The Power of Language: Does Vocabulary Richness Provides Values to Investors?

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Abstract

This paper investigates an unexplored linguistic feature, vocabulary richness, in earnings calls. By adopting the measurement from Yule (1944), we document a low vocabulary richness (high Yule's K) causes a decrease in initial market reaction and an increase in abnormal trading volume after earnings calls. Both the LDA topic analysis and Yule's K for pre-defined dictionaries support the idea that vocabulary richness captures the executive word choice, not the amount of information disclosed during earnings calls. Additional analyses using the change-on-change regressions and the shock-based instrumental variable approach, suggest the effect of vocabulary richness on market outcomes is causal. In terms of the underlying economic mechanisms, we show that the initial expectation of vocabulary richness plays an important role. Firms with a high market value, a significant analyst following, high R&D costs, and low current earnings are particularly prominent in the relationship between market outcomes and linguistic richness. Furthermore, we demonstrate that our richness proxy has long-term effects because the likelihood of future stock crash risk rises as word diversity decreases. Analysts also react to the linguistic diversity as a high Yule's K (low linguistic diversity) decreases both analysts' forecast speed and forecast likelihood when the earnings surprise is big. We conclude that vocabulary richness provides value to investors by helping them understand executives' messages more easily.

Keywords: Vocabulary Richness; Earnings Conference Calls; Textual Analysis; Yule's K characteristic; Stock Crash Risk; Analysts Forecast Speed

“Language is power... Language can be used as a means of changing reality.”

—by Adrienne Rich (American poet)

“We tend to look through language and not realize how much power language has.”

—by Deborah Tannen (American author)

1 Introduction

Financial disclosures comprise a variety of components, but language is one of the most crucial. Although many characteristics of language within financial disclosures have been studied in the finance and accounting literature (Li, 2008; Loughran and McDonald, 2011; Loughran and McDonald, 2016; Blankespoor et al., 2020), to the best of our knowledge, no previous business research has examined the vocabulary richness.

Vocabulary richness, also known as lexical diversity, refers to the vocabulary range of speakers (Bradac et al., 1979; Daller et al., 2003). Texts that are lexically diverse use a wide range of vocabulary, avoid repetition, utilize exact language, and make use of synonyms to convey ideas. In contrast to the readability index, which evaluates sentence complexity, vocabulary richness captures linguistic flexibility, which involves communicating your idea in a competent and convincing manner so that your audience can easily understand your point.

Previous linguistic research has demonstrated that the "desire for complexity" principle influences how audiences evaluate a speaker's vocabulary (Bradac et al., 1977a). In particular, diverse language is preferred by audiences because it is engaging, competent and convincing. Therefore, we want to test this principle in a business context. To be more explicit, we want to know whether a vocabulary-rich earnings call adds value to investors. The reason we use conference calls is twofold. First, earnings conference calls contain spontaneous sections that managers cannot prepare in advance. In addition, Yu (2010) indicates a considerable disparity between the lexical diversity of speaking and writing activities. Using the spontaneous portion of earnings calls, we may directly determine the level of executives’ vocabulary richness since prior research establishes a link between vocabulary richness and communicative ability and efficiency (Crossley et al., 2012). Second, the immediate market outcomes following earnings conference calls enable us to exclude other confounding variables and focus on the relationship between vocabulary richness and investor responses. In conclusion, the textual data we analyzed was built on the response provided by executives during the discussion session.

To measure vocabulary richness, we employ the index developed by Yule (1944), one of the earliest metrics in history. Yule's K characteristic is described as the coefficient variance of λ, when the word in the text follows a Poisson distribution. Therefore, Yule's K counts the frequency of repeated words in a text. A high Yule's K indicates that the vocabulary is concentrated, and words are repeated frequently. In contrast, a low Yule's K value implies that the vocabulary is more diverse and less reliant on a few specific words. After creating the measurement and combing it with all available firm information, our final sample from 2007 to 2020 consists of 79,884 conference calls for 3,095 unique companies.

Before presenting our investors' reaction results, we first demonstrate the validity of the vocabulary richness and present the factors that determine our richness index. On average, we find the level of vocabulary richness is higher for U.S. firms than for non-U.S. firms, supporting the notion that firms in countries with significant language barriers in English have poor language skills (Brochet et al., 2016).

Our determinants analysis reveals the level of Yule's K is inversely correlated to fog index, indicating that a high vocabulary richness is typically linked with difficult sentences. In addition, we also observe a negative correlation between Yule's K and the number of total words. For firm fundamentals, we find executives from large firms tend to use more diverse words during the discussion session. On the contrary, book to market ratios and special items are negatively associated with vocabulary richness.

One potential question is whether the vocabulary richness captures the word usage of executives or the various types of information discussed during earnings calls. To explore the answer, we conduct two tests. First, we perform an LDA topic analysis model developed by Blei (2003) to determine the number of topics within each call. Suppose vocabulary richness presents more facts of the company that have been discussed during the earnings calls, then we should observe a negative relation between the number of topics and our Yule's K ratio, since a high Yule's K indicates content with fewer unique words. On the contrary, if we observe a positive correlation, it means that high vocabulary richness does not imply more topics embedded within the text, but rather more diverse words used under the same subject. Our results support the latter explanation as we observe a positive and statistically significant relation between the number of topics and Yule’s K ratio.

Second, we construct the Yule’s K for pre-defined dictionaries, such as those created by Loughran and McDonald (2011) and Mastomoto et al. (2011). If our results are influenced by the fact that more features of companies are discussed during earnings calls, we should not find significant results when calculating Yule’s K for some pre-defined word lists as they are intended to be under the same subject. Our results support the same conclusion as the LDA analysis since we obtain similar market outcome results if we use the new Yule’s K from these two pre-defined dictionaries. These results convey a consistent message that vocabulary richness captures the linguistic diversity of executives and not the quantity of information disclosed.

In our market outcomes tests, we find support for the “preference for complexity” principle (Bradac et al., 1977a). A large Yule’s K within earnings calls, which means less diverse language, yields a negative market reaction after controlling for all firm fundamentals and textual features within the calls. In addition, we also find supporting results by using abnormal trading volume. We provide a positive correlation between abnormal trading volume and Yule’s K, which is consistent with the idea that trading volume represented a lack of consensus regarding the appropriate price level (Beaver, 1968).

Besides, our initial results incorporate firm and year fixed effects to account for time-invariant firm unobservables and yearly changes in macro conditions. Our findings still hold with additional, more restricted fixed effects. For instance, our results are consistent if we account for firm per year and call date fixed effects. In addition, to account for the differences in company characteristics other than lexical diversity that may bias our results, we adopt the propensity score matching method, and the matched sample results are still supporting our main findings. Following the introduction of Yule's K, linguistic literature provides numerous more proxies for lexical variation (Guiraud, 1954; Carroll, 1964; Somers, 1966; Mass, 1972; Dugast, 1978). Our robustness test also reveals that our results are statistically significant in the same direction when applying all other lexical diversity indices.

By utilizing both the change-on-change regressions and the shock-based instrumental variable (IV) approach, we establish a causal effect of vocabulary richness on short-term market outcomes. Consistent with our main findings, we discover that the change of Yule's K is followed by a significant decline in investors' initial reactions. In our shock IV analysis, we use the passage of the state's paid sick leave law as an exogenous change to the lexical diversity within earnings calls. The two-stage least squares regressions show that the instrumented Yule's K is negatively (positively) related to the short-term market reaction (trading volume). All the above results suggest that the influence of vocabulary richness on initial investors' response is likely to be causal.

In the channel analysis, we find investors initial expectations have a significant impact on the relationship between vocabulary richness and investor reactions. To be more specific, if audiences anticipate a high diversity message from the executives, they will reward executives for meeting this expectation and punish them for failure to do so. We first demonstrate that high-profile firms, measured by market value and analysts following, are punished more by investors if their language is less diverse. This finding supports the idea that speakers' social status influences audiences' judgment of high or low word diversity messages (Bradac et al., 1976). In addition, we find information within earnings calls also affects the relation between vocabulary richness and market outcomes. When the underlying material is difficult for people to understand, investors anticipate explanations with a high lexical diversity. Specifically, we find firms with higher R&D expenses, negative earnings, or missed analysts' forecasts, where investors expect more explanation from executives, have poor initial market reactions than their counterparties.

Next, we show that our results are not only significant for initial reaction, but also for long-term consequences. In particular, the long-term effect we are examining is the stock crash risk. We discover that low vocabulary richness (high Yule's K ratio) will increase the chance of future crash as investors infer that difficult-to-digest statements containing more risk (Bloomfield, 2002). Further, we illustrate that other stakeholders also react to the level of vocabulary richness within earnings calls. Specifically, we find a high Yule's K reduce both analysts' forecast speed and forecast likelihood when the earnings surprise for that quarter is large.

Finally, we demonstrate that our vocabulary richness proxy is still applicable in various contexts, such as annual reports and the analysis of CEOs' lexical diversity. Using our vocabulary richness proxy, we reproduce the finding of Li (2008), who analyses the persistence of earnings and linguistic readability. We find that if the Yule's K is large, indicating a low word richness, earnings are less persistent, which is consistent with the notion that managers have the incentive to suppress undesirable information. Regarding individual vocabulary richness, we first choose all answers from CEOs, aggregate our original data into speaker per year level, compute Yule's K for the new yearly CEO's response during earnings calls, and then merge it with Execucomp data. By investigating which CEO characteristics contribute to vocabulary richness, we find that females and older CEOs use a greater variety of words during earnings calls.

Overall, our research highlights the notion that how you talk matters as using a wide range of language adds value to investors by helping them understand embedded information easily. Consequently, our research makes three significant contributions. First, as the first paper to investigate the vocabulary richness issue in a business context, our paper contributes to the literature in discovering important linguistic features within financial disclosures. Previous research finds that linguistic features, such as readability and tone, affect investors' perceptions of a company's future performance. In this study, we add another linguistics attribute, vocabulary richness, and argue that messages with diverse languages are competent and convincing to investors.

More broadly, we add to the growing literature that applies computational linguistics and a variety of machine-learning-based techniques in finance and accounting research, such as topic analysis, linguistic similarity, and text embeddings, to generate various company proxies (Cazier and Pfeiffer, 2017; Dyer et al.,2017; Hassan et al., 2019; Li et al., 2021). Due to the black box problem in machine learning, traditional statistical-driven methods in linguistic research are more robust and transparent. Other than vocabulary richness, there are many linguistic attributes that can be explored by researchers in finance and accounting, such as language intensity (Bower, 1963) and verbal immediacy (Wiener and Mehrabian, 1967) to better interpret business communication.

Second, our results improve the understanding of the information content of earnings calls. Prior research examines how tone, readability, or vocal cues affects market participants (Li, 2008; Loughran and Mcdonald, 2011; Mayew and Venkatachalam, 2012; Price et al., 2012). Consistent with previous literature, linguistic features within conference calls influence investors' ability to process disclosures (Blankespoor et al., 2020). We demonstrate that vocabulary richness, a previously unexplored linguistic attribute in business research, affects disclosure processing costs by facilitating market participants' interpretation of conference call information. Specifically, we show high Yule's K (poor vocabulary richness) within executives' answers during earnings calls is associated with unfavorable initial market reactions.

Third, our findings also contribute to the field in computational linguistic by constructing a large sample analysis for vocabulary richness in a business context. The majority of early research on vocabulary richness involves experimental approaches by interviewing individuals or conducting controlled experiments. However, because of the high expense of these procedures, their sample size is relatively small. Nowadays, many studies exploit this feature in social media and use it to distinguish robot-generated content from humans (Inuwa-Dutse et al., 2018). However, none of previous research studies vocabulary richness in the business context. Our paper tries to fill this gap by providing the first systematic analysis of how vocabulary richness influences business communication and how stakeholders response to it.

Remainder of the paper is organized as follows. Section 2 discusses our vocabulary richness measurement and develops the main hypotheses. Section 3 outlines the research design and sample construction. In Section 4, we present our baseline empirical analyses and further tests to demonstrate the causality. Section 5 provides additional analyses to illustrate the applicability of our vocabulary richness proxy in other business contexts. Finally, Section 6 concludes the paper.

2 Background and Hypothesis Development

2.1 Vocabulary Richness: Yule's K Characteristics

Vocabulary richness, or lexical diversity, is one of the key linguistic features that has been widely studied by linguistic researchers since early 1940s. Vocabulary richness refers to the vocabulary range that speaker exhibits and is measured as the proportion of unique words generated relative to the overall number of words (Bradac et al., 1979; Daller et al., 2003; Zhang, 2014). Low vocabulary richness indicates that a speaker's vocabulary is relatively redundant, whereas high vocabulary richness suggests that it is fairly diverse.

In this paper, we apply the vocabulary richness measurement developed by Yule (1944), which is one of the oldest measurements in history. The detail definition can be expressed as follow: let N be the total number of words in a text, $V(N)$ be the number of distinct words, $V(m,N)$ be the number of words appearing m times in the text. Yule's K is then defined as the first and second moments of the vocabulary population distribution of V(m,N), where $S_1 = N = \sum_m mV(m,N)$ and $S_2 = \sum_m m^2V(m,N)$ (Yule 1944; Herdan 1964):

$$Yule's\ K = C * \frac{S_2 - S_1}{S_1^2} \qquad (1)$$

where C is a constant enlarging of the value of K, defined by Yule (1944) as C = 10,000. K is designed to measure the vocabulary richness of a text: The larger Yule's K, the less rich the vocabulary is. A simple example can be given in terms of S_2 in this formula. Suppose a text is 10 words long: if each of the 10 words is distinct (high diversity), then S_2 = 1 × 1 × 10 = 10; whereas, if each of the 10 words is identical (low diversity), then S_2 = 10 × 10 × 1 = 100. As a result, the text with 10 identical words has a much higher Yule's K ratio ($Yule's\ K$ =900) than the sentence with 10 distinct words ($Yule's\ K$ =0). The detail mathematical construction for the Yule's K can be found in Appendix I.

Previous research demonstrates that vocabulary richness affects listeners' judgment of speakers through a principle of "preference for complexity" (Bradac et al., 1977a). To be specific, audiences prefer complexity in vocabulary because it is interesting, competent, and persuasive. Following this study Bradac and his colleagues conducted a series of experimental studies confirming the above relationship and concluding that vocabulary richness is directly related to perceptions of a speaker's competence, socioeconomic status, and message effectiveness (Bradac et al., 1976; Bradac et al., 1977b; Bradac et al., 1977c). Recently, vocabulary richness has been linked to the competence and effectiveness of individuals' communication skills (Crossley et al., 2012; Lu, 2012). For instance, Lu (2012) concludes that lexical diversity can be effectively used as an indicator of the quality of the speaking performance quality of English as a second language learners.

On the other hand, another line of research investigates the factors influencing individuals' vocabulary richness. For instance, several experimental studies find that increases in anxiety leads to an increase in word repetition and a decrease in vocabulary richness (Kasl and Mahl, 1965; Mahl, 1956; Miller, 1964). In studies of adult aphasia, vocabulary richness has been identified as an effective general index for distinguishing aphasia patients from general public (Holmes and Singh, 1996; Wright et al., 2003). In addition, neuroscientists today use advanced medical technologies to establish a connection between vocabulary richness and aphasia. For example, Fergadiotis and Wright (2011) argue that the human brain undergoes a series of processes before a person can produce vocabulary-rich speech. To be specific, a speaker needs to possess implicit vocabulary knowledge and access and retrieve target words. However, these brain activities are impaired in aphasic individuals. Using MRI-based image analysis on the brains of adults with and without aphasia, Wilmskoetter et al. (2019) found that reduced lexical variety is associated with language hub regions of the brain, a core for language processing. Overall, this line of research reveals that the determinants of a person's vocabulary depth are influenced by both psychological and physical aspects.

As a result, we could summarize from previous linguistic literature that audiences take into account the speaker’s vocabulary richness and prefer speech with a high vocabulary richness. A wide range of vocabulary will grab the attention of the audience and earn their trust. On the other hand, psychological factors also affect the language usage of speakers. In particular, a person who is more anxious will have a less broad vocabulary during communication. However, to the best of our knowledge, none of the previous studies links the vocabulary richness to the business context. In this paper, we will investigate how audiences, in this case investors, react to the vocabulary richness of quarterly earnings calls and what factors influence the lexical diversity.

2.2 Literature Review and Hypothesis Development

The textual features within business context have been studied in recent years. One of the first papers that systematically analyze textual features within annual reports is developed by Li (2008). In that paper, Li investigates linguistic complexity and finds that disclosures of unfavorable information tend to be less readable, and that linguistic complexity can be interpreted as an indicator of future earnings. In recent years, several scholars have investigated readability in other business contexts or used other proxies for linguistic complexity and reached the same conclusion. (e.g., Merkley 2014; Bonsall et al. 2017). The primary reason is that high linguistic complexity increases investors’ disclosure processing costs. Consequently, investors are less incentivized to acquire the information within disclosures (Blankespoor et al., 2020).

The other important textual feature that has been widely studied is linguistic tone. Davis et al. (2015) suggest that the tone of earnings release is positively correlated with future performance. Moreover, Price et al. (2012) investigate the sentiment within earnings calls and find the textual tone conveys additional information beyond traditional firm fundamentals in predicting future stock returns. The other line of research looks into the determinants for sentiment within different business disclosures and argues that managers' characteristics and external factors, such as weather, are effective determinants for linguistic tone (Huang et al., 2014; Francis et al., 2021).

Nowadays, studies are trying to extract other linguistic features from business contexts by using advanced natural language processing (NLP) technologies, such as topic analysis, linguistic similarity, and text embeddings. For example, Cazier and Pfeiffer (2017) find a slower price response to 10-K filings, which contain a higher percentage of repeating paragraphs from the previous year. In addition, Dyer et al. (2017) use the LDA topic analysis model to determine the number of topics inside 10-K filings and conclude that the growth in length of 10-K is mainly due to the rise in the number of subjects associated with each annual report. Other recent articles also employ machine learning methods to extract new information within various disclosures (Hassan et al., 2019; Li et al., 2021).

As Blankespoor et al. (2020) explain, all these linguistic features within various disclosures eventually influence investors' ability to process those disclosures. Blankespoor et al. (2019) categorize investor information processing into three broad types: information awareness, information acquisition, and information integration. As vocabulary richness is also a linguistic feature within the text, we can anticipate that it influences investors' information processing.

Since vocabulary richness is directly related to the message effectiveness, investors prefer complexity in word selections because it is engaging, contains precise words to explain current situation, and are more likely to capture investors' attention than speech with repeated words. Thus, we could conclude that a high vocabulary richness will reduce investors' processing costs, particularly information integration costs. Therefore, a high vocabulary diversity eventually increases initial market reaction, as investors can easily digest the executives' information. Since our Yule's K exhibits an inverse relation with vocabulary richness, we could hypothesize that:

H1: There is a negative relation between market reaction and Yule's K ratio.

On the other hand, trading volume has been tied to disclosure processing cost since Beaver (1968), which states that trading volume reactions reflect a lack of consensus regarding the appropriate price level. According to Kim and Verrecchia (1991), trading around a public announcement is a joint function of prior differential precision and the absolute price change at the announcement. In addition, a high vocabulary richness actually decreases the disagreement among all investors, eventually making the embedded information more transparent for all investors. Thereby, investors' disagreement will increase when there is a low vocabulary richness, which will increase the trading volume after the earnings calls. As a high Yule's ratio indicates a low vocabulary richness, we can hypothesize that:

H2: There is a positive relation between market reaction and Yule's K ratio.

In Bradac et al. (1976), they study how speaker's social status influences audiences' evaluation of message with high or low words diversity. After implementing an experiment with college students, they find that the initial perception of a speaker's status would influence their judgment. To be more explicit, if audiences anticipate a high diversity message from high-status speakers, audiences will reward those who meet this expectation and punish those who do not.

If we extend this logic to a business context, we might assume that investors anticipate a vocabulary-rich discourse from prominent corporations. When a company's messages falls short of expectations, investors will be disappointed and depreciate the company. Consequently, we could hypothesize that:

H3: The relation between market outcomes and vocabulary richness is mitigated by the reputation of companies.

Since the expectation of vocabulary richness has a significant impact on investors' valuations, we can assume that the type of information contained in earnings calls are equally important to investors. As a result, we can expect that investors would require more specific or simple-to-understand information from companies with complex concepts or news. For instance, investors expect more diverse language when firms have more R&D expenses, which helps investors to understand the current situation. Moreover, according to loss aversion, individuals have a greater aversion for losses than gains, which is consistent with prospect theory (Kahneman and Tversky, 1979; Thaler, 1985). Therefore, bad news will grab more attention than good news, and investors seek an explanation with diverse language to help them process the bad news. Thus, we hypothesized that:

H4: The relation between market outcomes and vocabulary richness is mitigated by the complexity of the underlying information.

3 Data and Methodology

3.1 Sample Construction

We begin our data with all earnings conference calls from Capital IQ. In comparison to other data sources, Capital IQ provides complete sets of transcripts with detail speaker information within each transcript. Table 1 describes the selection process of our sample. The initial sample consists of 106,913 earnings calls for which earnings transcripts are accessible through Capital IQ.

[insert Table 1]

Due to the limited coverage of earnings calls in Capital IQ before 2007, we choose 2007 as the start year of our sample. Thus, our sample further reduces to 106,449. Then, we combine the financial information from Compustat, analysts' forecasts from I/B/E/S, stock trading data from CRSP, and security issuance data from SDC. After these steps, our final sample consists of 79,884 conference calls from 3,095 unique companies.

3.2 Variable Definition

3.2.1 Dependent Variable: Market Outcomes

Our primary dependent variable is investor reactions, which rely on the returns and trading volumes in CRSP data. Following Blankespoor et al. (2020), we construct the measurements for the market outcomes as a 2-day cumulative abnormal return (CAR) or abnormal trading volumes after the earnings call date. To be specific, CAR is calculated based on the Fama-French three-factor model and cumulated over a two-day window [0.+1] around earnings calls date. The abnormal trading volume is measured as the average daily volume over trading days [0,+1] divided by the average daily volume over days [-41,-11]. In our additional analysis section, we also look at analysts' reactions and long-term market consequences, such as the stock crash risk. We will introduce the detail definition for these variables in the later section.

3.2.2 Key Independent Variable: Vocabulary Richness

As discussed in our background section, we rely on Yule's K characteristics (Yule, 1944) to measure vocabulary richness. Therefore, to construct a comparable measurement across all firms, we take the actual value of Yule's K and standardized the variable around mean 0 and variance 1 as follows:

$$ZYule's\ K = \frac{Yule's\ K - Mean(Yule's\ K)}{\sigma(Yule's\ K)}$$

where $ZYule's\ K$ is the standardized vocabulary richness measurements, $Mean(Yule's\ K)$ is the average of Yule's K in our sample, and the $\sigma(Yule's\ K)$ is the sample standard deviation of Yule's K. We use this standardized measure in all our estimations, but all of our results remain valid with the actual measure as well.

Previous research emphasizes the importance of information content within earnings calls, especially the Q&A section. Lee (2016) argues that investors reward spontaneous answers compared to scripted ones during the discussion section. To this end, we intentionally separate our conference call transcripts into three distinguish sections: presentation sections, executives' discussion section, and analysts' discussion section. Then, we compute Yule's K for all three sections. Figure 1 illustrates the yearly Yule's K ratio trend in each section within earnings calls.

[insert Figure 1]

As depicted in the graph, it is evident that Yule's K for the presentation section and discussion section follow opposite trends. To be specific, there is a decreasing trend in Yule's K for presentation section, which means presentation section contains more diverse words in recent years. However, Yule's K has been increased in the Q&A section for both executives and analysts. This divergence between Q&A and presentation sections provides supporting evidence that the style of written language in the presentation section differs from spontaneous answers in the discussion section (Rowley-Jolivet and Carter-Thomas 2005).

Besides the yearly changes, we also study the distribution of mean vocabulary richness across industries. To do so, we calculate the average Yule's K ratio for the above three different sections based on the Fama-French 12 industries classification, and the results are shown in Figure 2.

[insert Figure 2 here]

We observe variations among these 12 industries. For instance, consumer non-durable, utilities, and healthcare industries employ more diverse language during the discussion sessions. On the contrary, executives in the telephone and television industry answer analysts' questions with a limited choice of words. Furthermore, we may also find that many industries exhibit a divergency between presentation sections and Q&A sections. For example, manufacturing, oil and gas, and wholesale industries display an opposite direction between their Yule's K ratio between presentation section and Q&A section.

3.2.3 Control Variables

To explain how vocabulary richness influences market outcomes, we deploy univariate and multivariate regression analysis. In our multivariate analyses, in addition to our standardized Yule's K measurement, we include three types of control variables that are known to affect short-term market outcomes. The first set relates to firm status and financial performance in each quarter. Specifically, we use the logarithm of firm size (measured as the natural log of total assets), book value to market value ratio, return on total assets, accruals (measured as accruals relative to total assets), and a binary variable indicating negative earnings as our controls for quarterly firm performances.

The second set of control variables relates to monitoring from outside stakeholders such as investors and analysts. The variables are surprise earnings (measured as the difference between actual earnings and the consensus analyst forecast divided by the actual earnings), the logarithm of the number of analysts present in the earnings conference call in each quarter, and an indicator variable to distinguish whether the firm meets earnings expectations in that quarter.

The last set of control variables relates to the textual features within earnings calls. Prior literature demonstrates that soft information within earnings calls matters to market participants. For example, Price et al. (2012) conclude that the sentiment within earnings calls is positively related to the stock market reaction. Also, to mitigate the concerns that our vocabulary richness measurement is correlated with readability index, we further control the fog index within the transcript as an additional control. Last but not least, recent literature has identified the language mirroring between analysts and executives during earnings calls (Brightbill et al., 2022). As a result, we also control for the vocabulary richness of analysts' language during the discussion session to relieve the concern that our results may be driven by analysts' language diversity. Detailed variable definitions are provided in Appendix II.

3.3 Descriptive Statistics

Table 2 displays descriptive statistics for the variables in our primary analyses. As discussed above, our standardized vocabulary richness measurements have an average equal to zero, and a standard deviation equal to one. In terms of market reaction, we find two days market reaction after the earnings call is 0.3%, which is consistent with previous literature. We also find the abnormal trading volume is 0.643, which means the trading volume is 64.3% higher than normal trading period.

Our sample firms have an average of 2.137 billion of assets, book-to-market ratio (*Book to Market*) of 0.553, accruals (*Accrual*) of 0.007, and return-on-assets (*Return on Assets*) of 0.003. In addition, 16.3% of the firms in our sample report a loss in a given quarter, and 64.7% of the observations meet the consensus analyst earnings forecast. The table also reports that the average sampled firm has 6.53 following analysts in a given quarter.

3.4 The Uniqueness of Vocabulary Richness

Before formally examining how vocabulary richness influences initial market outcomes, it's important to present the uniqueness of vocabulary richness. In other words, why do we need to look at vocabulary richness in the business context? Therefore, we conduct several analyses to prove that the vocabulary richness measurement we introduced in this paper is unique from other major textual features.

3.4.1 U.S. Firms and International Firms Comparison

Because our sample consists of all firms listed in the U.S. market, we first compare the textual features between U.S. firms and non-U.S. firms. Brochet et al. (2016) conclude that earnings calls of firms in countries with greater language barriers are more likely to contain non-plain English and erroneous expressions. Following their argument, we divide our sample into two subgroups based on the headquarter location. The results are shown in Panel A of Table 3.

[insert Table 3]

As foreign managers are assumed to have worse language skills than managers based in the United States, we find that the Yule's K ratio is lower for U.S managers compared to non-U.S. executives in the Panel A of Table 3. Moreover, we observe a similar trend for analysts' questions. Interestingly, we also discover an opposite trend in the presentation section as the vocabulary richness is much higher for foreign firms than US firms, highlighting the difference between written and speaking language. Further, we also show the difference between three other major linguistic features within earnings calls. For instance, we find earnings calls from U.S. firms have more words, more positive sentiment, and lower linguistic complexity within the Q&A section than calls from foreign firms.

3.4.2 Correlation Analysis

Then, we performance a correlation analysis for our Yule's K with all other textual features, such as sentiment, the total number of words, fog index, and the richness measurements in the other two distinguish sections in earnings calls. Panel B of Table 3 reports the correlation matrix.

Panel B clearly supports the argument that the readability index and Yule's K ratio measure different aspects of the text as the correlation coefficient is negative and statistically significant at 1% level. If these two measurements are supplements to each other, we should observe a positive correlation here as both high fog index and high Yule's K ratios are proxied for high complexity, which eventually increases the disclosure processing cost. Further, we also observe a positive correlation between any two of the three Yule's K ratios for different sections. Interestingly, we find the total number of words is negatively correlated with Yule's K, which means more words will increase the vocabulary richness index. This negative coefficient raises concerns about whether our vocabulary richness measurement measures the word diversity or just the scope of the talk during the discussion section. As a result, we will provide a direct test on this relation by performing a topic analysis in the later part of this section. Last but not least, there is also a positive correlation between the sentiment and vocabulary richness index. However, the coefficient is quite small compared to the other correlation pairs.

3.4.3 Determinants Analysis

Following Li (2008), we implement a similar determinants analysis to find the factors that influence the vocabulary richness om earnings calls. To do so, we employ the following regression model:

$$ZYule's\ K_{i,t} = X_{i,t}^{li}\beta + I_i + W_T + \epsilon_{i,t} \qquad (2)$$

where $X_{i,t}^{li}$ is the vector of firm-level characteristics that described in Li (2008) paper. For instance, Li mainly separate controls into several boarder categories, such as firm fundamentals, firm performance volatility, business complexity, and current year external financing event. A detail description of these controls can be found in Appendix II.

Before we perform the determinants test for the vocabulary richness index, we first replicate Li (2008) by investigating how his identified factors influence the readability level in earnings calls. To be specific, we run the above equation (2) by replacing the dependent variable with the fog index in Q&A section. The result is shown in column (1) of Panel C.

As you can see from the results, all the coefficients are consistent with Li (2008), which uses annual reports as the disclosure outlet. For example, we still find the readability index is positively related to firm size and negatively related to special items. On the contrary, if we switch our variable of interest to vocabulary richness, we find the opposite coefficient for these two variables. Specifically, large firms exhibit a diverse world selection to form their answers to analysts' questions, and firms with a high percentage of special items use more concentrated words. This divergence in coefficients for determinants of readability and vocabulary richness provides additional support for our argument that these two textual features capture a different aspect of underlying textual content.

Column (3) and (4) further investigate the above correlation in a regression setting by putting textual feature controls and fixed effects into it. The difference between column (3) and (4) is the last column replace the industry fixed effect with a more restricted firm fixed effect. However, all the results are still consistent with our univariate correlation analysis in Panel B. In the next subsection, we want to answer whether the high vocabulary richness means more aspects of firms have been disclosed to the market or this high index means more diverse word usage under the same subject.

3.4.4 Content Analysis

Previous sections illustrate a negative relation between the number of words and Yule's K ratio within earnings calls, which raises the question of what does vocabulary richness really capture? In this section, we employ a Latent Dirichlet Allocation (LDA) model developed by Blei et al. (2003) on the corpus of all earnings calls. If vocabulary richness presents more aspects or facts that have been discussed during the earnings calls, we should observe a negative coefficient between the number of topics and our Yule's K ratios, as a high Yule's K index represents content with more limited unique words. On the contrary, if we observe a positive relation, which indicates high vocabulary richness does not mean more topics embedded with text but more diverse words used under the same subject.

To empirically test the above argument, we employ the similar regression model as equation (2) but replace our dependent variable with the number of topics within each earnings transcript. Because the LDA model provides topics with probability to each textual content, we limit to the topics that have more than 25% of confidence level to relief the concerns that our results are driven by some topics with a small probability. The detail of our steps for implementing the LDA model can be found in appendix III. Furthermore, the result is shown in the Panel D of Table 3

All coefficients for our vocabulary richness measurements are negatively and statistically significant across all three model specifications. These negative coefficients provide evidence for the later explanation that high vocabulary richness actually means more diverse word selection when answering questions from analysts.

4 Research Design and Empirical Results

4.1 Univariate Analysis

After confirming that our vocabulary richness measurement actually introduces a new textual feature, we begin our empirical analysis by providing univariate results of the market outcome variable for a different level of vocabulary richness. To do so, we separate our Yule's K ratio into quintiles and calculate each group's mean market outcome variables. Table 4 reports our univariate results for different quintiles.

[insert Table 4]

In the last two columns of the table, we could see a significant difference in market outcome between calls in the bottom quintile (low Yule's K ratio means high vocabulary richness in the content) and calls in the top quintile (calls with limited word diversification). For instance, compared to the bottom quintile, the top quintile group, on average, has 18 basis points lower 2-days market reaction, which accounts for more than 50% reduction from the bottom quintile group. The result is consistent if we use the abnormal trading volume as our market reaction proxy. The bottom quintile group has lower trading volume than the top quintile group.

[insert Figure 3]

Figure 3 plots the cumulative abnormal return for the above two groups in a 10-days window after earnings calls. On average, the market reaction for the top quintile group is significantly smaller than the bottom quintile group. However, all above results only give us the univariate relation between vocabulary richness and market outcomes. In addition, many confounding factors may influence the market outcomes. For example, earnings calls with high vocabulary richness may have low earnings in that quarter, which may simultaneously influence market outcomes. To mitigate the concerns, we employ multivariate analysis in the following section.

4.2 Vocabulary Richness and Market Reaction

4.2.1 Research Design

In order to test our primary predictions, we examine the relation between Yule's K ratio and market reactions to earnings calls while controlling for the determinants that influence market reactions based on prior literature (e.g., Berkman and Truong, 2009; Huang et al., 2014; Davis et al., 2015). In particular, we estimate the following model using all of the firm-quarters in our sample:

$$Y_{i,t} = \alpha_1 ZYule's\ K_{i,t} + X_{i,t}\beta + v_i + W_T + \epsilon_{i,t} \qquad (3)$$

where $Y_{i,t}$ is the market reaction variables, in our case, which are the absolute value cumulative abnormal return (*CARs [0,+1]*) and the abnormal trading volume (*Volumes[0,+1]*). The definition for $ZYule's\ K_{i,t}$ is standardized yule's K measurement for vocabulary richness. A high number in

$ZYule's\ K_{i,t}$ means the content is less words diverse. We include a set of controls ($X_{i,t}$) that influence the market reactions to earnings calls as described in previous sections.

We also augment each model with firm and year fixed effects to control for heterogeneity across companies and time. Firm fixed effects control for time-invariant unobserved differences across firm that jointly affect market reactions to the vocabulary richness. Year fixed effects control for macroeconomic conditions and time trends for short-term reactions. In our robustness check section, we also implement more restricted fixed effects, and our results are still survived.

4.2.2 Result

Table 5 presents results from estimating equation (3). Column (1) and (4) report the results when only the firm and year fixed effects are included. The coefficient on *ZYule's K in ExeQnA* is negative (-0.002) in column (1) and positive (0.007) in column (4). Both of them are statistically significant at the 1% level, suggesting that earnings calls with high Yule's K ratio (low vocabulary richness) have high information processing costs, which eventually lower short-term market reactions and increase the short-term trading volume.

[insert Table 5 here]

Column (2) and (5) of Table 5 further include a series of time-varying firm performance characteristics. We find the better financial performance (*ROA*) is associated with positive short-term market reaction and high trading volume. Also, firms that meet analysts' forecast yield a positive abnormal return and negative abnormal trading amount. Besides, the magnitude of the estimated coefficient on *ZYule's K in ExeQnA* for market reaction (trading volume) changes as -0.002 (0.010) with 1% (1%) significance level. The negligible magnitude change suggests that our vocabulary richness proxy is likely uncorrelated with other known firms' characteristics that affect the short-term market outcomes of earnings calls.

Further, we add other textual features mentioned in prior section in column (3) and (6). Surprisingly, after controlling for all textual measurements that may influence market reactions, the magnitude of our variable of interest becomes larger than previous specifications, and the coefficients are still statistically significant at 1% level.

To this stage, our results in Table 5 support our hypothesis that the calls with low vocabulary richness are hard to digest and need more effort from investors to discover the useful information within the transcripts. This argument is consistent with Blankespoor et al. (2019) that high information processing costs will increase the information asymmetry between firms and investors, which eventually achieve an unfavored initial market outcome. However, our results may suffer several endogenous concerns. For instance, some unobserved systematic differences for firms with different levels of vocabulary richness may influence market reactions. Even though we could not test all endogenous issues directly, we will show several tests in the following subsections to relieve this concern.

4.3 Change-on-change Analysis

We next try to demonstrate that our results are not driven by unobserved characteristics. To do so, we provide a change-on-change specification as vocabulary richness may represent the executive's personality instead of firm characteristics. Originally, the Yule's K characteristic was designed to identify the authorship of books (Yule, 1944). As a result, vocabulary richness is an indicator of the person's overall intelligence (Sternberg, 1987). In this case, a standard firm fixed effect cannot capture all the unobserved variables, such as the intelligence level of executives.

To tackle this issue, we employ a change-on-change regression specification, which helps us to capture the variation in our variable of interest, while removing time-invariant unobservable. Previous literature also uses this change-on-change model to investigate how technology improvement influences the capital structures (Bloom et al., 2016; Bena and Xu, 2017). As a result, we employ the following regression model:

$$\Delta Y_{i,t} = \alpha_1 \Delta ZYule's\ K_{i,t} + \Delta X_{i,t}\beta + v_i + W_T + \epsilon_{i,t} \qquad (4)$$

where $\Delta Y_{i,t}$ is the change in market outcome from previous quarter to current quarter. The definitions of all right-hand side variables are similar to our equation (3), except we use the different between current quarter and previous quarter as the value input in our equation (4) instead of the raw value in original equation (3). Finally, we also include firm and year fixed effects to account for the temporal shocks. Using the above model specification, we try to ask whether the changes in vocabulary richness are followed by changes in market outcomes. Table 6 presents the result.

[insert Table 6]

Table 6 shows that the effect of a change in Yule's ratios is negatively (positively) related to the short-term market reaction (abnormal trading volume) in different model specifications, similar to Table 5. Overall, the change-on-change regressions provide suggestive evidence that vocabulary richness has a causal effect on market reactions to earnings calls. Moreover, the change-on-change relief the concerns that our results are driven by some unobservable that is constant throughout the time.

4.4 Shock-Based IV Analysis

In this section, we seek to address a potential endogenous issue by using a shock that influences executives' vocabulary richness in the discussion section. The shock-IV method has been widely used in previous literature. An ideal shock would change the vocabulary richness level exogenously, and the effect of the shock on the outcome must come only through the shock (Atanasov and Black, 2016). To be specific, we need to find a shock that will change the vocabulary level within the earnings calls, but this shock does not have a direct link with short-term market outcomes.

The shock we choose to use is the passage of state Paid Sick Leave laws (PSL). The availability of PSL ensures that employees are protected from wage deductions when they are unable to work due to some unforeseen illness. A recent paper by Chunyu and Zhu (2022) documents the staggered implementation of PSL leads to higher firm productivity and profitability. They attribute this positive relation to the improvement of employee health. On the contrary, as PSL law can be viewed as an opportunity for executives to learn the importance of employees, we can expect that the vocabulary within earnings calls will be increased as managers can discover more links between firms and their employees. However, there is no direct link between the passage of PSL on short-term market reaction.

To do so, we employ a two-stage least squares (S2SLS) regression to construct our fitted value for our Yule's K from the shock and then use the fitted value to test the relation between vocabulary richness and market outcomes:

$$ZYule's\ K_{i,t} = \alpha + \beta * PSL\ law_{it} + X_{i,t}\beta + v_i + W_T + \epsilon_{i,t} \qquad (5a)$$

$$Y_{i,t} = \alpha_1 Z\widehat{Yule's}\ K_{i,t} + X_{i,t}\beta + v_i + W_T + \epsilon_{i,t} \qquad (5b)$$

where $PSL\ law_{it}$ is an indicator variable that equals one if the earnings call is held after the effective of PSL. Appendix IV provides the detail enactment dates and the effective date of each state-level PSL mandate. Further, we also include a battery of characteristics, X_{it} could affect both market reactions and vocabulary richness within earnings calls, which have been discussed in the previous sections. Equation (5b) is the second-stage regression where we regress the short-term market outcomes on the expected vocabulary richness index estimated from equation (5a). Last but not least, we also control for firm fixed effect and year fixed effect to account for the time invariance firm characteristics and general time trend.

[insert Table 7]

Panel A of Table 7 reports the direct test between the shock and our market reaction variable. As you can see from the table, we didn't find a significant relation between either the CARs or trading volume, and the passage of the PSL law. Panel B shows our first-stage regression results in equation (5a). The significant and negative coefficient between PSL and vocabulary richness measurement confirms our argument that there is an increase in vocabulary richness, which is equivalent to the decrease in Yule's ratio. Column 3 of Panel B tests the parallel trend and found our results are only significant after the passage of PSL law. Moreover, we find the F-stat is larger than 10, which passes the weak instrumental variable condition.

Recent literature identifies that the time-varying treatment effect in staggered adoption design cause bias results (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Baker et al., 2022). As a result, we apply both estimators from Callaway and Sant'Anna and stacked DiD analysis in our appendix V and VI to show that our results between PSL and vocabulary richness is still held after correcting errors from the staggered adoption design.

Panel C of Table 7 shows that the coefficient on the instrumented $ZYule's\ K$ is consistent with our main regression results in Table 5. Overall, the instrumental variable analysis suggests that the effect of vocabulary richness on firm-level short-term market reactions after earnings calls is likely to be causal.

4.5 Propensity Score Matching

In this section, we seek to address a potential endogenous issue in our main analysis by applying an alternative to the standard multivariate regression approach. We adopt propensity score matching (PSM) method, which is specifically designed to create a platform for comparison of earnings calls that contain high and low degrees of vocabulary richness but are similar in all other features.

In particular, we define *High Yule's K* as an indicator variable that equals one if a firm's $ZYule's\,K$ is located in the top quintile of sample, and zero otherwise. Then we construct the prediction model by using the *High Yule's K* as the dependent variable and perform a logit regression on all firm characteristics discussed in our previous sections. The result is reported in Panel A of Table 8.

[insert Table 8]

Next, for each observation with a *High Yule's K* of one, we match an observation with *High Yule's K* of zero that has the closest estimated probability (without replacement) from Panel A. After applying the above-described PSM process, we obtain a matched sample of 31,146 earnings calls, consisting of 15,573 calls in the treatment group, and 15,573 calls in the control group. Panel B of Table 8 shows summary statistics for my matched sample. The matching result works well since the differences between control variables in the treatment and control groups are not statistically significant.

We rerun our main regression analysis examining the relationship between vocabulary richness index and the investors' reactions. All of these results are shown in Panel C of Table 8. These results are similar to those in Table 5, which indicates that our results are not driven by any differences in firm characteristics for earnings calls between firms with different level of vocabulary richness.

4.6 Subgroup Analysis

4.6.1 Research Design

We next conduct tests to investigate how the effect of vocabulary richness on market outcomes varies by type of information associated with earnings calls. In our third hypothesis, we state that firms' status plays an important role in defining the expectation for vocabulary richness. High-profile firms are expected to have speech with high vocabulary richness. If firms can't fulfill investors' expectations, shareholders can vote by their feet by selling the stock.

To test this hypothesis, we define firms with more analysts following and high market value as high-profile firms as these firms are easy to be seen by investors. To be specific, we assign a firm to a high-profile group if the market value of the company or the number of following analysts is above the median in a given year.

As indicated in our last hypothesis, the quality of information is also important in determining the expectation for vocabulary richness within the text. If the information is hard to interpret, investors expect an explanation with a diverse vocabulary, which helps them to digest the information easily. Similar to what we described in the hypothesis section, we expected that firms with more R&D expenses and with bad news are associated with hard-to-digest information.

To measure the R&D expense, we use the ratio of R&D expense over sales as the proxy and construct an indicator variable as we assign a firm with a higher than median R&D expense ratio to the high R&D expense group. On the other hand, we define the bad news as whether the quarterly earnings miss earnings forecast or whether current quarterly earnings are negative. Both situations grab investors' attention due to the loss aversion condition and require more explanation from investors.

Then, we estimate a similar regression model on equation (3) by adding an interaction term between our vocabulary richness proxy and our specified group indicator. If the interaction terms are significant, we can assert that there is a statistically significant difference between these two groups and support our hypotheses.

4.6.2 Result

Table 9 reports the results for our subgroup analysis based on the profile of the company or type of information embedded with earnings calls. The first two columns of Table 9 show our results relate to our third hypothesis regarding the firm's status and market reactions. We observe that firms with high market value or with high analyst following have more pronounced effects between vocabulary richness and short-term market returns, as the coefficient for the interaction terms is negative and statistically significant at 1% level. The results are also true if we switch our market outcomes to trading volume in column (6) and (7).

Next, we look at how the information within earnings calls influence market reactions. Our last hypothesis states that hard-to-digest information needs diverse vocabulary explanations. The next three columns after column (2) support our argument that hard-to-digest information expects a high vocabulary richness explanation. We present the negative coefficient for the interaction term, which indicates that the negative effect between Yule's K ratio and market reaction is more pronounced for firms with hard-to-digest information. However, if we use trading volume as our dependent variable, we find this effect is only significant if we use R&D expense as the measurement for information complexity.

Overall, our results support the hypothesis that the effect of vocabulary richness on market outcomes is mainly through the firm status or the type of information within earnings calls. Specifically, the effect between market reaction and vocabulary richness is more pronounced for firms with a large asset or with more analysts following. Further, the effect is also more significant if the underlying firm information is more complicated and needs more explanation.

4.7 Robustness Check

In this section, we want to demonstrate that our results are consistent under various scenarios, including vocabulary richness within certain words list, other vocabulary richness proxies, and additional fixed effects.

4.7.1 Vocabulary Richness for Pre-defined Words List

To rule out the potential concerns that our results are driven by some unique words that are invented or used by certain firms, we construct Yule's K for two heavily used word lists in finance and accounting: the dictionary from Loughran and McDonald (2011) (LM Dict) and the financial dictionary from Mastomoto et al. (2011) (Fin Dict)[1]. By using these two dictionaries, we want to demonstrate that our results are not driven by the amount of information in the earnings calls but by the diversity that helps investors digest information more easily.

[insert Table 10]

Table 10 reports the results by using the standardized Yule's K from LM Dict and Fin Dict. All these results yield a similar coefficient as our main analysis in Table 5. For example, we find a negative relation between market reaction and Yule's K for both LM Dict and Fin Dict. Besides, the abnormal trading volume results are also in line with our main argument that high Yule's K

[1] Appendix VII provides the detail words list from the financial dictionary developed by Matsumoto et al. (2011), which contains a total of 137 words.

ratio for both pre-defined word lists is positively related to trading volume. Overall, results in Table 10 support our argument that vocabulary richness measures how executives use the words diversly that help investor to absorb the information within earnings call.

4.7.2 Other Vocabulary Richness Proxies

The next set of analyses deals with the concerns about the validity of our vocabulary richness proxies. Because all of our previous results are based on Yule's K, someone may argue whether our results survived in other vocabulary richness measurements.

To relieve this concern, we also construct other proxies used in previous linguistic literature to measure vocabulary richness. We discussed each of these measurements below.

1. Root Type-Token Ratio: The root type-token ratio is developed by Guiraud (1954). We create the root type-token ratio as

$$Root\ Type\text{–}Token = \frac{V(N)}{\sqrt{N}}$$

   where $V(N)$ is the number of unique words in the text and N is the number of total words in the text. For instance, the sentence "The Cat in the Hat." has 4 unique words and a total of 5 words in it. A higher ratio means higher vocabulary richness.
2. Corrected Type-Token Ratio: Carroll (1964) corrected type-token ratio which is defined

$$Corrected\ Type\text{–}Token = \frac{V(N)}{\sqrt{2N}}$$

   where the definition for V(N) and N are similar to the root type-token ratio. A higher ratio means higher vocabulary richness.
3. Somers Index (Somers, 1966):

$$Somers\ Index = \frac{\log(\log(V(N)))}{\log(\log(N)))}$$

   where the definition for V(N) and N are similar to the root type-token ratio. A higher ratio means higher vocabulary richness.
4. Dugast Index (Dugast, 1978):

$$Dugast\ Index = \frac{(\log(N))^2}{\log(N) - \log(V(N))}$$

   where the definition for V(N) and N are similar to the root type-token ratio. A higher ratio means higher vocabulary richness.

5. Mass Index (Mass, 1972):

$$Mass\ Index = \frac{\log(N) - \log(V(N))}{\log(N^2)}$$

where the definition for V(N) and N are similar to the root type-token ratio. A higher ratio means lower vocabulary richness.

After constructing these five new vocabulary richness measurements, we rerun our main regression in Table 5 with these new proxies, which are listed in Table 11.

[Insert Table 11]

As shown in the above table, all results are consistent with our main argument in Table 5. For instance, we find high root type-token ratio has a positive effect on firm short-term market reaction and a negative effect on trading volume. Further, all the coefficients for these five new measurements are significant at 1% level. These consistent results provide supporting evidence that vocabulary richness provides value to investors as more verbal diverse language help market participants to digest information.

4.7.3 Additional Fixed Effects

To rule out the potential omitted variable concerns, we include additional fixed effects in equation (3). First, Attig et al. (2022) report that there is a hike in words related to firm's ESG engagement during the fourth quarter of each year. Because managers or analysts may shift their focus on each quarter's earnings calls within a year, we consider controlling for the year-quarter fixed effect instead of year fixed effect to account for the quarterly difference in earnings calls' content. Column (1) and (2) of Table 12 report the results with year per quarter fixed effects, and we see that all market outcomes are still statistically significant at 1% level in the same direction as we reported in Table 5.

[insert Table 12]

Second, we also notice a significant different in vocabulary richness within different industries in Figure 2. To relieve the concern that our results are driven by some common industry trend in word usage that changes yearly, we include industry per year fixed effects to account for some unobservable yearly industry trends. The results show in column (3) and (4) with a similar sign and significance to our main findings.

Third, the vocabulary richness only captures the affected firm's textual feature within earnings calls but ignores the overall disclosure environment during the date, which may affect investors' reactions. Prior studies demonstrate that the number of other firms announcing earnings on the same day may affect the processing ability of individuals as busy earnings days strain investor resources and increase the opportunity cost of processing a particular firm's disclosure (Hirshleifer et al., 2009; deHaan et al., 2015). Following them, we replace the year-quarter fixed effects with call date fixed effect to account for the specific characteristics of each earnings call date within our sample. Column (5) and (6) indicates that the magnitude of $ZYule's\ K$ is not affected by controlling the individual's processing power or unobserved characteristics that are constant during the date.

The last set of tests mitigates the potential omitted variable within yearly firm-specific variables. For instance, prior studies link vocabulary richness to individuals' communicative competence and effectiveness (Crossley et al., 2012; Lu, 2012). Our firm per year fixed effect can relief the concerns that specific executives combinations drive our results as most executives' contracts are renewed on a yearly basis. Our firm per year fixed effect can capture these omitted variables. Therefore, in the last two columns of Table 8's Panel A, we replace firm fixed effect with firm per year fixed effects and also include the call date fixed effect into regression. The coefficient for $ZYule's\ K$ remains as statistically significant as in Table 5.

5 Additional Analysis

In this section, we supplement our findings of vocabulary richness on the consequences of other market participants by examining the effect on analysts. Moreover, we also look at the long-term consequence, such as the stock crash risk. To demonstrate that our vocabulary richness measurement is not only valid for conference calls, we construct the same measurement for 10K reports and replicate the results in Li (2008) by examining the future earnings persistence with vocabulary richness. At the end of this section, we also look at the vocabulary richness at the CEO-year level to explore which CEO characteristics matter for executive's vocabulary richness during the discussion session of earnings calls.

5.1 Analysts Reaction

Compared to general public, analysts assume to have a better ability to digest the information within earnings transcripts since they have a wide range of information sources. However, if the earnings are higher than their expectation, they need to review all available information carefully, including earnings conference calls, to figure out the reasons for this earnings surprise. To this end, vocabulary richness may play a role as easy-to-digest calls will help analysts to speed up the information integration process. As a result, we expect analysts to issue their reports faster in such conditions. To measure how analysts impound earnings news into their future forecast, we construct two measurements developed by previous literature: analyst forecast likelihood and analyst forecast speed (Zhang, 2008; deHaan et al., 2015; Blankespoor et al., 2020).

Following Blankespoor et al. (2020), we measure the analyst forecast likelihood as the percentage of analysts following the firm that issue a forecast within days [0,6] of the earnings announcement. In terms of analysts' forecast speed, we calculate the same measurement as deHaan et al. (2015):

$$Analysts\ Forecast\ Speed = -1 * \ln\left(\frac{1}{j}\sum_{j=1}^{j}\left[1 + Weekdays\ until\ forecast\ update_j\right]\right. \quad (6)$$

where j stands for the analysts forecast, and we restrict to all estimates that are updated within 30 days after earnings announcement. This measurement calculates the inverse of the number of weekdays between the earnings announcement date and forecast issue date. A larger number means average shorten delay in issuing analysts forecast after earnings announcement.

To formally test this relation, we employ a similar model specification as equation (3):

$$Analysts\ Outcome_{i,t} = \alpha_1 ZYule's\ K_{i,t} + X_{i,t}\beta + v_i + W_T + \epsilon_{i,t} \qquad (7)$$

where $Analysts\ Outcome_{i,t}$ presents either the analysts forecast likelihood or analysts forecast speed for current quarterly earnings. $Same\ Day_{it}$ is an indicator variable when the firms experience the same day release in current quarter. Similar to previous models, $X_{i,t}$ is the vector of firm-level characteristics that influence the analysts forecast behavior. We also put industry and year fixed effect in our model to control for heterogeneity across industries and time. A detailed definition for each control variable can be found in Appendix II.

To explore whether higher earnings surprise influence analysts' forecast revision speed, we also employ a modified model of equation (7) by adding an interaction term between earnings surprise and the Yule's K ratio. We expect the coefficient for the interaction term to be negative as positive earnings surprise with a high Yule's K will take more time for analysts to digest the information embedded before they can issue the report.

[insert Table 13]

Column (1) and (3) of Table 13 shows that $ZYule's\ K$ along is not statistically significant to either the analysts forecast speed or the likelihood of forecast, indicating that analysts didn't think vocabulary richness, in general, will influence their judgment for the company's future performance. Furthermore, we document in column (2) and (4) that the interaction term between $ZYule's\ K$ and $Surprise\ Earnings$ is negative and statistically significant. Therefore, these negative and statistically significant interaction terms in column (2) and (4) confirm our argument that vocabulary richness only matters to analysts when there is a large earnings surprise for that quarter.

5.2 Stock Crash Risk

Until now, our previous analysis focuses on short-term market outcomes and finds that vocabulary richness decreases the processing cost for investors. In this section, we investigate whether the vocabulary richness within earnings calls has some long-term consequences since low vocabulary richness can be viewed as a tool for managers to hide bad information by increasing the disclosure processing cost.

Etrugrul et al. (2017) investigate the relation between textual features within annual reports and future crash risk. They conclude that low readability and more ambiguous word usage positively relate to future crash risk. In line with their argument, we should expect low vocabulary richness (high Yule's K ratio) will increase the probability of future crash risk as investors will assume hard-to-digest disclosures embedded with more risk (Bloomfield, 2002).

To examine the relation between vocabulary richness and future crash risk, we first construct two measures of stock price crash risk following Chen et al. (2001). Our first measure, NCSKEW, is the negative conditional skewness of firm-specific weekly returns over the next fiscal quarter. It is calculated by taking the negative of the third moment of firm-specific weekly returns for each quarter and normalizing it by the standard deviation of firm-specific weekly returns raised to the third power. Our second measure, DUVOL, is the down-to-up volatility measure of the crash likelihood. For each firm over a fiscal-quarter period, firm-specific weekly returns are separated into two groups: "down" weeks when the returns are below the quarterly mean, and "up" weeks when the returns are above the quarterly mean. Standard deviation of firm-specific weekly returns is calculated separately for each of these two groups, and DUVOL is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. Then, we run an OLS regression similar to equation (3) but replacing the dependent variable with our two new established stock crash estimations. The results are listed in Table 14.

[insert Table 14]

Columns (1) and (2) of Table 14 report the results for NCSKEW, and columns (3) and (4) report the results for DUVOL. We find that, on average, a high Yule's K ratio (low vocabulary richness) is associated with a high risk of future stock price crash risk, which is significant at least at 5% level. These results highlight the importance of vocabulary richness as capital markets participants can infer future performance from the language vocabulary richness within earnings calls.

5.3 Vocabulary Richness for Annual Reports

So far, we find that the vocabulary richness for earnings calls plays an important role in investors' valuation of companies. In this section, we want to demonstrate that our vocabulary richness proxy is not only valuable for earnings call settings, but also meaningful in other disclosure settings. To do so, we download all annual reports (10-K) from the EDGAR system and use the same method to process each 10-K filing. After cleaning the data as described in our data section, we construct the vocabulary richness index for each annual report.

To test the validity of vocabulary richness for annual reports, we decide to replicate the main results from Li (2008), which investigates the earnings persistence and the complexity of annual reports. In his paper, the major takeaway is that firms with easier-to-read annual reports have high persistent future earnings. Therefore, our analysis is to test whether the vocabulary richness also provides us a clue for future earnings.

To investigate the relation between earnings persistent and vocabulary richness, we employ the same regression as Li (2008):

$$Earnings_{future} = Earnings_{i,t} + ZYule's\ K_{i,t} + Earnings_{i,t} * ZYule's\ K_{i,t} + X_{i,t}^{li}\beta + I_i + W_T + \epsilon_{i,t} \quad (8)$$

where $Earnings_{future}$ is either earnings in next year or two years after. $Earnings_{i,t}$ is the current year's operating earnings. $ZYule's\ K_{i,t}$ is the standardized Yule's ratio for each annual report. We also include the same set of control as Li (2008). The variable of interest here is the interaction terms between current earnings and report's vocabulary richness index.

As Li (2008) argues, high textual complexity in annual reports means the information within earnings calls is less easily extracted, so managers will have more incentive to obfuscate information when performance is bad. In our prior analysis, we already demonstrate that low vocabulary richness will increase the processing cost for investors. In line with his argument, we should expect a less persistent earnings if Yule's K is high, which means a low vocabulary richness. As a result, we should expect a negative coefficient for the interaction term between earnings and Yule's K. Appendix VIII reports the results.

As you can see from the table in appendix VIII, we observe a consistent negative coefficient across all model specifications. Importantly, our results are still significant if we control for the readability index within the text and replace the industry fixed effect with firm fixed effects in column (2) to (3) and column (5) to (6). All these results are consistent with Li (2008) explanation that high information processing cost within disclosures is related to firm's incentive to hide bad financial information.

5.4 Vocabulary Richness for CEOs

In our last set of tests, we transform our original earnings calls data into executive level and investigate which factors influence individual's vocabulary richness. To do so, we first collect all sentences spoken by CEOs during a fiscal year and use the similar method described in prior data section to clean all the text content. Then, we calculate the Yule's K ratio for each CEO in each fiscal year and combine it with all available firm fundamentals and executive characteristics from Compustat and Execucomp, respectively. Finally, we got a sample with 10,487 CEO-year observations.

To examine the relation between CEO characteristics with vocabulary richness, we employ the similar regression as equation (2) but add several additional controls from Execucomp: age, gender, total compensation, and two incentive measurements, which are delta and vega from Coles et al. (2006). The results are reported in Appendix IX.

Column (1) of Appendix IX shows the results with only CEO characteristics, and we find that gender and age play an important role in determining the vocabulary richness of CEOs during earnings calls. To be specific, we find female CEO chooses to use more diverse words compared to her male counterparties. Moreover, we also show that age is an important factor in influencing vocabulary richness as older CEO will have higher vocabulary richness during the speech than young ones. Last but not least, we also notice that total compensation is positively related to Yule's K ratio, which means CEOs with high compensation are more likely to speak in limited words during earnings calls. However, CEO compensation is related to various firm characteristics, and we cannot make any conclusions without control for firm characteristics. Therefore, we control for firm fundamentals in column (2), and all the CEO characteristics are still statistically significant, at least at 10% level. These results provide initial evidence that CEO characteristics matter for vocabulary richness during earnings calls. Future research can look at how vocabulary richness can be used as a factor to determine future CEO's behavior.

6 Conclusion

In this paper, we highlight the concept that how you talk matters to investors. By examining the unexplored linguistic feature, vocabulary richness, in the business context, we find high vocabulary richness provides value to investors by helping them easily understand the embedded information within earnings calls. In return, high vocabulary richness also yields favorable short-term market outcomes, such as high initial market reaction and low abnormal trading volume.

To establish causality, we employ both the change-on-change regressions and the shock-based IV method. By using the change-on-change specification, we find that the change of Yule's K is followed by a significant deterioration in investors' initial reactions, which is consistent with our main findings. In our shock IV analysis, we use the passage of paid sick leave law as a shock to the information content within earnings calls. The two-stage least squares regression confirms the causal relation by showing that the instrumented Yule's K is negatively (positively) and significantly associated with short-term market reaction (trading volume). In terms of the channels, we find investors' initial expectation plays a vital role in mitigating the relation between vocabulary richness and investors' reactions. To be specific, we observe that both company profile and underlying information within earnings calls play an important mitigation role between market outcomes and vocabulary richness.

We next show that our results are also significant for long-term consequences. We show that low vocabulary richness (high Yule’s K ratio) will increase the probability of future crash risk since investors will assume a hard-to-digest message embedded with more risk (Bloomfield, 2002). Further, we illustrate that a high Yule’s K ratio decreases both analysts' forecast speed and forecast likelihood when the earnings surprise is big in that quarter. Finally, we demonstrate that our vocabulary richness proxy is valid for not only conference call settings but also other disclosure settings, such as annual reports and investigating lexical diversity of CEOs.

Overall, our paper provides the initial evidence that vocabulary richness provides value to investors by helping them digest executive messages more easily. Future research can explore the reactions of other stakeholders, such as creditors, institutional investors, and journalists. On the contrary, researchers can also look at other determinants for vocabulary richness, including the executive’s personal experience, local economic condition, and analysts’ coverage.

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Figure 1

Yearly Trend

This figure displays the yearly Yule's K trend for 2007-2020. We present three distinguish Yule's K from earnings calls: presentation section (*Yule's K in Pre*), executives' answers in discussion section (*Yule's K in ExeQnA*), and analysts' question in discussion section (*Yule's K in AnaQnA*).

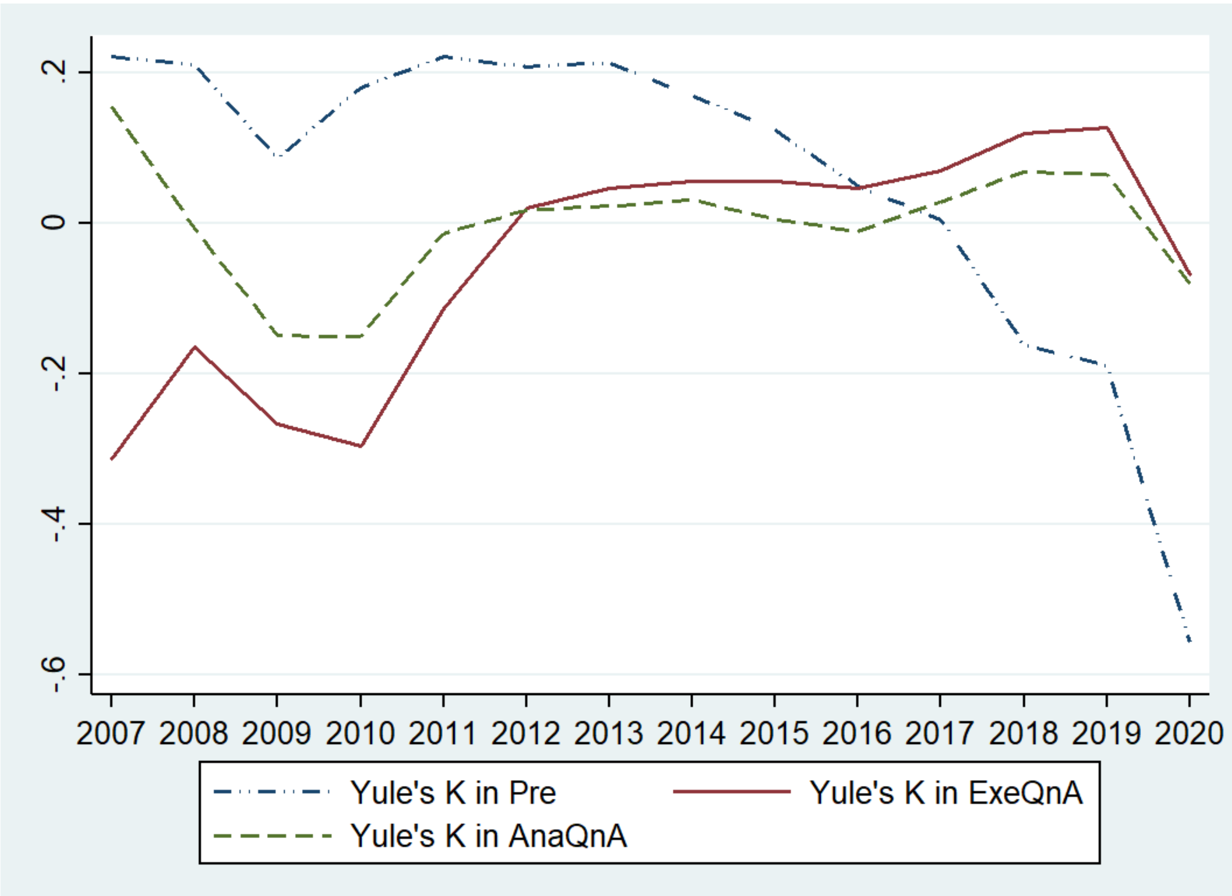

Figure 2

Industry Distribution

The figure shows the average vocabulary richness value in three distinct sections across Fama-French 12 industry classification over the sample period 2007-2020. Fama-French Industries: 1- Consumer NonDurables; 2 - Consumer Durables; 3- Manufacturing; 4 - Energy Oil and Gas Products; 5 - Chemicals and Allied Products; 6 - Business Equipment; 7- Telephone and Television Transmission; 8- Utilities; 9- Wholesale and Retail; 10- Healthcare, Medical Equipment; 11 – Finance; 12 – Other.

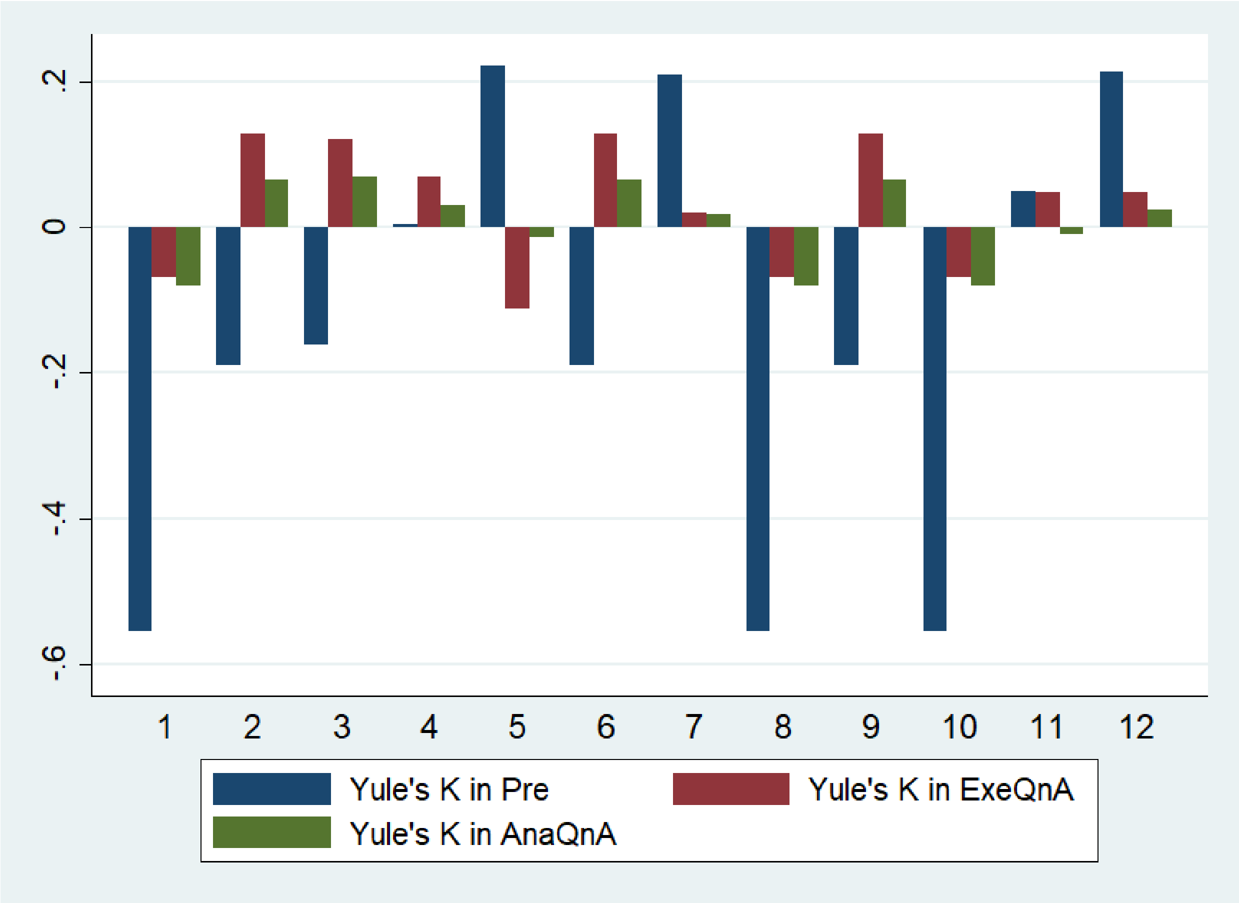

Figure 3

Market Reaction Around Earnings Announcement

This figure shows the cumulative abnormal returns relative to earnings calls with Yule's K in bottom quintile (highest vocabulary richness) and top quintile (lowest vocabulary richness).

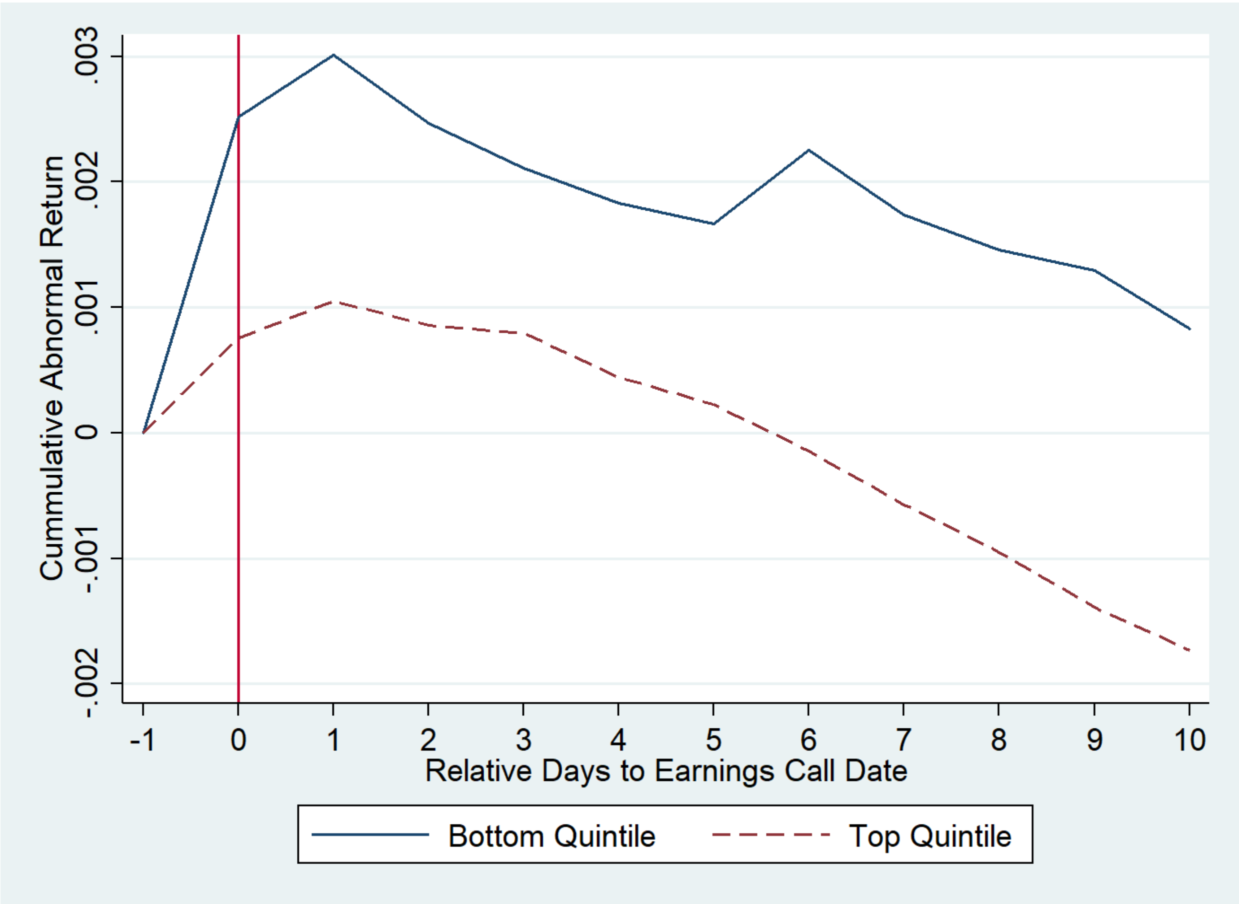

Table 1

Sample construction

This table reports our sample construction process from Capital IQ database. Our final sample contains 79,884 conference calls for 3,095 unique firms from 2007 to 2020.

	Total Number of Remaining Calls
All Earnings Calls with Available Transcripts from Capital IQ	106,913
Deleted calls before 2007 due to limited coverage of Capital IQ	106,449
Merged with available Compustat & CRSP Data	99,227
Drop observations with missing IBES values	**79,884**

Table 2

Descriptive Statistics

This table presents summary statistics for all variables in our sample. The sample period is 2007-2020. Detailed definitions for each variable are provided in Appendix II. All continuous variables are winsorized at 1% and 99% levels.

	(1) N	(2) mean	(3) sd	(4) p25	(5) p50	(6) p75
Dependent Variable						
CARs[0,+1]	79,884	0.003	0.079	-0.037	0.002	0.043
Volumes[0,+1]	79,884	0.643	0.585	0.258	0.619	1.007
Forecast Likelihood	76,811	0.901	0.140	0.833	1	1
Analysts Speed	77,875	-1.014	0.593	-1.386	-0.916	-0.588
NCSKEW (Quarterly)	78,379	0.075	2.270	-1.586	0.0658	1.718
DUVOL (Quarterly)	78,234	0.063	1.074	-0.656	0.044	0.769
Textual Features						
Yule's K in Pre	79,884	7.531	2.487	5.771	7.006	8.714
Yule's K in ExeQnA	79,884	5.914	1.146	5.117	5.738	6.510
Yule's K in AnaQnA	79,884	6.547	1.473	5.577	6.258	7.162
ZYule's K in Pre	79,884	0	1.000	-0.708	-0.211	0.476
ZYule's K in ExeQnA	79,884	0	1.000	-0.695	-0.153	0.521
ZYule's K in AnaQnA	79,884	0	1.000	-0.659	-0.196	0.417
Root Type-Token in ExeQnA	79,884	15.99	1.865	14.84	16.11	17.26
Corrected Type-Token in ExeQnA	79,884	11.31	1.319	10.49	11.39	12.21
Somer Index in ExeQnA	79,884	0.938	0.00873	0.932	0.937	0.944
Dugast Index in ExeQnA	79,884	63.58	7.496	58.48	62.39	67.32
Mass Index in ExeQnA	79,884	0.015	0.002	0.015	0.016	0.017
Net Tone	79,884	0.007	0.006	0.003	0.007	0.011
Fog Index in ExeQnA	79,884	12.86	1.605	11.76	12.79	13.88
Ln(LDA Topics)	79,884	0.859	0.210	0.693	0.693	1.099
Ln(Total Words)	79,884	8.750	0.341	8.533	8.806	9.004
Yule's K in ExeQnA (LM Dict)	79,884	123.1	12.27	114.6	122.1	130.4
Yule's K in ExeQnA (Fin Dict)	79,884	924.4	587.5	557.3	775	1,111
ZYule's K in ExeQnA (LM Dict)	79,884	0	1.000	-0.689	-0.0766	0.600
ZYule's K in ExeQnA (Fin Dict)	79,884	0	1.000	-0.625	-0.254	0.318
Firm Fundamentals						
Ln(Size)	79,884	7.745	1.877	6.440	7.717	8.970
Book to Market	79,884	0.553	0.508	0.234	0.440	0.741
Return on Assets	79,884	0.003	0.042	0.000	0.001	0.020
Negative Earnings	79,884	0.163	0.370	0	0	0
Accrual	79,884	0.007	0.099	0.001	0.016	0.044

Ln(Analysts)	79,884	1.837	0.833	1.386	1.946	2.485
Meet Expectation	79,884	0.647	0.478	0	1	1
Surprise Earnings	79,884	0.001	0.011	-0.001	0.001	0.003
Firm Age	79,884	25.76	18.01	11	21	35
Delaware Incorporate	79,884	0.600	0.490	0	1	1
M&A Event	79,884	0.155	0.362	0	0	0
SEO Event	79,884	0.103	0.304	0	0	0
Special Items	79,884	-0.001	0.009	-0.001	0	0
Return Volatility	79,884	0.106	0.062	0.063	0.091	0.131
Earnings Volatility	79,884	191.8	476.0	15.33	41.56	131.0
Ln(Non-missing Items)	79,884	5.729	0.145	5.613	5.690	5.852
Ln(Geo Segments)	79,884	1.584	1.060	0.693	1.609	2.485
Ln(Business Segments)	79,884	1.736	0.819	1.386	1.386	2.398

Table 3

The Uniqueness of Vocabulary Richness

This table shows several panels to demonstrate the uniqueness of our vocabulary richness proxy. Panel A reports the textual features comparison between firms headquartered in the U.S and overseas. Panel B provides a correlation matrix among major textual features within earnings calls. Panel C shows the determinants analysis for vocabulary richness. Panel D reports the result of our topic analysis. All the variables are described in Appendix II. Standard errors are clustered by firm, and t-statistics are shown in the bracket. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Foreign firms and US firm Comparison

	U.S. Firms	Non-U.S. Firms	Diff	T-stat
ZYule's K in ExeQnA	-0.103	0.217	-0.320***	25.292
Fog Index in ExeQnA	12.835	13.256	-0.421***	8.333
ZYule's K in AnaQnA	-0.116	0.029	-0.145***	11.804
ZYule's K in Pre	0.036	-0.085	0.122***	21.968
Net Tone	0.007	0.005	0.002***	18.045
Ln(Total Words)	8.752	8.724	0.027***	5.542
N	74,853	5,031		

Panel B: Correlation Table

	ZYule's K in ExeQnA	Fog Index in ExeQnA	ZYule's K in AnaQnA	ZYule's K in Pre	Net Tone	Ln(Total Words)
ZYule's K in ExeQnA	1					
Fog Index in ExeQnA	-0.198***	1				
ZYule's K in AnaQnA	0.330***	-0.053***	1			
ZYule's K in Pre	0.231***	-0.102***	0.135***	1		
Net Tone	0.035***	0.080***	-0.0038	-0.082***	1	
Ln(Total Words)	-0.262***	0.009***	-0.4549***	-0.187***	0.069***	1

Panel C: Determinants Analysis

VARIABLES	(1) Fog Index in ExeQnA	(2) ZYule's K in ExeQnA	(3) ZYule's K in ExeQnA	(4) ZYule's K in ExeQnA
ZYule's K in Pre			0.148***	0.102***
			[15.431]	[14.437]
ZYule's K in AnaQnA			0.242***	0.197***
			[29.512]	[40.610]
Fog Index in ExeQnA			-0.093***	-0.096***
			[-18.757]	[-27.223]
Net Tone			7.479***	5.654***
			[6.740]	[7.800]
Ln(Total Words)			-0.327***	-0.365***
			[-12.567]	[-17.936]
Ln(Size)	0.029*	-0.075***	0.017**	-0.013
	[1.725]	[-9.709]	[2.241]	[-0.841]
Book to Market	0.081**	0.090***	0.044**	0.001
	[2.242]	[4.705]	[2.526]	[0.070]
Firm Age	-0.001	0.000	-0.001	0.004
	[-0.951]	[0.047]	[-1.377]	[0.647]
Special Items	-2.935***	2.084***	0.619*	0.075
	[-4.069]	[5.675]	[1.847]	[0.274]
Return Vol	1.096***	-0.192	0.293**	0.082
	[4.247]	[-1.493]	[2.496]	[0.966]
Earnings Vol	0.000*	-0.000	-0.000	-0.000
	[1.657]	[-0.839]	[-0.555]	[-0.394]
Ln(Non-Missing Items)	-0.223	-0.293***	-0.264***	-0.068
	[-1.167]	[-3.370]	[-3.381]	[-0.946]
Ln(Geo Segments)	0.013	0.003	-0.001	0.001

	[0.541]	[0.309]	[-0.134]	[0.110]
Ln(Business Segments)	0.004	0.026*	0.013	-0.013
	[0.129]	[1.738]	[0.982]	[-0.808]
SEO Event	-0.009	-0.056***	-0.005	-0.019*
	[-0.225]	[-3.178]	[-0.295]	[-1.715]
M&A Event	-0.008	-0.023	-0.010	0.002
	[-0.250]	[-1.561]	[-0.749]	[0.252]
Delaware Incorp	0.116**	-0.073***	-0.040*	
	[2.492]	[-2.937]	[-1.792]	
Constant	13.673***	2.164***	5.295***	4.711***
	[12.651]	[4.418]	[10.963]	[8.288]
Industry FE	YES	YES	YES	NO
Firm FE	NO	NO	NO	YES
Year FE	YES	YES	YES	YES
Observations	79,882	79,882	79,882	79,882
R-squared	0.169	0.117	0.251	0.514
Adjusted R-squared	0.166	0.115	0.249	0.495

Panel D: Content Analysis

VARIABLES	(1) Ln(LDA Topics)	(2) Ln(LDA Topics)	(3) Ln(LDA Topics)
ZYule's K in ExeQnA	0.004***	0.004***	0.004***
	[2.994]	[3.209]	[3.367]
Ln(Size)		0.010***	0.010***
		[2.770]	[2.776]
Market to Book		0.005*	0.002
		[1.814]	[0.833]
Firm Age		-0.003*	-0.002
		[-1.853]	[-1.221]
Special Items		-0.070	-0.062
		[-0.930]	[-0.822]
Return Vol		-0.022	-0.023
		[-1.084]	[-1.148]
Earnings Vol		-0.000	-0.000**
		[-1.123]	[-2.129]
Ln(Non-Missing Items)		0.000	0.019
		[0.019]	[1.131]
Ln(Geo Segments)		0.003	0.002
		[0.846]	[0.500]
Ln(Business Segments)		-0.002	-0.004
		[-0.430]	[-0.937]
SEO Event		0.001	-0.001
		[0.414]	[-0.253]
M&A Event		-0.000	-0.003
		[-0.091]	[-1.324]
Constant	0.859***	0.859***	0.738***
	[8,362.879]	[6.956]	[6.019]
Firm FE	YES	YES	YES
Year FE	YES	YES	NO
Industry-Year FE	NO	NO	YES
Observations	79,884	79,884	79,884
R-squared	0.402	0.403	0.450
Adjusted R-squared	0.378	0.379	0.405

Table 4

Univariate Analysis

This table shows univariate analyses for major outcome variables in our sample. We separate our sample based on the quintile level in vocabulary richness and compare major market outcomes between bottom quintile and top quintile. The last columns show the difference. Detailed definitions for each variable are provided in Appendix II. Significance level: *** p<0:01, ** p < 0:05, * p < 0:1.

Quantile for ZYule's K in ExeQnA	Fog Index in ExeQnA	Surprise Earnings	CARs[0,+1]	Volumn[0,+1]
Bottom Quintile	13.393	0.025%	0.318%	0.601
2nd Quintile	13.017	0.036%	0.331%	0.647
3rd Quintile	12.838	0.010%	0.354%	0.657
4th Quintile	12.645	0.010%	0.306%	0.658
Top Quintile	12.413	0.031%	0.141%	0.653
Diff(Top-Bottom)	-0.979***	0.006%***	-0.177%***	0.052***

Table 5

Investor Reaction and Vocabulary Richness

This table shows the main regression result between investors' reactions and vocabulary richness. Column (1) to (3) reports the results by using abnormal market reaction as the dependent variable. In contrast, we use abnormal trading volume as dependent variable in column (4) to (6). Column (1) and (4) presents the results with only fixed effects. Column (2) and (5) further add firm fundamentals as controls. Column (3) and (6) add additional textual feature within earnings calls as control. Detailed definitions for each variable are provided in Appendix II. Standard errors are clustered by firm and t-statistics are shown in bracket. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CARs[0,+1]	CARs[0,+1]	CARs[0,+1]	Volumes[0,+1]	Volumes[0,+1]	Volumes[0,+1]
ZYule's K in ExeQnA	-0.002***	-0.002***	-0.003***	0.009***	0.010***	0.021***
	[-4.693]	[-5.300]	[-6.346]	[2.844]	[3.376]	[6.486]
Ln(Size)		-0.013***	-0.012***		0.027***	0.014
		[-12.074]	[-11.141]		[3.057]	[1.561]
Book to Market		0.026***	0.029***		-0.048***	-0.043***
		[18.281]	[20.136]		[-5.616]	[-4.903]
Return on Asset		0.132***	0.107***		0.402***	0.423***
		[7.152]	[5.872]		[3.425]	[3.636]
Negative Earnings		-0.002	-0.000		-0.082***	-0.079***
		[-1.225]	[-0.105]		[-8.487]	[-8.219]
Accruals		-0.033***	-0.033***		0.005	-0.012
		[-4.494]	[-4.533]		[0.097]	[-0.232]
Surprise Earnings		0.651***	0.616***		1.212***	1.252***
		[14.702]	[14.150]		[4.729]	[4.891]
Ln(Analysts)		0.001	0.004***		0.028***	0.003
		[1.523]	[4.399]		[4.487]	[0.400]
Meet Expectation		0.038***	0.034***		-0.062***	-0.057***
		[45.368]	[42.451]		[-13.118]	[-11.936]

ZYule's K in AnaQnA			-0.004***			0.008***
			[-7.902]			[2.640]
Fog Index in ExeQnA			-0.001**			-0.002
			[-2.459]			[-0.846]
Net Tone			2.275***			-0.330
			[30.202]			[-0.674]
Ln(Total Words)			-0.012***			0.230***
			[-7.468]			[20.991]
Constant	0.003***	0.065***	0.145***	0.644***	0.462***	-1.387***
	[74.665]	[7.746]	[9.445]	[2,569.248]	[6.939]	[-12.260]
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	79,884	79,884	79,884	79,884	79,884	79,884
Adjusted R-squared	0.0102	0.0957	0.112	0.272	0.278	0.284

Table 6

Change-on-Change Regression Analysis

This table reports the results for our change-on-change regression. Instead of using level value as in Table 5, we use the change between current quarter and previous quarter as the dependent and independent variable here. The format is the same as Table 5. Detailed definitions for each variable are provided in Appendix II. Standard errors are clustered by firm and t-statistics are shown in bracket. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ΔCARs[0,+1]	ΔCARs[0,+1]	ΔCARs[0,+1]	ΔVolumes[0,+1]	ΔVolumes[0,+1]	ΔVolumes[0,+1]
ΔZYule's K in ExeQnA	-0.003***	-0.003***	-0.004***	0.016***	0.014***	0.028***
	[-5.100]	[-4.816]	[-6.101]	[4.111]	[3.498]	[6.762]
ΔLn(Size)		-0.050***	-0.050***		0.109***	0.104***
		[-10.436]	[-10.509]		[3.732]	[3.573]
ΔBook to Market		0.097***	0.107***		-0.244***	-0.251***
		[24.437]	[26.090]		[-13.296]	[-13.475]
ΔReturn on Asset		0.088***	0.064**		0.308**	0.348**
		[3.564]	[2.569]		[2.171]	[2.479]
ΔNegative Earnings		-0.004*	-0.003		-0.069***	-0.062***
		[-1.685]	[-1.181]		[-5.516]	[-4.946]
ΔAccruals		-0.010	-0.013		0.044	0.015
		[-1.101]	[-1.404]		[0.636]	[0.217]
ΔSurprise Earnings		0.712***	0.659***		1.797***	1.981***
		[11.874]	[10.999]		[5.452]	[6.009]
ΔLn(Analysts)		0.007***	0.008***		-0.080***	-0.087***
		[5.103]	[5.454]		[-7.955]	[-8.741]
ΔMeet Expectation		0.040***	0.036***		-0.067***	-0.064***
		[39.933]	[36.777]		[-11.947]	[-11.350]
ΔZYule's K in AnaQnA			-0.003***			0.013***

			[-4.881]			[3.332]
ΔFog Index in ExeQnA			-0.000			-0.001
			[-0.157]			[-0.375]
ΔNet Tone			3.414***			0.539
			[30.463]			[0.808]
ΔLn(Total Words)			-0.012***			0.310***
			[-5.276]			[20.170]
Constant	0.000***	0.000***	0.001***	-0.009***	-0.009***	-0.011***
	[22.701]	[3.726]	[4.786]	[-118.955]	[-14.125]	[-16.737]
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	74,538	72,369	71,417	74,535	72,366	71,414
R-squared	0.010	0.118	0.140	0.018	0.027	0.037
Adjusted R-squared	-0.0326	0.0809	0.104	-0.0239	-0.0134	-0.00368

Table 7

Shock Based Analysis

This table reports the our shock based instrumental variable method. Panel A reports the results for the direct test between paid sick leave law and short-term market reaction. Panel B reports our first stage analysis by constructing the fitted value of vocabulary richness that will be used in Panel C. Then, panel C presents the results by using the fitted value generated from Panel B as our key variable of interest. Detailed definitions for each variable are provided in Appendix II. Standard errors are clustered by state in first two panels and by firms in panel C. Out t-statistics are shown in bracket. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

Panel A: Relation between Market Outcomes and PSL law

	(1)	(2)	(3)	(4)
VARIABLES	CARs[0,+1]	CARs[0,+1]	Volumes[0,+1]	Volumes[0,+1]
PSL Law	0.000	0.002	-0.008	-0.017
	[0.246]	[1.575]	[-0.781]	[-1.539]
Ln(Size)		-0.011***		0.022**
		[-8.501]		[2.451]
Book to Market		0.009***		-0.011
		[6.456]		[-1.509]
Return on Asset		0.123***		0.449***
		[7.084]		[3.695]
Negative Earnings		0.001		-0.087***
		[0.998]		[-8.631]
Accruals		-0.038***		0.010
		[-5.751]		[0.179]
Surprise Earnings		0.723***		1.308***
		[12.833]		[4.766]
Ln(Analysts)		0.000		0.033***
		[0.742]		[5.046]
Meet Expectation		0.038***		-0.064***
		[41.873]		[-13.117]
Constant	0.003***	0.060***	0.645***	0.476***
	[11.997]	[6.227]	[352.623]	[7.049]
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	74,853	74,853	74,853	74,853
Adjusted R-squared	0.009	0.092	0.274	0.279

Panel B: PSL Law on Vocabulary Richness

VARIABLES	(1) ZYule's K in ExeQnA	(2) ZYule's K in ExeQnA	(3) ZYule's K in ExeQnA
PSL Law	-0.047**	-0.038**	
	[-2.610]	[-2.137]	
PSL Law (-5)			-0.014
			[-0.500]
PSL Law (-4)			-0.027
			[-0.627]
PSL Law (-3)			0.022
			[0.702]
PSL Law (-2)			-0.005
			[-0.119]
PSL Law (-1)			-0.029
			[-1.355]
PSL Law (+1)			-0.072**
			[-2.059]
PSL Law (+2)			-0.007
			[-0.233]
PSL Law (+3)			-0.019
			[-0.406]
PSL Law (+4)			-0.053**
			[-2.316]
PSL Law (+5)			-0.041*
			[-1.738]
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	74,853	74,853	74,853
Adjusted R-squared	0.406	0.409	0.411
F-Statistics		27.89	

Panel C: Fitted Vocabulary Richness and Investor Reaction

VARIABLES	(1) CARs[0,+1]	(2) Volumes[0,+1]
Fitted ZYule's K in ExeQnA	-0.085***	0.464*
	[-2.617]	[1.653]
Ln(Size)	-0.018***	0.041**
	[-7.700]	[2.133]
Book to Market	0.028***	-0.034***
	[17.393]	[-3.325]
Return on Asset	0.138***	0.281*
	[6.194]	[1.812]
Negative Earnings	0.003	-0.094***
	[1.568]	[-6.489]
Accruals	-0.041***	0.023
	[-5.009]	[0.386]
Surprise Earnings	0.685***	1.267***
	[14.427]	[4.495]
Ln(Analysts)	-0.005	0.051*
	[-1.348]	[1.779]
Meet Expectation	0.033***	-0.055***
	[40.017]	[-10.473]
ZYule's K in AnaQnA	-0.004***	0.012***
	[-9.087]	[3.807]
Fog Index in ExeQnA	-0.000	-0.004**
	[-1.014]	[-2.146]
Net Tone	2.263***	-0.169
	[29.098]	[-0.334]
Ln(Total Words)	-0.011***	0.230***
	[-6.785]	[20.533]
Constant	0.185***	-1.612***
	[7.498]	[-8.262]
Firm FE	YES	YES
Year FE	YES	YES
Observations	74,853	74,853
Adjusted R-squared	0.114	0.286

Table 8

Propensity Score Matching

This table reports our propensity score method. Panel A reports the logit model that we defined High Yule's K as the calls with vocabulary richness allocates in the top quintile of our full sample. Panel B reports the univariate analysis for our matched sample. Panel C replicate our main regression results in Table 5 by using the matched sample. Detailed definitions for each variable are provided in Appendix II. Standard errors are clustered by firm and t-statistics are shown in bracket. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

Panel A: Logit Regression Model

VARIABLES	(1) High Yule's K
Ln(Size)	0.017
	[0.813]
Book to Market	0.061
	[1.313]
Return on Asset	0.418
	[0.880]
Negative Earnings	-0.015
	[-0.268]
Accruals	-0.068
	[-0.323]
Surprise Earnings	2.181**
	[2.123]
Ln(Analysts)	0.041
	[1.111]
Meet Expectation	-0.063**
	[-2.306]
ZYule's K in AnaQnA	0.488***
	[26.361]
Fog Index in ExeQnA	-0.209***
	[-13.475]
Net Tone	4.898
	[1.425]
Ln(Total Words)	-1.037***
	[-13.877]
Constant	9.904***
	[11.015]
Industry FE	YES
Year FE	YES
Observations	79,882
Pseudo R-squared	0.0967

Panel B: Univariate Analysis for PSM Sample

	High Yule's K = 0	High Yule's K = 1		
	Mean	Mean	Diff	T-Stats
ZYule's K in AnaQnA	0.233	0.239	-0.006	0.59
Fog Index in ExeQnA	12.433	12.446	-0.013	0.69
Net Tone	0.007	0.007	0.000	1.12
Ln(Total Words)	8.624	8.626	-0.002	0.59
Ln(Size)	7.440	7.448	-0.008	0.42
Book to Market	0.600	0.597	0.003	0.44
Return on Asset	0.004	0.004	0.000	0.27
Negative Earnings	0.159	0.159	0.000	0.05
Accurals	0.011	0.010	0.000	0.34
Surprise Earnings	0.000	0.000	0.000	0.37
Ln(Analysts)	1.662	1.662	0.000	0.01
Meet Expectation	0.636	0.635	0.001	0.14
N	15,573	15,573		

Panel C: Regression Results for PSM

VARIABLES	(1) CARs[0,+1]	(2) Volumes[0,+1]
ZYule's K in ExeQnA	-0.003***	0.013***
	[-4.605]	[2.912]
Ln(Size)	-0.013***	0.021
	[-7.347]	[1.571]
Book to Market	0.030***	-0.048***
	[14.317]	[-3.544]
Return on Asset	0.107***	0.445**
	[3.435]	[2.517]
Negative Earnings	-0.001	-0.083***
	[-0.600]	[-5.391]
Accruals	-0.024*	0.147*
	[-1.769]	[1.650]
Surprise Earnings	0.697***	0.751*
	[10.018]	[1.841]
Ln(Analysts)	0.002*	-0.002
	[1.855]	[-0.169]
Meet Expectation	0.038***	-0.042***
	[29.474]	[-5.475]
ZYule's K in AnaQnA	-0.003***	0.000
	[-4.168]	[0.099]
Fog Index in ExeQnA	-0.001**	-0.003
	[-2.230]	[-0.973]
Net Tone	2.213***	0.132
	[19.528]	[0.172]
Ln(Total Words)	-0.010***	0.210***
	[-3.978]	[11.972]
Constant	0.137***	-1.219***
	[5.559]	[-7.016]
Firm FE	YES	YES
Year FE	YES	YES
Observations	30,890	30,890
Adjusted R-squared	0.128	0.273

Table 9

Subgroup Analysis

This table shows multiple regression results for our subgroup analysis. We define high market value as firm's market value located above median in a given year. High analysts follow means the firms have above median number of analysts follow in a given year. Similar to the above two variables, high R&D means the R&D expense in terms of sales is allocated in the top half of our sample in a given year. Negative earnings means the earnings is negative. Miss expectation as the quarterly earnings miss analysts' forecast. Detailed definitions for each variable are provided in Appendix II. Standard errors are clustered by firm and t-statistics are shown in bracket. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	CARs[0,+1]	CARs[0,+1]	CARs[0,+1]	CARs[0,+1]	CARs[0,+1]	Volumes[0,+1]	Volumes[0,+1]	Volumes[0,+1]	Volumes[0,+1]	Volumes[0,+1]
ZYule's K in ExeQnA	-0.002***	-0.002***	-0.002***	-0.002***	-0.001**	0.006	0.006*	0.010***	0.013***	0.013***
	[-2.779]	[-3.368]	[-4.485]	[-4.377]	[-2.068]	[1.586]	[1.656]	[2.972]	[3.969]	[3.678]
High Market Value	-0.010***					0.007				
	[-7.324]					[0.777]				
ZYule's K in ExeQnA * High Market Value	**-0.002****					**0.013****				
	[-2.370]					**[2.338]**				
High Analysts Follow		0.002*					0.025***			
		[1.771]					[3.393]			
ZYule's K in ExeQnA * High Analysts Follow		**-0.002****					**0.014*****			
		[-2.180]					**[2.628]**			
High R&D			-0.003					0.004		
			[-1.405]					[0.277]		
ZYule's K in ExeQnA *High R&D			**-0.003****					**0.017***		
			[-2.236]					**[1.819]**		
Negative Earnings	-0.000	0.000	0.000	-0.000	0.000	-0.083***	-0.083***	-0.083***	-0.083***	-0.083***
	[-0.142]	[0.011]	[0.075]	[-0.072]	[0.017]	[-8.496]	[-8.546]	[-8.526]	[-8.556]	[-8.532]
ZYule's K in ExeQnA *Negative Earnings				**-0.002***					**-0.006**	
				[-1.955]					**[-0.752]**	
Miss Expectations					-0.034***					0.060***
					[-42.721]					[12.534]
ZYule's K in ExeQnA *Meet Expectations					**-0.004*****					**-0.003**
					[-4.524]					**[-0.667]**
Other Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	79,884	79,884	79,884	79,884	79,884	79,884	79,884	79,884	79,884	79,884
Adjusted R-squared	0.111	0.111	0.111	0.112	0.112	0.278	0.278	0.278	0.278	0.278

Table 10

Vocabulary Richness with Pre-defined Words Lists

This table reports our results by constructing Yule's K ratio with two pre-defined dictionaries. LM Dict stands for the words from Loughran and McDonald (2011) paper. Fin Dict stands for the words from Mastomoto et al (2011). The model specification is similar to those in column (3) or (6) in Table 5, but replacing the key independent variable with our newly constructed Yule's K. Detailed definitions for each variable are provided in Appendix II. Standard errors are clustered by firm and t-statistics are shown in bracket. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

	(1)	(2)	(3)	(4)
VARIABLES	CARs[0,+1]	Volumes[0,+1]	CARs[0,+1]	Volumes[0,+1]
ZYule's K in ExeQnA (LM Dict)	-0.004***	0.026***		
	[-8.689]	[9.120]		
ZYule's K in ExeQnA (Fin Dict)			-0.002***	0.010***
			[-4.842]	[3.880]
Ln(Size)	-0.012***	0.012	-0.012***	0.012
	[-10.968]	[1.403]	[-11.271]	[1.390]
Book to Market	0.029***	-0.044***	0.029***	-0.042***
	[20.250]	[-5.019]	[20.135]	[-4.781]
Return on Asset	0.106***	0.431***	0.107***	0.395***
	[5.831]	[3.704]	[5.842]	[3.383]
Negative Earnings	-0.000	-0.079***	-0.000	-0.079***
	[-0.115]	[-8.213]	[-0.077]	[-8.176]
Accruals	-0.034***	-0.006	-0.033***	0.014
	[-4.649]	[-0.109]	[-4.386]	[0.273]
Surprise Earnings	0.618***	1.242***	0.626***	1.269***
	[14.197]	[4.860]	[14.294]	[4.947]
Ln(Analysts)	0.004***	0.002	0.004***	0.003
	[4.418]	[0.382]	[4.456]	[0.440]
Meet Expectation	0.034***	-0.056***	0.034***	-0.057***
	[42.330]	[-11.734]	[42.490]	[-11.928]
Yule's K in AnaQnA	-0.004***	0.011***	-0.004***	0.012***
	[-8.849]	[3.428]	[-9.227]	[3.821]
Fog Index in ExeQnA	-0.000	-0.004**	-0.000	-0.004*
	[-1.343]	[-1.984]	[-1.513]	[-1.856]
Net Tone	2.281***	-0.374	2.252***	-0.219
	[30.280]	[-0.762]	[29.986]	[-0.448]
Ln(Total Words)	-0.011***	0.227***	-0.011***	0.223***
	[-7.164]	[20.854]	[-7.214]	[20.431]
Constant	0.136***	-1.321***	0.139***	-1.291***
	[8.862]	[-11.826]	[9.091]	[-11.461]
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	79,884	79,884	79,884	79,884
Adjusted R-squared	0.113	0.284	0.112	0.283

Table 11

Other Proxies for Vocabulary Richness

This table reports the results for other vocabulary richness proxies. The root type-token ratio is developed by Guiraud (1954). Corrected Type-Token Ratio is created by Carroll (1964). Somers Index is calculated by Somers (1966). Dugast Index is developed by Dugast (1978). The last index is invented by Mass (1972). Detailed definitions for each variable are provided in Appendix II. Standard errors are clustered by firm and t-statistics are shown in bracket. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

VARIABLES	(1) CARs[0,+1]	(2) Volumes[0,+1]	(3) CARs[0,+1]	(4) Volumes[0,+1]	(5) CARs[0,+1]	(6) Volumes[0,+1]	(7) CARs[0,+1]	(8) Volumes[0,+1]	(9) CARs[0,+1]	(10) Volumes[0,+1]
Root Type-Token in ExeQnA	0.003***	-0.029***								
	[9.432]	[-12.963]								
Corrected Type-Token in ExeQnA			0.004***	-0.042***						
			[9.432]	[-13.305]						
Somers Index in ExeQnA					0.358***	-1.204***				
					[5.581]	[-2.578]				
Dugast Index in ExeQnA							0.000***	-0.001***		
							[4.942]	[-3.216]		
Mass Index in ExeQnA									-1.765***	8.400***
									[-6.205]	[4.170]
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	79,884	79,884	79,884	79,884	79,884	79,884	79,884	79,884	79,884	79,884
Adjusted R-squared	0.113	0.285	0.113	0.285	0.112	0.284	0.112	0.283	0.113	0.284

Table 12

Robustness Check: Additional Controls

This table shows our results with more restricted fixed effects. Column (1) and (2) report the results with year per quarter fixed effects. Column (3) and (4) add industry per year fixed effect. Column (5) and (6) replace year per quarter fixed effect with call date fixed effects. The last two columns further relace firm fixed effect with firm per year fixed effect. Detailed definitions for each variable are provided in Appendix II. Standard errors are clustered by firm and t-statistics are shown in bracket. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	CARs[0,+1]	Volumes[0,+1]	CARs[0,+1]	Volumes[0,+1]	CARs[0,+1]	Volumes[0,+1]	CARs[0,+1]	Volumes[0,+1]
ZYule's K in ExeQnA	-0.003***	0.018***	-0.003***	0.017***	-0.003***	0.018***	-0.003***	0.014***
	[-7.810]	[6.557]	[-7.492]	[6.222]	[-7.186]	[6.473]	[-5.458]	[3.872]
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	NO	NO	NO	NO
Firm FE	YES	YES	YES	YES	YES	YES	NO	NO
Industry-Year FE	NO	NO	YES	YES	YES	YES	NO	NO
Call Date FE	NO	NO	NO	NO	YES	YES	YES	YES
Firm-Year FE	NO	NO	NO	NO	NO	NO	YES	YES
Observations	79,884	79,884	79,884	79,884	79,578	79,578	77,436	77,436
Adjusted R-squared	0.116	0.318	0.116	0.328	0.129	0.358	0.137	0.391

Table 13

Vocabulary Richness and Analysts Reactions

This table shows the estimated coefficients from a regression of vocabulary richness on analysts' reaction. Column (1) and (2) presents the results for analysts forecast likelihood, which is the percentage of analysts following the firm that issue a forecast within days [0,6] of the earnings announcement. Column (3) and (4) reports the results for analysts forecast speed, which is the inverse of the logged average number of days it takes analysts to update their future forecasts following the conference call. Detailed definitions for each variable are provided in Appendix II. Standard errors are clustered by firm and t-statistics are shown in bracket. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

	(1)	(2)	(3)	(4)
VARIABLES	Analysts Speed	Analysts Speed	Forecast Likelihood	Forecast Likelihood
ZYule's K in ExeQnA	0.001	0.002	-0.000	-0.000
	[0.299]	[0.347]	[-0.173]	[-0.121]
ZYule's K in ExeQnA* Surprise Earnings		-0.541**		-0.119*
		[-2.231]		[-1.950]
Surprise Earnings	-0.971***	-0.999***	-0.227***	-0.233***
	[-3.725]	[-3.817]	[-3.341]	[-3.418]
Other Controls	YES	YES	YES	YES
Indsutry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	77,873	77,873	76,809	76,809
Adjusted R-squared	0.191	0.191	0.178	0.178

Table 14

Vocabulary Richness and Stock Crash Risk

This table reports the effects of vocabulary richness on the future stock price crash risk. The dependent variable in columns (1) and (2) is the negative conditional skewness of firm-specific weekly returns over the next fiscal quarter. The dependent variable in columns (3) and (4) is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. Detailed definitions for each variable are provided in Appendix II. Standard errors are clustered by firm and t-statistics are shown in bracket. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

	(1)	(2)	(3)	(4)
VARIABLES	NCSKEW (Quarterly)	NCSKEW (Quarterly)	DUVOL (Quarterly)	DUVOL (Quarterly)
ZYule's K in ExeQnA	0.025**	0.046***	0.013**	0.021***
	[2.125]	[3.760]	[2.207]	[3.455]
Ln(Size)		0.312***		0.157***
		[12.762]		[12.131]
Book to Market		-0.872***		-0.353***
		[-24.285]		[-21.692]
Return on Asset		-0.123		-0.103
		[-0.289]		[-0.512]
Negative Earnings		-0.017		-0.019
		[-0.487]		[-1.117]
Accruals		0.003		-0.040
		[0.019]		[-0.457]
Surprise Earnings		-6.377***		-2.402***
		[-7.013]		[-5.469]
Ln(Analysts)		-0.095***		-0.024**
		[-4.387]		[-2.233]
Meet Expectation		-0.583***		-0.232***
		[-25.176]		[-22.136]
ZYule's K in AnaQnA		0.027**		0.015**
		[2.152]		[2.522]
Fog Index in ExeQnA		0.006		0.001
		[0.878]		[0.416]
Net Tone		-42.866***		-16.802***
		[-21.760]		[-17.740]
Ln(Total Words)		0.206***		0.083***
		[4.747]		[4.055]
Constant	0.077***	-2.876***	0.065***	-1.386***
	[80.103]	[-6.960]	[135.405]	[-6.926]
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	78,360	78,360	78,215	78,215
Adjusted R-squared	-0.0167	0.0229	-0.00440	0.0243

Appendix I

Yule's K Characteristics Calculation

This appendix provides a mathematical deviation for Yule's k characteristics formula from Yule (1944). The following paragraphs are directly excerpted from the book.

The homogeneous set of m words will be given by the Poisson distribution,

$$me^{-\lambda}(1+\lambda+\frac{\lambda^2}{2!}+\frac{\lambda^3}{3!}+\cdots)$$

As a result, the entire distribution we suppose to be compounded of a number of such components as the above equation with different λ. Let the mean of the λ-distribution be $\bar{\lambda}$ and its standard deviation σ_λ, and let the mean of the complete word distribution be M_c and its standard deviation σ_c. We evidently have at once

$$M_c = \bar{\lambda}$$

and since the total variance is the mean variance of the component distributions, which is $\bar{\lambda}$, plus the variance of the means, which is σ_λ^2,

$$\sigma_c^2 = \bar{\lambda} + \sigma_\lambda^2 = M_c + \sigma_\lambda^2$$

Now since all λ's are directly proportional to the total number of occurrences, doubling say the number of occurrences will double $\bar{\lambda}$ and also double σ_λ. Hence the coefficient of variation of λ or

$$v_\lambda = \frac{\sigma_\lambda}{\lambda}$$

is independent of the number of occurrences. But

$$v_\lambda^2 = \frac{\sigma_\lambda^2}{\lambda^2} = \frac{\sigma_c^2 - M_c}{M_c^2}$$

and hence the fraction on the right of this equation is independent of the number of occurrences, that is, of size of sample. It's a 'characteristics' of the complete distribution, independent of size of sample.

Furthermore, let's assume S_1 and S_2 are the first and second moments of the distribution. W is the whole number of unique words in the distribution, we therefore have

$$M_c = \frac{S_1}{W}$$

and

$$\sigma_c^2 = \frac{S_2}{W} - \frac{S_1^2}{W^2}$$

Hence the quantity on the right of formula for v_λ^2, which is independent of the number of occurrences may be written as

$$\frac{W^2}{S_1^2}\left(\frac{S_2}{W} - \frac{S_1^2}{W^2} - \frac{S_1}{W}\right) = \frac{S_2 - S_1}{S_1^2} W - 1$$

But W is independent of the number of occurrences. Hence, if the whole expression of the right is independent of the number of occurrences,

$$\frac{S_2 - S_1}{S_1^2}$$

must be independent of the number of occurrences and forms the ‘characteristic’ of the incomplete distribution we have been seeking. As a result, we can write the characteristic as

$$K = 10{,}000 * \frac{S_2 - S_1}{S_1^2}$$

The factor 10,000 is introduced only to avoid the inconvenience of handling small decimal.

Appendix II

Variable Definitions

Variable	Definition
CARs[0,+1]	Cumulative Abnormal Return from -1 days to +1 days around earnings related 8-K filings date
Volumes[0,+1]	Percentage of CARs [0,1]
Forecast Likelihood	Percentage of analysts following the firm that issue a forecast within days [0,6] of the earnings announcement. Following analysts are identified as those that issue or confirm at least one forecast in both the year before and after the EA.
Analysts Speed	The inverse of the logged average number of days it takes analysts to update their future forecasts following the EAs (deHaan et al., 2015)
Negative Earnings	A binary variable equals one if the firm has negative earning in that quarter
Meet Expectations	A dummy variable equals one if the firm meets analyst expectation in that quarter
Surprise Earnings	The difference between actual earnings and analysts' forecast
Ln(Size)	Natural log of the firm's total asset
Book to Market	Book equity over market equity
Return on Assets	Net income over assets
Accrual	Quarterly accrual over total assets. Accrual is defined as IBCY-OANCFY using Compustat quarterly
Ln(Analysts)	Natural log of the number of analyst follows the firm during the quarter for the company
PSL	An indicator variable equals one if the firm locates in the states after the paid sick leave law pass according to the Appendix IV.
PSL (#)	An indicator variable equals one if there are # of years between the current years and the law passage year.
Fog Index in ExeQnA	The fog index for executives' answers during discussion section
Root Type-Token in ExeQnA	The root type-token ratio for executives' answers during discussion section
NCSKEW (Quarterly)	Negative conditional skewness of firm-specific weekly returns over the next fiscal quarter
DUVOL (Quarterly)	Natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks.
Yule's K in Pre	The Yule's K ratio in presentation section
Yule's K in ExeQnA	The Yule's K ratio for executives' answers during discussion section
Yule's K in AnaQnA	The Yule's K ratio for analysts' question during discussion section
ZYule's K in Pre	Standardized Yule's K in Pre
ZYule's K in ExeQnA	Standardized Yule's K in ExeQnA
ZYule's K in AnaQnA	Standardized Yule's K in AnaQnA
Corrected Type-Token in ExeQnA	The corrected root type-token ratio for executives' answers during discussion section

Somer Index in ExeQnA	The Somer Index for executives' answers during discussion section
Dugast Index in ExeQnA	The Dugast Index for executives' answers during discussion section
Mass Index in ExeQnA	The Mass Index for executives' answers during discussion section
Net Tone	The difference between the number of positive words and negative words in earnings call transcripts, scaled by the total number of words
Ln(LDA Topics)	The total number of topics within the executives' answer during discussion section
Ln(Total Words)	The total number of words within the earning calls
Yule's K in ExeQnA (LM Dict)	The Yule's K ratio for the dictionary from Loughran and McDonald (2011) for executives' answers during discussion section
Yule's K in ExeQnA (Fin Dict)	The Yule's K ratio for the dictionary from Matsumoto et al. (2011) for executives' answers during discussion section
ZYule's K in ExeQnA (LM Dict)	Standardized Yule's K in ExeQnA (LM Dict)
ZYule's K in ExeQnA (Fin Dict)	Standardized Yule's K in ExeQnA (Fin Dict)
Return on Assets	Net income over assets
Miss Expectation	A dummy variable equals one if the firm miss analyst expectation in that quarter
Surprise Earnings	The difference between actual earnings and analysts' forecast in terms of the stock price
Firm Age	The number of years since a firm shows up in Compustat Database
Delaware Incorporate	A dummy variable equals one if a company is incorporated in Delaware and 0 otherwise
M&A Event	A dummy variable equals one if a firm appears as an acquirer in this year in SDC Platinum M&A database and 0 otherwise
SEO Event	A dummy variable equals if a firm has seasoned equity offering in this year according to SDC Global New Issues database and 0 otherwise.
Special Items	The special item scaled by total assets
Return Volatility	The standard deviation of the monthly stock returns in the last year
Earnings Volatility	The standard deviation of the operating earnings in the last five fiscal years
Ln(Non-missing Items)	The number of non-missing items on Compustat
Ln(Geo Segments)	Number of geographic segments from Compustat
Ln(Business Segments)	Number of business segments from Compustat

Appendix III

Topic Analysis Details

Following Huang et al. (2018), we can summarize the topic analysis for earnings calls into three significant steps: cleaning the data, choosing the optimal parameters of the LDA topic algorithm, and constructing the topic vector of earnings calls.

Clean the earnings call data

As described in our paper, we mainly focus on the Q&A section of earnings calls. As a result, we first extract all answers from executives in the Q&A section for each earnings call by implementing our segment separation algorithm for conference calls. Then, we remove all common stop words and high-frequency words that appear in more than 80% of all the call transcripts.

Choose the parameters for LDA model

The LDA algorithm we are using the the Gensim Library in Python. After cleaning the original conference call transcript in the first step, we first use the "Gensim.Corpora" to create the dictionary and covert all documents into vectors. Furthermore, we use the "LdaModel" duction to conduct the LDA analysis.

To choose the optimal number of topics, we generate the perplexity score as discussed in Huang et al. (2018) and choose the topic number with the lowest number. Table IIIA displays the value for the number of topics and perplexity score combination. After this step, we determine the optimal number of topics is 6.

Number of Topics	Perplexity Score
2	2072.751
5	1937.748
6	**1914.603**
7	1939.937
9	1954.210
9	1996.338
10	2078.427
20	2463.357
30	2848.887
40	3378.242
50	3995.454

LDA results

After selecting the optimal parameters for earnings calls, we implement the LDA model for all transcripts and generate the keywords for each topic. The keywords for each topic can be founded in Table IIIB.

Topics	Key Words
1	'0.009*"price" + 0.008*"cost" + 0.007*"project" + 0.005*"oper" + 0.005*"got" + 0.005*"cash" + 0.005*"demand" + 0.004*"capit" + 0.004*"they" + 0.004*"certainli" + 0.004*"volum" + 0.004*"could" + 0.004*"obvious" + 0.004*"impact" + 0.004*"level" + 0.004*"capac" + 0.004*"plan" + 0.003*"month" + 0.003*"side" + 0.003*"improv"'
2	'0.017*"custom" + 0.008*"revenu" + 0.006*"margin" + 0.005*"servic" + 0.005*"they" + 0.005*"technolog" + 0.004*"invest" + 0.004*"sale" + 0.004*"strong" + 0.004*"grow" + 0.004*"peopl" + 0.004*"impact" + 0.004*"obvious" + 0.004*"use" + 0.004*"side" + 0.003*"team" + 0.003*"solut" + 0.003*"abl" + 0.003*"provid" + 0.003*"platform"'
3	'0.008*"store" + 0.007*"brand" + 0.007*"custom" + 0.006*"sale" + 0.005*"peopl" + 0.005*"great" + 0.005*"margin" + 0.005*"they" + 0.005*"consum" + 0.005*"retail" + 0.005*"got" + 0.005*"price" + 0.005*"obvious" + 0.004*"categori" + 0.004*"better" + 0.004*"impact" + 0.004*"team" + 0.004*"inventori" + 0.004*"feel" + 0.004*"cost"'
4	'0.019*"patient" + 0.010*"data" + 0.009*"studi" + 0.006*"trial" + 0.006*"clinic" + 0.005*"use" + 0.005*"program" + 0.004*"abl" + 0.004*"obvious" + 0.004*"phase" + 0.004*"they" + 0.004*"care" + 0.004*"dose" + 0.004*"could" + 0.004*"import" + 0.003*"drug" + 0.003*"potenti" + 0.003*"believ" + 0.003*"month" + 0.003*"test"'
5	'0.009*"revenu" + 0.008*"okay" + 0.008*"user" + 0.007*"servic" + 0.006*"foreign" + 0.006*"languag" + 0.006*"platform" + 0.006*"believ" + 0.006*"content" + 0.006*"regard" + 0.005*"alreadi" + 0.005*"onlin" + 0.005*"oper" + 0.005*"cost" + 0.005*"cours" + 0.005*"mention" + 0.005*"interpret" + 0.005*"answer" + 0.004*"china" + 0.004*"student"'
6	'0.006*"portfolio" + 0.006*"asset" + 0.006*"capit" + 0.006*"loan" + 0.005*"they" + 0.005*"obvious" + 0.004*"invest" + 0.004*"peopl" + 0.004*"basi" + 0.004*"interest" + 0.004*"bank" + 0.004*"could" + 0.004*"manag" + 0.004*"credit" + 0.004*"got" + 0.004*"level" + 0.003*"sort" + 0.003*"deal" + 0.003*"side" + 0.003*"cost"'

As shown in the above table, we listed the top 20 keywords for each topic. The number before each keyword is the weight for those keywords. Large number means a higher weight for that keyword than the others.

Appendix IV

Law Pass Date for Paid Sick Leave Law

This table reports the detailed date for each state passing the paid sick leave law.

State	Law Pass	Law Effective
Washington, DC	May 13,2008	Nov 13,2008
Connecticut	July 1,2011	Jan 1,2012
California	Sept 19,2014	July 1,2015
Massachusetts	Nov 4,2014	July 1,2015
Oregon	June 22,2015	Jan 1,2016
Vermont	March 9,2016	Jan 1,2017
Arizona	Nov 8,2016	July 1,2017
Washington	Nov 8,2016	Jan 1,2018
Maryland	Jan 12,2018	Feb 11,2018
New Jersey	May 2,2018	Oct 28,2018
Michigan	Dec 13,2018	March 28,2019

Appendix V

Callaway and Sant'Anna Difference-in-Differences Estimators

This table shows the estimated coefficients from Callaway and Sant'Anna (2021) (CS Method). Panel A reports the results for the Average Treatment of Treated Group (ATT) from CS Method With Controls using nerve-treated firms as control samples. Panel B shows the dynamic effect. Detailed definitions for each variable are provided in Appendix II. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

Panel A: ATT Effects

CS Method	Coefficient	Std. Err	z	P>|z|
ATT	-0.286	0.083	-3.46	0.001

Panel B: Dynamic Effects

VARIABLES	(1) ZYule's K in ExeQnA
PSL (-3)	0.134
	[0.672]
PSL (-2)	0.113
	[1.587]
PSL (-1)	0.110
	[1.142]
PSL (0)	-0.189*
	[-1.772]
PSL (+1)	-0.303***
	[-3.321]
PSL (+2)	-0.335
	[-1.412]
PSL (+3)	-0.802
	[-1.512]

Appendix VI

Stacked Difference-in-Differences Method

This table reports the results by using the Stacked Difference-in-Differences Specification. In particular, we use the following procedure to create a stacked sample. First, we group treated firms by the PSL passage quarter. For each group, we choose firms which located in states that never adopted PSL law as control firms. This procedure ensures that we include never treated firms as control firms, thereby eliminating the bias in the standard staggered difference-in-differences specification. Panel A reports the summary statistics for our stacked sample and panel B reports the regression results. Detailed definitions for each variable are provided in Appendix II. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1..

Panel A: Summary Statistics

	(1) N	(2) mean	(3) sd	(4) p25	(5) p50	(6) p75
Dependent Variable						
ZYule's K in ExeQnA	1,441,253	-0.0811	0.847	-0.674	-0.205	0.371
Firm Fundamentals						
Ln(Size)	1,441,253	7.912	1.850	6.673	7.868	9.105
Book to Market	1,441,253	0.586	0.513	0.264	0.476	0.778
Return on Assets	1,441,253	0.00657	0.0349	0.00189	0.00921	0.0195
Negative Earnings	1,441,253	0.130	0.337	0	0	0
Accrual	1,441,253	0.0177	0.0793	0.00395	0.0184	0.0451
Ln(Analysts)	1,441,253	1.844	0.826	1.386	1.946	2.485
Meet Expectation	1,441,253	0.635	0.481	0	1	1
Surprise Earnings	1,441,253	-2.02e-05	0.0115	-0.000735	0.000435	0.00206
Firm Age	1,441,253	28.17	18.90	13	23	42
Delaware Incorporate	1,441,253	0.594	0.491	0	1	1
M&A Event	1,441,253	0.159	0.366	0	0	0
SEO Event	1,441,253	0.101	0.301	0	0	0
Special Items	1,441,253	0.553	0.507	0.234	0.440	0.741
Return Volatility	1,441,253	0.102	0.0593	0.0613	0.0868	0.125
Earnings Volatility	1,441,253	205.3	490.7	16.61	44.97	143.1
Ln(Non-missing Items)	1,441,253	5.739	0.146	5.617	5.704	5.864
Ln(Geo Segments)	1,441,253	1.502	1.040	0	1.386	2.303
Ln(Business Segments)	1,441,253	1.764	0.857	1.386	1.792	2.485

Panel B: Regression Results

VARIABLES	(1) Yule's K in ExeQnA	(2) Yule's K in ExeQnA
PSL	-0.053**	-0.044**
	[-2.624]	[-2.145]
Controls	NO	YES
Firm FE & Year FE	YES	YES
Observations	1,441,253	1,441,253
Adjusted R-squared	0.424	0.427

Appendix VII

Financial Words List from Matsumoto et al. (2011)

This table reports the full words lists from Matsumoto et al. (2011) There are a total of 137 words in their list.

accounting	covenants	financially	losses	revenues
accrual	currencies	financials	margin	roa
accruals	debentures	financing	margins	roe
accrued	debt	financings	obligations	roi
allowance	debts	gain	payable	sales
allowances	deferrals	gains	payables	securities
amortization	deposit	goodwill	payment	securitization
amortize	deposits	hedge	payments	security
amortized	depreciation	hedged	pound	selling
asset	derivative	hedges	pounds	shares
assets	derivatives	hedging	prepaid	swaps
bond	dividend	impaired	prepayment	tax
borrowed	dividends	impairment	prepayments	taxable
borrowing	dollar	impairments	pretax	taxes
borrowings	dollars	income	profit	unamortized
budget	earnings	interest	profitability	unleveraged
budgeted	ebit	investment	profits	warrants
budgeting	ebitda	investments	receivable	
buybacks	eps	lease	receivables	
capex	equities	leased	redeemable	
capital	equity	leases	refinance	
capitalization	euro	leasing	refinanced	
capitalize	euros	lending	refinancing	
capitalized	expenditure	leverage	rent	
cash	expenditures	liabilities	rental	
cent	expense	liability	rentals	
cents	expenses	liquidity	repurchasing	
convertible	finance	loan	reserve	
cost	financed	loans	reserves	
costs	financial	loss	revenue	

Appendix VIII

Vocabulary Richness for 10-K fillings

This table shows the relation between earnings persistence and vocabulary richness. Column (1) to (3) report the results for earnings for next year. Column (4) to (6) show the results for earnings in two years ahead. Column (1) and (4) presents the results with only fixed effects. Column (2) and (5) further add firm fundamentals as controls. Column (3) and (6) replace industry fixed effect with firm fixed effect. Detailed definitions for each variable are provided in Appendix II. Standard errors are clustered by firm and t-statistics are shown in bracket. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

VARIABLES	(1) Earnings (t+1)	(2) Earnings (t+1)	(3) Earnings (t+1)	(4) Earnings (t+2)	(5) Earnings (t+2)	(6) Earnings (t+2)
Earnings (t)	0.990***	0.909***	0.750***	0.963***	0.843***	0.546***
	[35.242]	[32.409]	[23.248]	[24.725]	[20.860]	[13.225]
Yule's K Ratio in 10K	0.002***	0.005***	0.005***	0.004***	0.006***	0.006***
	[5.442]	[9.784]	[8.445]	[5.526]	[9.750]	[7.908]
Earnings (t)*Yule's K Ratio in 10K	-0.003***	-0.003***	-0.004***	-0.004***	-0.004***	-0.004***
	[-7.556]	[-6.946]	[-7.710]	[-7.748]	[-6.593]	[-6.676]
Fog Index in 10K		-0.022***	-0.020***		-0.021***	-0.013*
		[-5.585]	[-3.935]		[-3.595]	[-1.880]
Ln(Size)		0.063***	-0.019		0.112***	-0.031*
		[14.725]	[-1.570]		[16.798]	[-1.783]
Market to Book		-0.280***	-0.400***		-0.263***	-0.298***
		[-25.019]	[-24.796]		[-17.765]	[-15.710]
Firm Age		0.005***	-0.287		0.007***	-0.694
		[9.688]	[-0.944]		[9.419]	[-1.386]
Special Item		-0.767***	-0.680***		-0.994***	-0.693***
		[-9.152]	[-7.611]		[-9.173]	[-6.497]
Return Vol		-1.066***	-0.624***		-1.289***	-0.554***
		[-15.990]	[-8.290]		[-14.828]	[-6.093]
Earnings Vol		0.000***	0.000***		0.000***	0.000
		[4.887]	[2.795]		[3.450]	[0.737]
Ln(Non-Missing Items)		-0.208**	-0.791***		-0.185	-1.215***
		[-2.437]	[-6.195]		[-1.404]	[-6.590]
Ln(Geo Segments)		0.010	0.022*		0.013	0.019
		[1.538]	[1.872]		[1.328]	[1.148]
Ln(Business Segments)		0.015*	0.027*		-0.004	0.008
		[1.719]	[1.861]		[-0.260]	[0.356]
SEO Event		-0.105***	-0.033*		-0.149***	-0.030
		[-5.688]	[-1.668]		[-6.000]	[-1.209]
M&A Event		-0.023*	-0.002		-0.011	0.021
		[-1.677]	[-0.112]		[-0.602]	[1.141]
Delaware Incorp		-0.024**			-0.019	
		[-2.176]			[-1.055]	
Constant	0.027	1.451***	11.146*	0.087*	0.999	21.776**
	[0.834]	[2.920]	[1.860]	[1.913]	[1.310]	[2.191]
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	NO	YES	YES	NO
Firm FE	NO	NO	YES	NO	NO	YES
Observations	101,676	97,042	95,665	89,974	86,091	84,758
R-squared	0.619	0.637	0.695	0.472	0.498	0.622
Adjusted R-squared	0.618	0.636	0.660	0.470	0.496	0.580

Appendix IX

Vocabulary Richness for CEOs

This table shows the determinants for CEO's vocabulary richness. Column (1) presents the results with only CEO characteristics as controls. Column (2) further adds firm fundamentals as controls. Detailed definitions for each variable are provided in Appendix II. Standard errors are clustered by firm, and t-statistics are shown in the bracket. Significance level: *** p < 0:01, ** p < 0:05, * p < 0:1.

	(1)	(2)
VARIABLES	ZYule's K for CEO	ZYule's K for CEO
Female CEO	-0.175**	-0.182**
	[-2.287]	[-2.372]
Vega	0.000	-0.000
	[0.459]	[-0.583]
Delta	0.000	-0.000
	[0.465]	[-0.132]
Ln(CEO Age)	-1.444***	-1.391***
	[-8.470]	[-8.202]
Ln(Total Compensation)	0.194***	0.047*
	[8.263]	[1.700]
Leverage		0.066
		[0.564]
Ln(Size)		0.148***
		[6.586]
Book to Market		-0.252***
		[-5.546]
Firm Age		-0.003**
		[-2.182]
Special Items		0.615*
		[1.792]
Return Vol		-0.465
		[-1.551]
Earnings Vol		-0.000***
		[-3.902]
Ln(Non-Missing Items)		0.593
		[1.247]
Ln(Geo Segments)		-0.026
		[-1.080]
Ln(Business Segments)		0.025
		[0.956]
SEO Event		0.125***
		[3.054]
M&A Event		0.036
		[1.207]
Delaware Incorp		0.081
		[1.539]
Constant	4.233***	0.755
	[6.243]	[0.252]
Industry FE	YES	YES
Year FE	YES	YES
Observations	10,783	10,487
R-squared	0.272	0.299
Adjusted R-squared	0.257	0.282