent levels in columns (1) and (2), respectively. This finding is in line with Hypothesis 1, suggesting that our main results in Table 3 are robust to the use of discretionary linguistic information quality measure.

Analyses of event-based M&A decisions

Our event-based analyses on the investment payoffs of supplier firms' M&A decisions (another proxy for investment quality) are provided in detail in online Appendix F. The causality inferences from these findings are in support of the view that linguistic information quality of a customer firm's forward-looking disclosure matters to the investment decisions of its suppliers along the supply chain.[20]

5. Conclusion

This study maintains that forward-looking corporate disclosures via MEFRs mitigate the information asymmetry inherent between customers and their outside suppliers and thus facilitates suppliers' making better investment decisions. Under this maintained hypothesis, we test whether and how linguistic information quality of customer firms' MEFRs affects supplier firms' investment decisions. As the first study to address the impact of customers' forward-looking disclosure quality on real investment decisions of suppliers, we provide important initial evidence that a firm's forward-looking disclosure quality, both linguistic and numerical, matters not only to investment decisions in the equity market but also to real investment decisions by other outside stakeholders—namely, suppliers along the supply chain.

Our analyses on the investment efficiency of supplier firms' capital expenditure reveal the following. First, we find that supplier firms' investment efficiency is positively associated with linguistic information quality (measured by linguistic readability) of prior MEFRs issued by their major customers. Second, we find that the positive association between suppliers' investment efficiency and numerical information quality of MEFRs issued by their major customers is stronger in supplier firms with more readable customer MEFRs. These findings indicate that linguistic information quality of customer firms' forward-looking disclosures improves investment efficiency of supplier firms directly and does so indirectly as well by enhancing the impact of numerical information in customer MEFRs on suppliers' capital investment decisions. We also find that suppliers' investment efficiency associates positively (negatively) with their institutional ownership and analysts following (with their dependence on major customers) and that the association is stronger (weaker) in supplier firms with more readable customers' MEFRs. These findings together indicate that linguistic information quality in customer firms' MEFRs (i) improves the monitoring of supplier firms by their outside stakeholders, such as institutional investors and financial analysts, and (ii) weakens the impact of suppliers'

20. Additional robustness checks are explained in online Appendix G.

customer-dependence on reducing suppliers' investment efficiency. These results are robust to a battery of alternative checks. Given the scarcity of empirical evidence on the effect of customer linguistic disclosure quality on suppliers in relation to their short-term operational decisions and long-term investment decisions as well as financing decisions, we recommend further research in this direction.

Appendix 1

Figures

These figures illustrate the timeline for measuring customer MEFRs' linguistic information quality, numerical information quality, the supplier's future sales growth, and forecast news (our independent variables of interest) relative to the measures of supplier's investment efficiency, investment decisions, investment level, relationship-specific investment, supplier-customer relationship length, acquisition announcement returns, and change in performance (our dependent variables).

Figure 1 Timeline for measuring linguistic information quality and numerical information quality of customer's MEFRs relative to investment efficiency measurement period [Color figure can be viewed at wileyonlinelibrary.com]

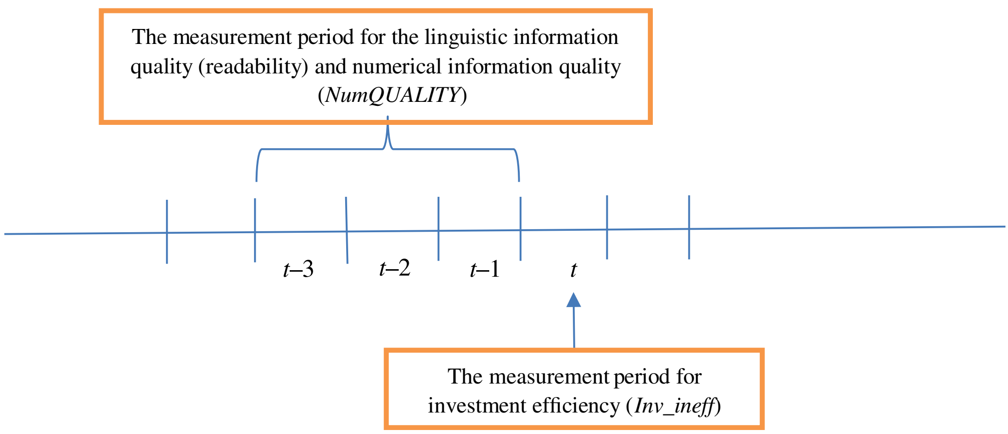


Figure 2 Timeline for measuring linguistic information quality and forecast news of customer's MEFRs relative to supplier's investment decision measurement period [Color figure can be viewed at wileyonlinelibrary.com]

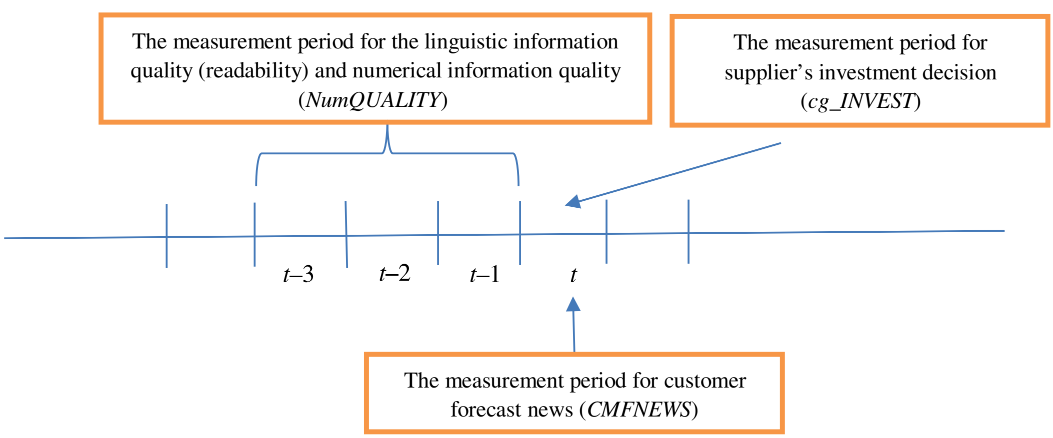


Figure 3 Timeline for measuring linguistic information quality of customers' MEFRs relative to the measurement periods for supplier's investment level, supplier-customer relationship length, the relationship-specific investment, and supplier's future sales growth [Color figure can be viewed at wileyonlinelibrary.com]

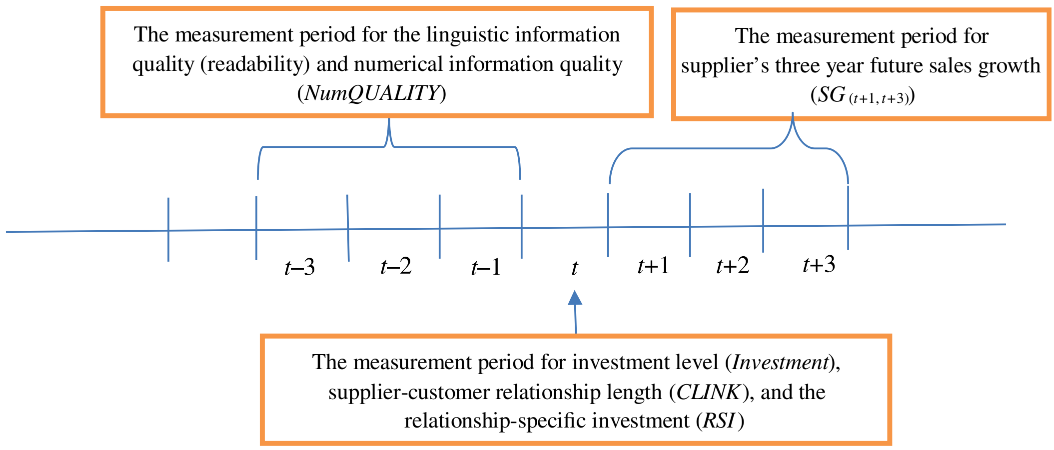


Figure 4 Timeline for measuring linguistic information quality and numerical information quality of customer's MEFRs relative to acquisition announcement returns measurement period [Color figure can be viewed at wileyonlinelibrary.com]

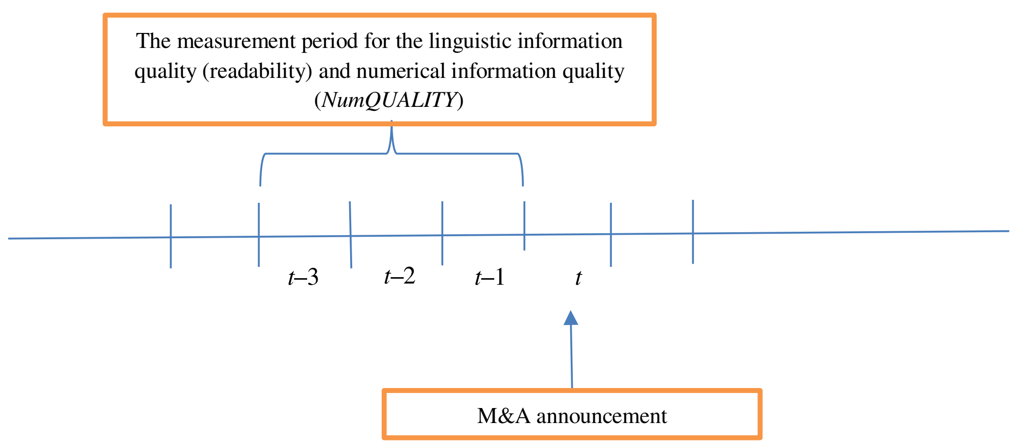
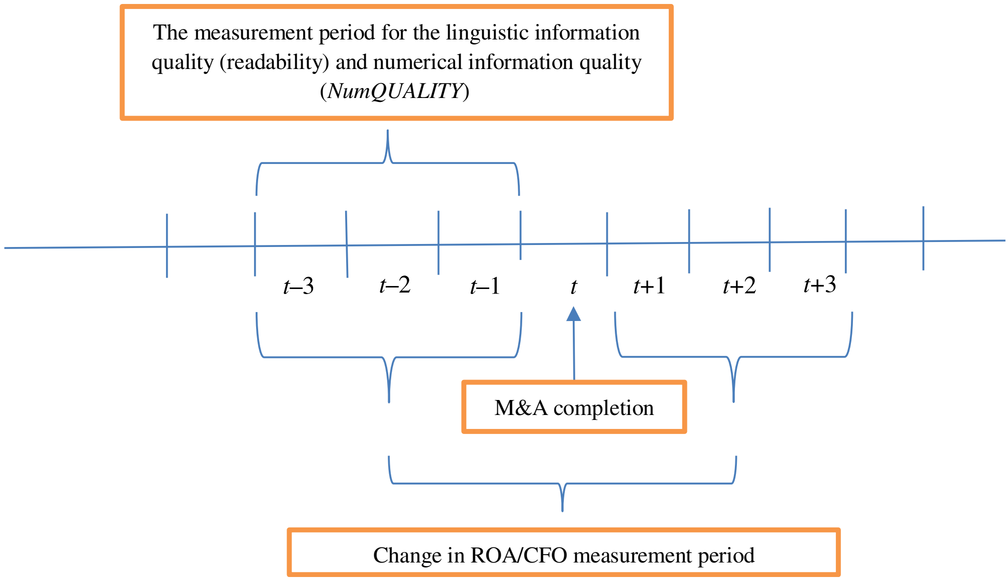


Figure 5 Timeline for measuring linguistic information quality and numerical information quality of customer's MEFRs relative to change in ROA/CFO measurement period [Color figure can be viewed at wileyonlinelibrary.com]



Appendix 2

Variable definitions

Dependent variables: Investment efficiency	
Resid	The deviations from expected investment level, measured by the firm-level residuals estimated from Biddle et al. (2009)'s model. The model is a regression of investment on lagged percentage change in sales (SG). The model is estimated for each industry-year with at least 20 observations in a given year based on the Fama and French (1997) 48-industry classification
Inv_ineff	Investment inefficiency, defined as the absolute value of *Resid.* A higher value of *Inv_ineff* indicates lower investment efficiency or higher investment inefficiency
Investment	Investment level, calculated as the sum of R&D expenditure (XRD), capital expenditure (CAPX), and acquisition expenditure (AQC) less cash receipts from sale of property, plant, and equipment (SPPE), multiplied by 100 and scaled by lagged total assets (AT)
SG	The percentage changes in sales
Testing variables: Linguistic information quality-readability measures	
CFOG	The average Fog index of the customer's MEFRs issued in the three years prior to the investment efficiency measurement/acquisition period. For each MEFR, it is calculated as (average no. of words per sentence + percent of complex words) × 0.4, where complex words are the words of three or more syllables
CFK	The average Flesch-Kincaid index of the customer's MEFRs issued in the three years prior to the investment efficiency measurement/acquisition period. For each MEFR, it is calculated as (11.8 × syllables per word) + (0.39 × words per sentence) − 15.59

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CFRE	The average Flesch reading ease index of the customer's MEFRs issued in the three years prior to the investment efficiency measurement/ acquisition period. For each MEFR, it is calculated as $-1 \times (206.8 - (1.015 \times \text{words per sentence}) - (84.6 \times \text{syllables per word}))$
CSMOG	The average SMOG grading of the customer's MEFRs issued in the three years prior to the investment efficiency measurement /acquisition period. For each MEFR, it is calculated as $1.0430 \times \sqrt{\text{No. of polysyllables} \times \frac{30}{\text{No. of sentences}}} + 3.1291$, where polysyllables are the words of three or more syllables
CCLI	The average Coleman-Liau index of the customer's MEFRs issued in the three years prior to the investment efficiency measurement/acquisition period. For each MEFR, it is calculated as $0.0588\,L - 0.296S - 15.8$, where L is the average number of letters per 100 words and S is the average number of sentences per 100 words
CARI	The average automated Readability Index of the customer's MEFRs issued in the three years prior to the investment efficiency measurement/acquisition period. For each MEFR, it is calculated as $4.71 \times$ (characters/words) + $0.5 \times$ (words/sentences) $-$ 21.43, where characters is the number of letters, numbers, and punctuation marks; words is the number of spaces; and sentences is the number of sentences
Readability-Word	The aggregate readability measure; we rank each component into percentiles—*CFOG*, *CFK*, *CFRE*, *CSMOG*, *CCLI*, and *CARI*—from 1 to 100 and take the average across the six components. The higher *Readability-Word* is, the lower is the readability of an MEFR
CLFILE	The average file size in megabytes of the customer's MEFRs issued in the three years prior to the investment efficiency measurement/acquisition period. We take the natural logarithm of this measure
CWORD	The average number of words in the customer's MEFRs issued in the three years prior to the investment efficiency measurement/acquisition period. We take the natural logarithm of this measure
CCHARACTER	The average number of characters in the customer's MEFRs issued in the three years prior to the investment efficiency measurement/acquisition period. We take the natural logarithm of this measure
Readability-Length	The aggregate readability measure; we rank each component into percentiles—*CLFILE*, *CWORD*, and *CCHARACTER* — from 1 to 100 and take the average across the three components. The higher *Readability-Length* is, the lower is the readability of a customer's MEFR
IND-LENGTH	Indicator variable equal to one if the *Readability-Length* of the customer's MEFRs is greater than the sample median of the same measure, suggesting lower linguistic information quality
IND-WORD	Indicator variable equal to one if the *Readability-Word* of the customer's MEFRs is greater than the sample median of the same measure, suggesting lower linguistic information quality
Supplier-based control variables	
INSTITUTION	Institutional ownership, measured by the percentage of firm shares held by institutional investors
ANALYST	The natural logarithm of one plus the number of analysts following the firm, as provided by I/B/E/S
IND-SAME	Indicator variable, equal to one if at least one analyst follows the supplier and its customer at the same time, and zero otherwise
AQ	Accrual quality, measured by the SDs of the firm-level residuals from the Dechow and Dichev (2002) model, as modified by McNichols (2002) and Francis et al. (2005), during the year $t - 5$ to $t - 1$. We multiplied *AQ* by negative one, with a higher *AQ*

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Appendix 2 (continued)

	indicating higher accruals quality. The model is a regression of working capital accruals on lagged, current, and future cash flows plus the change in revenue and PPE. All variables are scaled by average AT. The model is estimated for each industry with at least 20 observations in a given year based on the Fama and French (1997) 48-industry classification
SIZE	The natural log of market value of equity (CSHO×PRCC_F)
MTB	Market-to-book ratio, calculated as the ratio of the market value of AT (AT + (CSHO×PRCC_F) − CEQ − TXDB) to the book value of AT
ZScore	Bankruptcy risk, calculated as 3.3 × (PI) + (SALE) + 0.25 × (RE) + 0.5 × [(ACT − LCT)/AT]. The higher the score is, the lower is the likelihood of bankruptcy
LEV	Leverage, measured as the ratio of total liabilities to AT
OperatingCycle	Business operating cycle, measured by the natural log of receivables to sales (RECT/SALE) plus inventory to cost of goods sold (INVT/COGS) multiplied by 360
LOSS	Indicator variable equal to one if net income before extraordinary items (IB) is negative
CFOVOL	Cash flow volatility, measured by the SD of the cash flow from operations (OANCF) deflated by average AT from years $t-5$ to $t-1$
SALESVOL	Sales volatility, measured by the SD of the sales (SALE) deflated by average AT from years $t-5$ to $t-1$
INVESTVOL	Investment volatility, measured by the SD of investment from year $t-5$ to $t-1$. Investment is calculated as the sum of R&D expenditure (XRD), capital expenditure (CAPX), and acquisition expenditure (AQC) less cash receipts from sale of property, plant, and equipment (SPPE), multiplied by 100 and scaled by lagged AT
CC	The level of customer-based concentration, calculated as $\mathrm{CC}_{it} = \sum_{j=1}^{J}\left(CSALE_{ijt}/SALE_{it}\right)^2$, where $CSALE_{ijt}$ represents the sales of supplier *i* to customer *j* in year *t* and SALE_{it} is supplier *i*'s total sales in year *t.* A higher CC indicates more dependence of the supplier firm on its major customers
AGE	Firm age
NO_CUST	The number of identified major customers
Customer-based control variables	
CSIZE	The natural log of market value of equity (CSHO×PRCC_F) of identified customers
CLINK	The duration of the relationship between supplier and its identified customers
CDEP	The identified customers' dependency on supplier, measured by the supplier's sales to its identified customers divided by the customers' costs of goods sold in the same year
CSALESVOL	The identified customers' sales volatility. The sales volatility is measured by the SD of the sales (SALE) deflated by average AT from years $t-5$ to $t-1$
CCFOVOL	The identified customers' cash flow volatility. The cash flow volatility is measured by the SD of the cash flow from operations (OANCF) deflated by average AT from years $t-5$ to $t-1$
CAQ	The identified customers' accruals quality. *CAQ* is measured by the SDs of the firm-level residuals from the Dechow and Dichev (2002) model, as modified by McNichols (2002) and Francis et al. (2005), during the years $t-5$ to $t-1$. We multiplied *CAQ* by negative one, with a higher *CAQ* indicating higher accruals quality. The model is a regression of working capital accruals on lagged, current, and future cash flows plus the change in revenue and PPE. All variables are scaled by average AT. The model is estimated for each industry-year with at least 20 observations in a given year based on the Fama and French (1997) 48-industry classification
CAGE	Firm age of identified customers
NumQUALITY	Average numerical forward-looking information quality, measured in the three-year period prior to the investment efficiency measurement/acquisition period. For each year, it is computed as the natural log of (1+ [*Issuance*×*Frequency*×*Precision*]) (Baginski et al. 2002). The higher the value is, the better quality is the forward-looking numerical information

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Issuance	Indicator variable equal to one if an identified customer firm issues at least one management earnings forecast in a given year
Frequency	The number of management earnings forecasts issued by an identified customer firm in a given year
Precision	Precision of management earnings forecast; equals 0 if no forecast exists, 1 for general impression forecasts, 2 for minimum and maximum forecasts, 3 for range forecasts, and 4 for point forecasts
CABSCG_TONE	The aggregate measure of tone surprise of the customer's MEFRs, a proxy firm-specific linguistic information tone in a customer's MEFR. To form it, we first calculate four tone surprise measures by using four word lists (*GI*, *Diction*, *LM*, and *Henry*). Tone surprise measures are calculated as the aggregate absolute value of tone surprise of the customer's MEFRs issued in the year prior to the investment efficiency measurement/ acquisition period. Then, we rank each of these four measures into percentiles from 1 to 100 and take the average across four measures. The larger the *CABSCG_TONE* is, the greater is the absolute value of tone surprise of the customer's MEFRs
IND-CTONE	Indicator variable equal to one if the *CABSCG_TONE* of the customer's MEFRs is greater than the sample median of the same measure, suggesting a big absolute value of tone surprise of the customer's MEFRs that contain information about customer's future prospects

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:
Appendix A: Detailed description of four other key variable measurements.
Appendix B: Sample management earnings forecasts reports.
Appendix C: A discussion of selection-bias and endogeneity issues.
Appendix D: Probit regression on the issuance of customers' MEFRs.
Appendix E: Probit regressions for low linguistic information quality of customers' MEFRs.
Appendix F: Event-based M&A analyses.
Appendix G: Additional robustness checks.
Appendix H: Definitions for variables used in the Supporting Document.