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The semantic complexity of financial disclosures

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Abstract

We quantify the semantic complexity of firms' financial disclosures by capturing the connotation-altering impact of 'valence shifters,' which include adjectives (e.g., 'tiny'), adverbs (e.g., 'barely'), negators (e.g., 'cannot'), and adversative conjunctions (e.g., 'but,' 'although') that significantly modify the interpretation of sentences. The semantic complexity index (SCI) of a disclosure is defined as the proportion of sentences in the text containing at least one valence shifter. We show that an increase in disclosures' semantic complexity corresponds to significantly higher post-filing return volatility, indicating increased uncertainty among market participants. Our metric also renders most other competing measures insignificant in its presence. We also examine the effect of the Plain Writing Act of 2010 on the semantic complexity of disclosures and find that firms with the most complex disclosures prior to the Act significantly reduce their complexity after the Act.

Keywords: Financial disclosure, Information environment, Textual analysis, Plain English, Readability, Semantic complexity

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1. Introduction

Consider the sentence: 'We increased profits', and contrast it with a slight variation: 'We increased profits despite the pandemic'. The inclusion of the word 'despite' injects nuance and significantly alters the sentence's connotation. In principle, usage of such modifiers can materially influence investors' perception of the firm's performance. However, excessive usage of such qualifiers makes the text interpretation process harder, and can be strategically exploited by management to withhold or obfuscate negative information about the firm. We quantify the complexity of disclosures by the usage of such language and show that it aggravates uncertainty and significantly increases firms' post-filing volatility. Our metric of disclosures' semantic complexity is transparent, conceptually sound and is relatively immune from weakness afflicting other competing measures.

In general, firms' communication strategies with stakeholders are shaped by their desire to manage information asymmetry effectively. There must be a balance between providing sufficient transparency to build trust, and maintaining some level of confidentiality to protect proprietary information. Information asymmetry pervades the relationship between management and shareholders since insiders possess privileged information about the firm, and are privy to internal financial data, strategic plans, and operational insights that external stakeholders lack. This information disparity can exacerbate agency costs, engender mistrust and uncertainty among investors and can hinder efficient capital allocation. For example, managers have ample incentives—and abilities—to understate or use language that downplays the impact of negative information in dislcosure documents in order to mitigate short-term market reactions, avoid scrutiny, or create a facade of stability. However, this can be risky, since complex or opaque language can erode investor trust, hinder accurate valuation of the firm, and lead to increased speculation and volatility due to heightened uncertainty.[1] In extreme cases, it may even invite regulatory scrutiny and legal repercussions

[1] Kim *et al.* (2019); Li (2008) term this phenomenon the 'management obfuscation hypothesis'. Such concerns are also reflected in the 'incomplete revelation hypothesis' which posits that public information

if stakeholders perceive intentional deception.

Disclosure by firms can be impacted by an array of factors ranging from career concerns of the managers (Baginski *et al.*, 2018) to the social media opinion about the firm (Campbell *et al.*, 2022). Clear information dissemination and accurate financial disclosures by firms are critical to the functioning of financial markets. From this perspective, it is vital to understand the manner in which information is conveyed, the language employed, and the nuances of linguistic expression in firms' disclosures. In this paper, we argue that the semantic complexity of financial disclosures—as measured by the usage of text modifiers, which alter the connotation of sentences but have been relatively ignored in financial text analysis—may have profound implications for investor uncertainty and firm volatility. Further, insofar as higher semantic complexity makes text difficult to read, it is inversely related to a text's readability. Moreover, unreadable disclosures, employing verbose or hyper-technical writing engender ambiguity among its readers and could be used to obfuscate or understate unpleasant news from the shareholders (Securities and Exchange Commission, 2007). Several academic studies have found that poor readability of financial disclosures such as 10-K filings is associated with poor financial performance (Li, 2008), more earnings management (Lo *et al.*, 2017), and higher stock price crash risk (Kim *et al.*, 2019).

We quantify the semantic complexity index (SCI) of a financial text by defining it as the proportion of sentences containing at least one 'valence shifter'. Valence shifters are adjectives (e.g., 'tiny,' 'large'), adverbs (e.g., 'faintly,' 'strongly'), adversative conjunctions (e.g., 'but,' 'however,' 'although,' 'despite') and negators (e.g., 'cannot,' 'never') which significantly alter the connotation of text (Schulder *et al.*, 2018). A text with sentences featuring no valence shifters is assigned an SCI of zero, while that with at least one valence shifter in each sentence will have an SCI of 100%. For example, a financial document with an SCI of 30% contains at least one valence shifter in 30% of its sentences, and when compared with

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which is costly to acquire or process may not be fully reflected in stock prices and this incentivizes managers to hide bad news in unreadable text (Bloomfield, 2002).

a document with an SCI of 20%, displays more semantic complexity.

Insofar as semantically complex text is more challenging to interpret, and hence hinders the text's reading, high semantic complexity denotes poor readability. We note however, that while more semantically complex text necessarily suffers from poor readability, the two concepts are not identical. Text readability focuses on how easily the text can be understood based on its syntactic structure and language use, and emphasizes the use of shorter sentences and avoidance of polysyllabic words. Semantic complexity, on the other hand, emphasizes the role of qualifiers: adverbs, adjectives, (adversative) conjunctions, etc. which inject more nuance and modifications into the sentence's connotation. With this caveat in mind, we compare the semantic complexity of firms' disclosures with their readability.

Textual analysis of corporate disclosures has grown as an important research method (Bochkay *et al.*, 2023). In such analyses, there is an emphasis on syntactic or simple semantic features of corporate disclosures relating to the text's readability (or lack thereof). Currently popular metrics of readability can be divided into two broad types: i) formula-based measures such as Fog/SMOG/Flesch-Kincaid indices, and ii) quantity-based measures such as count of total words and file size. El-Haj *et al.* (2019) criticize formula-based metrics since they fail to reflect context and meaning. Additionally, Loughran and McDonald (2014a,b) criticize them for their emphasis on word-complexity as proxied by polysyllabic words such as 'telecommunication' or 'depreciation' which, they argue, are not complex for readers of financial documents; and further, are 'misspecified and difficult to measure.' In advocating for readability metrics based on writing style, Bonsall *et al.* (2017) criticize quantity-based measures such as file size and the total word count since they only capture the extent of superfluous words—merely one aspect of the plain English advice advocated by Securities and Exchange Commission (SEC). On the other hand, Loughran and McDonald (2016) criticize writing style-based measures as they fail to distinguish among the vast majority of accounting disclosures.

Our measure of semantic complexity is immune to such weaknesses since it is neither formula-based, nor is it reliant on polysyllabic word complexity, or writing-style-based considerations. It is a sentence-level metric based on the presence of nuance-injecting, connotation-modifying valence shifters and circumvents the problems associated with formula-based, quantity-based or writing style-based metrics. Yet another advantage of the SCI is its compatibility with new-age data structures and analysis of text in financial disclosures.[2] With the improvement in text analysis technology, all stakeholders—investors, analysts, hedge funds etc.—pore over the language employed and look for nuances in company disclosures.[3] Valence shifter usage can be an important accessory to the growing technological advances in financial disclosure text analysis. Since the SEC is also planning to introduce eXtensible Business Reporting Language (XBRL) tags for 'Management Discussion and Analysis' (MD&A) and 'Risk Factors' sections, to ensure easy extraction and analysis of the qualitative discussion, the usage of metrics based on semantic complexity can prove to be less cumbersome and more advantageous (Arnold *et al.*, 2012).

Our paper makes several contributions. First, we introduce a new, bottom-up, theoretically sound metric that quantifies a disclosure's semantic complexity while avoiding the pitfalls associated with prior measures. Second, based on a US sample of 45,208 firm-years from 1994–2018, we show that an increase in semantic complexity of firms' disclosures is associated with significantly higher post-filing firm volatility, which lends weight to the hypothesis that more complex disclosures induce more uncertainty among market participants. Third, this effect retains its impact in the presence of other readability metrics, and renders them insignificant in its presence, indicating that our measure captures features not represented in current metrics. Fourth, we show that for firms which issue restatements, the impact of semantic complexity on subsequent volatility weakens, suggesting a supplementary and clarifying role of restatements in supplying key material information to investors. Finally, we use the passage of the Plain Writing Act of 2010 as a quasi-natural experiment,

[2]For example, IFRS (2008) specify how new sources of data such as tone and emotion of executives can be grouped with traditional measures.

[3]For example, 'profits,' 'large profits,' 'not-so-large profits,' etc.

and show that the Act was a success insofar as it induced firms with the most complex disclosures prior to the Act to significantly reduce their disclosure complexity in its wake.[4] Our results retain their impact under a variety of robustness tests and are applicable for the text corresponding to the MD&A section, the Risk Factors section, as well as for the full 10-K.

Our approach to measuring semantic complexity, as described, offers several distinct advantages over more recent and popular techniques like BERT or ChatGPT, which employ transformer models but come at the cost of reduced interpretability. First, our metric is simple, transparent, and quite straightforward to interpret—quite the opposite behavior compared to 'black box' models such as BERT or ChatGPT. Second, consistent with the requirements of the regulator, the SCI for a firm's disclosure is reproducible, as well as replicable as opposed to BERT or ChatGPT. Third, our metric has significantly lower resource requirements compared to either BERT or ChatGPT, both of which require estimation of billions of parameters, and demand major investments into computational power and memory.

The findings of this study have the potential to inform regulators, accounting professionals, and corporate executives on the importance of clear and transparent financial communication. By recognizing the implications of semantic complexity in financial disclosures, stakeholders can make informed decisions to enhance the quality and effectiveness of financial reporting practices, leading to more efficient capital markets and improved investor outcomes.

The remainder of the paper proceeds as follows. Section 2 discusses the background and reviews the literature. Section 3 reviews the existing readability measures and introduces the new readability measure. Section 4 describes data collection and sample creation. Section 5 presents main findings. Section 6 reports robustness results. Section 7 concludes.

[4]Our results are consistent with related findings reported in Hwang and Kim (2017).

2. Background

To improve the state of communication in firms' financial disclosure filings, the SEC adopted the 1998 *Plain English Mandate*, SEC Rule 421(d), complemented with a handbook entitled "*A Plain English Handbook: How to Create Clear SEC Disclosure Documents*". The handbook encouraged registrants to adopt plain English writing principles by avoiding (among others) long sentences, passive voice, superfluous words, unnecessary details, and unreadable design and layout (Securities and Exchange Commission, 1998).

The SEC classified components of plain English in the following six categories: 'average sentence length,' 'average word length,' 'passive voice,' 'legalese,' 'personal pronouns,' and 'negative/superfluous phrases.' While the rule officially applied only to prospectus filings, the SEC stated its clear preference for usage of plain English in all communication with stakeholders. In particular, Loughran and McDonald (2014b) find that firms with better corporate governance policies are more likely to file more readable 10-K filings. In a related paper, Bonsall and Miller (2017) used difference-in-differences to show that the 1998 Plain English Mandate led to the impacted firms' filings becoming more readable which led to lower costs of debt.

The Plain Writing Act of 2010 was signed into law on October 13, 2010 with the objective of making the government more transparent to its citizenry. The law requires that Federal agencies use clear government communication that the public can understand and use. From the perspective of disclosures' readability, the Act has had a positive impact. Hwang and Kim (2017) show that the Plain Writing Act (2010) disproportionately improved readability scores of funds with poorly readable disclosures prior to the Act. Kim *et al.* (2022) study the impact of the Plain Writing Act and show that 10-K files have become easier to read, leading to more effective risk management.

An early, prominent study of readability of financial texts is Li (2008) which examines the impact of readability—proxied by the Fog index—on earnings' persistence and finds that annual reports of firms with lower earnings are hard to read. Another early paper is

Biddle *et al.* (2009) which examines the impact of financial reports' readability on investment efficiency and reports significant results. On a related note, Miller (2010) finds that more complex financial reports are associated with lower trading due to reduced activity by small investors. Lehavy *et al.* (2011) also use the Fog index as a measure of readability and find that a higher Fog index (lower readability) is associated with significantly higher analyst following. Lawrence (2013) also uses the Fog index, as well as financial disclosures' log of word count, and finds that individuals invest more with firms which have clear and concise disclosures. On the other hand, Loughran and McDonald (2014a) argue that readability measures based on average words per sentence and percentage of complex words as constituents (e.g., Fog index, SMOG index, and Flesch–Kincaid index) are misleading for the purposes of financial reports and disclosures. Instead, they advocate the usage of the file size of the financial report as a metric of readability. Lo *et al.* (2017) analyze the association between the readability of the MD&A section of the 10-K reports and earnings management using the Fog index as a measure of readability. Ertugrul *et al.* (2017) and Kim *et al.* (2019) further examine the impact of readability using file size and a modified Fog index respectively as proxies and report that firms with more complex reports have higher risk of future stock price crashes. They also note how file size suffers from a severe measurement error problem in gauging information obfuscation, since graphics, XBRL and HyperText Markup Language (HTML) significantly enlarge the file sizes of 10-K reports but actually improve the informational content of disclosures.

3. Disclosure Text Measures

3.1. The Semantic Complexity Index

Which features contribute to increasing semantic complexity of a text? There are many non-equivalent ways of arranging text leading to the same connotation—some more complex to parse and/or interpret, others much less so. Among two connotation-preserving textual mappings, the one with more semantic complexity is more difficult to parse and interpret.

For example, consider two simple sentences: 'Last quarter was profitable,' and 'Last quarter was profitable despite the pandemic.' While superficially similar, the two sentences carry different connotations. In particular, the usage of the adversative conjunction 'despite' in the second sentence increases its semantic complexity and modifies the connotation by adding more nuance to its interpretation. The word 'despite' in our example, is an instantiation of a 'valence shifter,' which are adjectives, adverbs, conjunctions, negations, etc. which modify the connotation of sentences but have remained relatively ignored in the literature.

We define a new measure of financial texts' semantic complexity: the 'semantic complexity index' (SCI). The semantic complexity index captures the incremental connotation of that part of a sentence which features the usage of text modifiers such as amplifiers ('very'), de-amplifiers ('barely'), negators ('never'); and adjectives, adverbs and (adversative) conjunctions (e.g., 'slightly,' 'massively,' 'despite,' 'but,' etc.)—all of which alter the connotation of noun-forms with which they are used. Increased usage of valence shifters makes ascribing meaning to sentences more difficult, and therefore, makes the text harder to interpret. Financial disclosures that display high levels of semantic complexity necessarily employ more modifiers, negators, adjectives, adverbs and (adversative) conjunctions. In principle, such complex, nuanced writing could be used to obfuscate, prevaricate or create ambiguity with regard to the connotation of the underlying text. From this perspective, financial disclosure documents with high SCI can create ambiguity and uncertainty among investors, analysts, as well retail investors who are primary readers of such documents.

We define the SCI of a financial text as the proportion of sentences containing at least one valence shifter. A text with sentences featuring no valence shifters will be assigned an SCI of zero, while that with at least one valence shifter in each sentence will have an SCI of 100%. Of course, empirical values of semantic complexity for financial documents lie between these two theoretical extremes. For example, a financial document with SCI 50% contains at least one valence shifter in half of its sentences, and when comparing with a document with an SCI of 25%, displays more semantic complexity. Equivalently, the readability of a financial document with SCI 50% is lower than one with an SCI value of 25%.

An increase in a firm's disclosures' semantic complexity can lead to a variety of negative reactions from its stakeholders, all of which ultimately stem from the information asymmetry between insiders (management) and outsiders (stakeholders). Among shareholders, it can generate perceptions of mistrust and incompetence with its management, which can further shake the confidence of investors leading to questions about governance. Such increase in mistrust and uncertainty among shareholders, analysts, and other market participants can amplify the volatility of the firm after the 10-K filing.

We follow Loughran and McDonald (2011) in parsing text from 10-K reports and removing tables and exhibits during the parsing process. In our methodology, the sentence is the unit of analysis, which we define as sequences of words delimited by: (1) two periods (full stops), (2) a period (full stop) and a question mark, and (3) two question marks.

3.2. Formula-based Measures Reliant on Word Complexity

Complex words are identified as words with three or more syllables. The percentage of complex words, and average words per sentence form the components of three major formula-based readability metrics: the Fog index, the Flesh-Kincaid index, and the SMOG index. While such formula-based readability metrics are widely used, Loughran and McDonald (2014a) criticize them by pointing out that polysyllabic words, such as 'telecommunication' or 'depreciation' are not necessarily complex for readers of financial documents.

3.3. Measures based on Vocabulary and Size

The 'Vocabulary' measure is calculated as the number of unique words in the 10-K divided by the the number of entries in the LM dictionary (Loughran and McDonald, 2014a). 'Financial terminology' is defined by the number of unique words in the 10-K report which appear in Campbell Harvey's hypertextual finance glossary (`http://people.duke.edu/~charvey/Classes/wpg/glossary.htm`) divided by the total number of unique words in the MD&A (Loughran and McDonald, 2014a). Size-based measures include the log of the total number of words in the 10-K; and the log of net, as well as the gross file size of the 10-K (Loughran and McDonald, 2014a).

4. Data and Sample

Data used in this study are retrieved from several databases. First, we download all 10-K files available on EDGAR for the period of 1994–2018. Second, we download several dictionaries for computing readability measures: the Loughran and McDonald word list is downloaded from the website: `https://sraf.nd.edu/textual-analysis/resources/` for constructing the LM based vocabulary measure. Similarly, the Harvey Campbell word list is downloaded from: `http://people.duke.edu/~charvey/Classes/wpg/glossary.htm`. Third, data on market returns are downloaded from Kenneth French's website: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. Finally, we retrieve stock price and firm characteristics data from CRSP and COMPUSTAT to construct the control variables that are detailed in Section 5.3.

Table 1 presents the sample creation process for our study. We start with all 10-K files for the period of 1994–2018 (10-K, 10-KSB, 10-K405 and 10-KSB40) and extract the MD&A section from these files leading to an initial sample of 242,181 observations. In line with Loughran and McDonald (2014a) we remove duplicate filings with respect to CIK and year combination, and also if the filing date is fewer than 180 days from prior filing which reduces our sample size to 239,423 firm-year observations. Next, we drop files for which relevant control variables are not available from CRSP and COMPUSTAT, which narrows down our sample size to 137,474 observations. We then retain ordinary common stock according to CRSP, drop 10-K files for which the RMSE value is missing, and require the stock price of at least $3 to minimize market microstructure effects. This brings the final sample to 45,208 firm-year observations. Table 1 reports the sample formation process in detail.

[Table 1 about here.]

5. Results

5.1. Descriptive Results

Table 2 reports descriptive statistics for the sample variables. Panel A reports variable means by time period. The first three columns divide the sample period in three parts (1994–2002; 2003–2011; 2012–2018) while the last column of the table lists the averages for the entire period (1994–2018). The average value for the *Fog index* for the entire sample period is 21.4, which is greater than the threshold value of 18 and hence implies that the average 10-K is difficult to read.[5] The mean values for the *Financial terminology* display very small changes over time. In contrast, the mean values of the *Fog index*, *SMOG index*, *Vocabulary*, and *Log(# of words)* display significant increases over time, indicating increased 10-K text complexity due to more complex words and lengthier documents in the later years. The mean semantic complexity index (SCI) shows a significant increase from the period 1994–2011 (22%–25.3%) but falls thereafter during the period 2012–2018 (24%). Panel B reports summary statistics for the entire sample duration (1994–2018). The mean and medians of the readability metrics are not very distant, as are the standard deviations and inter-quartile range (IQR) suggesting low asymmetry in their distributions.

Table 3 reports pairwise correlation between SCI and the existing readability measures. SCI is positively and significantly correlated with all existing readability measures at the 1% level, except for *Financial terminology* which is negatively correlated with SCI. The correlations of SCI with other readability metrics range from −0.01.2 to 0.41, which suggest that there are features captured by SCI that are relatively uncorrelated with those captured by other readability measures.

[Tables 2 and 3 about here.]

[5] Informally, a *Fog index* of, say 20, implies that the reader needs 20 years of schooling to understand the text.

5.2. Are Disclosures Getting Lengthier?

To provide some context for our analysis, we check the evolution of the characteristics of sample firms' 10-K files over time. For the median firm, we compute the (log) word-length for the MD&A section as well as for the full 10-K reports for the period 1995–2018, and plot them in Figure 1. Similarly, we calculate for the median firm, the (log) 10-K file size for the same period and plot in Figure 2. In both figures, we observe a significantly increasing trend in the word-length of the disclosures, as well as its file size, consistent with prior studies. For example, Dyer *et al.* (2017) show that the length of 10-K in general as well as its various sections has increased over the years. Similar trends are reported in Bonsall *et al.* (2017), where they show that both the number of words and file size of 10-K have increased over the years. This trend of increasing disclosure length is especially noticeable for the median firm's (log) file size—especially after 2010.

[Figures 1 and 2 about here.]

5.3. Volatility of Firms With Semantically Complex Disclosures

The central idea we wish to test is the following: does the inclusion of valence shifters—which modify and/or qualify the connotation of sentences—create more unreadable text, which in turn is harder to interpret and leads to uncertainty and mistrust amongst investors and readers of the disclosures? Further, is this effect strong enough to be detected after controlling for relevant firm-level characteristics and extant readability metrics? And if yes, does it imply that firms with more semantically complex disclosures suffer more volatile stock returns in the wake of their 10-K filing?

In order to test this hypothesis, we choose firms' post-filing root mean square error (RMSE) as indicative of their post-filing information environment and track its sensitivity to SCI after including relevant controls. Our empirical strategy and regression specification follow the benchmark set in Loughran and McDonald (2014a).

$$
\begin{aligned}
\textit{Post-filing } RMSE_{i,t} = \alpha_0 + \alpha_1 SCI_{i,t-1} + \alpha_2 Readability_{i,t-1} \\
+ \sum_{j=3}^{8} \beta_j Controls_{i,t-1} + FE\_ind + FE\_year + \epsilon_{i,t}
\end{aligned}
\tag{1}
$$

The dependent variable, *Post-filing RMSE*, is the root mean square error (RMSE) from a market model estimated using trading days [6, 28] relative to the 10-K file date. *SCI* is the semantic complexity index as defined in Section 3.1. *Readability* refers to one of the existing readability measures: *Fog index*, *Flesh-Kincaid index*, *SMOG index*, *Vocabulary*, *Financial terminology*, or *Log(# of words)*. Following Loughran and McDonald (2014a), we include a set of firm-specific control variables that explain subsequent stock return volatility, which include: (1) *Pre-filing alpha*, the alpha from a market model using trading days ([–252, –6]) prior to the filing date; (2) *Pre-filing RMSE*, the RMSE from the prior-period ([–257, –6]) market model regression; (3) *Abs(filing period abnormal return)*, the absolute value of the two-day buy and-hold abnormal return from the filing date (day 0) to day +1; (4) *Log(size in \$ millions)*, the natural logarithm of market capitalization on the day before the filing date; (5) *Log(book-to-market)*, the natural logarithm of the book-to-market ratio based on the data reported prior to the filing date; and (6) *NASDAQ dummy*, a dummy variable equal to 1 if the firm trades on NASDAQ, and 0 otherwise.[6] The regression includes an intercept, calender year dummies, and Fama and French 48-Industry dummies; and industry and year fixed effects. Standard errors are robust, and clustered by industry and year.

Table 4 presents the results of the regression which evaluates the association between firms' subsequent idiosyncratic volatility (post-filing RMSE) and control variables; as well as the association with SCI for the MD&A section of the 10-K in the presence of other existing readability measures. Column (1) reports the benchmark results on the association between post-filing RMSE and control variables in the absence of any readability measure. We observe that increase in levels of pre-filing performance and size are associated with significantly lower

[6] Detailed variable definitions are reported in Appendix B.

levels of subsequent volatility. On the other hand, increase in levels of pre-filing stock return volatility, and larger absolute abnormal returns on the filing date have significantly higher post-filing RMSE. Our results for the control variables are consistent with those reported in Loughran and McDonald (2014a). Columns (2–6) report the results on the impact of MD&A SCI on post-filing return volatility in the presence of other readability measures. As the columns show, SCI has a positive and statistically significant association on the post-filing RMSE above and beyond that attributable to current readability measures. This suggests that for otherwise comparable firms, the one with more (lesser) semantic complexity in its MD&A section of the 10-K document suffers higher (lower) levels of subsequent volatility. Further, the SCI renders the *Fog* and *SMOG* indices, the *Log(# words)* and *Financial terminology* insignificant in its presence.

[Table 4 about here.]

5.4. Impact of the Plain English Rule and the Plain Writing Act

In our sample period, there were two major exogenous developments which altered firms' usual disclosure filing practices. The Plain English Rule (October 1998) and, later, the Plain Writing Act (2010) expressed the regulator's and the US government's preferences for simple and clear communication with all stakeholders. Although not directly relevant for firms' disclosure policy these developments have nonetheless had an impact on firms' disclosure standards (Loughran and McDonald, 2014b; Hwang and Kim, 2017; Kim *et al.*, 2022). The interventions could be considered a success if they changed firms' disclosure norms towards higher readability and/or lower semantic complexity.

To examine any impact, we combine a difference-in-differences (diff-in-diff) estimator with a matching strategy to establish a relevant control group for the treatment firms. Our diff-in-diff analysis is based on estimating the following regression equation:

$$Post\text{-}filing\ RMSE_{i,t} = \beta_0 + \beta_1 Treated_i + \beta_2 Post_t + \beta_3 Treated_i \times Post_t + \sum_{j=4}^{9} \beta_j Controls_{i,t-1} + FE + \epsilon_{i,t} \tag{2}$$

where *Post-filing RMSE*, as previously defined, is a proxy for firms' information environment. We focus on two changes in disclosure requirements in the United States, namely the Plain English Rule (October 1998) and the Plain Writing Act (October 2010), that avail an exogenous shock to firms' disclosure complexity. Firms with the highest levels of financial disclosure complexity are deemed to be those most affected by the Plain English rules and the Plain Writing Act. *Treated* is a treatment group indicator that equals one (zero) for firms with SCI in the top (bottom) 5^{th} percentile of its empirical distribution in the year before the treatment. *Post* is a dummy variable that equals one after the treatment year (1999 for the Plain English Rule and 2011 for the Plain Writing Act), and zero before the treatment year. The coefficient of interest is β_3, which measures the difference-in-changes in post-filing RMSE for the treatment firms relative to the control firms. If β_3 is statistically significant, then the Plain English Rule and/or the Plain Writing Act has had an impact on firm disclosure readability and in turn, the information environment.

The diff-in-diff approach ensures that model estimation is not influenced by permanent and unobserved differences between the treated and the control group or by common trends. We include a set of time-varying firm-level controls associated with post-filing RMSE to rule out the possibility that the estimates are influenced by a contemporaneous shock to these characteristics. We also include firm and year fixed effects (FE) to control for the effect of unobservable time-invariant firm characteristics and economy-wide shocks on firm return volatility respectively. Standard errors are clustered at the firm level.[7] We begin with matching the treated and control groups by a set of matching covariates that are identical to the control variables in Equation (1). We implement 1-to-1 nearest neighbour

[7]Results remain robust when standard errors are clustered by industry and year.

matching (Rosenbaum and Rubin, 1983) with no replacement and impose a caliper of 0.2 of the standard deviation of the logit transformation. Table 5 reports the balancing properties of the matching covariates. No statistically significant differences are found between the treatment and control groups, providing support for balance between the two groups.

[Table 5 about here.]

We use the propensity-score-matched sample to examine the difference in post-filing RMSE between the treated and control firms. Table 6 reports the diff-in-diff analysis results. Panel A reports results for the impact of the Plain English Rule (October 1998) based on a sample ranging from 1995 to 2004. The coefficient on the interaction term, *Treated*×*Post*, is not statistically significant for either specification (columns 1 and 2), indicating the introduction of the Plain English Rule had no major effect. This could be because the 1998 Plain English Rule was not mandatory but merely advisory. Panel B reports results for the effect of the 2010 Plain Writing Act in for sample period of 2005–2018. The coefficient on the interaction term is found to be negative and statistically significant for both specifications (columns 3 and 4). This means that firms that are affected most by the Plain Writing Act mandated in October 2010 reduced their disclosure complexity and hence improved their information environment significantly in the post treatment period.

[Table 6 about here.]

Several identifying assumptions must be satisfied in order to obtain reliable diff-in-diff estimates. First, the pre and post periods should be balanced in terms of having the same firms in both periods (Atanasov and Black, 2021). Our sample selection criterion of retaining only firms that are present throughout the sample period for the diff-in-diff analysis satisfies this condition. Second, the treatment should have a significant effect on the treatment group, as reported in Panel B of Table 6. Finally, the outcome variable for treatment and control groups must exhibit parallel trends over the pre-treatment period (Lennox, 2016; Atanasov and Black, 2021) i.e., in the absence of treatment, the average change in the outcome variable should have been the same for both the treatment and control groups. Because such counterfactual trends are not empirically observable, we perform a counterfactual analysis of the Plain Writing Act 2010 to compare post-filing RMSE of the treatment group with that of the control group. We estimate the counterfactual treatment effect based on Equation (3) below:

$$\begin{aligned} \textit{Post-filing } RMSE_{i,t} = \gamma_0 + \sum_{n=1}^{6} \gamma_n Treated_i \times Pre_n + \sum_{k=1}^{8} \gamma_k Treated_i \\ \times Post_k + \sum_{j=15}^{20} \beta_j Controls_{i,t-1} + FE + \epsilon_{i,t} \end{aligned} \tag{3}$$

We replace the interaction term *Treated*×*Post* in Equation (2) with separate interactions between Treated and year dummies (except for year 2010, which is set as the benchmark). Pre_1–Pre_6 refer to 1–6 years before the implementation of the Plain Writing Act (2005–2010), and $Post_1$–$Post_8$ refer to 1–8 years after the treatment (2011–2018). The same set of control variables in Equation (1) are included. FE refer to firm and year fixed effects. Our findings, reported in Table 7 and plotted in Figure 3, suggest that the counterfactual treatment effects do not build up in the period before the Plain Writing Act mandate, which satisfies the parallel trends assumption and further supports the diff-in-diff analysis results reported in Table 6.

[Table 7 about here.]

[Figure 3 about here.]

We further corroborate the impact of the Plain Writing Act on financial disclosure complexity and subsequent return volatility by performing two placebo tests based on the diff-in-diff model described in Equation (2). In the first test, we assume 2007 is the treatment year, and select both pre- and post-periods before the Plain Writing Act (2005–2006 as the pre period; 2007–2009 as the post period). In the second test, we assume 2015 is the treatment year, and select both pre- and post-periods after the Plain Writing Act (2011–2014 as the pre period; 2015–2018 as the post period). For both tests, we perform PSM again based on the same set of matching covariates in the year prior to the placebo treatment year. Results for these two tests are reported in Panels A and B of Table 8 respectively. For both specifications, we do not find any significant, negative coefficient on the interaction term ($Treated \times Post$), providing further support for the impact of the Plain Writing Act on firm financial disclosure readability and information environment.

[Table 8 about here.]

5.5. Semantic Complexity for Restatement-Issuing Firms' Disclosures

Firms issue restatements when prior disclosures contain material errors which could have occurred due to accounting mistakes, noncompliance, fraud, misrepresentation or other types of inaccuracies. A large portion of restatements are innocent mistakes but a sizeable fraction could be due to fraud or misrepresentation that could have major adverse impact on investors' decisions.

We look at the collection of firms which issue restatements and check their relation with their disclosures' semantic complexity. Table 9 presents results on the impact of SCI on firms' post-filing volatility in the presence of restatements by introducing an interaction between SCI and a dummy restatement variable which assumes the value 1 in the presence of restatement in Form 8-K after the 10-K date, and 0 in its absence. We replicate our benchmark finding which indicates a significant, positive relationship between SCI and subsequent firm volatility in terms of its RMSE. Further, we find a significantly negative relationship for the interaction term *Restatement*×*SCI*, which indicates that for the pool of firms which do issue restatements, the impact of their disclosures' semantic complexity weakens. In other words, while a high level of semantic complexity in disclosure continues to be positively associated with a firm's RMSE, its magnitude is smaller for those firms which have issued restatements. This is consistent with the prior view that restatements can be viewed as an opposing act to management obfuscation of key material weaknesses, and grant firms a communication tool to clarify key material information.

[Table 9 about here.]

6. Robustness

6.1. Business Complexity

A financial document's readability can be influenced by two factors: (1) operational complexity (ontological explanation); and (2) deliberate obfuscation on part of the firm's executives (opportunistic explanation) (Bloomfield, 2008). For example, it is possible that firms with complex businesses necessarily need to use more complex language in their 10-K filings, and hence their financial disclosures' unreadability may naturally be much more than their counterparts who have lower business complexity. To account for this aspect, we further control for business complexity (Loughran and McDonald, 2014a), which is measured by *Business segment index* and calculated as the sum of the squared business segment proportions as reported for the firm in the COMPUSTAT database. For our sample, the value for *Business segment index* ranges from 0.11 to 1.00, with lower values implying higher firm-specific complexity. We report this test results in Table 10. SCI retains its positive and statistically significant coefficient across all model specifications. The new control variable, *Business segment index*, also displays positive significance across all specifications, which is consistent with analogous results reported in Loughran and McDonald (2014a).

[Table 10 about here.]

6.2. Full 10-K

We repeat out main analysis based on readability measures for the entire 10-K disclosure document. Results reported in Table 11 are qualitative similar to those reported in Table 4.

However, the level of statistical significance lowers from the 1% to 5% level, which could be due to the noise induced by the sections in the 10-K with lower or no standardization.

[Table 11 about here.]

6.3. Risk Factors Section

Similar to the MD&A section, another important section of 10-K is the Risk Factors section, where companies discuss the most significant factors that make the firm speculative or risky. Considering that SEC made risk disclosure a prime focus of its corporate filing review and investors incorporate this information into stock prices (Campbell *et al.*, 2014, 2019), there have been multiple studies which examine the importance of Risk Factors section (Hope *et al.*, 2016; Brown *et al.*, 2018). Table 12 presents the results for the effect of SCI on post-filing RMSE based on the Risk Factors section of 10-K. We find that the results are similar to those reported for the MD&A section in Table 4 and for full 10-K in Table 11, with SCI being positive and statistically significant across all specifications.

[Table 12 about here.]

7. Conclusion

We introduce a new metric of financial texts' readability: the semantic complexity index—which captures the incremental impact of negators, modifiers, adjectives, adverbs and (adversative) conjunctions—the effect of which is to quantify the effect of hard-to-interpret text, higher values of which lead to increased ambiguity and investor uncertainty. This manifests in significant positive associations of SCI with firms' subsequent return volatility. We also show that our metric renders other competitors insignificant in its presence indicating that we account for features not captured in currently popular measures.

We also show that for firms which restate results, the impact of disclosure complexity on firm volatility weakens, suggesting that restatements act as an additional information release channel. Our results retain their impact for the text corresponding to the MD&A section, the Risk Factors section, as well as that for the full 10-K document.

Our results are consistent with the 'management obfuscation hypothesis' (Li, 2008; Kim *et al.*, 2019) as well as with the 'incomplete revelations hypothesis' (Bloomfield, 2002). Further, using the passage of the Plain Writing Act (2010) as a quasi-natural experiment we analyze its impact on the semantic complexity of corporate disclosures. Employing a difference-in-differences analysis, we show that the Act has significantly lowered the disclosure complexity of the worst offenders prior to the Act, leading to improved information environment for firms. These results are consistent with prior findings reported in Hwang and Kim (2017).

Our approach can be modified and adapted by regulators and investors alike for a variety of applications. Its simplicity, replicability and conceptual soundness make it immune from several weaknesses from which its competitors suffer. This includes formula-based, or quantity-based metrics of text readability, as well as opaque, black-box techniques such as BERT and ChatGPT.

Figures

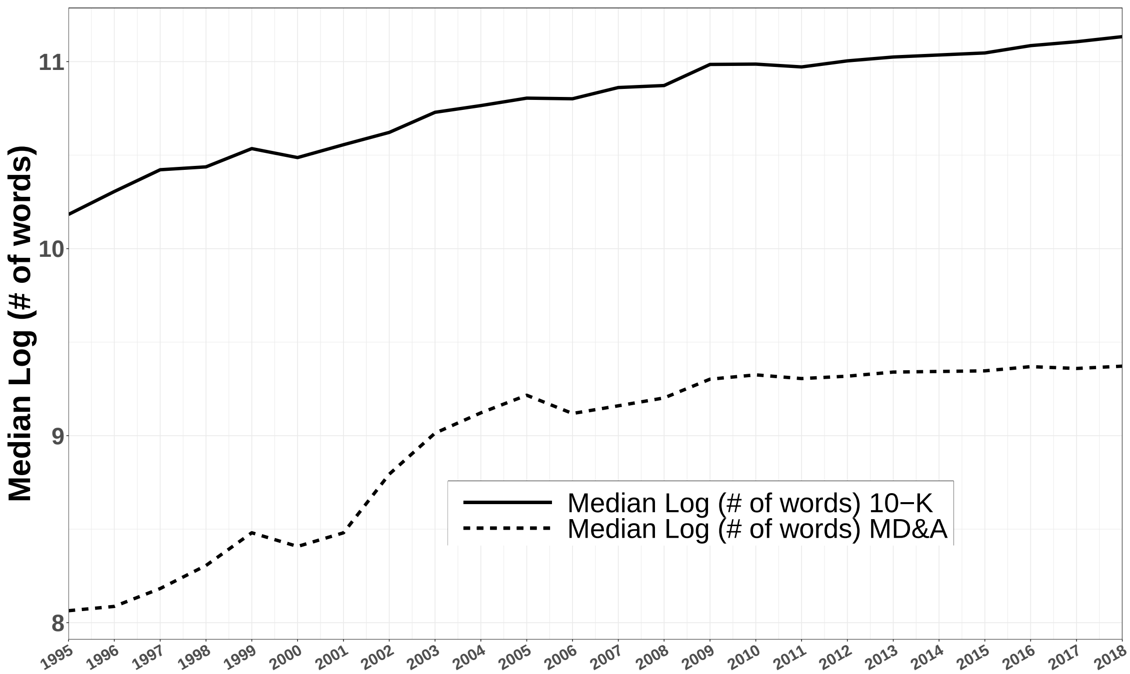

Figure 1: This figure presents the evolution of median value of Log(# of words) of 10-K files and the MD&A section from 1995 to 2018.

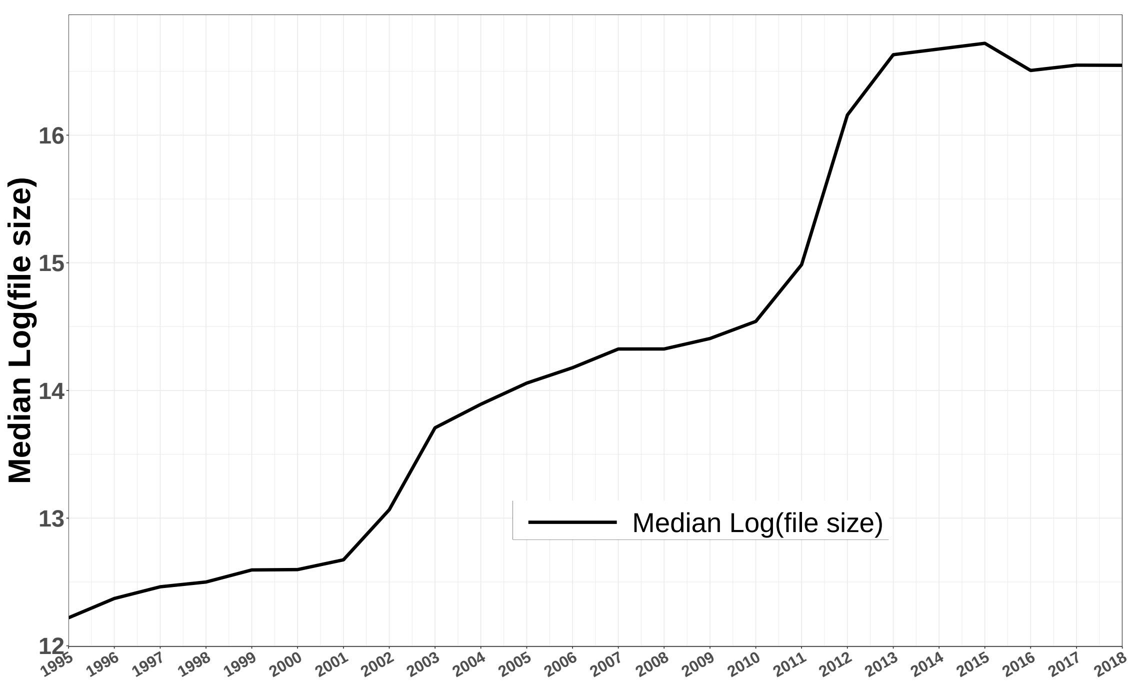

Figure 2: This figure presents the evolution of median value of Log(file size) of 10-K from 1995 to 2018.

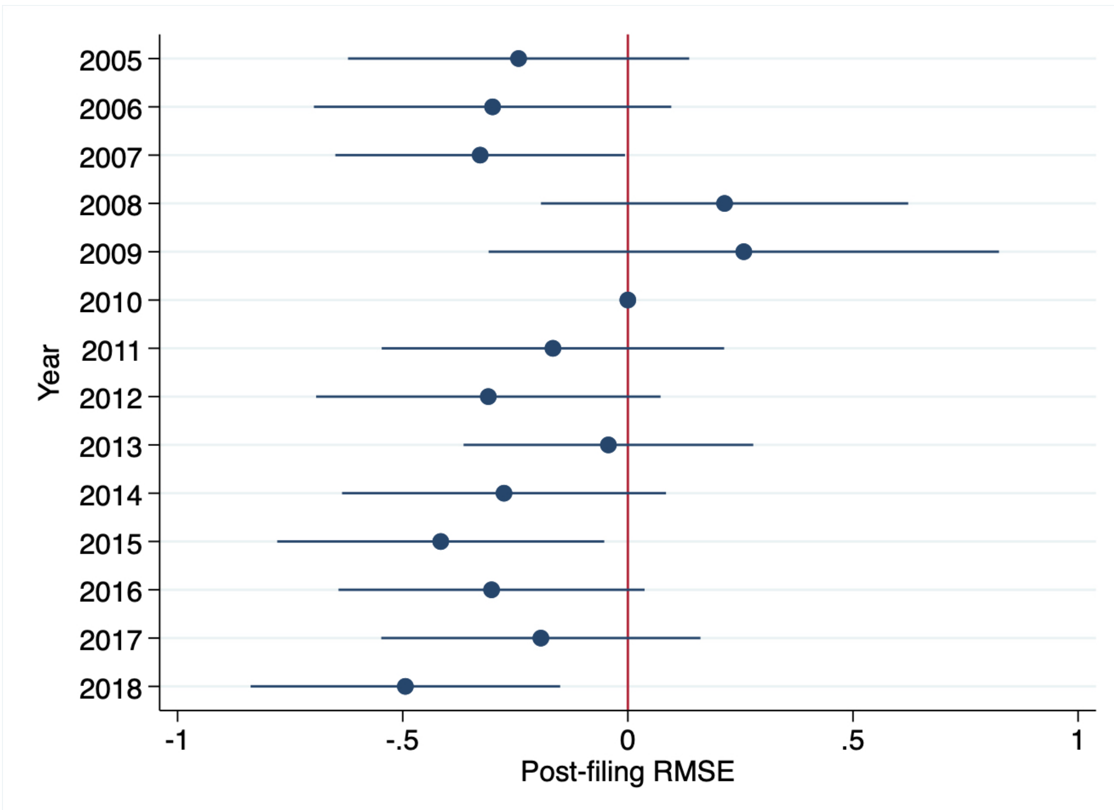

Figure 3: This figure plots the counterfactual treatment effects of the Plain Writing Act (October 2010). The year of the treatment (2010) is used as the benchmark (i.e., coefficient constrained to equal zero). The counterfactual treatment effects do not build up before the treatment, which satisfies the parallel trends assumption for reliable difference-in-differences estimates.

Tables

Table 1: Sample Creation

	Dropped	Sample Size
SEC 10-K files 1994–2018		242,181
Remove duplicates within year/CIK	2,409	239,772
Drop if file date < 180 days from prior filing	349	239,423
Drop if missing data in CRSP and COMPUSTAT	101,949	137,474
Reported on CRSP as ordinary common equity	3,901	133,573
Price on filing date minus one less than 3 USD	9,008	124,565
Drop if post-filing date market model RMSE value is missing	2,594	121,971
MD&A extracted from SEC 10-K files 1994–2018	76,565	45,406
Drop if MD&A has fewer than 250 words	198	45,208

Note: This table presents the details of sample construction and the number of observations dropped in each filtering step.

Table 2: Descriptive Statistics

Panel A. Variable Means by Time Period, 1994 to 2018

	1994–2002	2003–2011	2012–2018	1994–2018
Readability measures:				
Fog index	20.350	21.489	22.317	21.440
Flesch-Kincaid index	30.575	30.879	30.857	30.790
SMOG index	17.536	18.324	18.846	18.270
Vocabulary	0.399	0.633	0.703	0.590
Financial terminology	0.002	0.002	0.003	0.002
Log(# of words)	8.365	9.118	9.314	8.969
SCI	22.069	25.303	23.978	23.960
Dependent variable:				
Post-filing RMSE	3.551	2.099	1.617	2.387
Control variables:				
Pre-filing alpha	0.097	0.052	0.011	0.054
Pre-filing RMSE	3.870	2.650	2.135	2.864
Abs(filing period abnormal return)	0.040	0.029	0.028	0.032
Size (market capitalization) in $ millions	$1160.137	$2258.184	$5185.215	$2892.500
Book-to-market	0.632	0.665	0.623	0.642
NASDAQ dummy	0.665	0.607	0.552	0.610

Panel B. Summary Statistics

	Mean	Median	SD	IQR
Readability measures:				
Fog index	21.440	21.390	2.382	2.414
Flesch-Kincaid index	30.790	30.760	1.469	1.986
SMOG index	18.270	18.270	1.382	1.616
Vocabulary	0.590	0.567	0.238	0.311
Financial terminology	0.002	0.001	0.010	0.010
Log(# of words)	8.969	9.091	0.789	0.890
SCI	23.960	23.710	6.438	7.753
Dependent variable:				
Post-filing RMSE	2.387	1.814	2.005	1.810
Control variables:				
Pre-filing alpha	0.054	0.032	0.253	0.216
Pre-filing RMSE	2.864	2.413	1.939	2.037
Abs(filing period abnormal return)	0.032	0.018	0.043	0.031
Size (market capitalization) in $ millions	$2892.500	$404.500	$12724.140	$1365.615
Book-to-market	0.642	0.520	0.541	0.561
NASDAQ dummy	0.610	1.000	0.487	1.000

Note: This table presents mean summary statistics for the sample variables. *Financial terminology* is multiplied by 100 for ease of presentation. 'SD' and 'IQR' refers to standard deviation and interquartile range, respectively. Variable definitions are reported in Appendix B.

Table 3: Correlation among Readability Measures

	Fog index	*Flesch-Kincaid index*	*SMOG index*	*Vocabulary*	*Financial terminology*	*Log(# of words)*
Flesch-Kincaid index	0.136***	1				
SMOG index	0.936***	0.245***	1			
Vocabulary	0.237***	−0.089***	0.260***	1		
Financial terminology	0.008	−0.004	0.006	0.041***	1	
Log(# of words)	0.195***	−0.039***	0.228*** 93***	0.032***	1	
SCI	**0.364*** **	**0.233*** **	**0.410*** **	**0.164*** **	**−0.012*** **	**0.124*** **

Note: This table presents the correlations of various measures for financial disclosure readability. Variable definitions are reported in Appendix B.

Table 4: An Analysis of the Impact of SCI on Post-Filing Date Market Model Root Mean Square Error (RMSE)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Readability measures:							
Fog index			−0.001				
			(0.008)				
Flesch-Kincaid index				0.027***			
				(0.010)			
SMOG index					0.0002		
					(0.015)		
Vocabulary						0.228**	
						(0.090)	
Financial terminology							−80.414
							(60.359)
Log(# of words)			0.044	0.050*	0.044	−0.018	0.044
			(0.029)	(0.029)	(0.030)	(0.039)	(0.029)
SCI		**0.009*****	**0.009*****	**0.007*****	**0.009****	**0.008*****	**0.009*****
		(0.003)	**(0.003)**	**(0.003)**	**(0.004)**	**(0.003)**	**(0.003)**
Control variables:							
Pre-filing alpha	−0.547**	−0.547**	−0.542**	−0.536**	−0.542**	−0.542**	−0.542**
	(0.247)	(0.247)	(0.247)	(0.246)	(0.247)	(0.247)	(0.250)
Pre-filing RMSE	0.435***	0.433***	0.432***	0.430***	0.432***	0.431***	0.432***
	(0.051)	(0.051)	(0.053)	(0.053)	(0.054)	(0.054)	(0.053)
Abs(filing period abnormal return)	4.296***	4.296***	4.285***	4.281***	4.285***	4.286***	4.287***
	(0.778)	(0.779)	(0.779)	(0.775)	(0.779)	(0.778)	(0.779)
Log(size in $ millions)	−0.104***	−0.105***	−0.111***	−0.114***	−0.111***	−0.114***	−0.111***
	(0.024)	(0.024)	(0.029)	(0.027)	(0.030)	(0.027)	(0.027)
Log(book-to-market)	−0.094*	−0.096**	−0.100**	−0.101**	−0.100**	−0.104**	−0.100**
	(0.048)	(0.048)	(0.049)	(0.049)	(0.049)	(0.048)	(0.048)
NASDAQ dummy	0.215**	0.215**	0.215**	0.217***	0.215**	0.215**	0.216***
	(0.087)	(0.085)	(0.085)	(0.084)	(0.085)	(0.085)	(0.082)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	45,208	45,208	45,208	45,208	45,208	45,208	45,208
Adjusted R^2	0.461	0.461	0.462	0.461	0.462	0.461	0.461

Note: This table reports the results from the regression of post-filing RMSE on all readability measures of the MD&A section of 10-K and control variables. The dependent variable is the RMSE for trading days [6,28] (post-filing date market model root mean square error). The regression includes an intercept, calendar year dummies, and Fama and French 48-Industry dummies. The results are reported in line with Equation (1). The standard errors (reported in parentheses) are clustered by industry and year. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix B.

Table 5: Balancing Properties of the Covariates in Propensity Score Matching (PSM)

Panel A. PSM Nearest Neighbor Matching (1998)

	Treated	Control	%bias	t-statistic	p-value
Pre-filing alpha	0.056	0.066	−4.20	−0.43	0.665
Pre-filing RMSE	3.239	3.212	1.70	0.17	0.863
Abs(filing period abnormal return)	0.030	0.031	−1.10	−0.12	0.906
Log(size in $ millions)	5.248	5.294	−3.00	−0.28	0.779
Log(book-to-market)	−0.936	−0.939	0.30	0.04	0.971
NASDAQ dummy	0.659	0.637	4.70	0.44	0.659

Panel B. PSM Nearest Neighbor Matching (2010)

	Treated	Control	%bias	t-statistic	p-value
Pre-filing alpha	0.050	0.056	−3.10	−0.42	0.672
Pre-filing RMSE	2.462	2.492	−2.10	−0.28	0.778
Abs(filing period abnormal return)	0.027	0.027	−0.70	−0.10	0.920
Log(size in $ millions)	6.414	6.446	−1.80	−0.23	0.818
Log(book-to-market)	−0.556	−0.529	−3.50	−0.51	0.610
NASDAQ dummy	0.501	0.493	1.70	0.23	0.821

Note: This table reports the sample balancing properties of the matching covariates. Panel A reports the balancing properties of the matching covariates based on year 1998. Panel B reports the balancing properties of the matching covariates based on year 2010. Variable definitions are reported in Appendix B.

Table 6: A Difference-in-Differences Analysis of the Impact of SCI on Post-Filing Date Market Model Root Mean Square Error (RMSE)

	Panel A. SEC Plain English Rule		Panel B. The Plain Writing Act	
	(1)	(2)	(3)	(4)
Treated×Post	**−0.016**	**−0.036**	**−0.161****	**−0.200*****
	(0.256)	**(0.259)**	**(0.075)**	**(0.076)**
Post	0.169		−0.125**	
	(0.177)		(0.058)	
Pre-filing alpha	0.421	0.580	−0.322	−0.296
	(0.348)	(0.393)	(0.214)	(0.205)
Pre-filing RMSE	0.690***	0.548***	0.459***	0.380***
	(0.090)	(0.090)	(0.047)	(0.050)
Abs(filing period abnormal return)	2.513	2.655	3.304***	2.514***
	(2.639)	(2.506)	(0.864)	(0.845)
Log(size in $ millions)	−0.055	−0.027	−0.128***	−0.210***
	(0.142)	(0.148)	(0.048)	(0.046)
Log(book-to-market)	0.082	0.287	0.132**	0.067
	(0.194)	(0.208)	(0.059)	(0.061)
NASDAQ dummy	0.463	0.796	−0.067	−0.087
	(0.979)	(0.859)	(0.158)	(0.154)
Constant	0.724	1.121	1.679***	2.341***
	(1.043)	(1.033)	(0.365)	(0.369)
Sample	1995–2004	1995–2004	2005–2018	2005–2018
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Cluster Level	Firm	Firm	Firm	Firm
N	920	920	1,926	1,926
Adjusted R^2	0.364	0.387	0.517	0.545

Note: This table presents the difference-in-differences analysis results on the impact of the Plain English Rule and the Plain Writing Act on post-filing RMSE based on the MD&A section of 10-K. The dependent variable is the RMSE for trading days [6,28] (post-filing date market model root mean square error). The regression includes an intercept, calendar year dummies, and firm fixed effects. The results are reported in line with Equation (2). The standard errors (reported in parentheses) are clustered at the firm level. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix B.

Table 7: A Counterfactual Analysis of the Treatment Effects of the Plain Writing Act (October 2010)

	Coefficient	Standard errors
Dependent variable: *Post-filing RMSE*		
Treated×Year_2005	−0.243	(0.193)
Treated×Year_2006	−0.300	(0.202)
Treated×Year_2007	−0.328**	(0.164)
Treated×Year_2008	0.215	(0.208)
Treated×Year_2009	0.258	(0.289)
Treated×Year_2010	0.000	(0.000)
Treated×Year_2011	−0.166	(0.194)
Treated×Year_2012	−0.310	(0.195)
Treated×Year_2013	−0.043	(0.164)
Treated×Year_2014	−0.275	(0.183)
Treated×Year_2015	−0.416**	(0.185)
Treated×Year_2016	−0.303*	(0.173)
Treated×Year_2017	−0.193	(0.181)
Treated×Year_2018	−0.494***	(0.175)
Pre-filing alpha	−0.335	(0.213)
Pre-filing RMSE	0.366***	(0.053)
Abs(filing period abnormal return)	2.530***	(0.876)
Log(size in $ millions)	−0.165***	(0.049)
Log(book-to-market)	0.075	(0.065)
NASDAQ dummy	−0.051	(0.169)
Constant	2.067***	(0.461)
Sample	2005–2018	
Firm FE	Yes	
Year FE	Yes	
N	1,926	
Adjusted R^2	0.545	

Note: This table reports results for the counterfactual analysis of the treatment effects based on the model detailed in Equation (3). The dependent variable is the RMSE for trading days [6,28] (post-filing date market model root mean square error). The dummy variable *Treated* is interacted with individual years. The year 2010 is used as the benchmark (i.e., coefficient constrained to equal zero). The regression includes an intercept, calendar year dummies, and firm fixed effects. The standard errors (reported in parentheses) are clustered at the firm level. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix B.

Table 8: Placebo Tests for the Treatment Effects of the Plain Writing Act (October 2010)

	Panel A. The treatment in 2007		Panel B. The treatment in 2015	
	(1)	(2)	(3)	(4)
Treated×Post	**0.249**	**0.261**	**−0.063**	**−0.061**
	(0.167)	**(0.167)**	**(0.079)**	**(0.079)**
Post	0.073		0.141***	
	(0.129)		(0.052)	
Pre-filing alpha	−0.751*	−0.758*	−0.040	−0.016
	(0.397)	(0.406)	(0.247)	(0.255)
Pre-filing RMSE	0.536***	0.441***	0.302***	0.305***
	(0.081)	(0.089)	(0.067)	(0.069)
Abs(filing period abnormal return)	5.134**	4.104	1.905*	1.914*
	(2.518)	(2.498)	(1.089)	(1.076)
Log(size in $ millions)	−0.417**	−0.474**	−0.116*	−0.107
	(0.188)	(0.183)	(0.063)	(0.073)
Log(book-to-market)	−0.129	−0.313	0.075	0.092
	(0.201)	(0.213)	(0.085)	(0.085)
NASDAQ dummy	−0.369	−0.250	−0.353	−0.374
	(0.317)	(0.285)	(0.271)	(0.261)
Constant	3.184***	3.643***	1.780***	1.804***
	(1.152)	(1.159)	(0.479)	(0.537)
Sample	2005–2009	2005–2009	2011–2018	2011–2018
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
N	742	742	1,304	1,304
Adjusted R^2	0.455	0.480	0.549	0.553

Note: This table reports results for the placebo tests for the treatment effects based on the model detailed in Equation (2). In Panel A, the treatment year is assumed to be 2007. In Panel B, the treatment is assumed to occur in 2015. The dependent variable is the RMSE for trading days [6,28] (post-filing date market model root mean square error). The regression includes an intercept, calendar year dummies, and firm fixed effects. The standard errors (reported in parentheses) are clustered at the firm level. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix B.

Table 9: An Analysis of the Impact of SCI on Post-Filing Date Market Model Root Mean Square Error (RMSE) in the Presence of Restatements

	(1)	(2)	(3)	(4)	(5)	(6)
SCI	0.010***	0.010***	0.011***	0.009**	0.010***	0.010***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Restatement×SCI	**−0.011****	**−0.011****	**−0.011****	**−0.011****	**−0.011****	**−0.011****
	(0.006)	**(0.006)**	**(0.006)**	**(0.006)**	**(0.006)**	**(0.006)**
Log(# of words)		−0.020	−0.020	−0.013	−0.019	−0.098*
		(0.026)	(0.026)	(0.026)	(0.026)	(0.051)
Fog index			−0.002			
			(0.010)			
Flesch-Kincaid index				0.029		
				(0.019)		
SMOG index					0.004	
					(0.013)	
Vocabulary						0.289*
						(0.153)
Pre-filing alpha	−0.126	−0.127	−0.127	−0.125	−0.127	−0.126
	(0.084)	(0.084)	(0.084)	(0.083)	(0.084)	(0.084)
Pre-filing RMSE	0.541***	0.542***	0.542***	0.541***	0.542***	0.541***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Abs(filing period abnormal return)	4.092***	4.094***	4.095***	4.088***	4.093***	4.096***
	(0.409)	(0.409)	(0.409)	(0.409)	(0.409)	(0.409)
Log(size in $ millions)	−0.070***	−0.069***	−0.069***	−0.071***	−0.069***	−0.072***
	(0.025)	(0.025)	(0.025)	(0.024)	(0.025)	(0.025)
Log(book-to-market)	−0.033	−0.032	−0.032	−0.034	−0.032	−0.035
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.032)
NASDAQ dummy	0.082	0.083	0.083	0.083	0.084	0.090
	(0.073)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
Constant	0.884***	1.048***	1.091***	0.159	0.977**	1.620***
	(0.192)	(0.299)	(0.352)	(0.712)	(0.381)	(0.425)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	17,518	17,518	17,518	17,518	17,518	17,518
Adjusted R^2	0.531	0.531	0.530	0.531	0.530	0.531

Note: This table reports the results on the impact of SCI on firms' post-filing RMSE in the presence of restatements. The dependent variable is the RMSE for trading days [6,28] (post-filing date market model root mean square error). The regression includes an intercept, calendar year dummies, and firm fixed effects. The standard errors (reported in parentheses) are clustered by industry and year. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix B.

Table 10: An Analysis of the Impact of SCI on Post-Filing Date Market Model Root Mean Square Error (RMSE) Controlling for Business Complexity as Measured by a Business Segment Index

	(1)	(2)	(3)	(4)	(5)	(6)
Readability measures:						
Fog index		0.001				
		(0.008)				
Flesch-Kincaid index			0.025*			
			(0.013)			
SMOG index				0.001		
				(0.013)		
Vocabulary					0.318***	
					(0.113)	
Financial terminology						−123.794**
						(59.827)
Log(# of words)		0.075**	0.078**	0.075**	−0.006	0.075**
		(0.035)	(0.038)	(0.035)	(0.041)	(0.036)
SCI		**0.009****	**0.007****	**0.009****	**0.008****	**0.009****
		(0.004)	**(0.004)**	**(0.004)**	**(0.004)**	**(0.004)**
Control variables:						
Pre-filing alpha	−0.499**	−0.487**	−0.482**	−0.487**	−0.489**	−0.488**
	(0.238)	(0.237)	(0.235)	(0.236)	(0.236)	(0.236)
Pre-filing RMSE	0.436***	0.432***	0.430***	0.432***	0.431***	0.431***
	(0.059)	(0.061)	(0.062)	(0.061)	(0.061)	(0.061)
Abs(filing period abnormal return)	4.425***	4.409***	4.410***	4.409***	4.408***	4.408***
	(0.913)	(0.912)	(0.909)	(0.912)	(0.909)	(0.913)
Log(size in $ millions)	−0.096***	−0.107***	−0.110***	−0.107***	−0.110***	−0.107***
	(0.025)	(0.030)	(0.029)	(0.031)	(0.029)	(0.029)
Log(book-to-market)	−0.102**	−0.110**	−0.110**	−0.110**	−0.114**	−0.110**
	(0.052)	(0.053)	(0.053)	(0.053)	(0.053)	(0.055)
NASDAQ dummy	0.236**	0.235***	0.234***	0.235***	0.238***	0.236***
	(0.092)	(0.090)	(0.090)	(0.091)	(0.092)	(0.091)
Business segment index	0.133***	0.141***	0.141***	0.141***	0.150***	0.140***
	(0.046)	(0.045)	(0.046)	(0.045)	(0.045)	(0.045)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	28,291	28,291	28,291	28,291	28,291	28,291
Adjusted R^2	0.480	0.481	0.481	0.481	0.481	0.481

Note: This table reports the results from the regression of post-filing RMSE on all readability measures of the MD&A section of 10-K and business complexity as an additional control. The dependent variable is the RMSE for trading days [6,28] (post-filing date market model root mean square error). The regression includes an intercept, calendar year dummies, and Fama and French 48-Industry dummies. The results are reported in line with Equation (1). The standard errors (reported in parentheses) are clustered by industry and year. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively.

Table 11: An Analysis of the Impact of SCI on Post-Filing Date Market Model Root Mean Square Error (RMSE) Based on Full 10-K

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Readability measures:							
Fog index			−0.014*				
			(0.009)				
Flesch-Kincaid index				0.006			
				(0.005)			
SMOG index					−0.023**		
					(0.011)		
Vocabulary						0.064	
						(0.066)	
Financial terminology							43.563
							(80.720)
Log(# of words)			0.031	0.001	0.020	−0.044	−0.006
			(0.032)	(0.030)	(0.029)	(0.055)	(0.029)
Log(file size)			0.028	0.032*	0.031*	0.036*	0.036*
			(0.018)	(0.019)	(0.018)	(0.019)	(0.019)
SCI		**0.015****	**0.016****	**0.013****	**0.016****	**0.014****	**0.014****
		(0.006)	**(0.007)**	**(0.007)**	**(0.007)**	**(0.007)**	**(0.007)**
Control variables:							
Pre-filing alpha	−0.503**	−0.496**	−0.493**	−0.494**	−0.495**	−0.494**	−0.495**
	(0.237)	(0.237)	(0.240)	(0.240)	(0.240)	(0.240)	(0.240)
Pre-filing RMSE	0.468***	0.465***	0.463***	0.464***	0.463***	0.464***	0.464***
	(0.054)	(0.055)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
Abs(filing period abnormal return)	4.077***	4.066***	4.062***	4.060***	4.061***	4.064***	4.064***
	(0.806)	(0.804)	(0.808)	(0.809)	(0.809)	(0.810)	(0.810)
Log(size in $ millions)	−0.099***	−0.099***	−0.106***	−0.106***	−0.106***	−0.106***	−0.105***
	(0.021)	(0.024)	(0.027)	(0.027)	(0.027)	(0.027)	(0.026)
Log(book-to-market)	−0.078	−0.077	−0.082*	−0.082*	−0.082*	−0.082*	−0.082*
	(0.048)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.048)
NASDAQ dummy	0.196**	0.191**	0.191**	0.192**	0.191**	0.192**	0.193**
	(0.083)	(0.081)	(0.080)	(0.081)	(0.081)	(0.081)	(0.084)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	45,208	45,208	45,208	45,208	45,208	45,208	45,208
Adjusted R^2	0.461	0.461	0.462	0.461	0.462	0.461	0.461

Note: This table presents the results from the regression of post-filing RMSE on all readability measures of 10-K and control variables. The dependent variable is the RMSE for trading days [6,28] (post-filing date market model root mean square error). The regression includes an intercept, calendar year dummies, and Fama and French 48-Industry dummies. The results are reported in line with Equation (1). The standard errors (reported in parentheses) are clustered by industry and year. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix B.

Table 12: An Analysis of the Impact of SCI on Post-Filing Date Market Model Root Mean Square Error (RMSE) Based on the Risk Factors Section of 10-K

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Readability measures:							
Fog index			−0.0003				
			(0.007)				
Flesch-Kincaid index				−0.021**			
				(0.009)			
SMOG index					−0.003		
					(0.010)		
Vocabulary						0.533**	
						(0.242)	
Financial terminology							−17.390
							(70.358)
Log(# of words)		0.055***	0.056***	0.061***	0.058***	−0.024	0.055***
		(0.021)	(0.021)	(0.022)	(0.021)	(0.033)	(0.020)
SCI		**0.007*****	**0.007*****	**0.006*****	**0.007*****	**0.006****	**0.007*****
		(0.002)	**(0.002)**	**(0.002)**	**(0.002)**	**(0.003)**	**(0.002)**
Control variables:							
Pre-filing alpha	−0.570**	−0.548**	−0.548**	−0.550**	−0.548**	−0.534**	−0.548**
	(0.245)	(0.243)	(0.243)	(0.241)	(0.243)	(0.241)	(0.256)
Pre-filing RMSE	0.394***	0.385***	0.385***	0.385***	0.385***	0.379***	0.385***
	(0.058)	(0.060)	(0.061)	(0.062)	(0.062)	(0.059)	(0.060)
Abs(filing period abnormal return)	2.636***	2.586***	2.586***	2.581***	2.586***	2.567***	2.587***
	(0.421)	(0.421)	(0.420)	(0.431)	(0.420)	(0.442)	(0.419)
Log(size in $ millions)	−0.138***	−0.145***	−0.145***	−0.143***	−0.144***	−0.147***	−0.145***
	(0.023)	(0.027)	(0.028)	(0.029)	(0.028)	(0.025)	(0.026)
Log(book-to-market)	−0.007	−0.006	−0.006	−0.006	−0.006	−0.006	−0.006
	(0.040)	(0.039)	(0.040)	(0.040)	(0.040)	(0.039)	(0.039)
NASDAQ dummy	0.007	0.009	0.009	0.010	0.009	0.009	0.009
	(0.028)	(0.031)	(0.031)	(0.032)	(0.031)	(0.031)	(0.032)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	23,339	23,339	23,339	23,339	23,339	23,339	23,339
Adjusted R^2	0.409	0.411	0.411	0.411	0.411	0.412	0.411

Note: This table reports the results from the regression of post-filing RMSE on all readability measures for the Risk Factors section of 10-K and control variables. The dependent variable is the RMSE for trading days [6,28] (post-filing date market model root mean square error). The regression includes an intercept, calendar year dummies, and Fama and French 48-Industry dummies. The results are reported in line with Equation (1). The standard errors (reported in parentheses) are clustered by industry and year. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix B.

Appendix A. List of Valence Shifters

Word	Classification	Word	Classification
absolutely	amplifier	massively	amplifier
acute	amplifier	more	amplifier
acutely	amplifier	most	amplifier
almost	de-amplifier	much	amplifier
although	adversative-conjuction	neither	negator
but	adversative-conjuction	never	negator
cannot	negator	no	negator
cant	negator	nobody	negator
certain	amplifier	none	negator
certainly	amplifier	nor	negator
considerably	amplifier	not	negator
decidedly	amplifier	only	de-amplifier
deep	amplifier	particular	amplifier
deeply	amplifier	particularly	amplifier
definite	amplifier	partly	de-amplifier
despite	adversative-conjunction	purpose	amplifier
doesnt	negator	purposely	amplifier
dont	negator	quite	amplifier
enormous	amplifier	rarely	de-amplifier
especially	amplifier	real	amplifier
extreme	amplifier	really	amplifier
extremely	amplifier	seldom	de-amplifier
few	de-amplifier	serious	amplifier
greatly	amplifier	seriously	amplifier
havent	negator	severe	amplifier
heavily	amplifier	severely	amplifier
heavy	amplifier	significant	amplifier
high	amplifier	significantly	amplifier
highly	amplifier	slightly	de-amplifier
however	adversative-conjuction	somewhat	de-amplifier
huge	amplifier	sporadically	de-amplifier
hugely	amplifier	sure	amplifier
incredibly	de-amplifier	totally	amplifier
least	de-amplifier	true	amplifier
little	de-amplifier	truly	amplifier
massive	amplifier	uber	amplifier
vast	amplifier	werent	negator
vastly	amplifier	whereas	adversative-conjuction
very	amplifier	wont	negator

Note: This table presents the list of valence shifters along with their classification and weight.

Appendix B. Variable Definition

Variable	Definition
Readability measures:	
Average words per sentence	The number of words in the 10-K filing divided by the total number of sentence termination characters after removing those associated with headings and abbreviations.
Percent complex words	The percentage of 10-K words with more than two syllables.
Fog index	Calculated as $0.4 \times (\textit{average words per sentence} + \textit{percent complex words})$. High values of the *Fog index* imply less readable text.
Flesch-Kincaid index	Calculated as $0.39 \times \textit{average words per sentence} + 11.8 \times \frac{\textit{total syllables}}{\textit{total words}} - 15.59$
SMOG index	Calculated as $1.043 \times \sqrt{\textit{percent complex words} \times \frac{30}{\textit{number of sentences}}} + 3.1291$.
Vocabulary	The number of unique words appearing in the filing divided by the total number of entries in the Loughran–McDonald (2011) Master Dictionary and Harvery Dictionary.
Financial terminology	The number of unique words in a 10-K that appear in Campbell Harvey's Hypertextual Finance Glossary (https://people.duke.edu/%7Echarvey/Classes/wpg/glossary.htm) divided by the number of unique 10-K words. We remove abbreviations and phrases from his list.
Log(# of words)	The natural logarithm of the word count from the 10-K, based on words appearing in the Loughran–McDonald Master Dictionary.
Log(file size)	The natural logarithm of the file size in megabytes of the SEC EDGAR "complete submission text file" for the 10-K filing.
Dependent variable:	
Post-filing RMSE	The RMSE from a market model estimated using trading days [6, 28] relative to the 10-K file date (approximately one calendar month). A minimum of 10 observations are required to be included in the sample.
Control variables:	
Pre-filing alpha	The alpha from a market model using trading days [–252, –6]. At least 60 observations of daily returns must be available to be included in the sample.
Pre-filing RMSE	The RMSE from a market model estimated using trading days [–257, –6], with a minimum of 60 complete observations.
Abs(filing period abnormal return)	The absolute value of the filing date excess return, measured by the buy-and-hold return starting on filing date (day 0) through day +1 minus the buy-and-hold return of the CRSP value-weighted index over the same two-day period.
Log(size in \$ millions)	The natural logarithm of the CRSP stock price times shares outstanding on the day prior to the 10-K filing date (in \$millions).

Variable	Definition
Log(book-to-market)	The natural log of book-to-market, following Fama and French (2001) using data from both CRSP (market value of equity) and COMPUSTAT (book value from most recent year prior to filing date). After removing firms with negative book value, the variable is winsorized at the 1 percent level.
NASDAQ dummy	A dummy variable takes a value of one if a firm is listed on NASDAQ at the time of the 10-K filing, and zero otherwise.
Restatement	A dummy variable that equals one if a firm restates the results in Form 8-K after the 10-K date for the same fiscal year, and zero otherwise.
Business segment index	The sum of the squared business segment proportions reported for the firm in the COMPUSTAT Segment database based on sales data.

References

Arnold, V., Bedard, J.C., Phillips, J.R., Sutton, S.G. (2012). The impact of tagging qualitative financial information on investor decision making: Implications for XBRL. *International Journal of Accounting Information Systems*, **13**(1), 2–20.

Atanasov, V.A., Black, B.S. (2021). The trouble with instruments: The need for pretreatment balance in shock-based instrumental variable designs. *Management Science*, **67**(2), 1270–1302.

Baginski, S.P., Campbell, J.L., Hinson, L.A., Koo, D.S. (2018). Do career concerns affect the delay of bad news disclosure? *The Accounting Review*, **93**(2), 61–95.

Biddle, G.C., Hilary, G., Verdi, R.S. (2009). How does financial reporting quality relate to investment efficiency? *Journal of Accounting & Economics*, **48**(2-3), 112–131.

Bloomfield, R. (2008). Discussion of "Annual report readability, current earnings, and earnings persistence". *Journal of Accounting & Economics*, **45**(2-3), 248–252.

Bloomfield, R.J. (2002). The 'incomplete revelation hypothesis' and financial reporting. *Accounting Horizons*, **16**(3), 233–243.

Bochkay, K., Brown, S.V., Leone, A. J., Tucker, J.W. (2023). Textual analysis in accounting: What's next? *Contemporary Accounting Research*, **40**(2), 765–805.

Bonsall, S.B., Miller, B.P. (2017). The impact of narrative disclosure readability on bond ratings and the cost of debt. *Review of Accounting Studies*, **22**(2), 608–643.

Bonsall, S.B., Leone, A.J., Miller, B.P., Rennekamp, K. (2017). A plain English measure of financial reporting readability. *Journal of Accounting & Economics*, **63**(2-3), 329–357.

Brown, S.V., Tian, X., Tucker, J.W. (2018). The spillover effect of SEC comment letters on qualitative corporate disclosure: Evidence from the risk factor disclosure. *Contemporary Accounting Research*, **35**(2), 622–656.

Campbell, J.L., Chen, H., Dhaliwal, D.S., Lu, H., Steele, L.B. (2014). The information content of mandatory risk factor disclosures in corporate filings. *Review of Accounting Studies*, **19**(1), 396–455.

Campbell, J.L., Cecchini, M., Cianci, A.M., Ehinger, A.C., Werner, E.M. (2019). Tax-related mandatory risk factor disclosures, future profitability, and stock returns. *Review of Accounting Studies*, **24**, 264–308.

Campbell, J.L., D'Adduzio, J., Moon, J. (2022). Everyone has an opinion: The informativeness of the social media response to management guidance. *Working paper*.

Dyer, T., Lang, M., Stice-Lawrence, L. (2017). The evolution of 10-K textual disclosure: Evidence from Latent Dirichlet Allocation. *Journal of Accounting & Economics*, **64**(2-3), 221–245.

El-Haj, M., Rayson, P., Walker, M., Young, S., Simaki, V. (2019). In search of meaning: Lessons, resources and next steps for computational analysis of financial discourse. *Journal of Business Finance & Accounting*, **46**(3-4), 265–306.

Ertugrul, M., Lei, J., Qiu, J., Wan, C. (2017). Annual report readability, tone ambiguity, and the cost of borrowing. *Journal of Financial & Quantitative Analysis*, **52**(2), 811–836.

Hope, O.K., Hu, D., Lu, H. (2016). The benefits of specific risk-factor disclosures. *Review of Accounting Studies*, **21**(4), 1005–1045.

Hwang, B.H., Kim, H.H. (2017). It pays to write well. *Journal of Financial Economics*, **124**(2), 373–394.

IFRS. (2008). *Transforming the impact of financial information: The role of technology*. https://www.ifrs.org/news-and-events/news/2018/06/transforming-the-impact-of-financial-information-the-role-of-technology/.

Kim, C., Wang, K., Zhang, L. (2019). Readability of 10-K reports and stock price crash risk. *Contemporary Accounting Research*, **36**(2), 1184–1216.

Kim, D.S., Chung, C.Y., Fard, A. (2022). Effects of 10-K readability on institutional blockholder monitoring of risk management. *Applied Economics Letters*.

Lawrence, A. (2013). Individual investors and financial disclosure. *Journal of Accounting & Economics*, **56**(1), 130–147.

Lehavy, R., Li, F., Merkley, K. (2011). The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review*, **86**(3), 1087–1115.

Lennox, C. (2016). Did the PCAOB's restrictions on auditors' tax services improve audit quality? *The Accounting Review*, **91**(5), 1493–1512.

Li, F. (2008). Annual report readability, current earnings, and earnings persistence. *Journal of Accounting & Economics*, **45**(2-3), 221–247.

Lo, K., Ramos, F., Rogo, R. (2017). Earnings management and annual report readability. *Journal of Accounting & Economics*, **63**(1), 1–25.

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

Loughran, T., McDonald, B. (2014a). Measuring readability in financial disclosures. *The Journal of Finance*, **69**(4), 1643–1671.

Loughran, T., McDonald, B. (2014b). Regulation and financial disclosure: The impact of plain English. *Journal of Regulatory Economics*, **45**(1), 94–113.

Loughran, T., McDonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research*, **54**(4), 1187–1230.

Miller, B.P. (2010). The effects of reporting complexity on small and large investor trading. *The Accounting Review*, **85**(6), 2107–2143.

Rosenbaum, P., Rubin, D. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, **70**(1), 41–55.

Schulder, M., Wiegand, M., Ruppenhofer, J., Köser, S. (2018). Introducing a lexicon of verbal polarity shifters for English. *Proceedings of the Eleventh International Conference on Language Resources and Evaluation.*

Securities and Exchange Commission. (1998). *A plain English handbook: How to create clear SEC disclosure documents.* www.sec.gov/pdf/handbook.pdf.

Securities and Exchange Commission. (2007). *Speech by SEC Chairman: 'Plain Language and Good Business'. Keynote Address to the Center for Plain Language Symposium.* https://www.sec.gov/news/speech/2007/spch101207cc.htm.