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**Readability of 10-K Reports and Stock Price Crash Risk**


## ABSTRACT

This study shows that less readable 10-K reports are associated with higher stock price crash risk. The results are consistent with the argument that managers can successfully hide adverse information by writing complex financial reports, which leads to stock price crashes when the hidden bad news accumulates and reaches a tipping point. Cross-sectional analyses show that the effect of financial reporting complexity on crash risk is more pronounced for firms with persistent negative earnings news or transitory positive earnings news, greater chief executive officer stock option incentives, or lower litigation risk. Finally, accrual manipulation appears to be positively related to crash risk, even since the Sarbanes–Oxley Act, if the manipulation is accompanied by complex 10-K reports.



***Keywords*:** Readability; textual analysis; crash risk; SOX; 10-K
***JEL Classification*:** D82; G12; G17; G18; M41.

## 1. Introduction

Corporate managers have incentives to maximize investors' perceptions of firm value as reflected by stock prices. One way for managers to maintain the current level of stock prices is to obfuscate adverse information in financial reports because information that is more costly to extract from public disclosures is less completely revealed in market prices (Bloomfield 2002). Moreover, because of the feedback role of historical financial reports, managers hiding bad news elsewhere could also supply less readable annual reports to the stock market to prevent investors from obtaining any clues about their opportunistic behavior (Li 2008). Consistent with this observation, the US Securities and Exchange Commission (SEC) has recently been working on the textual analysis of annual reports to identify clues of potential earnings manipulation (Eaglesham 2013). In this paper, we examine whether complex language in annual reports is associated with future stock price crashes. Stock price crashes often have a devastating effect on investor welfare and it is therefore important to understand their determinants.

Jin and Myers (2006) have built a model in which some degree of opaqueness is essential for the occurrence of stock price crashes. While the natural arrival process of new information does not systematically differ between good and bad news, strategic bad news hoarding behavior by managers can make bad news lumpier than good news. In the model of Jin and Myers, lack of transparency enables managers to capture a portion of positive cash flows, hiding and personally absorbing negative firm-specific performance to protect their jobs. However, when the accumulation of bad news reaches a threshold, it will become too difficult or costly for managers to continue withholding it and they will therefore exercise the abandonment option. The previously unobserved negative information thus becomes public all at once, leading to stock price crashes. Therefore, if complex financial reports facilitate managers' hiding of adverse information, we expect less readable 10-K reports to be associated with more negatively skewed future returns or a higher likelihood of crashes, or, put simply, higher crash risk.

Following Li (2008), a growing literature uses the Fog Index as a measure of 10-K report readability. This measure, which originated from the computational linguistics literature, captures a document's level of complexity as a function of the number of syllables per word and the number of words per sentence. However, Loughran and McDonald (2014) argue that this traditional Fog Index can be poorly specified, because a large number of multisyllabic words, such as *company*, *corporation*, and *telecommunications*, in business texts are well understood by investors. Bearing this criticism in mind, we extract complex words (i.e., words with more than two syllables) from the Compustat variable lists and the Fama–French 49-industry description file and build a list of complex words that are presumably easy to comprehend in the context of financial disclosures. We then construct a modified Fog Index by reclassifying the complex words in our list as simple ones when parsing 10-K filings. We show that the modified Fog Index passes the validity tests recommended by Loughran and McDonald (2014).

Using the modified Fog Index as a measure of financial disclosure readability, we show that less readable 10-K reports are associated with more negatively skewed returns, or higher stock price crash risk, suggesting that managers can withhold adverse information by writing more complex financial reports. The results hold even after controlling for earnings management and other fundamental determinants of crash risk. In cross-sectional analyses, we find that the association between financial reporting readability and crash risk is stronger for firms with persistent negative earnings news or transitory positive earnings news, suggesting that such firms are more likely to hide adverse information using complex language (Li 2008). In addition, we find that the association between readability and crash risk is more pronounced when a firm's litigation risk is lower or when managers have more equity option incentives. Similar to Hutton et al. (2009), we find that earnings management predicts crash risk in the years before the Sarbanes–Oxley Act (SOX) but not afterward in the full sample. Interestingly, we show that earnings management is positively associated with crash risk for firms with less readable 10-K reports, even in the post-SOX period. These results suggest that complex financial reports appear to enhance the effectiveness of earnings management in hiding bad news (or to decrease the likelihood of earnings management being detected), particularly in the post-SOX period.

We conduct a series of robustness checks and additional tests. First, the results continue to hold after controlling for firm fixed effects and various time-varying determinants of 10-K readability. Second, we find that changes in 10-K complexity are positively related to changes in future crash risk, after controlling for changes in various measures of fundamental risk. Third, the results are robust to alternative measures of financial reporting complexity.

This paper contributes to the literature in the following ways. First, this study is one of the first to show that complex annual reports facilitate managerial news hoarding and increase the likelihood of future stock price crashes. In a related study, Li (2008) finds no robust evidence that less readable financial reports are associated with lower returns in the following 12 months (i.e., the first moment of the stock return distribution). We argue, however, that skewness, or large, negative outliers in stock returns (i.e., the third moment of the stock return distribution), is a more powerful indicator of adverse information hiding than the first moment is, because the former can help pinpoint managerial abandonment and the resulting sudden release of accumulated bad news (Jin and Myers 2006).[1] In addition, a recent stream of literature provides mounting evidence that supports the usefulness of negative return skewness or crash risk in

[1] Note that the first moment of return distribution (i.e., average returns) cannot differentiate stocks with large, negative price drops within a short period of time (e.g., one week) from stocks with a steady price decline over a long period of time (e.g., one year).

capturing bad news hoarding (e.g., Callen and Fang 2013; DeFond et al. 2015; Hong et al. 2017; Hutton et al. 2009; Kim et al. 2011a, b).

Second, our findings contribute to the growing literature on the determinants of stock price crash risk. Crashes have a devastating effect on investor welfare. This is the case even when the stock returns for the entire year or longer are not affected, because investors suffering from a crash may not be those earning high returns outside of the crash period. On average, one should observe that less informed investors suffer the losses from a crash, while more informed investors grab gains, say, prior to the crash. Therefore, understanding the determinants of crash risk allows regulators and governance practitioners to design mechanisms to mitigate such risk, which is important in recovering and maintaining investor confidence (Blanchard 2009). Moreover, investors' exposure to crash risk (i.e., the risk of extreme losses rather than the risk of return volatility) can be reduced only by screening and not by diversification (Sunder 2010). Our paper identifies 10-K readability as one potential factor for screening the risk of extreme losses. This finding would be of practical relevance for risk management applications focusing on tail events and allows investors to minimize their portfolios' exposure to crash risk and improve investment performance (Ak et al. 2016; Hutton et al. 2009). In a broader sense, we provide empirical evidence that corroborates the survey result that opaque SEC filing is one of the red flags for the misrepresentation of economic performance (Dichev et al. 2013).

Third, our research contributes to the literature on the real effects of the textual complexity of financial reporting. Prior research mainly focuses on the effects of disclosure complexity on investors' or analysts' behavior rather than their real welfare (e.g., Lehavy et al. 2011; Miller 2010; You and Zhang 2009). One exception is the work of Biddle et al. (2009), who show that firms issuing less readable 10-K reports have lower investment efficiency. Our study extends this line of research by showing that the textual complexity of financial reports is associated with a higher incidence of stock price crashes, which potentially significantly destroy shareholder welfare (DeFond 2010).

In a concurrent paper, Ertugrul et al. (2017) find that banks charge higher interest rates for loans issued to borrowing firms with larger 10-K report file sizes. They explain that this results from borrowing firms hiding bad news through complex annual reports and support this argument by showing that 10-K file size is positively related to subsequent crash risk. Our paper differs from theirs in at least three ways. First, while Ertugrul et al. focus on 10-K file size as the measure of information obfuscation, we use a modified version of the Fog Index that directly addresses the concerns raised by Loughran and McDonald (2014).[2] It is worth noting that 10-K file size has a severe measurement error problem in gauging information obfuscation, since graphics, HTML, and XBRL significantly enlarge the file sizes of 10-K reports but actually reduce the difficulty of gathering and processing information.[3] Second, we find that the positive relation between 10-K complexity and subsequent crash risk is more pronounced for firms that report transitory positive earnings news and persistent negative earnings news. According to Bloomfield (2008), this result is essential for linking low readability to the information obfuscation argument and mitigating the concern of alternative explanations because firms with transitory good performance or persistent poor performance indeed have bad news to obfuscate. Third, our paper shows that low 10-K readability strengthens the association between earnings management and subsequent crash risk, especially in the post-SOX period. This result indicates that managers could use textual information obfuscation and earnings manipulation as

[2] See section 3 for the detailed procedure of constructing the modified Fog Index.
[3] However, in the other direction, Allee et al. (2018) suggest that there is an increasing use of computer programs to process firm disclosures and that graphics and exhibits may increase the difficulty of gathering and processing information by computer programs.

complementary tools for hiding bad news, particularly when earnings manipulation is under more stringent public scrutiny and regulatory monitoring. Overall, our paper contributes to the literature beyond the scope of the study of Ertugrul et al. (2017).

This paper is organized as follows. Section 2 discusses the related literature and develops the hypothesis. Section 3 describes the sample selection and variable measurement. Section 4 presents our main empirical analyses. Section 5 conducts robustness checks and additional tests. Section 6 concludes the paper.

## 2. Hypothesis development

Corporate managers have an informational advantage over investors regarding the profitability and risks of their firms' business. The 10-K reports are one of the most comprehensive and credible channels through which managers convey their superior information to outside investors. Although many of the key numbers in the financial statements have already been disclosed well before the 10-K report filing dates, other sections of the reports, such as the Management Discussion and Analysis, provide investors with new and important supplementary information (Brown and Tucker 2011; Feldman et al. 2010; Griffin 2003; Jegadeesh and Wu 2013; Kothari et al. 2009a; Li 2010a; Loughran and McDonald 2011; You and Zhang 2009). Managers are required to explain in the 10-K reports the key driving forces responsible for changes in current performance, which helps investors to determine whether current performance is indicative of future performance.

Moreover, due to the limitations of accounting rules, financial statement information may not be able to capture the development of a firm's key success factors. For example, accounting rules do not allow managers to capitalize investments in research and development, employee training, or customer relations. The cash flow and risk implications of these investments, however, are critical to a firm's future performance. The 10-K report provides managers with a vehicle to disclose these types of critical inside information (e.g., Campbell et al. 2014; Kravet and Muslu 2013; Li 2006; Li et al. 2013; Merkley 2014). Finally, the notes to financial statements allow investors to understand how the accounting system maps the firm's business economics to the numbers presented in the financial statements. In addition, these notes enable investors to evaluate whether the performance changes are driven by real business trends or changes in accounting policies or estimations, which facilitates their judgment concerning the persistence of earnings performance.

However, a 10-K report is only used by investors when they can process the content of the report cost-effectively. Using a noisy rational expectation model, Grossman and Stigliz (1980) demonstrate that, in efficient markets, the returns to analyzing data should equal the cost of analysis. Based on this insight, Bloomfield (2002, 235) proposes the incomplete revelation hypothesis (IRH) that "[s]tatistics that are more costly to extract from public data are less completely revealed by market prices." Bloomfield further conjectures that managers can seek to prevent stock prices from declining by strategically increasing the processing cost of negative information. One could argue that, to maintain the current level of stock prices, managers can simply omit adverse information from the financial reports. We argue, however, that litigation and reputation concerns dissuade managers from the outright omission of important adverse information (e.g., Skinner 1994).

Li (2008) offers the first large-sample evidence supporting the IRH. Specifically, the author shows that firms with losses or transitory profits write more complex annual reports. The author, however, finds no robust evidence of the complexity of financial reports being negatively associated with the average level of stock returns over a 12-month period after the 10-K filing date. Li and Zhang (2015) find that managers strategically increase the complexity of bad news financial reports when under greater short-selling pressure to maintain the current level of stock prices, but the authors do not examine whether the obfuscation strategy is effective in maintaining stock prices. Thus, to our best knowledge, the literature does not document clear evidence on whether managers can successfully hide adverse information and maintain stock prices by writing complex disclosures.

Our study extends this literature by examining the effect of 10-K report readability on future return skewness or crash risk. Jin and Myers (2006) develop a model with incomplete transparency and predict that the managerial tendency to withhold bad news leads to occasional stock price crashes when the accumulated bad news reaches a tipping point. Consistent with this prediction, a growing body of research suggests that crash risk, or, more generally, negative return skewness, is associated with various incentives and mechanisms for managers to hide bad news. Hutton et al. (2009) find that accrual earnings management is associated with crash risk in the pre-SOX period. Kim et al. (2011a) show that complex tax shelter arrangements facilitate managerial bad news hoarding and increase crash risk. DeFond et al. (2015) provide evidence that the mandatory adoption of International Financial Reporting Standards is associated with a lower negative skewness of stock returns for non-financial firms, but not for financial firms. Kim and Zhang (2016) show that conservative accounting policies help mitigate bad news hoarding and reduce stock price crash risk. In addition, Kim et al. (2011b) provide evidence that chief financial officers' equity incentives motivate them to shelter bad news, as reflected by stock price crashes. Callen and Fang (2013) find that monitoring by institutional investors reduces crash risk.

We argue that complex financial reports increase information opacity and thus enable managers to hide adverse information for extended periods, up to a threshold. Once the threshold is crossed, the adverse information is suddenly released all at once, resulting in a stock price crash (Jin and Myers 2006).[4] Therefore, we predict a positive association between the complexity of 10-K reports and future stock price crash risk. Admittedly, managers can also have incentives to withhold good news in some scenarios, for example, when faced with intense competition from the product market. However, our argument is based on the assumption that managers *generally* tend to withhold or delay the disclosure of bad news. This assumption is consistent with the evidence documented by many prior studies (e.g., Kothari et al. 2009b). Moreover, prior research on 10-K readability suggests that managers tend to use complex writing to obfuscate adverse information rather than positive information (e.g., Li 2008; Li and Zhang 2015).[5] It is worth noting that the existence of stock price crashes does not necessarily mean lower average returns over a longer window. Jin and Myers (2006) imply that investors could partially anticipate stock price crashes and demand compensation for losses in a crash and crash-prone stocks could thus have *higher* required returns. In addition, in periods before crash events, stocks are likely overvalued because of the hidden bad news.

HYPOTHESIS. *Firms with less readable 10-K reports have higher future stock price crash risk.*

While we consider complex financial reports a way to obfuscate information, complex language could also be necessary to convey complex information and informative technical

[4] Before bad news has accumulated to the tipping point, some (but not all) investors may incur the high cost of information processing and avoid the loss by selling stocks before stock price crashes.
[5] In an untabulated test, we find no evidence that 10-K complexity is positively related to stock price jumps, suggesting that managers are unlikely to hide good news by writing complex reports.

details about the economic complexity of firms' business transactions and operating strategies (e.g., Bloomfield 2008; Bushee et al. 2018). If the information communication role of complex 10-K reports dominates their information obfuscation role, we would observe a negative relation between 10-K report complexity and future crash risk. This prediction adds tension to our empirical prediction. On the other hand, complex 10-K reports could also be positively associated with crash risk because complex reports reflect the underlying (high) risk of the firm's business due to the economic complexity of its business transactions. In our empirical analysis, we carefully address these concerns in several ways. First, one key innovation of our research is that we develop a refined measure of Fog Index that excludes common accounting and finance words from the list of complex words. We argue that it is more likely that managers use these words to convey complex information and informative technical details rather than to obfuscate information. Second, using change regressions and a battery of variables capturing fundamental risks, we alleviate the concern that our results are simply driven by changes in business risks. Finally, we show that our results are robust to controlling for 10-K file size, where file size is used as a control for overall business complexity and information quantity.

## 3. Sample selection, data, and research design

### *Sample selection*

Our initial sample includes all firm–years for which a 10-K report with at least 3,000 words was filed during 1994–2014.[6,7] We combine the initial sample with weekly stock return data from the Center for Research in Security Prices (CRSP) and financial data from Compustat.

[6] Our sample period starts in 1994 because it is the first year electronic 10-K filings were available from the SEC's online EDGAR system. The sample period ends in 2014 because our proxies for crash risk are measured one year ahead of our test and control variables.
[7] Following Li (2008), we exclude 10-K filings with fewer than 3,000 words from our initial sample after editing the raw filings by the procedure specified in Online Appendix A.

Specifically, for each firm–year observation, we match weekly returns to the fiscal year if the last trading day of a calendar week falls within the 12-month period ending three months after the firm's fiscal year-end. We then delete observations with non-positive total assets, financial firms (Standard Industrial Classification, or SIC, codes 6000–6999), utilities firms (SIC codes 4900–4999), low-priced firms (fiscal year-end price lower than $1), observations with fewer than 26 weeks of stock return data, and observations missing financial data used to construct the determinants of crash risk. The above procedure yields our sample of 52,879 firm–year observations for 7,012 unique firms.

***Measuring 10-K readability***

Following Li (2008), we measure 10-K report readability using the following formula for the Fog Index:

$$Fog = (\text{words per sentence} + \text{percentage of complex words}) \times 0.4, \tag{1}$$

where complex words are defined as words with three or more syllables.[8] Higher values of the Fog Index indicate that the text is more difficult to understand. Although widely used by the accounting and finance literature, Loughran and McDonald (2014, 1645) argue that the second component in the Fog Index, so-called complex words, is a poorly specified measure in business documents. Many multisyllabic words, such as *corporation*, *company*, *directors*, *business*,

[8] Other studies that use the Fog Index to measure readability include those of Allee and DeAngelis (2015), Biddle et al. (2009), Bonsall and Miller (2017), Bozanic and Thevenot (2015), Bushee et al. (2018), Callen et al. (2013), Guay et al. (2016), Laksmana et al. (2012), Lang and Stice-Lawrence (2015), Lawrence (2013), Lee (2012), Lehavy et al. (2011), Lo et al. (2017), Lundholm et al. (2014), Merkley (2014), Miller (2010), Nelson and Pritchard (2016), and Rogers et al. (2014) for corporate disclosures; De Franco et al. (2015) and Hsieh and Hui (2013) for financial analysts' reports; and Dougal et al. (2012) for news articles.

*operations*, and *telecommunications*, are presumably easy to understand in the context of financial disclosures.[9]

To address Loughran and McDonald's (2014) concerns, we first construct a list of words that have three or more syllables but are not difficult to comprehend in business or financial text. Specifically, we manually check the variable lists of all Compustat datasets and collect all complex words (i.e., words with at least three syllables) included in the variable descriptions. After accounting for inflections, we generate a list of 1,489 words. We also collect all complex words included in the Fama–French 49-industry description file. Since the Fama–French industry classification scheme is a regrouping of four-digit SIC industries, the file also includes the descriptions of the SIC industries. This second list contains 769 words, including inflections, 230 of which also appear in the first word list. Combining the above two word lists, we end up with 2,028 different words in total.[10] An average financial report user should have no difficulty understanding the words in the list.[11]

Next, we calculate a modified Fog Index (*MODFOG*) by reclassifying the 2,028 words that appear in the 10-K reports as two-syllable words. This procedure changes the word complexity component of the traditional Fog Index, while leaving the sentence length component of the index intact. We then check whether our modified version of the Fog Index can pass the validity tests proposed by Loughran and McDonald (2014). Online Appendix C presents the design of the validity tests and Table C.1 presents the test results. We find that our modified

[9] Loughran and McDonald (2014) suggest using the file size of 10-K reports as a simple and easy-to-replicate proxy for readability. However, this measure also has significant shortcomings (Bonsall et al. 2017). For example, graphics and advanced tools such as XBRL potentially reduce information processing costs borne by 10-K readers but significantly enlarge the file size of 10-K reports and thus increase gauged reporting complexity. In addition, larger 10-K filings are likely to indicate greater disclosure quantity rather than poorer disclosure quality. These arguments cast doubt on the construct validity of file size measuring annual report readability.
[10] See Table B.1 in Online Appendix B for our word list.
[11] We assume that the average reader of financial reports is familiar with general ledger account names and other general business terms and has some industry-specific knowledge.

version of the Fog Index (*MODFOG*) has a significant and positive loading on post-filing date return volatility after controlling for the 10-K file size (the measure of financial disclosure readability proposed by Loughran and McDonald in lieu of the traditional Fog Index), while the traditional Fog Index (*RAWFOG*) loses its statistical significance in the presence of file size. These results suggest that our modification procedure successfully addresses Loughran and McDonald's concerns.

***Measuring crash risk***

To measure firm-specific stock price crash risk, we first calculate firm-specific weekly returns (*W*) by estimating the following expanded index model for each firm and fiscal year:

$$r_{j\tau} = \alpha_j + \beta_{1j}\, r_{m\tau-1} + \beta_{2j}\, r_{i\tau-1} + \beta_{3j}\, r_{m\tau} + \beta_{4j} r_{i\tau} + \beta_{5j} r_{m\tau+1} + \beta_{6j} r_{i\tau+1} + \varepsilon_{j\tau}, \qquad (2)$$

where $r_{j\tau}$ , $r_{i\tau}$, and $r_{m\tau}$ are the returns in week $\tau$ on stock *j*, the Fama–French value-weighted index for industry *i*, and the CRSP value-weighted market index, respectively, and the fiscal year is defined as the 12-month period ending three months after the fiscal year-end. We include lead and lag terms for the market and industry returns to allow for nonsynchronous trading (Dimson 1979). The firm-specific weekly return for firm *j* and week $\tau$, $W_{j\tau}$ , is the natural logarithm of one plus the residual return ($\varepsilon_{j\tau}$) estimated from Eq. (2). Following prior studies, we use three measures of crash risk. The first measure is the negative skewness of weekly stock returns (e.g., Chen et al. 2001; DeFond et al. 2015; Hong et al. 2017; Kim et al. 2011a, b; Kim and Zhang 2016; Jin and Myers 2006):

$$NCSKEW_{jt} = -[n(n-1)^{3/2} \sum W_{j\tau}^{3}] \;/\; [(n-1)(n-2)\, (\sum W_{j\tau}^{2})^{3/2}, \qquad (3)$$

where $W_{j\tau}$ is defined as above. The second crash risk measure is the asymmetric volatility of the weekly stock return, $DUVOL_{j,t}$ (e.g., Chen et al. 2001; Hong et al. 2017; Kim et al. 2011b). It is the natural logarithm of the ratio of the standard deviation of $W_{j\tau}$ for *down* weeks to the standard deviation of $W_{j\tau}$ for *up* weeks, where the down (up) weeks are those with $W_{j\tau}$ below (above) $\overline{W_{j\tau}}$ over the fiscal year $t$. Our third measure is a crash indicator, $CRASH_{j,t}$, that takes the value of one if firm $j$ has at least one $W_{j\tau}$ falling 3.09 or more standard deviations below $\overline{W_{j\tau}}$ over the fiscal year $t$ and zero otherwise (e.g., Hong et al. 2017; Hutton et al. 2009; Kim et al. 2011a, b; Kim and Zhang 2016; Kim et al. 2016b).

### *Research design*

To test our prediction that firms with less readable 10-K reports are subsequently more prone to stock price crashes, we estimate the following model:

$$\begin{aligned} Crash\_Risk_{t+1} = \; & \beta_0 + \beta_1 MODFOG_t + \beta_2 OPAQUE_t + \beta_3 OPAQUE_t^2 + \beta_4 LOGMV_t \\ & + \beta_5 MTB_t + \beta_6 LEV_t + \beta_7 ROA_t + \beta_8 DTURN_t + \beta_9 NCSKEW_t \\ & + \beta_{10} SIGMA_t + \beta_{11} RET_t + \beta_{12} BETA_t + \beta_{13} EARNVOL_t \\ & + \beta_{14} CFVOL_t + \beta_{15} SALESVOL_t + \beta_{16} HHI_t + \varepsilon_t, \end{aligned} \tag{4}$$

where *Crash_Risk* is one of the measures discussed earlier (i.e., *NCSKEW*, *DUVOL*, or *CRASH*). We run ordinary least squares (OLS) regressions for *NCSKEW* and *DUVOL* and logistic regressions for *CRASH*. Our hypothesis is supported if $\beta_1$ is positive and significant.

Consistent with prior studies, we control for a set of known determinants of crash risk.[12] First, we include *OPAQUE* and its squared term, where *OPAQUE* is the three-year moving sum of the absolute value of abnormal accruals estimated from the modified Jones model (Hutton et al. 2009). We expect $\beta_2$ to be positive and $\beta_3$ negative since Hutton et al. (2009) find that firms that are more opaque have higher crash risk but that the relation is concave. It is important for our paper to show that 10-K readability has incremental explanatory power on crash risk over and above the opacity measure of Hutton et al. (2009). Second, we control for market value

[12] See the Appendix for detailed definitions of these control variables.

(*LOGMV*) and market-to-book (*MTB*) and expect $\beta_4$ and $\beta_5$ to be positive since prior studies show that large firms and growth firms are more likely to experience crashes (e.g., Chen et al. 2001; Hutton et al. 2009; Kim et al. 2011a, b; Kim and Zhang 2016). Third, financial leverage (*LEV*) should be negatively related to crash risk because more stable, less crash-prone firms are more capable of using debt finance (Hutton et al. 2009). Fourth, we control for firm performance (*ROA*). Hutton et al. (2009) suggest that better contemporaneous operating performance is associated with lower crash risk. Kim et al. (2011a, b) find that lagged firm performance is also negatively associated with crash risk. On the other hand, good operating performance could be a manifestation of earnings manipulation. Since prior studies also document higher crash risk for firms with more earnings manipulation (Hutton et al. 2009), we make no prediction for the sign of $\beta_7$. Fifth, prior studies find that stocks with higher detrended average monthly turnover (*DTURN*), return skewness (*NCSKEW*), return volatility (*SIGMA*), or past returns (*RET*) are more susceptible to crash risk (e.g., Chen et al. 2001; Kim et al. 2011a, b; Kim and Zhang 2016). Thus, we include these variables in our model and expect $\beta_8$, $\beta_9$, $\beta_{10}$, and $\beta_{11}$ to be positive.[13] Sixth, to help dispel the concern that the effect of readability on crash risk is driven by omitted business risk factors, we include several additional control variables, including systematic risk (*BETA*), earnings volatility (*EARNVOL*), cash flow volatility (*CFVOL*), and sales volatility (*SALESVOL*). We expect that these proxies for firm risk are positively related to crash risk. Finally, firms in more competitive markets could face more risks from the product market and have higher crash risk. However, prior research also suggests that product market competition acts as an external governance mechanism and increases transparency. We thus control for *HHI*,

[13] Following prior research, we control for the first, second, and third moments of past stock returns in all models. In the model with *NCSKEW* as the dependent variable, one of the control variables is essentially a lagged dependent variable.

the Herfindahl–Hirschman Index based on three-digit SIC codes (Giroud and Mueller 2010), but make no prediction for the sign of $\beta_{16}$.

## 4. Empirical analysis

### *Descriptive statistics*

Panel A of Table 1 presents the descriptive statistics. The mean values of our crash risk measures *NCSKEW*, *DUVOL*, and *CRASH* are 0.024, −0.051, and 0.225, respectively. The mean *CRASH* indicates that 22.5 percent of the firm–years in our sample experience at least one crash week. The unmodified Fog Index, denoted by *RAWFOG*, has a mean (median) value of 19.693 (19.592), with a standard deviation of 1.362 and an interquartile range of 1.584. These statistics correspond to those of prior studies in the readability literature (e.g., Lehavy et al. 2011; Li 2008; Miller 2010), suggesting that our 10-K parsing procedure is reliable without deviating much from those of prior studies. The mean *RAWFOG* of 19.693 indicates that, on average, a reader needs more than 19 years of formal education to understand the text of our sample 10-K reports on a first reading. The mean (median) value of the modified Fog Index, *MODFOG*, is 12.957 (12.768), much lower than that of *RAWFOG*. Our modification procedure changes the mean readability index from a post-graduate to a college-entry level. We interpret the level of *MODFOG* as the number of years of formal education needed for a reader with some financial reporting knowledge to understand 10-K reports on the first reading.

In panel B of Table 1, we sort our sample into tercile groups by the modified Fog Index and present the mean values of the one-year-ahead crash risk measures for each group. When measuring crash risk by *NCSKEW* and *CRASH*, we find that crash risk increases with *MODFOG* and that the differences in crash risk between the high- and low-*MODFOG* groups are statistically significant, consistent with our prediction that higher crash risk is related to lower 10-K readability. On the other hand, *DUVOL* decreases with *MODFOG*, inconsistent with our prediction. It is, however, noteworthy that these univariate comparisons do not consider other factors that affect crash risk.[14]

[Insert Table 1 about here]

Figure 1 depicts the time trends of *RAWFOG* and *MODFOG*, respectively, over the period 1994–2014. Panel A shows that the unmodified Fog Index (*RAWFOG*) gradually increases from 1995 to 1999, declines from 1999 to 2002, increases again after the passage of SOX in 2002, and finally drops after 2011. The trend of *RAWFOG* is similar to that reported by Li (2008). The time trend of the modified Fog Index, *MODFOG*, is similar to that of *RAWFOG*.[15] Overall, it appears that 10-K reports are more difficult to read in the post-SOX period than in the pre-SOX period.

[Insert Figure 1 about here]

Table 2 shows that *MODFOG* is positively correlated with one-year-ahead *NCSKEW* and *CRASH*, indicating that firms with less readable 10-K reports have higher subsequent crash risk. On the other hand, the correlation between *MODFOG* and *DUVOL* is negative, inconsistent with our prediction but consistent with the univariate comparison presented in panel B of Table 1. Similar to *MODFOG*, the level of earnings management (*OPAQUE*) has positive correlations with *NCSKEW* and *CRASH* but a negative correlation with *DUVOL*. Further, the correlations

[14] In unreported univariate comparisons, we do not find statistically significant differences in crash risk between the low- and medium-*MODFOG* groups or between the medium- and high-*MODFOG* groups.

[15] This is not surprising given that the Pearson (Spearman) correlation between *RAWFOG* and *MODFOG* is 0.901 (0.862) in our sample. The high correlation is consistent with our expectation in that (i) the modified Fog Index is still based on computational linguistics and thus similar to the raw Fog Index in nature; and (ii) our modification procedure alters the complex word component of the Fog Index but leaves the sentence length component intact. Despite the high correlation, the modified Fog Index passes the validity test as shown in Online Appendix C.

between *MODFOG* and *OPAQUE* are positive and significant, highlighting the importance of controlling for earnings management in our regression analyses.

[Insert Table 2 about here]

***Main results***

In the three columns in Table 3, we report the results where *NCSKEW*, *DUVOL*, and *CRASH* are specified as the dependent variable in successive regressions. The coefficient of *MODFOG* is positive and significant in all columns, consistent with our prediction that firms with more complex or less readable 10-K reports have higher subsequent stock price crash risk. This result strongly supports the prediction of the IRH that managers can successfully block the flow of negative information into the stock market by obfuscating textual information in 10-K reports. The coefficient of *OPAQUE* ($OPAQUE^2$) is positive (negative) and significant in the OLS regressions of *NCSKEW* and *DUVOL*, consistent with the findings of Hutton et al. (2009).[16] More importantly for our research question, our measure of textual complexity (*MODFOG*) is positive and significant in predicting crash risk, even after controlling for the level of earnings management. Our evidence implies that managers use both earnings manipulation and textual information obfuscation to withhold bad news from the market. The economic effect of 10-K readability on crash risk is comparable to the determinants of crash risk identified by prior research. Taking the coefficient of *MODFOG* in the third column, for example, a one-standard-deviation increase in the modified Fog Index is associated with a 0.52 percentage point increase

[16] In the logistic regression of *CRASH*, the coefficient of *OPAQUE* ($OPAQUE^2$) is positive (negative) but statistically insignificant. It is worth noting that, compared with Hutton et al. (2009), we include more control variables in our model, as well as industry and year fixed effects. In an unreported test, we use their more parsimonious model and find a significantly positive (negative) coefficient of *OPAQUE* ($OPAQUE^2$). Taking all of our three crash risk measures into account, we support the authors' finding that earnings manipulation is related to subsequent crash risk.

in the probability of a crash. For comparison, Hutton et al. (2009) show that a one-standard-deviation increase in accrual manipulation (*OPAQUE*) is associated with a 1.73 percentage point increase in the crash probability and Kim and Zhang (2016) find that a one-standard-deviation increase in accounting conservatism is associated with a 1.23 percentage point decrease in the probability of a crash.[17] Given the rarity of crashes, we argue that these findings are meaningful to investors in positioning their investment portfolios to avoid crashes or their purchasing options to insure investment performance against crashes (e.g., Ak et al. 2016; Kim and Zhang 2014).

[Insert Table 3 about here]

***Cross-sectional variation***

*Current earnings performance and earnings persistence*

We have established a positive association between the textual complexity of 10-K reports and future stock price crash risk, consistent with our prediction that managers can mask adverse information by writing more complex financial reports. Bloomfield (2008) suggests that the observed effect of textual complexity on bad news hiding varies as a function of the earnings profile. Specifically, firms with negative earnings news or transitory good earnings news should have more adverse information to obfuscate and thus financial reporting complexity should have a stronger effect on future crash risk for firms with negative earnings news or transitory positive earnings news.

[17] The relatively lower economic magnitude of the readability effect is driven by two factors: (1) the sample variation in the modified Fog Index (*MODFOG*) is lower relative to abnormal accruals or conservatism (Li 2008) and (2) we include many more controls for fundamental risk factors than Hutton et al. (2009) and Kim and Zhang (2016) do.

To test the above conjecture, we define an earnings increase (i.e., $\Delta ROA > 0$) as good earnings news and an earnings decrease (i.e., $\Delta ROA < 0$) as bad earnings news.[18] Panel A of Table 4 shows that when crash risk is measured by *NCSKEW* or *DUVOL*, the coefficients of *MODFOG* are of greater magnitude and more significant in the subsample of firm–years with poor earnings performance. However, the differences in the coefficients of *MODFOG* between the two subsamples are insignificant. In addition, the coefficients of *MODFOG* are not significantly different between the two groups when crash risk is measured by *CRASH*. The somewhat weak results for the moderating effect of current earnings performance in panel A are probably due to our lack of distinction between persistent and transitory earnings news.

We next examine the moderating effect of earnings persistence. We estimate the firm-specific persistence of earnings news by comparing current-year earnings news with one-year-ahead earnings news. Specifically, we define current earnings news as persistent (transitory) if $\Delta ROA$ in year $t$ and $\Delta ROA$ in year $t$+1 carry the same (opposite) sign. We then decompose $MODFOG_t$ into $MODFOG\_PERSISTENT_t$ and $MODFOG\_TRANSITORY_t$, where $MODFOG\_PERSISTENT_t$ ($MODFOG\_TRANSITORY_t$) equals $MODFOG_t$ if $\Delta ROA_{t+1}$ carries the same (opposite) sign as $\Delta ROA_t$, and zero otherwise. Panel B of Table 4 shows the clear pattern that the positive association between textual complexity and crash risk is more pronounced for firm–years with persistent bad earnings news or transitory good earnings news.[19] Taken together,

[18] We use *ROA* to capture earnings performance, a widely used measure of overall firm performance in the capital markets. Changes in *ROA* can be driven by changes in total assets instead of earnings. We argue, however, that an increase in *ROA* driven by a decrease in assets also represents good earnings news, in that the firm earns the same amount by employing less invested assets. The results are qualitatively similar if we use earnings per share to measure earnings performance.

[19] In panel A of Table 4, the sample size is 52,860 (= 26,565 + 26,295), slightly smaller than 52,879 in Table 3, because we drop observations with $\Delta ROA_t$ equal to zero. In panel B of Table 4, the sample size further drops to 52,767 (= 26,516 + 26,251), since we delete observations with missing or zero $\Delta ROA_{t+1}$.

the results reported in Table 4 provide supporting evidence for our obfuscation argument developed from the IRH.[20]

[Insert Table 4 about here]

*CEO stock option incentives*

Previous research suggests that managers have greater incentives to hide bad news and inflate stock prices if they have more stock option incentives (e.g., Efendi et al. 2007; Kim et al. 2011b). Thus, if the documented relation between annual report readability and crash risk is driven by managerial bad news hoarding, we should observe a stronger effect when managers have more stock option incentives. To examine this conjecture, we re-estimate Eq. (4) using subsamples partitioned on the magnitude of CEO option incentives. Consistent with Efendi et al. (2007), we use in-the-money options holding to gauge option incentive. Overall, the results in panel A of Table 5 show that the significant relation between annual report readability and crash risk is largely driven by the subsample of firms with large stock option incentives. The coefficients of *MODFOG* are statistically different between the two subsamples for two out of three crash risk measures.

*Litigation risk*

It is more costly for a manager to withhold bad news if the manager's firm has higher litigation risk. Therefore, we should observe a weaker relation between annual report readability and crash risk for firms with higher litigation risk if the relation is indeed driven by bad news

[20] In an untabulated test, we also find that the relation between 10-K readability and subsequent crash risk is more pronounced for bad-news 10-K reports, that is, 10-K reports with negative tone relative to the tone of 10-K/10-Q reports filed by the same firm in the prior 400 calendar days (Feldman et al. 2010). We use the word lists developed by Loughran and McDonald (2011) to estimate the tone of 10-K/10-Q reports. This result is also consistent with our obfuscation argument.

hiding behavior. Motivated by this logic, we next re-estimate Eq. (4) using two subsamples partitioned on the level of litigation risk. Following Kim and Skinner (2012), we estimate the ex ante litigation risk for a firm in fiscal year *t* as follows:

$$\begin{aligned} LITIGATION_t = \; & -7.883 + 0.556 \times FPS_t + 0.518 \times LNASSETS_{t-1} \\ & + 0.982 \times SALESGRW_{t-1} + 0.379 \times RET_{t-1} - 0.108 \times RETSKEW_{t-1} \\ & + 25.635 \times RETVOL_{t-1} + 7 \times 10^{-7} \times TURNOVER_{t-1}, \end{aligned} \tag{5}$$

where *FPS* is an indicator variable for litigious industries that takes the value of one for firms in the biotech (SIC codes 2833–2836 or 8731–8734), computer (SIC codes 3570–3577 or 7370–7374), electronics (SIC codes 3600–3674), or retail (SIC codes 5200–5961) industry and zero otherwise (Francis et al. 1994); *LNASSETS* is the natural logarithm of total assets; *SALESGRW* is the change in sales scaled by lagged total assets; *RET* is the 12-month stock returns adjusted by CRSP value-weighted market returns; *RETSKEW* is the skewness of 12-month stock returns; *RETVOL* is the standard deviation of 12-month stock returns; and *TURNOVER* is the trading volume accumulated over the fiscal year scaled by shares outstanding at the beginning of the fiscal year.

We report the results in panel B of Table 5. Consistent with our expectations, the relation between annual report readability and crash risk is significant only for the subsample of firms with low litigation risk. The differences in the coefficients of *MODFOG* between the two subsamples are statistically significant for two out of three crash risk measures. Taken together, the cross-sectional results in Tables 4 and 5 further support our conclusion that financial reporting complexity is a determinant of stock price crashes.

[Insert Table 5 about here]

***Readability, earnings management, and SOX***

While Hutton et al. (2009) show that earnings manipulation leads to crash risk, our paper illustrates that textual information obfuscation has an incremental effect on crash risk beyond earnings manipulation. Given these results, one could naturally ask whether textual information obfuscation and earnings manipulation are interactively used to hide bad news and whether managers strategically choose between these two vehicles in hiding bad news. We thus examine the joint effects of textual complexity and earnings manipulation on crash risk.

In panel A of Table 6, we partition our sample into two subsamples based on 10-K readability and investigate whether the effect of earnings manipulation on crash risk varies systematically with textual information obfuscation. We find that earnings manipulation significantly affects crash risk only when 10-K readability is low and that the coefficients of *OPAQUE* and $OPAQUE^2$ are significantly different between the two subsamples. These results are consistent with the view that earnings manipulation and textual information obfuscation are complementary mechanisms for hiding bad news. Put differently, managers are likely to obfuscate textual disclosure in 10-K reports to mask earnings manipulation, which makes it difficult for investors to detect earnings manipulation (e.g., Lo et al. 2017). In this sense, disclosure complexity also has an indirect effect on crash risk in addition to the direct effect shown in Table 3.

Hutton et al. (2009) show that the power of accrual manipulation to predict crash risk has waned since the passage of SOX and attribute this change to increased penalties for earnings manipulation in the post-SOX period. In an unreported test, we find similar patterns. Given the results in panel A of Table 6 that firms can use textual information obfuscation as a mask for earnings manipulation, we next examine the effect of SOX on the complementary relation between the two. On one hand, the deterrent effect of SOX could be large enough and thus substantially discourage any attempts to manipulate earnings and hide bad news. On the other hand, managers are likely to rely more on textual information obfuscation as a subtle and unregulated approach to mask their earnings manipulation intent and activities.

Panel B of Table 6 shows no clear pattern for the joint effects of earnings manipulation and textual information obfuscation on crash risk in the pre-SOX period. In contrast, panel C of Table 6 shows that, in the post-SOX period, the effect of earnings manipulation on crash risk is positive and significant for firms with less readable 10-K reports but insignificant for firms with more readable 10-K reports. The subsample differences are statistically significant. These results suggest that managers are more likely to use complex language to hide accrual manipulation in the post-SOX period and that the strategy appears to be effective. The results complement the findings of Hutton et al. (2009) by showing that accrual manipulation is related to crash risk even in the post-SOX period if managers can mask their manipulation by writing more complex financial reports.

[Insert Table 6 about here]

## 5. Robustness checks and additional tests

### *Omitted variables*

In our main regression specification, we have included a battery of control variables to help confront the concern that our results are driven by other determinants of crash risk or omitted business risk factors. In this subsection, we gauge the severity of the omitted variable problem following the spirit of Altonji et al. (2005). Specifically, we estimate the degree of selection on observables and use it as a guide for the degree of selection on unobservables. Toward this end, Table D.1 in Online Appendix D includes the main determinants of financial reporting complexity as additional control variables (Li 2008): firm age (*AGE*), special items (*SI*), operational complexity (*NBSEG* and *NGSEG*), financial complexity (*NITEM*), unusual corporate events (*SEO* and *MA*), and incorporation state (*DLW*).[21] As shown in Table D.1, the coefficients of *MODFOG* continue to be significantly positive and become slightly larger in magnitude relative to those reported in Table 3. This result suggests that the omitted variable bias is unlikely to be severe. The reasoning is that if some unobserved variables were to explain our main results, the unobserved variables would have to be uncorrelated with observable confounds and their effects on crash risk would have to be economically huge.

We next conduct a falsification test following Christensen et al. (2016) and Ljungqvist et al. (2017). Specifically, we first estimate regressions of crash risk on the determinants of financial reporting complexity and obtain the predicted values of crash risk. Then, we regress the *predicted* values of crash risk on financial reporting complexity (i.e., *MODFOG*) and control variables, as in Table 3. Under the assumption that the observed or unobserved selection variables induce a spurious relation between crash risk and readability, the coefficients of *MODFOG* should be similar to those in Table 3. However, the results in Table D.2 in Online Appendix D show that the coefficients of *MODFOG* are tiny and statistically insignificant in the falsification test. Again, these results suggest that the omitted variable bias is not severe in our setting.

Although the falsification tests suggest that omitted variables or reverse causality is unlikely to drive our main results, we next use firm fixed effect regressions and change analysis to further alleviate endogeneity concerns. Table D.3 in Online Appendix D shows that the coefficients of *MODFOG* are positive and significant at least at the 5 percent level in all columns

[21] See the Appendix for definitions. The determinants of 10-K readability identified by Li (2008) also include firm size, growth opportunities, earnings volatility, and return volatility. These variables are already included in our main regression model.

after we include firm fixed effects in the regressions.[22] Table D.4 in Online Appendix D presents the change regressions.[23] The coefficient of $\Delta MODFOG$ is significantly positive at the 5 (10) percent level when $\Delta NCSKEW_{t+1}$ or $\Delta DUVOL_{t+1}$ ($\Delta CRASH_{t+1}$) is used as the dependent variable.[24,25] The results suggest that changes in the level of financial reporting complexity in year $t$ are positively and significantly associated with changes in crash risk in year $t$+1 after controlling for changes in other determinants of crash risk and changes in various measures of business risks.

Finally, we examine whether the positive association between financial reporting complexity and subsequent crash risk holds after controlling for several other factors that shape crash risk documented by recent studies. We particularly consider accounting conservatism (Kim and Zhang 2016), corporate tax avoidance (Kim et al. 2011a), stock liquidity (Chang et al. 2017), CEO overconfidence (Kim et al. 2016b), and accounting comparability (Kim et al. 2016a). Table D.5 in Online Appendix D presents the results. Our key variable, *MODFOG*, remains

[22] We drop $NCSKEW_t$ from the model in this test to avoid dynamic panel biases caused by including a lagged crash risk measure in firm fixed effect regressions (Nickell 1981). Intuitively, both lagged crash risk and firm fixed effects can capture time-invariant firm-specific factors that potentially affect crash risk, and we thus do not need to include both in the model. In any event, the results are similar if we include $NCSKEW_t$ in the regression.

[23] In Table D.4 in Online Appendix D, we use $\Delta ABACC\_DD$ instead of $\Delta OPAQUE$ and $\Delta OPAQUE^2$, where *ABACC_DD* is the absolute value of the cross-sectional regression residuals from the Dechow-Dichev (2002) model modified by Francis et al. (2005). Specifically, for each industry and year, we estimate a regression of current accruals on lagged, contemporaneous, and forward operating cash flows, changes in sales revenue, and property, plant, and equipment. We choose this measure for two reasons. First, it is difficult to interpret the first difference of *OPAQUE*, the three-year moving average of abnormal accruals. Second, changes in *ABACC* estimated from the modified Jones model may not capture changes in earnings management because the modified Jones model does not consider whether accruals can be mapped to realizations of operating cash flows. In untabulated tests, we find that our results are qualitatively unchanged by using (i) the first difference of an earnings management measure that explicitly accounts for accrual reversals (Dechow et al. 2012) and (ii) the first difference of a meet or beat measure that does not rely on any accrual model. Our results are also similar if we simply use *OPAQUE* or *ABACC* in the change regression.

[24] In the $\Delta CRASH_{t+1}$ regression, we only keep observations with $\Delta CRASH_{t+1}$ equal to zero or one. The coefficient of $\Delta MODFOG_t$ remains positive but loses significance ($p$ = 0.182) if we keep the observations with $\Delta CRASH_{t+1}$ equal to −1.

[25] Similar to our firm fixed effect regressions, we drop $\Delta NCSKEW_t$ from our change model. Including $\Delta NCSKEW_t$ does not materially change our results.

significantly positive at least at the 5 percent level in all regressions, indicating that 10-K readability has explanatory power for subsequent crash risk over and above these factors.[26]

***Alternative measures of 10-K readability***

In our main tests, we use the modified Fog Index as the measure of readability. In this subsection, we check the robustness of our main results to the use of alternative readability measures. The first alternative measure that we analyze is the modified version of the Flesch Reading Ease Score. The Flesch Reading Ease Score, which also originates from computational linguistics, is another popular readability index used in accounting research (e.g., De Franco et al. 2015; Li 2008). We calculate the measure using the following formula:

$$Flesch = 206.835 - (1.015 \times \text{words per sentence}) - (84.6 \times \text{syllables per word}). \quad (6)$$

The higher the Flesch Reading Ease Score, the easier it is to understand the text. For convenience in expressing and interpreting our results, we take the negative value of the Flesch Reading Ease Score to make it directionally consistent with our other measures of readability. Similar to the modification of the Fog Index explained in section 3, we modify the Flesch Reading Ease Score by treating all words listed in Online Appendix B as two-syllable words. The resulting modified score (*MODFLESCH*) is our first alternative readability measure.[27]

Our second alternative measure is the unmodified Fog Index (*RAWFOG*). Note, however, that the unmodified Fog Index may be misspecified in the context of financial disclosures (Loughran and McDonald 2014). The third alternative measure of financial reporting complexity

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[26] We thank Rodrigo Verdi for sharing the SAS program for constructing the accounting comparability measure.

[27] Another popular readability index is the Kincaid Index, calculated as (11.8 × syllables per word) + (0.39 × words per sentence) − 15.59. The higher the Kincaid Index, the more difficult it is to understand the text. We also create a modified version of the Kincaid Index in the same way that we constructed the modified Fog Index and Flesch Reading Ease Score. Since the modified Kincaid Index has nearly perfect correlations with the modified Fog Index (0.987 Pearson and 0.980 Spearman) in our sample, we do not report the results using the modified Kincaid Index to measure readability.

under study is the length of 10-K filings, *LENGTH*, which is the logarithm of the number of words in the edited 10-K files (e.g., Lawrence 2013; Lee 2012; Li 2008; Miller 2010; Peterson 2012; You and Zhang 2009). Longer financial reports are harder to read.[28] Our final measure is the file size of 10-K filings, *FILESIZE*, which is constructed following Loughran and McDonald (2014). These authors show that the unmodified Fog Index has no power in explaining their proxies for the information environment when they control for file size. We thus also examine whether the linguistics-based measures predict crash risk after controlling for file size.

Table D.6 in Online Appendix D presents the regression results using alternative measures of readability. All the above alternative readability measures except *FILESIZE* are significantly associated with future crash risk in the predicted direction.[29] In addition, Table D.6 shows that the power of the linguistics-based readability indices in predicting crash risk is not affected by controlling for the file size measure. Overall, the results in Table D.6 suggest that our main results are robust to alternative readability measures and that the modified readability indices have the power to explain crash risk, even when the regression model includes the file size measure.

***Readability of 10-K reports around crash events***

Our argument for the relation between 10-K readability and subsequent crash risk is that low readability helps managers stockpile negative information up to a tipping point and, afterward, a large amount of negative information is abruptly released to the market, resulting in

[28] A problem with the length measure is that longer 10-K reports can indicate greater information content rather than complexity (Li 2010b).

[29] The insignificant result for *FILESIZE* is probably driven by the SEC's XBRL mandate. When we limit our sample period to 1994–2008, the coefficient of *FILESIZE* is significantly positive at the 1 percent level. This is not surprising, in that XBRL significantly enlarges the 10-K file size, but this does not mean that 10-K reports become more complex or less readable. In fact, the purpose of XBRL adoption is to reduce information processing costs. Our results imply that 10-K file size may not be an effective readability measure, especially in the post-XBRL mandate era.

a sudden stock price decline. One could naturally ask what happens to 10-K readability after a crash event, in which the previously suppressed bad news is all released. To provide descriptive evidence on this issue, we match a firm with no crash event over the whole sample period (non-crash firm) with each firm with only one crash event (crash firm), assign a pseudo crash year for each matched non-crash firm, and compare their 10-K readability from three years before the crash event to one year afterward.[30] Figure 2 suggests that, for firms experiencing a stock price crash, the complexity of 10-K reports (proxied by the modified Fog Index) rises prior to the crash, peaks in the year right before the crash, and then drops after the crash. While crash firms generally have less readable 10-K reports than non-crash firms do, the two groups appear to exhibit the greatest difference one year before the crash event and converge after the crash. We, however, caution that the evidence presented in Figure 2 is descriptive rather than conclusive.

[Insert Figure 2 about here]

***Alternative methods of modifying the Fog Index***

In our main test, we identify a list of multisyllabic words from the Compustat variable definitions and the Fama–French industry description file, reclassify them as two-syllable words, and construct readability indices using the modified percentage of complex words or the modified number of syllables per word. An alternative way of modifying the readability indices is to use a term-weighting scheme to discount the role of high-frequency multisyllabic words in decreasing the calculated readability of 10-K reports. The rationale is that a word that appears in

[30] Specifically, we run a logistic regression of *CRASH* on the crash determinants and the readability determinants included in Table D.1 in Online Appendix D measured one year prior to the crash event, using firms with only one crash event or no crash event over the whole sample period. We drop firms with multiple crash events to avoid the confounding effect of one crash event on another. For each crash firm, we assign the non-crash firm with the closest propensity score using a caliper of 0.001 as the control firm, without replacement. This one-to-one matching procedure yields 861 pairs of crash and non-crash firms. We also assign a pseudo crash year to each matched non-crash firm.

more (fewer) 10-K reports should be more (less) familiar to investors with experience in reading 10-K reports and thus less (more) difficult to understand. We refer readers to Online Appendix E for details on this alternative modification method. Untabulated tests suggest that the modified Fog Index based on this term-weighting approach: (i) also passes the validity test recommended by Loughran and McDonald (2014), although not as strongly as that based on our word-list approach; and (ii) loads positively in Eq. (4) for all of our three measures of crash risk.

## 6. Conclusion

We find that firms with less readable 10-K reports have higher stock price crash risk. In addition, we show that the relation between financial reporting complexity and crash risk is more pronounced for firms with persistent negative earnings news or transitory positive earnings news, consistent with Bloomfield's (2008) prediction that these types of firms have more bad news to obscure. Further, the association between textual complexity and crash risk is more pronounced for firms with high CEO option incentives or low litigation risk, supporting a bad news hoarding interpretation of our results. Finally, we show that accrual manipulation is positively associated with crash risk for firms with less readable 10-K reports, even in the post-SOX period.

Our study contributes to the literature by examining the effect of financial reporting complexity on crash risk, a previously unexplored implication of textual complexity in financial reporting. Together with the findings of Li (2008), our results suggest that managers have both incentives and abilities to hide adverse information by writing more complex financial reports, consistent with the predictions of the IRH. In addition, we identify complex narratives as one potential factor for screening the risk of extreme losses, which is hard to reduce by diversification. This also echoes the SEC's view reported by Eaglesham (2013) that the textual analysis of securities filings is useful in detecting managerial opportunistic behavior. Moreover, unlike prior studies that focus on the effect of disclosure complexity on the information environment or investors' and analysts' behavior, our paper sheds light on the real effects of disclosure complexity by focusing on stock price crashes, which have the potential to significantly destroy investor welfare.

Our paper has at least two limitations. First, we do not explore whether and how the bad news obfuscated in annual reports is released through subsequent disclosures, particularly the textual information in those disclosures. Future research could use more advanced methodologies (e.g., topic modeling algorithms) to compare the topics covered in unreadable 10-K reports with those covered in subsequent earnings press releases, management forecast press releases, or 8-K filings, which potentially release stockpiled bad news and result in a stock price crash. Second, we do not account for differences among investors or wealth transfer from one group of investors to another around stock price crashes. On average, it could be that less informed investors suffer losses stemming from a crash but more informed investors enjoy the gains prior to it. Who sells right before a crash? Does the low readability of corporate disclosures create an unlevel playing field where large, skillful, informed investors avoid losses in a crash and leave other investors trapped? We leave these questions to future research.

## References


Ak, B. K., S. Rossi, R. Sloan, and S. Tracy. 2016. Navigating stock price crashes. *Journal of Portfolio Management* 42 (4): 28–37.

Allee, K. D., and M. D. DeAngelis. 2015. The structure of voluntary disclosure narratives: Evidence from tone dispersion. *Journal of Accounting Research* 53 (2): 241–274.

Allee, K. D., M. D. DeAngelis, and J. R. Moon. 2018. Disclosure "scriptability." *Journal of Accounting Research*, forthcoming.

Altonji, J. G., T. Elder, and C. Taber. 2005. Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools. *Journal of Political Economy* 113 (1): 151–184.

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

Blanchard, O. 2009. (Nearly) nothing to fear but fear itself. *The Economist* (January 31): 84.

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

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

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

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

Bozanic, Z., and M. Thevenot. 2015. Qualitative disclosure and changes in sell-side financial analysts' information environment. *Contemporary Accounting Research* 32 (4): 1595–1616.

Brown, S. V., and J. W. Tucker. 2011. Large-sample evidence on firms' year-over-year MD&A modifications. *Journal of Accounting Research* 49 (2): 309–346.

Bushee, B. J., I. D. Gow, and D. J. Taylor. 2018. Linguistic complexity in firm disclosures: Obfuscation or information? *Journal of Accounting Research*, 56 (1): 85–121.

Callen, J. L., and X. Fang. 2013. Institutional investor stability and crash risk: Monitoring versus short-termism? *Journal of Banking and Finance* 37 (8): 3047–3063.

Callen, J. L., M. Khan, and H. Lu. 2013. Accounting quality, stock price delay, and future stock returns. *Contemporary Accounting Research* 30 (1): 269–295.

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

Chang, X., Y. Chen, and L. Zolotoy. 2017. Stock liquidity and stock price crash risk. *Journal of Financial and Quantitative Analysis* 52 (4): 1605–1637.

Chen, J., H. Hong, and J. C. Stein. 2001. Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics* 61 (3): 345–381.

Christensen, H. B., L. Hail, and C. Leuz. 2016. Capital-market effects of securities regulation: Prior conditions, implementation, and enforcement. *Review of Financial Studies* 29 (11): 2885–2924.

Dechow, P. M., and I. D. Dichev. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (Suppl.): 35–59.

Dechow, P. M., A. P. Hutton, J. H. Kim, and R. G. Sloan. 2012. Detecting earnings management: A new approach. *Journal of Accounting Research* 50 (2): 275–334.

DeFond, M. L. 2010. Earnings quality research: Advances, challenges and future research. *Journal of Accounting and Economics* 50 (2–3): 402–409.

DeFond, M. L., M. Hung, S. Li, and Y. Li. 2015. Does mandatory IFRS adoption affect crash risk? *The Accounting Review* 90 (1): 265–299.

De Franco, G., O.-K. Hope, D. Vyas, and Y. Zhou. 2015. Analyst report readability. *Contemporary Accounting Research* 32 (1): 76–104.

Dichev, I. D., J. R. Graham, C. R. Harvey, and S. Rajgopal. 2013. Earnings quality: Evidence from the field. *Journal of Accounting and Economics* 56 (2–3): 1–33.

Dimson, E. 1979. Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics* 7 (2): 197–226.

Dougal, C., J. Engelberg, D. García, and C. A. Parsons. 2012. Journalists and the stock market. *Review of Financial Studies* 25 (3): 639–679.

Eaglesham, J. 2013. Accounting fraud targeted. *Wall Street Journal* (May 28): C1.

Efendi, J., A. Srivastava, and E. P. Swanson. 2007. Why do corporate managers misstate financial statements? The role of option compensation and other factors. *Journal of Financial Economics* 85 (3): 667–708.

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

Feldman, R., S. Govindaraj, J. Livnat, and B. Segal. 2010. Management's tone change, post earnings announcement drift and accruals. *Review of Accounting Studies* 15 (4): 915–953.

Francis, J., R. LaFond, P. Olsson, and K. Schipper. 2005. The market pricing of accruals quality. *Journal of Accounting and Economics* 39 (2): 295–327.

Francis, J., D. Philbrick, and K. Schipper. 1994. Shareholder litigation and corporate disclosures. *Journal of Accounting Research* 32 (2): 137–164.

Giroud, X., and H. M. Mueller. 2010. Does corporate governance matter in competitive industries? *Journal of Financial Economics* 95 (3): 312–331.

Griffin, P. A. 2003. Got information? Investor response to Form 10-K and Form 10-Q EDGAR filings. *Review of Accounting Studies* 8 (4): 433–460.

Grossman, S. J., and J. E. Stiglitz. 1980. On the impossibility of informationally efficient markets. *American Economic Review* 70 (3): 393–408.

Guay, W., D. Samuels, and D. Taylor. 2016. Guiding through the fog: Financial statement complexity and voluntary disclosure. *Journal of Accounting and Economics* 62 (2): 234–269.

Hong, H. A., J.-B. Kim, and M. Welker. 2017. Divergence of cash flow and voting rights, opacity, and stock price crash risk: International evidence. *Journal of Accounting Research* 55(5): 1167–1212.

Hsieh, C.-C., and K. W. Hui. 2013. Analyst report readability, earnings uncertainty and stock returns. Working paper, Hong Kong University of Science and Technology.

Hutton, A. P., A. J. Marcus, and H. Tehranian. 2009. Opaque financial reports, $R^2$, and crash risk. *Journal of Financial Economics* 94 (1): 67–86.

Jegadeesh, N., and D. Wu. 2013. Word power: A new approach for content analysis. *Journal of Financial Economics* 110 (3): 712–729.

Jin, L., and S. C. Myers. 2006. $R^2$ around the world: New theory and new tests. *Journal of Financial Economics* 79 (2), 257–292.

Kim, I., and D. J. Skinner. 2012. Measuring securities litigation risk. *Journal of Accounting and Economics* 53 (1–2): 290–310.
Kim, J.-B., L. Li, L. Y. Lu, and Y. Yu. 2016a. Financial statement comparability and expected crash risk. *Journal of Accounting and Economics* 61 (2–3): 294–312.
Kim, J.-B., Y. Li, and L. Zhang. 2011a. Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics* 100 (3): 639–662.
Kim, J.-B., Y. Li, and L. Zhang. 2011b. CFOs versus CEOs: Equity incentives and crashes. *Journal of Financial Economics* 101 (3): 713–730.
Kim, J.-B., Z. Wang, and L. Zhang. 2016b. CEO overconfidence and stock price crash risk. *Contemporary Accounting Research* 33 (4): 1720–1749.
Kim, J.-B., and L. Zhang. 2014. Financial reporting opacity and expected crash risk: Evidence from implied volatility smirks. *Contemporary Accounting Research* 31 (3): 851–875.
Kim, J.-B., and L. Zhang. 2016. Accounting conservatism and stock price crash risk: Firm-level evidence. *Contemporary Accounting Research* 33 (1): 412–441.
Kothari, S. P., X. Li, and J. E. Short. 2009a. The effect of disclosures by management, analysts, and business press on cost of capital, return volatility, and analyst forecasts: A study using content analysis. *The Accounting Review* 84 (5): 1639–1670.
Kothari, S. P., S. Shu, and P. D. Wysocki. 2009b. Do managers withhold bad news? *Journal of Accounting Research* 47 (1): 241–276.
Kravet, T., and V. Muslu. 2013. Textual risk disclosures and investors' risk perceptions. *Review of Accounting Studies* 18 (4): 1088–1122.
Laksmana, I., W. Tietz, and Y.-W. Yang. 2012. Compensation discussion and analysis (CD&A): readability and management obfuscation. *Journal of Accounting and Public Policy* 31 (2): 185–203.
Lang, M., and L. Stice-Lawrence. 2015. Textual analysis and international financial reporting: Large sample evidence. *Journal of Accounting and Economics* 60 (2–3): 110–135.
Lawrence, A. 2013. Individual investors and financial disclosure. *Journal of Accounting and Economics* 56 (1): 130–147.
Lee, Y.-J. 2012. The effect of quarterly report readability on information efficiency of stock prices. *Contemporary Accounting Research* 29 (4): 1137–1170.
Lehavy, R., F. Li, and K. Merkley. 2011. The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review* 86 (3): 1087–1115.
Li, F. 2006. Do stock market investors understand the risk sentiment of corporate annual reports? Working paper, University of Michigan.
Li, F. 2008. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics* 45 (2–3): 221–247.
Li, F. 2010a. The information content of forward-looking statements in corporate filings—A naïve Bayesian machine learning approach. *Journal of Accounting Research* 48 (5): 1049–1102.
Li, F.. 2010b. Textual analysis of corporate disclosures: A survey of the literature. *Journal of Accounting Literature* 29: 143–165.
Li, F., R. Lundholm, and M. Minnis. 2013. A measure of competition based on 10-K filings. *Journal of Accounting Research* 51 (2): 399–436.

Li, Y., and L. Zhang. 2015. Short selling pressure, stock price behavior, and management forecast precision: Evidence from a natural experiment. *Journal of Accounting Research* 53 (1): 79–117.

Ljungqvist, A., L. Zhang, and L. Zuo. 2017. Sharing risk with the government: How taxes affect corporate risk taking. *Journal of Accounting Research* 55 (3): 669–707.

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

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

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

Lundholm, R., R. Rogo, and J. L. Zhang. 2014. Restoring the tower of Babel: How foreign firms communicate with US investors. *The Accounting Review* 89 (4): 1453–1485.

Merkley, K. 2014. Narrative disclosure and earnings performance: evidence from R&D disclosures. *The Accounting Review* 89 (2): 725–757.

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

Nelson, K. K., and A. C. Pritchard. 2016. Carrot or stick? The shift from voluntary to mandatory disclosure of risk factors. *Journal of Empirical Legal Studies* 13 (2): 266–297.

Nickell, S. 1981. Biases in dynamic models with fixed effects. *Econometrica* 49 (6): 1417–1426.

Peterson, K. 2012. Accounting complexity, misreporting, and the consequences of misreporting. *Review of Accounting Studies* 17 (1): 72–95.

Rogers, J. L., C. Schrand, and S. L. C. Zechman. 2014. Do managers tacitly collude to withhold industry-wide bad news? Working paper, University of Colorado, University of Pennsylvania, and University of Chicago.

Skinner, D. J. 1994. Why firms voluntarily disclose bad news. *Journal of Accounting Research* 32 (1): 38–60.

Sunder, S. 2010. Riding the accounting train: From crisis to crisis in eighty years. Presentation at the Conference on Financial Reporting, Auditing and Governance, Lehigh University, April 23.

You, H., and X. Zhang. 2009. Financial reporting complexity and investor underreaction to 10-K information. *Review of Accounting Studies* 14 (4): 559–586.

## Appendix. Variable definitions

***Dependent variables: Crash risk measures***

| | |
|---|---|
| $CRASH_{t+1}$ | An indicator variable that takes the value of one if at least one value of $W$ over the fiscal year $t$+1 falls 3.09 or more standard deviations below the mean $W$ for the fiscal year and zero otherwise. $W$ is firm-specific weekly return, defined as the natural logarithm of one plus the residual return from estimating the following expanded index for each firm and each fiscal year: $r_{j\tau} = \alpha_j + \beta_{1j} r_{m\tau-1} + \beta_{2j} r_{i\tau-1} + \beta_{3j} r_{m\tau} + \beta_{4j} r_{i\tau} + \beta_{5j} r_{m\tau+1} + \beta_{6j} r_{i\tau+1} + \varepsilon_{j\tau}$, where $j$, $m$, and $i$ denote firm, market, and industry, respectively. |
| $DUVOL_{t+1}$ | The natural logarithm of the ratio of the standard deviation of $W$ for the *down* weeks to the standard deviation of $W$ for the *up* weeks, where the down and up weeks are those with $W$ below and above, respectively, the mean over the fiscal year $t$+1. $W$ is defined above. |
| $NCSKEW_{t+1}$ | The negative skewness of $W$ over fiscal year $t$+1. A fiscal year is defined as the 12-month period ending three months after the fiscal year-end in constructing the crash risk measures and other stock return variables to avoid look-ahead biases. $W$ is defined above. |

***Key variable: Modified Fog Index***

| | |
|---|---|
| $MODFOG_t$ | The modified Fog Index of the 10-K report filed for fiscal year $t$. The Fog Index is calculated as (words per sentence + percentage of complex words) × 0.4. A higher Fog Index means the report is more difficult to read. To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as simple words in calculating *MODFOG*. |

***Alternative readability measures***

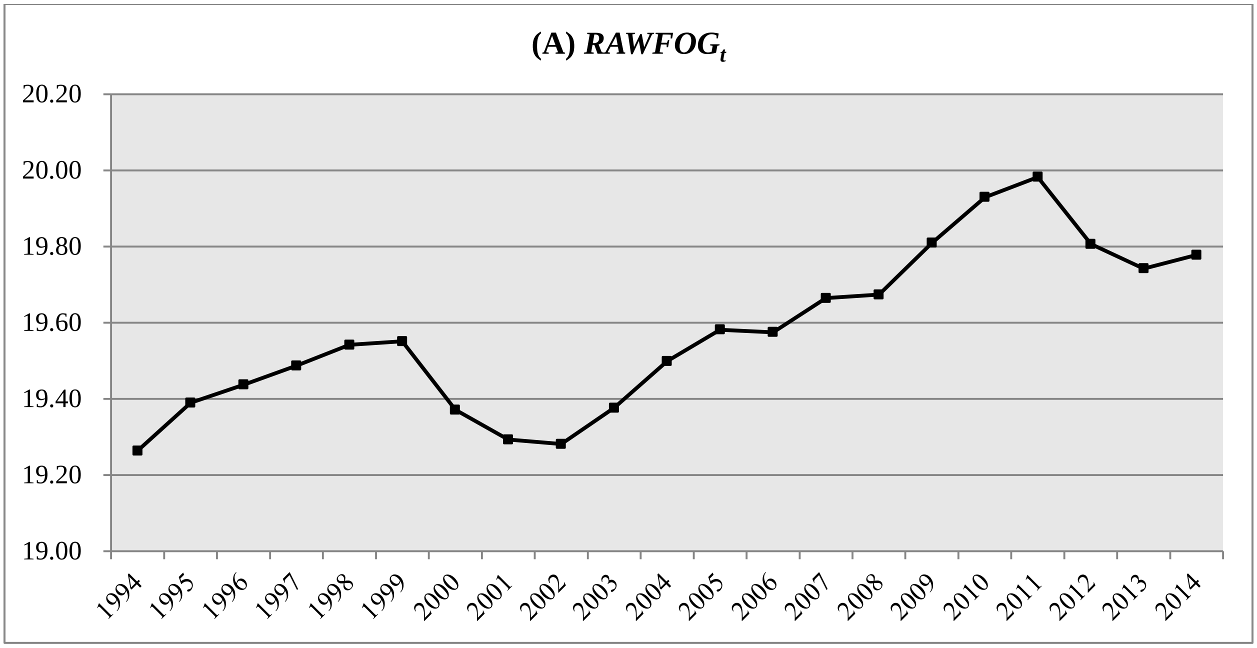
| | |
|---|---|
| $FILESIZE_t$ | The natural logarithm of the file size (in megabytes) of the 10-K report filed for fiscal year $t$. |
| $LENGTH_t$ | The natural logarithm of the total number of words of the 10-K report filed for fiscal year $t$. |
| $MODFLESCH_t$ | The modified Flesch Reading Ease Score of the 10-K report filed for fiscal year $t$. The Flesch Reading Ease Score is calculated as 206.835 − (1.015 × words per sentence) − (84.6 × syllables per word). A higher Flesch Reading Ease Score means the report is more readable. To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as two-syllable words in calculating *MODFLESCH*. For convenience in expressing and interpreting our results, we take the negative value. |
| $RAWFOG_t$ | The Fog Index of the 10-K report filed for fiscal year $t$, calculated as (words per sentence + percentage of complex words) × 0.4. A higher Fog Index means the report is more difficult to read. |

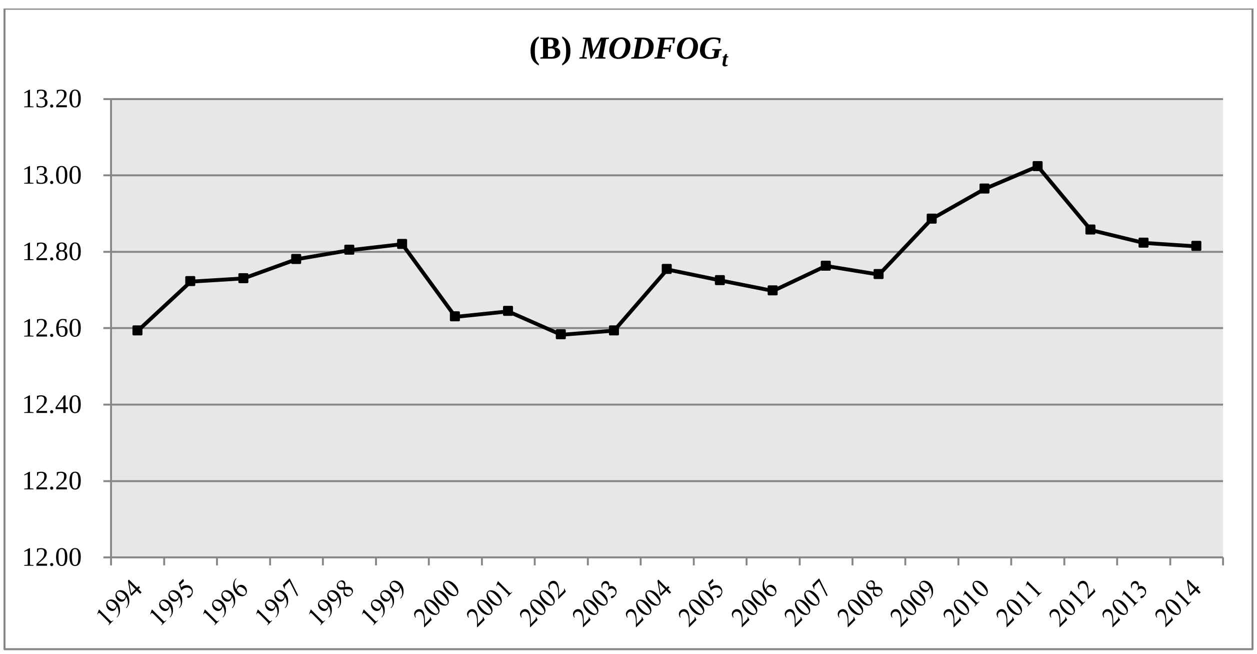
***Control variables: Determinants of crash risk***

| | |
|---|---|
| $BETA_t$ | The market beta estimated from the capital asset pricing model using daily stock returns and value-weighted market returns over fiscal year $t$. |

| | |
|---|---|
| $CFVOL_t$ | The standard deviation of operating cash flows (*#oancf*) scaled by lagged total assets (*#at*) over the five fiscal years from $t-4$ to $t$. |
| $DTURN_t$ | The average monthly share turnover over fiscal year $t$ minus the average monthly share turnover over fiscal year $t-1$. The monthly share turnover is calculated as the trading volume over the month scaled by the total number of shares outstanding at the end of the month. |
| $EARNVOL_t$ | The standard deviation of *ROA* over the five fiscal years from $t-4$ to $t$. |
| $HHI_t$ | The Herfindahl–Hirschman Index based on three-digit SIC codes. |
| $LEV_t$ | Total liabilities (*#lt*) scaled by the book value of total assets (*#at*) at the end of fiscal year $t$. |
| $LOGMV_t$ | The natural logarithm of the market value of equity (*#csho* × *#prcc_f*) at the end of fiscal year $t$. |
| $MTB_t$ | The ratio of the market value of equity (*#csho* × *#prcc_f*) to the book value of equity (*#ceq*) at the end of fiscal year $t$. |
| $NCSKEW_t$ | The negative skewness of *W* over fiscal year $t$, where *W* is defined above. |
| $OPAQUE_t$ | The moving sum of the absolute value of abnormal accruals in the prior three years (i.e., $ABACC_t + ABACC_{t-1} + ABACC_{t-2}$), where abnormal accruals are estimated using the modified Jones model. |
| $RET_t$ | The mean of *W* over fiscal year $t$ times 100, where *W* is defined above. |
| $ROA_t$ | The operating income (*#oiadp*) for fiscal year $t$ divided by the book value of total assets (*#at*) at the beginning of fiscal year $t$. |
| $SALESVOL_t$ | The standard deviation of sales revenue (*#sale*) scaled by lagged total assets (*#at*) over the five fiscal years from $t-4$ to $t$. |
| $SIGMA_t$ | The standard deviation of *W* over fiscal year $t$, where *W* is defined above. |
| ***Control variables: Determinants of readability*** | |
| $AGE_t$ | The number of entire years since the firm's first appearance in Compustat. |
| $DLW_t$ | An indicator variable that takes the value of one if the company's state of incorporation is Delaware in fiscal year $t$ and zero otherwise. |
| $MA_t$ | An indicator variable that takes the value of one if the firm is an acquirer in fiscal year $t$ according to the Securities Data Company database and zero otherwise. |
| $NBSEG_t$ | The natural logarithm of one plus the number of business segments at the end of fiscal year $t$. |
| $NGSEG_t$ | The natural logarithm of one plus the number of geographic segments at the end of fiscal year $t$. |
| $NITEM_t$ | The number of non-missing items on Compustat for the fiscal year $t$. |
| $SEO_t$ | An indicator variable that takes the value of one if the firm has a seasoned equity offering in fiscal year $t$ according to the Securities Data Company database and zero otherwise. |
| $SI_t$ | The special items (*#spi*) at the end of fiscal year $t$ scaled by the book value of total assets (*#at*) at the beginning of fiscal year $t$. |

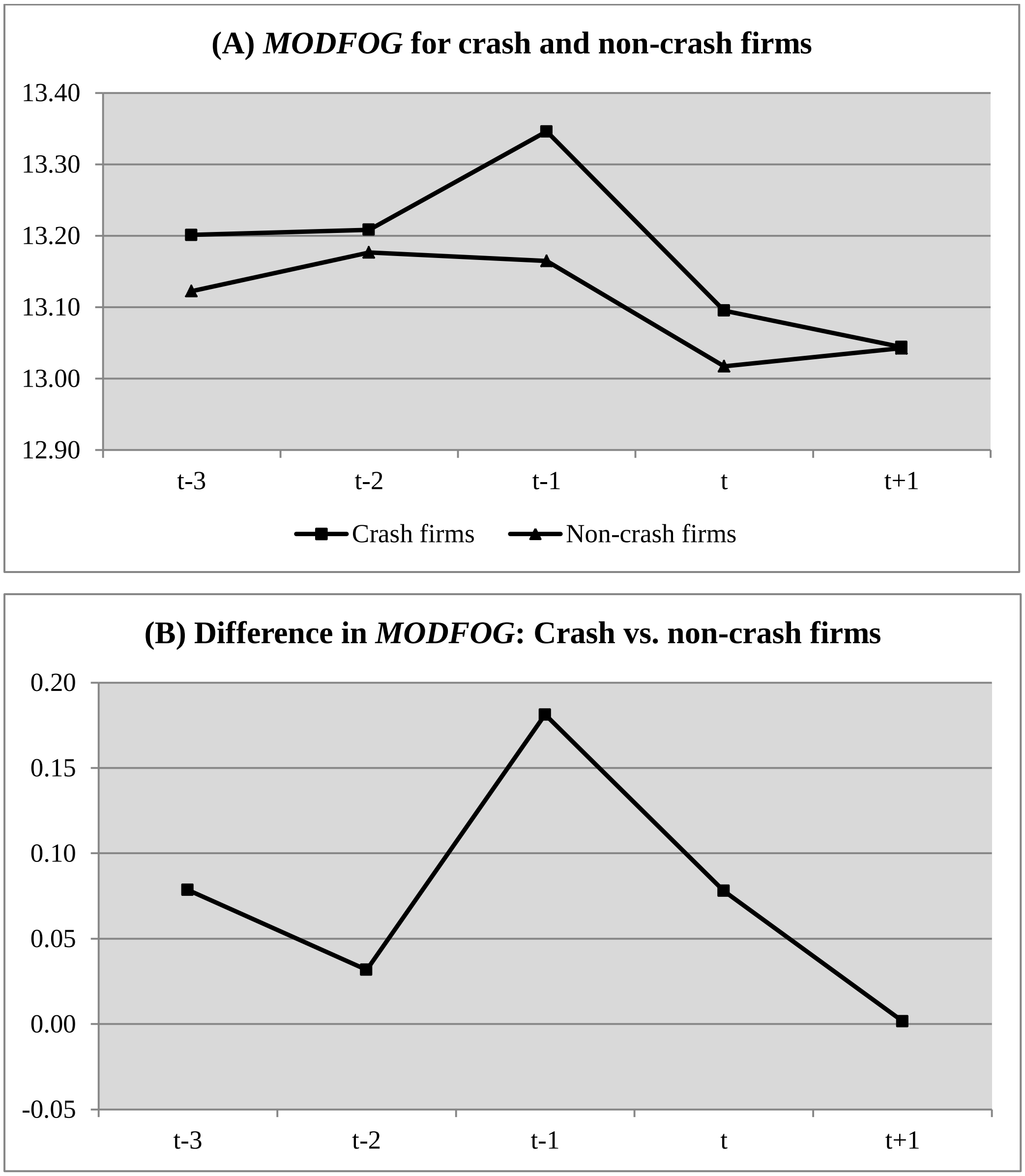
**Figure 1** Time trend of the raw versus modified Fog Index




This figure shows the sample medians of (A) $RAWFOG_t$ and (B) $MODFOG_t$ on an annual basis, where $RAWFOG_t$ is the raw Fog Index for the 10-K report filed in year $t$, calculated as (words per sentence + percentage of complex words) × 0.4, and $MODFOG_t$ is the modified Fog Index for the 10-K report filed in year $t$, generated similarly except for the definition of complex words. Specifically, we identify a list of 2,028 words that have at least three syllables but which are not difficult to understand in the financial context and reclassify these words as simple words.

**Figure 2** The variable *MODFOG* for crash versus non-crash firms around the crash year




Panel A shows the average *MODFOG* values for crash and non-crash firms from year *t*−3 to year *t*+1, where *t* is the year the crash occurs. We use propensity scores to match each crash firm with a firm with no crash event through the whole sample period, using a matching model that includes all crash determinants and readability determinants. We then assign a pseudo crash year to each matched non-crash firm. Panel B depicts the difference in *MODFOG* between the crash firms and matched non-crash firms.

TABLE 1
Descriptive statistics

**Panel A:** Descriptive statistics

| Variable | $N$ | Mean | Std | Q1 | Median | Q3 |
|---|---|---|---|---|---|---|
| $NCSKEW_{t+1}$ | 52,879 | 0.024 | 0.855 | −0.453 | −0.013 | 0.437 |
| $DUVOL_{t+1}$ | 52,879 | −0.051 | 0.377 | −0.303 | −0.063 | 0.185 |
| $CRASH_{t+1}$ | 52,879 | 0.225 | 0.418 | 0.000 | 0.000 | 0.000 |
| $MODFOG_t$ | 52,879 | 12.957 | 1.646 | 11.867 | 12.768 | 13.794 |
| $RAWFOG_t$ | 52,879 | 19.693 | 1.362 | 18.832 | 19.592 | 20.416 |
| $OPAQUE_t$ | 52,879 | 0.369 | 0.375 | 0.139 | 0.251 | 0.453 |
| $LOGMV_t$ | 52,879 | 5.936 | 2.002 | 4.482 | 5.856 | 7.235 |
| $MTB_t$ | 52,879 | 2.971 | 4.256 | 1.212 | 2.045 | 3.551 |
| $LEV_t$ | 52,879 | 0.480 | 0.246 | 0.290 | 0.471 | 0.634 |
| $ROA_t$ | 52,879 | 0.042 | 0.209 | 0.005 | 0.079 | 0.143 |
| $DTURN_t$ | 52,879 | 0.004 | 0.098 | −0.028 | 0.000 | 0.030 |
| $NCSKEW_t$ | 52,879 | 0.022 | 0.821 | −0.446 | −0.021 | 0.417 |
| $SIGMA_t$ | 52,879 | 0.062 | 0.033 | 0.037 | 0.054 | 0.078 |
| $RET_t$ | 52,879 | −0.242 | 0.282 | −0.301 | −0.142 | −0.068 |
| $BETA_t$ | 52,879 | 0.918 | 0.598 | 0.466 | 0.875 | 1.299 |
| $EARNVOL_t$ | 52,879 | 0.117 | 0.220 | 0.027 | 0.053 | 0.110 |
| $CFVOL_t$ | 52,879 | 0.112 | 0.177 | 0.035 | 0.061 | 0.112 |
| $SALESVOL_t$ | 52,879 | 0.338 | 0.432 | 0.104 | 0.200 | 0.385 |
| $HHI_t$ | 52,879 | 0.153 | 0.144 | 0.060 | 0.101 | 0.188 |

**Panel B:** Univariate comparisons

| | $MODFOG_t$ tercile group | | | |
|---|---|---|---|---|
| Crash risk measure | (1) Low | (2) Medium | (3) High | $p$-value: (3) − (1) |
| $NCSKEW_{t+1}$ | 0.017 | 0.020 | 0.034 | 0.064 |
| $DUVOL_{t+1}$ | −0.045 | −0.052 | −0.055 | 0.038 |
| $CRASH_{t+1}$ | 0.219 | 0.225 | 0.232 | 0.002 |

Panel A presents descriptive statistics on crash risk, 10-K readability, and the control variables. Our initial sample includes all firm–years that file a 10-K report with at least 3,000 words in the period 1994–2014. After combining the initial sample with the CRSP and Compustat databases, we require that (i) total assets be greater than zero, (ii) the share price at the fiscal year-end be higher than \$1, (iii) at least 26 weekly returns be available in the 12-month period ending three months after the end of fiscal year $t$+1, and (iv) all financial data used to construct the other determinant variables of crash risk be available from the CRSP and Compustat. See the Appendix for the definitions of these variables. All the financial and stock return variables are winsorized at the top and bottom 1%. In panel B, we sort our sample into three groups by the modified Fog Index (*MODFOG*), report the average crash risk for each group, and test the difference in crash risk between the high- and low-*MODFOG* groups.

TABLE 2
Correlation matrix

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|---|
| $NCSKEW_{t+1}$ | (1) | | **0.978** | **0.621** | 0.002 | 0.008 | **0.161** | **0.101** | **−0.018** | **0.110** |
| $DUVOL_{t+1}$ | (2) | **0.957** | | **0.574** | **−0.012** | **−0.009** | **0.195** | **0.105** | **−0.014** | **0.140** |
| $CRASH_{t+1}$ | (3) | **0.638** | **0.591** | | **0.016** | **0.024** | **0.077** | **0.061** | **−0.013** | **0.058** |
| $MODFOG_t$ | (4) | **0.014** | −0.003 | **0.013** | | **0.105** | **−0.044** | **0.083** | **−0.054** | **−0.167** |
| $OPAQUE_t$ | (5) | **0.009** | **−0.009** | **0.021** | **0.080** | | **−0.177** | **0.082** | **−0.113** | **−0.160** |
| $LOGMV_t$ | (6) | **0.143** | **0.184** | **0.069** | **−0.026** | **−0.122** | | **0.402** | **0.129** | **0.396** |
| $MTB_t$ | (7) | **0.055** | **0.052** | **0.027** | **0.059** | **0.096** | **0.199** | | **−0.044** | **0.260** |
| $LEV_t$ | (8) | **−0.022** | **−0.020** | **−0.011** | −0.007 | **−0.055** | **0.105** | **−0.046** | | **0.011** |
| $ROA_t$ | (9) | **0.061** | **0.103** | **0.033** | **−0.171** | **−0.249** | **0.302** | **−0.053** | **0.022** | |
| $DTURN_t$ | (10) | **0.049** | **0.048** | **0.030** | **0.018** | **0.013** | **0.052** | **0.094** | **0.026** | **0.024** |
| $NCSKEW_t$ | (11) | **0.043** | **0.043** | **0.032** | 0.004 | −0.007 | **0.116** | −0.008 | **−0.021** | **0.055** |
| $SIGMA_t$ | (12) | **−0.041** | **−0.099** | **−0.033** | **0.131** | **0.258** | **−0.491** | **0.032** | **−0.033** | **−0.419** |
| $RET_t$ | (13) | **0.044** | **0.096** | **0.036** | **−0.109** | **−0.243** | **0.410** | **−0.043** | 0.008 | **0.405** |
| $BETA_t$ | (14) | **0.081** | **0.078** | **0.047** | **0.039** | **0.106** | **0.361** | **0.100** | **−0.045** | **−0.040** |
| $EARNVOL_t$ | (15) | 0.005 | **−0.026** | 0.006 | **0.119** | **0.404** | **−0.152** | **0.136** | **−0.132** | **−0.429** |
| $CFVOL_t$ | (16) | 0.003 | **−0.029** | 0.006 | **0.127** | **0.408** | **−0.182** | **0.141** | **−0.119** | **−0.420** |
| $SALESVOL_t$ | (17) | **0.010** | **−0.011** | 0.002 | **0.042** | **0.272** | **−0.184** | **0.028** | **−0.052** | **−0.029** |
| $HHI_t$ | (18) | −0.003 | 0.008 | 0.000 | **−0.099** | **−0.146** | **0.032** | **−0.063** | **0.095** | **0.149** |

| | | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) |
|---|---|---|---|---|---|---|---|---|---|---|
| $NCSKEW_{t+1}$ | (1) | **0.057** | **0.045** | **−0.046** | **0.046** | **0.084** | −0.005 | −0.005 | **0.012** | −0.003 |
| $DUVOL_{t+1}$ | (2) | **0.056** | **0.046** | **−0.098** | **0.099** | **0.083** | **−0.039** | **−0.038** | **−0.009** | **0.010** |
| $CRASH_{t+1}$ | (3) | **0.033** | **0.026** | **−0.027** | **0.027** | **0.054** | 0.008 | **0.009** | **0.009** | **−0.009** |
| $MODFOG_t$ | (4) | 0.005 | −0.005 | **0.163** | **−0.163** | **0.058** | **0.178** | **0.171** | **0.032** | **−0.174** |
| $OPAQUE_t$ | (5) | **−0.009** | −0.008 | **0.295** | **−0.295** | **0.106** | **0.372** | **0.407** | **0.256** | **−0.231** |
| $LOGMV_t$ | (6) | **0.098** | **0.134** | **−0.539** | **0.541** | **0.423** | **−0.307** | **−0.341** | **−0.253** | **0.026** |
| $MTB_t$ | (7) | **0.135** | 0.005 | **−0.104** | **0.104** | **0.198** | **0.124** | **0.102** | **−0.010** | **−0.130** |
| $LEV_t$ | (8) | **0.049** | **−0.016** | **−0.095** | **0.095** | **−0.054** | **−0.277** | **−0.244** | **−0.064** | **0.175** |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| $ROA_t$ | (9) | **0.111** | **0.070** | **−0.399** | **0.400** | **−0.013** | **−0.283** | **−0.250** | **−0.027** | **0.181** |
| $DTURN_t$ | (10) | | **0.021** | **0.098** | **−0.097** | **0.021** | **−0.050** | **−0.032** | **−0.046** | 0.006 |
| $NCSKEW_t$ | (11) | **0.016** | | **−0.014** | **0.027** | **0.101** | **−0.013** | **−0.020** | 0.005 | 0.000 |
| $SIGMA_t$ | (12) | **0.169** | 0.004 | | **−1.000** | **0.030** | **0.540** | **0.509** | **0.349** | **−0.185** |
| $RET_t$ | (13) | **−0.185** | **0.037** | **−0.958** | | **−0.028** | **−0.540** | **−0.509** | **−0.349** | **0.185** |
| $BETA_t$ | (14) | **0.029** | **0.093** | **0.061** | **−0.049** | | **0.117** | **0.051** | **0.016** | **−0.123** |
| $EARNVOL_t$ | (15) | **0.013** | −0.008 | **0.367** | **−0.349** | **0.108** | | **0.742** | **0.517** | **−0.259** |
| $CFVOL_t$ | (16) | **0.022** | **−0.013** | **0.367** | **−0.346** | **0.070** | **0.881** | | **0.496** | **−0.217** |
| $SALESVOL_t$ | (17) | **−0.019** | 0.003 | **0.292** | **−0.258** | **0.029** | **0.403** | **0.409** | | 0.004 |
| $HHI_t$ | (18) | −0.004 | −0.001 | **−0.144** | **0.122** | **−0.087** | **−0.130** | **−0.125** | **−0.036** | |

This table shows the Pearson and Spearman correlations between crash risk, 10-K readability, and other determinants of crash risk below and above the diagonal, respectively. See the Appendix for the variable definitions. Boldface represents the significance level of 0.05.

TABLE 3
Impact of 10-K readability on stock price crash risk

| | Dependent variable = | | |
|---|---|---|---|
| | $NCSKEW_{t+1}$ | $DUVOL_{t+1}$ | $CRASH_{t+1}$ |
| $MODFOG_t$ | 0.008*** | 0.003*** | 0.018*** |
| | (3.67) | (2.86) | (2.65) |
| $OPAQUE_t$ | 0.069** | 0.031** | 0.041 |
| | (2.36) | (2.48) | (0.52) |
| $OPAQUE_t^2$ | −0.038** | −0.016** | −0.024 |
| | (−2.51) | (−2.46) | (−0.60) |
| $LOGMV_t$ | 0.059*** | 0.029*** | 0.064*** |
| | (19.82) | (21.88) | (7.40) |
| $MTB_t$ | 0.003*** | 0.001*** | 0.001 |
| | (2.68) | (2.59) | (0.33) |
| $LEV_t$ | −0.084*** | −0.046*** | 0.046 |
| | (−4.66) | (−5.86) | (0.93) |
| $ROA_t$ | 0.212*** | 0.124*** | 0.532*** |
| | (8.45) | (11.55) | (7.60) |
| $DTURN_t$ | 0.295*** | 0.145*** | 0.640*** |
| | (7.34) | (8.37) | (5.67) |
| $NCSKEW_t$ | 0.013** | 0.005** | 0.037*** |
| | (2.56) | (2.38) | (2.74) |
| $SIGMA_t$ | 4.239*** | 1.182*** | 8.166*** |
| | (8.46) | (5.43) | (5.39) |
| $RET_t$ | 0.447*** | 0.164*** | 1.016*** |
| | (8.72) | (7.41) | (6.22) |
| $BETA_t$ | 0.030*** | 0.009** | 0.016 |
| | (3.75) | (2.57) | (0.67) |
| $EARNVOL_t$ | 0.035 | 0.009 | 0.074 |
| | (0.90) | (0.55) | (0.72) |
| $CFVOL_t$ | 0.046 | 0.018 | 0.132 |
| | (0.94) | (0.83) | (1.06) |
| $SALESVOL_t$ | 0.025** | 0.009* | 0.025 |
| | (2.35) | (1.84) | (0.82) |
| $HHI_t$ | 0.014 | −0.002 | 0.091 |
| | (0.39) | (−0.11) | (0.93) |
| Year fixed effects | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes |
| Observations | 52,879 | 52,879 | 52,879 |
| Adjusted/pseudo-$R^2$ | 0.040 | 0.054 | 0.021 |

This table presents the results for the OLS regressions of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ and the logistic regression of $CRASH_{t+1}$ on our readability measure $MODFOG_t$. The variable $NCSKEW_{t+1}$ is the negative skewness of $W$ over fiscal year $t$+1; $DUVOL_{t+1}$ is the natural logarithm of the ratio of the standard deviation of $W$ on *down* weeks to the standard deviation of $W$ on *up* weeks, where the down and up weeks are, respectively, those with $W$ below and above the mean over fiscal year $t$+1, respectively; $CRASH_{t+1}$ is an indicator variable that takes the value of one if at least one value of $W$ over the fiscal year $t$+1 falls 3.09 or more standard deviations below the mean $W$ for the fiscal year, and zero otherwise; and $W$ is the firm-specific weekly return, defined as the natural logarithm of one plus the residual return from estimating an expanded index model including lead and lag terms for the market and industry indexes. We define a fiscal year as the 12-month period ending three months after the fiscal year-end to avoid look-ahead bias. The variable $MODFOG_t$ is the modified version of the Fog Index for the 10-K report filed for fiscal year $t$. The Fog Index is calculated as (words per sentence + percentage of complex words) × 0.4. To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as simple words in calculating *MODFOG*. See the Appendix for the definitions of the control variables. All the models also include an unreported intercept. The *t*- and *z*-statistics reported in parentheses are based on standard errors clustered by firm. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

TABLE 4

Cross-sectional analysis: Effect of current earnings performance and earnings persistence

**Panel A:** Poor versus good current earnings performance

| | $NCSKEW_{t+1}$ | | $DUVOL_{t+1}$ | | $CRASH_{t+1}$ | |
|---|---|---|---|---|---|---|
| | Poor current performance | Good current performance | Poor current performance | Good current performance | Poor current performance | Good current performance |
| $MODFOG_t$ | 0.011*** | 0.006* | 0.005*** | 0.001 | 0.018* | 0.019* |
| | (3.39) | (1.77) | (3.19) | (0.83) | (1.88) | (1.93) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 26,565 | 26,295 | 26,565 | 26,295 | 26,565 | 26,295 |
| Adjusted/pseudo-$R^2$ | 0.041 | 0.038 | 0.057 | 0.050 | 0.022 | 0.023 |
| Subsample difference: $MODFOG_t$ | $\chi^2 = 1.25$ ($p = 0.264$) | | $\chi^2 = 2.66$ ($p = 0.103$) | | $\chi^2 = 0.00$ ($p = 0.953$) | |

**Panel B:** Current earnings performance and earnings persistence

| | | $NCSKEW_{t+1}$ | | $DUVOL_{t+1}$ | | $CRASH_{t+1}$ | |
|---|---|---|---|---|---|---|---|
| | | Poor current performance | Good current performance | Poor current performance | Good current performance | Poor current performance | Good current performance |
| $MODFOG\_PERSISTENT_t$ | (1) | 0.015*** | −0.001 | 0.006*** | −0.002 | 0.025*** | −0.003 |
| | | (4.57) | (−0.37) | (4.41) | (−1.21) | (2.58) | (−0.29) |
| $MODFOG\_TRANSITORY_t$ | (2) | 0.005 | 0.009*** | 0.002 | 0.003* | 0.003 | 0.026*** |
| | | (1.45) | (2.79) | (1.21) | (1.80) | (0.26) | (2.60) |
| Testing (1) = (2) | | $p < 0.001$ | $p < 0.001$ | $p < 0.001$ | $p < 0.001$ | $p < 0.001$ | $p < 0.001$ |
| Control variables | | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | | 26,516 | 26,251 | 26,516 | 26,251 | 26,516 | 26,251 |
| Adjusted/pseudo-$R^2$ | | 0.047 | 0.044 | 0.063 | 0.055 | 0.026 | 0.028 |

Panel A presents the results for the subsample OLS regressions of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ and the logistic regressions of $CRASH_{t+1}$ on our readability measure $MODFOG_t$. We partition our sample by current performance, where good (poor) current performance means $\Delta ROA_t > 0$ ($\Delta ROA_t < 0$). Panel B reports the results when the firm–years are further divided by earnings persistence. The variable $MODFOG\_PERSISTENT_t$ ($MODFOG\_TRANSITORY_t$) equals $MODFOG_t$ if $\Delta ROA_{t+1}$ and $\Delta ROA_t$ have the same (opposite) sign and zero otherwise; $NCSKEW_{t+1}$ is the negative skewness of $W$ over fiscal year $t$+1; $DUVOL_{t+1}$ is the natural logarithm of the ratio of the standard deviation of $W$ on *down* weeks to the standard deviation of $W$ on *up* weeks, where the down and up weeks are, respectively, those with $W$ below and above the mean over fiscal year $t$+1; $CRASH_{t+1}$ is an indicator variable that takes the value of one if at least one of the values of $W$ over the fiscal year $t$+1 falls 3.09 or more standard deviations below the mean $W$ for the fiscal year and zero otherwise; and $W$ is the firm-specific weekly return, defined as the natural logarithm of one plus the residual return from estimating an expanded index model including lead and lag terms for the market and industry indexes. We define the fiscal year as the 12-month period ending three months after the fiscal year-end to avoid look-ahead bias. The variable $MODFOG_t$ is the modified version of the Fog Index for the 10-K report filed for fiscal year $t$. The Fog Index is calculated as (words per sentence + percentage of complex words) × 0.4. To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as simple words in calculating *MODFOG*. All the models include the determinants of crash risk as control variables, although the coefficients are not reported for brevity. See the Appendix for the definitions of the control variables. All the models also include an unreported intercept. The $t$- and $z$-statistics reported in parentheses are based on standard errors clustered by firm. * and *** represent significance levels of 0.10 and 0.01, respectively.

TABLE 5
Cross-sectional analysis: CEO stock options holding and litigation risk

**Panel A:** CEO stock options

| | $NCSKEW_{t+1}$ | | $DUVOL_{t+1}$ | | $CRASH_{t+1}$ | |
|---|---|---|---|---|---|---|
| | High | Low | High | Low | High | Low |
| $MODFOG_t$ | 0.014*** | 0.002 | 0.006*** | −0.000 | 0.038*** | 0.011 |
| | (3.04) | (0.52) | (2.77) | (−0.20) | (2.89) | (0.75) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 11,543 | 11,543 | 11,543 | 11,543 | 11,543 | 11,543 |
| Adjusted/pseudo-$R^2$ | 0.025 | 0.025 | 0.026 | 0.033 | 0.026 | 0.023 |
| Subsample difference: | | | | | | |
| $MODFOG_t$ | $\chi^2 = 3.26$ ($p = 0.071$) | | $\chi^2 = 4.27$ ($p = 0.039$) | | $\chi^2 = 1.97$ ($p = 0.161$) | |

**Panel B:** Litigation risk

| | $NCSKEW_{t+1}$ | | $DUVOL_{t+1}$ | | $CRASH_{t+1}$ | |
|---|---|---|---|---|---|---|
| | High | Low | High | Low | High | Low |
| $MODFOG_t$ | 0.004 | 0.012*** | 0.001 | 0.005*** | 0.015 | 0.024** |
| | (1.25) | (3.81) | (0.67) | (3.30) | (1.50) | (2.40) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 25,359 | 25,358 | 25,359 | 25,358 | 25,359 | 25,358 |
| Adjusted/pseudo-$R^2$ | 0.037 | 0.038 | 0.054 | 0.051 | 0.021 | 0.023 |
| Subsample difference: | | | | | | |
| $MODFOG_t$ | $\chi^2 = 2.84$ ($p = 0.092$) | | $\chi^2 = 3.06$ ($p = 0.080$) | | $\chi^2 = 0.40$ ($p = 0.528$) | |

This table presents the results for the subsample OLS regressions of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ and the logistic regressions of $CRASH_{t+1}$ on our readability measure $MODFOG_t$. In panel A, we assign a firm–year observation to the high (low) options holding subsample if the CEO exercisable in-the-money options holding scaled by total compensation is greater (smaller) than the sample median. In panel B, we assign a firm–year observation to the high (low) litigation risk subsample if the Kim–Skinner (2012) measure of litigation risk is greater (smaller) than the sample median. The variable $NCSKEW_{t+1}$ is the negative skewness of $W$ over fiscal year $t$+1; $DUVOL_{t+1}$ is the natural logarithm of the ratio of the standard deviation of $W$ on *down* weeks to the standard deviation of $W$ on *up* weeks, where the down and up weeks are, respectively, those with $W$ below and above the mean over fiscal year $t$+1; $CRASH_{t+1}$ is an indicator variable that takes the value of one if at least one of the values of $W$ over the fiscal year $t$+1 falls 3.09 or more standard deviations below the mean $W$ for the fiscal year, and zero otherwise; and $W$ is the firm-specific weekly return, defined as the natural logarithm of one plus the residual return from estimating an expanded index model including lead and lag terms for the market and industry indexes. We define the fiscal year as the 12-month period ending three months after the fiscal year-end to avoid look-ahead bias. The variable $MODFOG_t$ is the modified version of the Fog Index for the 10-K report filed for fiscal year $t$. The Fog Index is calculated as (words per sentence + percentage of complex words) × 0.4. To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as simple words in calculating *MODFOG*. See the Appendix for the definitions of the control variables. All the models also include an unreported intercept. The $t$- and $z$-statistics reported in parentheses are based on standard errors clustered by firm. ** and *** represent significance levels of 0.05 and 0.01, respectively.

TABLE 6
Impact of 10-K readability on the association between earnings manipulation and stock price crash risk

**Panel A:** Full sample (N = 52,879)

| | $NCSKEW_{t+1}$ | | $DUVOL_{t+1}$ | | $CRASH_{t+1}$ | |
|---|---|---|---|---|---|---|
| | High $MODFOG_t$ | Low $MODFOG_t$ | High $MODFOG_t$ | Low $MODFOG_t$ | High $MODFOG_t$ | Low $MODFOG_t$ |
| $OPAQUE_t$ | 0.127*** | 0.006 | 0.058*** | 0.002 | 0.216** | −0.149 |
| | (3.16) | (0.14) | (3.32) | (0.09) | (2.00) | (−1.25) |
| $OPAQUE_t^2$ | −0.066*** | −0.005 | −0.029*** | 0.000 | −0.102* | 0.071 |
| | (−3.28) | (−0.19) | (−3.37) | (0.03) | (−1.95) | (1.12) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 27,690 | 25,189 | 27,690 | 25,189 | 27,690 | 25,189 |
| Adjusted/pseudo-$R^2$ | 0.039 | 0.041 | 0.054 | 0.055 | 0.022 | 0.023 |
| Subsample difference: | | | | | | |
| $OPAQUE_t$ | $\chi^2$ = 4.23 ($p$ = 0.040) | | $\chi^2$ = 4.96 ($p$ = 0.026) | | $\chi^2$ = 5.12 ($p$ = 0.024) | |
| $OPAQUE_t^2$ | $\chi^2$ = 3.82 ($p$ = 0.051) | | $\chi^2$ = 4.85 ($p$ = 0.028) | | $\chi^2$ = 4.40 ($p$ = 0.036) | |

**Panel B:** Pre-SOX period (N = 18,848)

| | $NCSKEW_{t+1}$ | | $DUVOL_{t+1}$ | | $CRASH_{t+1}$ | |
|---|---|---|---|---|---|---|
| | High $MODFOG_t$ | Low $MODFOG_t$ | High $MODFOG_t$ | Low $MODFOG_t$ | High $MODFOG_t$ | Low $MODFOG_t$ |
| $OPAQUE_t$ | 0.139** | 0.151** | 0.064** | 0.055* | 0.131 | 0.178 |
| | (2.12) | (2.12) | (2.22) | (1.69) | (0.60) | (0.73) |
| $OPAQUE_t^2$ | −0.090*** | −0.078** | −0.044*** | −0.029* | −0.071 | −0.036 |
| | (−2.70) | (−2.23) | (−3.03) | (−1.72) | (−0.66) | (−0.28) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 9,876 | 8,972 | 9,876 | 8,972 | 9,876 | 8,948 |
| Adjusted/pseudo-$R^2$ | 0.064 | 0.066 | 0.081 | 0.081 | 0.024 | 0.025 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Subsample difference: | | | | | | |
| $OPAQUE_t$ | $\chi^2 = 0.01$ ($p = 0.907$) | | $\chi^2 = 0.04$ ($p = 0.832$) | | $\chi^2 = 0.02$ ($p = 0.885$) | |
| $OPAQUE_t^2$ | $\chi^2 = 0.06$ ($p = 0.806$) | | $\chi^2 = 0.47$ ($p = 0.493$) | | $\chi^2 = 0.04$ ($p = 0.837$) | |

**Panel C:** Post-SOX period (N = 34,031)

| | $NCSKEW_{t+1}$ | | $DUVOL_{t+1}$ | | $CRASH_{t+1}$ | |
|---|---|---|---|---|---|---|
| | High $MODFOG_t$ | Low $MODFOG_t$ | High $MODFOG_t$ | Low $MODFOG_t$ | High $MODFOG_t$ | Low $MODFOG_t$ |
| $OPAQUE_t$ | 0.115** | −0.033 | 0.052** | −0.009 | 0.252** | −0.234* |
| | (2.33) | (−0.61) | (2.43) | (−0.41) | (1.99) | (−1.68) |
| $OPAQUE_t^2$ | −0.057** | 0.015 | −0.025** | 0.006 | −0.118* | 0.101 |
| | (−2.31) | (0.53) | (−2.31) | (0.47) | (−1.93) | (1.39) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 17,814 | 16,217 | 17,814 | 16,217 | 17,814 | 16,217 |
| Adjusted/pseudo-$R^2$ | 0.030 | 0.027 | 0.039 | 0.037 | 0.018 | 0.017 |
| Subsample difference: | | | | | | |
| $OPAQUE_t$ | $\chi^2 = 4.04$ ($p = 0.044$) | | $\chi^2 = 3.85$ ($p = 0.050$) | | $\chi^2 = 6.57$ ($p = 0.010$) | |
| $OPAQUE_t^2$ | $\chi^2 = 3.51$ ($p = 0.061$) | | $\chi^2 = 3.44$ ($p = 0.064$) | | $\chi^2 = 5.29$ ($p = 0.021$) | |

This table presents the results for the subsample OLS regressions of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ and the logistic regressions of $CRASH_{t+1}$ on the measure of opacity of Hutton et al. (2009), $OPAQUE_t$. Panels A to C report the results for the full sample, the pre-SOX period (i.e., 1994–2001), and the post-SOX period (i.e., 2002–2014), respectively. We assign a firm–year observation to the high (low) disclosure complexity subsample if the $MODFOG_t$ is greater (smaller) than the industry–year median. The variable $NCSKEW_{t+1}$ is the negative skewness of *W* over fiscal year $t$+1; $DUVOL_{t+1}$ is the natural logarithm of the ratio of the standard deviation of *W* on *down* weeks to the standard deviation of *W* on *up* weeks, where the down and up weeks are, respectively, those with *W* below and above the mean over fiscal year $t$+1; $CRASH_{t+1}$ is an indicator variable that takes the value of one if at least one of the values of *W* over the fiscal year $t$+1 falls 3.09 or more standard deviations below the mean *W* for the fiscal year and zero otherwise; and *W* is the firm-specific weekly return, defined as the natural logarithm of one plus the residual return from estimating an expanded index model including lead and lag terms for the market and industry indexes. We define the fiscal year as the 12-month period ending three months after the fiscal year-end to avoid look-ahead bias. The variable $MODFOG_t$ is the modified version of the Fog Index for the 10-K report filed for fiscal year $t$. The Fog Index is calculated as (words per sentence + percentage of complex words) × 0.4. To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as simple words in calculating *MODFOG*. The variable $OPAQUE_t$ is the moving sum of the absolute value of abnormal accruals in the prior three years (i.e., $ABACC_t + ABACC_{t-1} + ABACC_{t-2}$), where abnormal accruals are estimated using the modified Jones model. All the models include the determinants of crash risk as control variables, although the coefficients are not reported for brevity. See the Appendix for the definitions of the control variables. All the models also include an unreported intercept. The *t*- and *z*-statistics reported in parentheses are based on standard errors clustered by firm. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

# Readability of 10-K Reports and Stock Price Crash Risk

## ONLINE APPENDIX

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This online appendix provides supporting information to accompany the paper "Readability of 10-K Reports and Stock Price Crash Risk." The contents are as follows:

**Online Appendix A** introduces the procedure of parsing 10-K filings.

**Online Appendix B** presents the word list.

**Online Appendix C** presents the validity test of the modified Fog Index

**Online Appendix D** reports the results of the robustness checks discussed in Section 5.

**Online Appendix E** introduces an alternative method of modifying the Fog Index.

## Online Appendix A. Parsing 10-K filings

We download all 10-K and 10-K405 documents from the SEC online EDGAR system and generally follow the procedure specified by Li (2008) to edit these documents.[1,2] First, we delete the heading information that begins with <SEC-HEADER> or <IMS-HEADER> and ends with </SEC-HEADER> or </IMS-HEADER>. Second, for each part of the text between <DOCUMENT> and </DOCUMENT>, we check whether the part's <TYPE> tag is followed by text beginning with *10* or *EX* and whether its <FILENAME> tag is followed by text ending with *.txt* or *.htm*. If these two criteria are not both satisfied, part of text is purged, because it is an embedded graphic, an electronic form, or some other type of file that unduly increases the file size and confuses the language processing program.[3] Third, we translate encoded characters starting with *&*, such as * * (blank), *&amp* (&), and *&#8211* (en dash), back to their original form. Fourth, we delete tables that are contained between <TABLE> and </TABLE> if more than 25 percent of the non-blank characters are numbers.[4] Paragraphs that contain <S> or <C> are also deleted, because some firms use these tags to present tables, especially in the early years of our sample period. Fifth, all HTML tags in the <…> format are replaced with blanks. Finally, we delete all paragraphs with more than 50 percent non-alphabetic (i.e., numeric or blank space) characters to ensure that tables such as financial statements and schedules are excluded from our analysis.

[1] We thank Andrew Leone for making his web-crawling program publicly available on his personal website.
[2] See Appendix A of Li (2008) for the author's parsing procedure. We thank Feng Li for providing us with more details about the procedure.
[3] Unlike Loughran and McDonald (2011), we do not drop all 10-K exhibits. Some 10-K filers use template language in the main part while referring to exhibits (or, more specifically, Exhibit 13) for their annual reports. Therefore, deleting all exhibits could unduly reduce useful textual content. We agree with Loughran and McDonald to the extent that some exhibits (e.g., Exhibit 31.1 in the post-SOX period) are more likely to contain template language, but we believe this creates no systematic bias in our estimate of readability indices. Therefore, our approach to handling 10-K exhibits should not affect the inferences in this paper.
[4] This step differs from the method used by Li (2008), who deletes all tables, regardless of their content. Some 10-K filers tabulate all of their text. Therefore, deleting all tables could inappropriately drop useful textual information. It is worth noting that Loughran and McDonald (2011) raise the same issue in their Internet Appendix. We thus follow them in choosing 25 percent as the cutoff point.

## Online Appendix B. Word list

In Table B.1, we list all the complex words collected from the Compustat variable lists and the Fama–French 49-industry description file. To save space, we do not include inflections, but the full list of complex words (including inflections) is available upon request.[5]

[5] We use an example to illustrate how we account for inflections. The original word list (excluding inflections) includes the terms *consolidated* and *consolidation*. We include word inflections such as *consolidate*, *consolidates*, *consolidating*, and *consolidations*.

TABLE B.1
Word list (excluding inflections)

| | | | | |
|---|---|---|---|---|
| abandonments | consolidation | gaming-related | nonferrous | relationship |
| abrasive | constituent | gasoline | non-ferrous | remainder |
| absorptions | construction | general | non-financial | remuneration |
| accelerated | consulting | generation | noninsurance | repayments |
| acceptance | consumed | generations | noninterest | replacement |
| acceptances | consumer | geographic | non-interest | reported |
| accessories | containers | geographical | non-metalic | reporting |
| accident | contingencies | government | non-metallic | reproduction |
| accounting | contingency | governments | nonoperating | repurchase |
| accumulated | contingent | groceries | non-operating | repurchased |
| acquired | continuing | grocery | non-ordinary | requested |
| acquisition | contractors | guaranteed | nonperforming | requirement |
| acquisitions | contribute | guarantees | nonqualified | requirements |
| activities | contribution | headquarters | nonrecurring | reserves |
| additional | contributions | historical | non-recurring | residential |
| additions | controlling | history | nonredeemable | residual |
| adjusted | convenience | holiday | non-redeemable | residuals |
| adjustment | conversion | homebuilding | non-residential | resources |
| adjustments | converted | homeowners | nontaxable | restatement |
| administrative | convertible | homesites | nonutility | restaurants |
| admission | corporate | hospitals | nonwoven | restricted |
| admissions | corporations | household | normalized | restructured |
| adoption | cosmetics | households | novelty | restructuring |
| advancements | covering | hydraulic | numeric | retailers |
| advances | credited | identifiable | nurseries | retained |
| advertising | creditors | identification | obligation | retainer |
| affiliates | cumulative | identifier | obligations | retirement |
| aftertax | currency | identifiers | observable | retirements |
| after-tax | custody | impairment | observations | retrieval |
| agencies | customer | impairments | occupancy | reupholster |
| aggregate | customers | improvements | offering | revaluation |
| aggregates | database | inactivation | officer | revenue |
| agreements | debentures | inactive | officers | revenues |
| agricultural | decimals | incentive | offices | reversal |
| agriculture | decision | incidental | opened | revision |
| allocated | declaration | including | operating | risk-adjusted |
| allocation | declared | incorporation | operation | salaries |
| allowance | deductions | indebtedness | operations | salary |
| allowances | deferral | indexes | operative | sanitary |
| allowed | deferred | indicated | operator | secondary |
| aluminum | definition | indicates | operators | secured |

| | | | | |
|---|---|---|---|---|
| amendment | deleted | indicator | ophthalmic | securities |
| american | deletion | indicators | opinion | security |
| amortization | delivered | individual | optical | segregated |
| amusement | deliveries | individuals | optional | semiannual |
| analytical | department | industrial | option-related | semi-annual |
| animals | depletion | industries | ordinary | separate |
| annually | deposit | industry | organic | sequencial |
| annuity | deposited | ineffective | organizations | services |
| anthracite | depository | inflation | ornamental | servicing |
| anticipated | deposits | informat | outpatient | settlement |
| apartment | deprecated | information | outstanding | settlements |
| apparatus | depreciation | initial | overdrafts | severity |
| apparel | derivative | inorganical | overlaps | shareholders |
| appliances | derivatives | insider | ownership | shipbuilding |
| applicable | describing | inspection | paperboard | signaling |
| application | description | institution | parenthesis | silverware |
| applications | descriptor | institutional | participant | simulators |
| appropriations | destination | institutions | participation | situation |
| architect | detection | instruments | partnerships | specialty |
| architectural | detective | insurance | passenger | standardized |
| articles | detergents | insured | passengers | statement |
| asbestos | developed | intangible | penalties | stationery |
| assessment | developers | intangibles | percentage | statutory |
| associated | development | integrated | percentile | stockholders |
| assumed | devices | interactive | performance | structural |
| assumption | diagnostics | intercity | perfumes | subdivisions |
| auditing | different | interconnect | periodic | sub-industries |
| auditor | diluted | interconnections | periodicals | subindustry |
| auditors | dilution | interdepartmental | periodicity | subordinated |
| australian | director | interest | peripherals | subscription |
| authorities | directors | interim | permanent | subsidiaries |
| authorized | directory | interlocks | personal | subsidiary |
| automatic | disallowances | internal | personnel | subsurface |
| automation | discontinued | international | petrochemicals | summarized |
| automobile | dispensing | intersegment | petroleum | summary |
| automobiles | disposal | in-the-money | pharmaceutical | supplementary |
| automotive | disposals | inventories | phonographic | surety |
| availability | distillates | inventory | photofinishing | surgeries |
| available | distilled | invested | photographic | surgery |
| average | distributable | investing | physical | surrenders |
| awarded | distribution | investment | pipelines | syndicates |
| bakeries | distributions | investments | plan-based | synthetic |
| bakery | dividend | investors | policy | tangible |

| | | | | |
|---|---|---|---|---|
| balances | dividends | involuntary | policyholders | taxable |
| batteries | document | irrigation | political | taxation |
| beginning | domestic | issuance | pollution | taxicabs |
| beneficial | drycleaning | japanese | population | tax-regulated |
| benefit | duplicate | jewelers | porcelain | telecommunications |
| benefits | durable | jewelry | position | telegraph |
| beverage | duration | jurisdiction | positions | telephone |
| beverages | earthenware | justification | postretirement | terminal |
| bicycles | economic | kilometers | potato | terminals |
| biological | educational | launderers | pottery | termination |
| bituminous | effective | liabilities | preacquisition | terminations |
| black-scholes | electric | liability | preference | territory |
| bonuses | electrical | liberalized | preferred | textiles |
| bookkeeping | electromedical | library | preliminary | thereafter |
| book-to-bill | electronic | licensed | premises | timestamp |
| borrowed | element | limitations | preparations | tobacco |
| borrowings | elevators | limited | prepared | totalizing |
| botanic | eliminations | liquefied | prepayments | transaction |
| break-even | emoluments | liquidating | presentation | transactions |
| broadcasters | employment | liquidation | preserved | transition |
| brokerage | enabled | litigation | primary | translation |
| business | encryption | livestock | principal | transmission |
| calculate | energy | logical | procedures | transparency |
| calculation | engineering | long-lived | processing | transportation |
| calendar | engines | machinery | produced | transported |
| camera | engraving | machines | producer | treasury |
| canada | enrollment | magnetic | production | turbines |
| canadian | entertainers | maintenance | professional | turnover |
| cancelled | entertainment | managed | programming | ultimate |
| capability | equipment | management | promotional | unadjusted |
| capacity | equity | managers | properties | unamortized |
| capital | equivalent | mandatory | property | unappropriated |
| capitalized | equivalents | manifold | proposed | unbilled |
| case-sensitive | estimate | manufactured | proprietary | unconsolidated |
| casino | estimated | marginal | protection | underfunded |
| casualty | evaluation | marketable | protective | underground |
| catalog | excluded | marketing | provision | underlying |
| category | excluding | material | provisions | undertakings |
| certificate | executed | materials | publishing | underwriting |
| certificates | executive | maximum | purchased | undeveloped |
| certification | exercisable | measurement | purchases | undivided |
| certified | exercise | measuring | purchasing | unearned |
| character | exercised | medicaid | quality | unemployment |

| | | | | |
|---|---|---|---|---|
| charge-offs | existing | medical | quarterly | unexercisable |
| chemicals | expected | medicare | quotation | unexercised |
| classification | expenditures | medicinal | realized | unfunded |
| classified | expenses | membership | receivable | unlisted |
| closed-end | expiration | merchandise | receivables | unobservable |
| cogeneration | exploration | metalworking | received | unrealized |
| collating | external | mineral | recipient | unrecognized |
| collection | extinguishment | minerals | reclaimed | unrestricted |
| combination | extraction | minimum | recognized | unsecured |
| combined | extraordinary | minority | recording | untaxed |
| combustion | fabricated | miscellaneous | recoveries | unusual |
| commercial | face-amount | missiles | recreation | unutilized |
| commissions | facilities | mnemonic | recreational | unvested |
| commitment | fasteners | modified | redeemable | upholstery |
| commitments | federal | mortgages | redeemed | utilities |
| committee | ferroalloy | motorcycle | redemption | utility |
| commodity | filename | motorcycles | reduction | utilized |
| communication | financial | movements | reductions | validated |
| communications | financing | musical | reference | valuation |
| communities | finished | national | referred | variable |
| companies | finishing | natural | referring | variety |
| company | fiscal-year | navigation | refined | vegetable |
| comparability | fixtures | needlework | refineries | vegetables |
| comparable | flavoring | newsdealers | refining | vehicles |
| compensating | flowed-through | newspapers | refrigerating | vehicular |
| compensation | forecast | nominal | refrigerator | vitreous |
| components | forestry | nonaccrual | registrant | volatility |
| comprehensive | forwarding | nonadmitted | regulated | wallpaper |
| compression | frequency | nonconsolidated | regulatory | warehousing |
| compustat | fundamental | noncontrolling | reinsurance | wholesale |
| computer | fundamentals | non-current | reinsurers | withdrawals |
| computers | funeral | nondepository | reinvested | writedowns |
| conditioner | furnaces | nondistributable | rejoined | year-to-date |
| conditioning | furnishings | nondurable | related | |
| confectionery | furniture | non-earning | relates | |
| consolidated | galleries | non-equity | relations | |

## Online Appendix C. Validity of the modified Fog Index

In this appendix, we test the validity of our modified Fog Index by examining whether it alleviates the problems raised by Loughran and McDonald (2014). These authors argue that traditional readability measures (e.g., the Fog Index) are substantially misspecified in the context of financial disclosures and thus fragile in explaining uncertainty in the information environment attributable to textual complexity. Specifically, they find that the Fog Index is no longer associated with the information environment after controlling for 10-K file size and they further argue that file size is a simpler but better measure of the readability of 10-Ks compared to the Fog Index and its two components (i.e., number of words per sentence and the percentage of complex words). To show the validity of our modified indices, we start with replicating their main results and then replace the Fog Index with our modified Fog Index. If our modification procedure successfully addresses the problems associated with the Fog Index, we expect the result of the modified Fog Index to be robust, even after controlling for the file size of 10-K documents.

We estimate the following OLS model that links 10-K readability metrics to the information environment proxy:

$$RETVOL = \beta_0 + \beta_1 FOG + \beta_2 FILESIZE + \gamma\, Control\_Variables + \varepsilon, \qquad \text{(C.1)}$$

where *RETVOL* is the post-filing date return volatility measured by the root mean squared error from the Fama–French three-factor model estimated for days [6, 28] following the 10-K filing; *FOG* is either *RAWFOG* or *MODFOG*, as defined in the Appendix, calculated from the 10-K reports; and *FILESIZE* is the natural log of the 10-K file size in megabytes. The set of control variables includes *ALPHA*, the alpha from the three-factor model estimated using days [−252, −6] relative to the 10-K filing date; *RMSE*, the root mean squared error from the three-factor model estimated using days [−252, −6] relative to the 10-K filing date; *ABRET*, the absolute value of the filing period excess return measured by the buy-and-hold return over the two-day period [0, +1] relative to the 10-K filing date minus the buy-and-hold value-weighted market return over the same period; *LOGMV*, the market value of equity (in billions of US dollars) on the 10-K filing date; *BTM*, the book value of equity divided by the market value of equity at the most recent fiscal year-end prior to the 10-K filing date; and *NASDAQ*, an indicator variable that takes the value of one if the firm is listed on NASDAQ at the time of the 10-K filing and zero otherwise. For expositional ease, *RETVOL*, *ALPHA*, and *RMSE* are multiplied by 100.

We start our sample selection with all 10-K and 10-K405 documents available on EDGAR during 1994–2011 and follow the parsing procedure described in Online Appendix A. We require a minimum of 10 return observations available from the CRSP for days [6, 28] following the 10-K filing to estimate *RETVOL* and a minimum of 60 return observations for days [−252, −6] to estimate *ALPHA* and *RMSE*. We further delete the firm-filing date observations with missing or negative book values of equity for the most recent fiscal year-end available from Compustat. We are left with a final sample of 63,430 observations that satisfy the above criteria and have complete data to calculate all the control variables. In all regressions in this appendix, the variable *BTM* is winsorized at the top and bottom 1 percent of our observations.

Table C.1 shows the results of our validity tests. Column (1) replicates column (2) of Table III of Loughran and McDonald (2014), while columns (3) and (4) replicate, respectively, columns (1) and (2) of their Table VI. Consistent with these authors' results, we find that both *RAWFOG* and *FILESIZE* have significantly positive loadings on post-filing date return volatility when they are separately included in the model. When these two readability measures are included in the model together, *FILESIZE* subsumes *RAWFOG* in explaining variation in the dependent variable. This finding supports Loughran and McDonald's (2014) argument that *FILESIZE* (against *RAWFOG*) is a simple yet better readability proxy. It is worth noting that the magnitude and significance level of all the explanatory variables in our tests are also comparable to theirs. In column (2) of Table C.1, we replace *RAWFOG* with *MODFOG* and estimate the same regression model as in column (1). We find that the magnitude and the *t*-statistic of the coefficient of *MODFOG* are both larger than for *RAWFOG*. More importantly, the coefficient of *MODFOG* remains significant at the 5 percent level, even after we control for *FILESIZE* in column (5).[6] This provides evidence that we are at least partly successful in addressing the concerns raised by Loughran and McDonald (2014), insofar as *FILESIZE* cannot subsume *MODFOG* in explaining the information environment. Our result demonstrates that *MODFOG* has incremental explanatory power for the overall quality of the information environment and therefore can be used by future research on the textual analysis of corporate disclosures.

[6] Alternatively, we measure post-filing date return volatility by the standard deviation of daily stock returns relative to the value-weighted CRSP index over days [6, 28] relative to the 10-K file date. The results are similar.

TABLE C.1
Testing the validity of the modified Fog Index

| | Dependent variable = *RETVOL* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *RAWFOG* | 0.016*** | | | 0.007 | |
| | (2.83) | | | (1.27) | |
| *MODFOG* | | 0.025*** | | | 0.015** |
| | | (4.10) | | | (2.55) |
| *FILESIZE* | | | 0.083*** | 0.079*** | 0.068*** |
| | | | (4.50) | (4.26) | (3.72) |
| *ALPHA* | −0.874*** | −0.867*** | −0.858*** | −0.857*** | −0.855*** |
| | (−6.34) | (−6.32) | (−6.33) | (−6.34) | (−6.33) |
| *RMSE* | 0.542*** | 0.540*** | 0.538*** | 0.538*** | 0.537*** |
| | (12.33) | (12.30) | (12.06) | (12.08) | (12.10) |
| *ABRET* | 4.860*** | 4.851*** | 4.848*** | 4.847*** | 4.843*** |
| | (15.99) | (15.95) | (16.04) | (16.05) | (16.01) |
| *LOGMV* | −0.115*** | −0.116*** | −0.129*** | −0.128*** | −0.127*** |
| | (−5.63) | (−5.70) | (−5.82) | (−5.79) | (−5.75) |
| *BTM* | −0.173*** | −0.172*** | −0.181*** | −0.181*** | −0.179*** |
| | (−3.21) | (−3.19) | (−3.33) | (−3.32) | (−3.31) |
| *NASDAQ* | 0.234*** | 0.234*** | 0.236*** | 0.237*** | 0.236*** |
| | (3.10) | (3.10) | (3.11) | (3.12) | (3.12) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 63,430 | 63,430 | 63,430 | 63,430 | 63,430 |
| Adj. $R^2$ | 0.453 | 0.453 | 0.453 | 0.453 | 0.453 |

This table reports the results of testing the validity of our readability measure *MODFOG*. The dependent variable is *RETVOL*, measured by the root mean squared error from the Fama–French three-factor model estimated for days [6, 28] following the 10-K filing date. The variable *RAWFOG* is the Fog Index calculated as (words per sentence + percentage of complex words) × 0.4 and *MODFOG* is our modified version of the Fog Index. To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as simple words in calculating *MODFOG*. The variable *FILESIZE* is calculated as the natural logarithm of the 10-K file size in megabytes; *ALPHA* and *RMSE* are the alpha and root mean squared error, respectively, from the three-factor model estimated using days [−252, −6] relative to the 10-K filing date; *LOGMV* is the natural logarithm of the market value of equity (in billions of US dollars) on the 10-K filing date; *BTM* is the natural logarithm of the book value of equity divided by the market value of equity at the most recent fiscal year-end prior to the 10-K filing date; *NASDAQ* is an indicator variable that takes the value of one if the firm is listed on NASDAQ at the time of the 10-K filing and zero otherwise; and *ABRET* is the absolute value of filing period excess return measured by the buy-and-hold return over the two-day period [0,+1] relative to the 10-K filing date minus the buy-and-hold value-weighted market return over the same period. All the models include an intercept, calendar year dummies, and Fama–French 48-industry dummies. The *t*-statistics reported in parentheses are based on standard errors clustered by industry and year. ** and *** represent significance levels of 0.05 and 0.01, respectively.

## Online Appendix D. Robustness checks

TABLE D.1
Controlling for determinants of 10-K readability

| | Dependent variable = | | |
|---|---|---|---|
| | $NCSKEW_{t+1}$ | $DUVOL_{t+1}$ | $CRASH_{t+1}$ |
| $MODFOG_t$ | 0.010*** | 0.003*** | 0.024*** |
| | (3.97) | (3.15) | (3.14) |
| $OPAQUE_t$ | 0.085*** | 0.039*** | 0.088 |
| | (2.69) | (2.79) | (0.98) |
| $OPAQUE_t^2$ | −0.045*** | −0.019*** | −0.037 |
| | (−2.77) | (−2.64) | (−0.80) |
| $LOGMV_t$ | 0.058*** | 0.028*** | 0.060*** |
| | (15.75) | (17.13) | (5.64) |
| $MTB_t$ | 0.003*** | 0.001*** | 0.002 |
| | (2.84) | (2.65) | (0.77) |
| $LEV_t$ | −0.063*** | −0.036*** | 0.153*** |
| | (−3.02) | (−3.98) | (2.63) |
| $ROA_t$ | 0.283*** | 0.156*** | 0.696*** |
| | (10.01) | (12.82) | (8.11) |
| $DTURN_t$ | 0.215*** | 0.111*** | 0.551*** |
| | (4.75) | (5.67) | (4.16) |
| $NCSKEW_t$ | 0.017*** | 0.007*** | 0.045*** |
| | (2.86) | (2.75) | (2.90) |
| $SIGMA_t$ | 3.289*** | 0.758*** | 5.939*** |
| | (5.82) | (3.08) | (3.38) |
| $RET_t$ | 0.365*** | 0.127*** | 0.805*** |
| | (6.34) | (5.09) | (4.25) |
| $BETA_t$ | 0.029*** | 0.009** | 0.006 |
| | (3.22) | (2.36) | (0.25) |
| $EARNVOL_t$ | −0.010 | −0.012 | −0.013 |
| | (−0.22) | (−0.59) | (−0.10) |
| $CFVOL_t$ | 0.067 | 0.026 | 0.138 |
| | (1.25) | (1.07) | (0.88) |
| $SALESVOL_t$ | 0.024** | 0.007 | 0.003 |
| | (2.02) | (1.45) | (0.08) |
| $HHI_t$ | 0.021 | −0.003 | 0.130 |
| | (0.56) | (−0.19) | (1.25) |
| $AGE_t$ | −0.002*** | −0.001*** | −0.003*** |
| | (−4.77) | (−4.52) | (−3.04) |
| $SI_t$ | 0.041 | 0.050 | 0.084 |
| | (0.52) | (1.41) | (0.35) |
| $NBSEG_t$ | −0.031*** | −0.015*** | −0.023 |
| | (−2.70) | (−2.97) | (−0.67) |
| $NGSEG_t$ | −0.003 | −0.001 | 0.010 |
| | (−0.24) | (−0.26) | (0.32) |
| $NITEM_t$ | 0.001** | 0.000** | 0.002 |
| | (2.49) | (2.41) | (1.39) |
| $SEO_t$ | 0.119*** | 0.055*** | 0.158*** |
| | (7.02) | (7.49) | (3.47) |
| $MA_t$ | 0.015* | 0.007* | 0.064** |
| | (1.73) | (1.87) | (2.46) |
| $DLW_t$ | −0.002 | −0.002 | −0.017 |

| | | | |
|---|---|---|---|
| | (−0.22) | (−0.41) | (−0.64) |
| Year fixed effects | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes |
| Observations | 42,473 | 42,473 | 42,473 |
| Adjusted/pseudo-$R^2$ | 0.046 | 0.061 | 0.023 |

This table presents the results for the OLS regressions of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ and the logistic regression of $CRASH_{t+1}$ on our readability measure $MODFOG_t$, controlling for a battery of determinants of readability. The variable $NCSKEW_{t+1}$ is the negative skewness of $W$ over fiscal year $t$+1; $DUVOL_{t+1}$ is the natural logarithm of the ratio of the standard deviation of $W$ on *down* weeks to the standard deviation of $W$ on *up* weeks, where the down and up weeks are, respectively, those with $W$ below and above the mean over fiscal year $t$+1; $CRASH_{t+1}$ is an indicator variable that takes the value of one if at least one of the values of $W$ over the fiscal year $t$+1 falls 3.09 or more standard deviations below the mean $W$ for the fiscal year and zero otherwise; and $W$ is the firm-specific weekly return, defined as the natural logarithm of one plus the residual return from estimating an expanded index model including lead and lag terms for the market and industry indexes. We define a fiscal year as the 12-month period ending three months after the fiscal year-end to avoid look-ahead bias. The variable $MODFOG_t$ is the modified version of the Fog Index for the 10-K report filed for fiscal year $t$. The Fog Index is calculated as (words per sentence + percentage of complex words) × 0.4. To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as simple words in calculating *MODFOG*. See the Appendix for the definitions of the control variables. All the models also include an unreported intercept. The *t*- and *z*-statistics reported in parentheses are based on standard errors clustered by firm. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

Table D.2
Falsification test

| | Dependent variable = | | |
|---|---|---|---|
| | $Pred\_NCSKEW_{t+1}$ | $Pred\_DUVOL_{t+1}$ | $Pred\_CRASH_{t+1}$ |
| $MODFOG_t$ | 0.0000 | −0.0002 | −0.0001 |
| | (0.06) | (−1.17) | (−0.69) |
| $OPAQUE_t$ | −0.0073* | −0.0058*** | −0.0037*** |
| | (−1.94) | (−3.19) | (−3.62) |
| $OPAQUE_t^2$ | 0.0023 | 0.0017* | 0.0012** |
| | (1.28) | (1.93) | (2.39) |
| $LOGMV_t$ | 0.0171*** | 0.0091*** | 0.0044*** |
| | (32.47) | (36.50) | (32.85) |
| $MTB_t$ | −0.0008*** | −0.0005*** | −0.0002*** |
| | (−6.25) | (−8.27) | (−7.51) |
| $LEV_t$ | −0.0062** | −0.0014 | −0.0015** |
| | (−2.21) | (−1.03) | (−2.10) |
| $ROA_t$ | −0.0105*** | −0.0017 | −0.0008 |
| | (−2.88) | (−0.99) | (−0.83) |
| $DTURN_t$ | 0.0544*** | 0.0270*** | 0.0124*** |
| | (12.96) | (13.25) | (11.11) |
| $NCSKEW_t$ | 0.0022*** | 0.0008*** | 0.0005*** |
| | (4.63) | (3.49) | (4.28) |
| $SIGMA_t$ | 0.6941*** | 0.1352*** | 0.1249*** |
| | (11.35) | (4.49) | (7.76) |
| $RET_t$ | 0.0743*** | 0.0207*** | 0.0148*** |
| | (12.33) | (6.99) | (9.35) |
| $BETA_t$ | 0.0100*** | 0.0037*** | 0.0015*** |
| | (8.74) | (6.83) | (5.08) |
| $EARNVOL_t$ | −0.0023 | −0.0037 | −0.0018 |
| | (−0.47) | (−1.56) | (−1.38) |
| $CFVOL_t$ | −0.0040 | −0.0034 | −0.0006 |
| | (−0.65) | (−1.14) | (−0.36) |
| $SALESVOL_t$ | 0.0088*** | 0.0031*** | 0.0026*** |
| | (5.79) | (4.19) | (6.75) |
| $HHI_t$ | −0.0006 | 0.0014 | 0.0008 |
| | (−0.11) | (0.52) | (0.56) |
| Year fixed effects | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes |
| Observations | 42,473 | 42,473 | 42,473 |
| Adjusted $R^2$ | 0.705 | 0.710 | 0.870 |

This table presents the results for the regressions of predicted $NCSKEW_{t+1}$, $DUVOL_{t+1}$, and $CRASH_{t+1}$ on our readability measure $MODFOG_t$. In the first stage, we run OLS regressions of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ and the logistic regression of $CRASH_{t+1}$ on the following readability determinants: $AGE_t$, $SI_t$, $NBSEG_t$, $NGSEG_t$, $NITEM_t$, $SEO_t$, $MA_t$, and $DLW_t$, as well as year and industry dummies. This first-stage regression generates *predicted* crash risk conditional on observable determinants of readability. We then replace the raw values of crash risk by the predicted values and re-estimate our main model used for Table 3 of the paper. Note that we use OLS regressions for all measures, because the predicted value of crash dummy becomes a continuous variable. The variable $NCSKEW_{t+1}$ is the negative skewness of $W$ over fiscal year $t$+1; $DUVOL_{t+1}$ is the natural logarithm of the ratio of the standard deviation of $W$ on *down* weeks to the standard deviation of $W$ on *up* weeks, where the down and up weeks are, respectively, those with $W$ below and above the mean over fiscal year $t$+1; $CRASH_{t+1}$ is an indicator variable that takes the value of one if at least one of the values of $W$ over the fiscal year $t$+1 falls 3.09 or more standard deviations below the mean $W$ for the fiscal year and zero otherwise; and $W$ is the firm-specific weekly return, defined as the natural logarithm of one plus the residual return from estimating an expanded index model including lead and lag terms for the market and industry indexes. We define a fiscal year as the 12-month period ending three months after the fiscal year-end to avoid look-ahead bias. The variable $MODFOG_t$ is the modified version of the Fog Index for the 10-K report filed for fiscal year $t$. The Fog Index is calculated as (words per sentence + percentage of complex words) × 0.4. To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as simple words in calculating *MODFOG*. See the Appendix of the paper for detailed variable definitions. All the models also include an unreported intercept. The $t$- and $z$-statistics reported in parentheses are based on standard errors clustered by firm. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

TABLE D.3
Controlling for firm fixed effects

| | Dependent variable = | | |
|---|---|---|---|
| | $NCSKEW_{t+1}$ | $DUVOL_{t+1}$ | $CRASH_{t+1}$ |
| $MODFOG_t$ | 0.011*** | 0.004*** | 0.024** |
| | (3.42) | (2.85) | (2.49) |
| $OPAQUE_t$ | 0.025 | 0.006 | −0.038 |
| | (0.59) | (0.31) | (−0.31) |
| $OPAQUE_t^2$ | −0.020 | −0.006 | 0.013 |
| | (−0.90) | (−0.62) | (0.21) |
| $LOGMV_t$ | 0.182*** | 0.086*** | 0.399*** |
| | (19.54) | (21.13) | (15.04) |
| $MTB_t$ | 0.002 | 0.001* | −0.004 |
| | (1.41) | (1.65) | (−1.06) |
| $LEV_t$ | 0.069* | 0.017 | 0.391*** |
| | (1.75) | (0.97) | (3.62) |
| $ROA_t$ | 0.244*** | 0.132*** | 0.605*** |
| | (5.06) | (6.38) | (4.45) |
| $DTURN_t$ | 0.169*** | 0.082*** | 0.470*** |
| | (3.31) | (3.66) | (3.31) |
| $SIGMA_t$ | −0.513 | −0.498 | −4.478** |
| | (−0.69) | (−1.56) | (−2.14) |
| $RET_t$ | −0.029 | −0.023 | −0.125 |
| | (−0.39) | (−0.73) | (−0.57) |
| $BETA_t$ | −0.015 | −0.008 | −0.037 |
| | (−1.24) | (−1.52) | (−1.07) |
| $EARNVOL_t$ | −0.070 | −0.044 | −0.227 |
| | (−0.98) | (−1.41) | (−1.04) |
| $CFVOL_t$ | 0.172** | 0.084** | 0.214 |
| | (2.01) | (2.24) | (0.86) |
| $SALESVOL_t$ | −0.013 | −0.010 | −0.012 |
| | (−0.61) | (−1.05) | (−0.20) |
| $HHI_t$ | 0.025 | 0.011 | 0.087 |
| | (0.34) | (0.33) | (0.41) |
| $AGE_t$ | −0.007 | −0.006 | 0.030 |
| | (−0.22) | (−0.41) | (0.31) |
| $SI_t$ | 0.222** | 0.116*** | 0.488* |
| | (2.38) | (2.79) | (1.74) |
| $NBSEG_t$ | −0.036* | −0.017* | −0.024 |
| | (−1.71) | (−1.82) | (−0.37) |
| $NGSEG_t$ | 0.016 | 0.008 | 0.125** |
| | (0.76) | (0.84) | (1.99) |
| $NITEM_t$ | 0.001** | 0.000* | 0.001 |
| | (2.03) | (1.94) | (0.52) |
| $SEO_t$ | 0.074*** | 0.035*** | 0.063 |
| | (3.64) | (3.93) | (1.20) |
| $MA_t$ | 0.012 | 0.007 | 0.053* |
| | (1.15) | (1.40) | (1.80) |
| $DLW_t$ | −0.045 | −0.021 | −0.076 |
| | (−0.98) | (−1.03) | (−0.60) |
| Year fixed effects | Yes | Yes | Yes |
| Industry fixed effects | No | No | No |

| | | | |
|---|---|---|---|
| Observations | 42,473 | 42,473 | 35,227 |
| Adjusted/pseudo-$R^2$ | 0.084 | 0.092 | 0.029 |

This table presents the results for the firm fixed effects regressions of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ and the conditional logistic regression of $CRASH_{t+1}$ on our readability measure $MODFOG_t$. The variable $NCSKEW_{t+1}$ is the negative skewness of $W$ over fiscal year $t$+1; $DUVOL_{t+1}$ is the natural logarithm of the ratio of the standard deviation of $W$ on *down* weeks to the standard deviation of $W$ on *up* weeks, where the down and up weeks are, respectively, those with $W$ below and above the mean over fiscal year $t$+1; $CRASH_{t+1}$ is an indicator variable that takes the value of one if at least one of the values of $W$ over the fiscal year $t$+1 falls 3.09 or more standard deviations below the mean $W$ for the fiscal year and zero otherwise; and $W$ is the firm-specific weekly return, defined as the natural logarithm of one plus the residual return from estimating an expanded index model including lead and lag terms for the market and industry indexes. We define a fiscal year as the 12-month period ending three months after the fiscal year-end to avoid look-ahead bias. The variable $MODFOG_t$ is the modified version of the Fog Index for the 10-K report filed for fiscal year $t$. The Fog Index is calculated as (words per sentence + percentage of complex words) × 0.4. To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as simple words in calculating *MODFOG*. See the Appendix for the definitions of the control variables. The $t$- and $z$-statistics reported in parentheses are based on standard errors clustered by firm. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

TABLE D.4
Changes analysis

| | Dependent variable = | | |
|---|---|---|---|
| | $\Delta NCSKEW_{t+1}$ | $\Delta DUVOL_{t+1}$ | $\Delta CRASH_{t+1}$ |
| $\Delta MODFOG_t$ | 0.010*** | 0.004** | 0.016* |
| | (2.62) | (2.17) | (1.72) |
| $\Delta ABACC\_DD_t$ | 0.031 | −0.015 | −0.307 |
| | (0.21) | (−0.23) | (−0.97) |
| $\Delta LOGMV_t$ | 0.340*** | 0.165*** | 0.251*** |
| | (22.77) | (24.86) | (7.58) |
| $\Delta MTB_t$ | 0.001 | 0.000 | −0.000 |
| | (0.44) | (0.46) | (−0.03) |
| $\Delta LEV_t$ | 0.275*** | 0.111*** | −0.034 |
| | (4.26) | (3.94) | (−0.24) |
| $\Delta ROA_t$ | 0.385*** | 0.184*** | 0.345** |
| | (5.81) | (6.42) | (2.40) |
| $\Delta DTURN_t$ | −0.046 | −0.041 | 0.061 |
| | (−0.78) | (−1.60) | (0.49) |
| $\Delta SIGMA_t$ | −15.085*** | −5.694*** | −7.526*** |
| | (−14.77) | (−13.21) | (−3.78) |
| $\Delta RET_t$ | −1.497*** | −0.598*** | −0.622*** |
| | (−14.81) | (−14.12) | (−3.26) |
| $\Delta BETA_t$ | −0.023 | −0.011 | −0.025 |
| | (−1.46) | (−1.54) | (−0.76) |
| $\Delta EARNVOL_t$ | −0.066 | −0.028 | −0.225 |
| | (−0.58) | (−0.57) | (−0.91) |
| $\Delta CFVOL_t$ | 0.043 | 0.024 | 0.231 |
| | (0.34) | (0.42) | (0.80) |
| $\Delta SALESVOL_t$ | 0.017 | 0.008 | −0.005 |
| | (0.49) | (0.50) | (−0.07) |
| $\Delta HHI_t$ | 0.115 | 0.069 | −0.226 |
| | (0.87) | (1.18) | (−0.70) |
| $\Delta SI_t$ | 0.312*** | 0.162*** | 0.124 |
| | (2.82) | (3.25) | (0.52) |
| $\Delta NBSEG_t$ | −0.003 | −0.004 | 0.164* |
| | (−0.07) | (−0.22) | (1.85) |
| $\Delta NGSEG_t$ | 0.020 | 0.005 | 0.167* |
| | (0.48) | (0.25) | (1.75) |
| $\Delta NITEM_t$ | 0.001 | 0.000 | 0.002 |
| | (0.62) | (0.42) | (1.00) |
| $\Delta SEO_t$ | 0.013 | 0.004 | −0.009 |
| | (0.56) | (0.41) | (−0.17) |
| $\Delta MA_t$ | 0.007 | 0.002 | 0.002 |
| | (0.57) | (0.40) | (0.08) |
| $\Delta DLW_t$ | −0.056 | −0.039 | −0.078 |
| | (−0.61) | (−0.95) | (−0.32) |
| Year fixed effects | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes |
| Observations | 32,613 | 32,613 | 27,242 |
| Adjusted/pseudo-$R^2$ | 0.049 | 0.054 | 0.016 |

This table presents the results for the change regressions of $NCSKEW_{t+1}$, $DUVOL_{t+1}$, and $CRASH_{t+1}$ on our readability measure $MODFOG_t$. All the change variables are measured by taking first differences. For the logistic regression of $\Delta CRASH_{t+1}$, we drop observations with $\Delta CRASH_{t+1}$ equal to −1. The variable $NCSKEW_{t+1}$ is the negative skewness of *W* over fiscal year $t$+1; $DUVOL_{t+1}$ is the natural logarithm of the ratio of the standard deviation of *W* on *down* weeks to the standard deviation of *W* on *up* weeks, where the down and up weeks are, respectively, those with *W* below and above the mean over fiscal year $t$+1; $CRASH_{t+1}$ is an indicator variable that takes the value of one if at least one of the values of *W* over the fiscal year $t$+1 falls 3.09 or more standard deviations below the mean *W* for the fiscal year and zero otherwise; and *W* is the firm-specific weekly return, defined as the natural logarithm of one plus the residual return from estimating an expanded index model including lead and lag terms for the market and industry indexes. We define a fiscal year as the 12-month period ending three months after the fiscal year-end to avoid look-ahead bias. The variable $MODFOG_t$ is the modified version of the Fog Index for the 10-K report filed for fiscal year $t$. The Fog Index is calculated as (words per sentence + percentage of complex words) × 0.4. To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as simple words in calculating *MODFOG*. *ABACC_DD* is the absolute value of the cross-sectional regression residuals from the Dechow–Dichev (2002) model modified by Francis et al. (2005). Specifically, for each industry and year, we estimate a regression of current accruals on lagged, contemporaneous, and forward operating cash flows, changes in sales revenue, and property, plant, and equipment. See the Appendix for the definitions of the control variables. All the models also include an unreported intercept. The *t*- and *z*-statistics reported in parentheses are based on standard errors clustered by firm. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

TABLE D.5
Controlling for accounting conservatism, tax avoidance, stock liquidity, CEO overconfidence, and accounting comparability

| | Dependent variable = | | | | | |
|---|---|---|---|---|---|---|
| | $NCSKEW_{t+1}$ | $DUVOL_{t+1}$ | $CRASH_{t+1}$ | $NCSKEW_{t+1}$ | $DUVOL_{t+1}$ | $CRASH_{t+1}$ |
| $MODFOG_t$ | 0.010*** | 0.003*** | 0.024*** | 0.008*** | 0.003** | 0.026*** |
| | (3.89) | (3.08) | (3.22) | (2.67) | (2.01) | (2.68) |
| $CSCORE_t$ | −0.658*** | −0.311*** | −1.071** | −0.372* | −0.196** | −0.573 |
| | (−4.16) | (−4.42) | (−2.26) | (−1.75) | (−2.08) | (−0.92) |
| $LRETR_t$ | −0.061*** | −0.024** | −0.147** | −0.054** | −0.019 | −0.177** |
| | (−2.90) | (−2.51) | (−2.24) | (−1.98) | (−1.54) | (−2.06) |
| $LIQ_t$ | 0.037*** | 0.013*** | 0.077*** | 0.042*** | 0.016*** | 0.067** |
| | (5.40) | (4.55) | (3.03) | (4.50) | (3.93) | (2.09) |
| $OC_t$ | 0.032*** | 0.013*** | 0.069*** | 0.035*** | 0.012** | 0.061* |
| | (3.65) | (3.25) | (2.62) | (3.12) | (2.44) | (1.81) |
| $ACCTCOMP_t$ | | | | −0.011 | −0.003 | −0.040 |
| | | | | (−0.52) | (−0.33) | (−0.64) |
| $OPAQUE_t$ | 0.058 | 0.025* | 0.075 | 0.027 | 0.009 | 0.043 |
| | (1.64) | (1.65) | (0.77) | (0.57) | (0.44) | (0.33) |
| $OPAQUE_t^2$ | −0.035* | −0.014 | −0.059 | −0.020 | −0.004 | −0.055 |
| | (−1.68) | (−1.54) | (−1.07) | (−0.66) | (−0.28) | (−0.71) |
| $LOGASSET_t$ | 0.023*** | 0.013*** | 0.008 | 0.029*** | 0.016*** | 0.032 |
| | (4.21) | (5.29) | (0.48) | (4.13) | (5.03) | (1.54) |
| $MTB_t$ | 0.012*** | 0.006*** | 0.009 | 0.012*** | 0.005*** | 0.011 |
| | (4.95) | (5.13) | (1.30) | (3.69) | (3.56) | (1.22) |
| $LEV_t$ | −0.132*** | −0.076*** | 0.021 | −0.175*** | −0.092*** | −0.048 |
| | (−4.26) | (−5.55) | (0.23) | (−4.35) | (−5.19) | (−0.41) |
| $ROA_t$ | 0.415*** | 0.212*** | 0.958*** | 0.392*** | 0.203*** | 0.963*** |
| | (10.76) | (12.83) | (8.58) | (7.62) | (9.30) | (6.53) |
| $DTURN_t$ | 0.222*** | 0.109*** | 0.471*** | 0.206*** | 0.103*** | 0.281 |
| | (4.65) | (5.20) | (3.39) | (3.36) | (3.79) | (1.54) |
| $NCSKEW_t$ | 0.014** | 0.006** | 0.030* | 0.016** | 0.007** | 0.032 |
| | (2.35) | (2.36) | (1.95) | (2.08) | (2.13) | (1.57) |
| $SIGMA_t$ | 3.937*** | 1.145*** | 8.752*** | 4.323*** | 1.462*** | 10.803*** |
| | (6.53) | (4.36) | (4.61) | (5.30) | (4.15) | (4.18) |
| $RET_t$ | 0.434*** | 0.172*** | 1.189*** | 0.474*** | 0.207*** | 1.422*** |
| | (6.53) | (5.93) | (5.16) | (5.11) | (5.18) | (4.42) |
| $BETA_t$ | 0.038*** | 0.015*** | 0.038 | 0.040*** | 0.016*** | 0.033 |
| | (4.03) | (3.63) | (1.37) | (3.35) | (3.08) | (0.93) |

| | | | | | | |
|---|---|---|---|---|---|---|
| $EARNVOL_t$ | 0.056 | 0.011 | 0.072 | 0.093 | 0.006 | 0.107 |
| | (0.97) | (0.44) | (0.50) | (1.06) | (0.16) | (0.46) |
| $CFVOL_t$ | 0.016 | 0.004 | 0.190 | 0.031 | 0.042 | 0.281 |
| | (0.24) | (0.14) | (1.12) | (0.30) | (0.92) | (1.04) |
| $SALESVOL_t$ | 0.036*** | 0.013** | 0.035 | 0.056*** | 0.022** | 0.055 |
| | (2.74) | (2.31) | (0.92) | (2.61) | (2.45) | (0.95) |
| $HHI_t$ | 0.005 | −0.006 | 0.017 | 0.056 | 0.021 | −0.004 |
| | (0.12) | (−0.35) | (0.17) | (1.20) | (1.03) | (−0.03) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 42,133 | 42,133 | 42,133 | 25,820 | 25,820 | 25,820 |
| Adjusted/pseudo-$R^2$ | 0.040 | 0.050 | 0.023 | 0.036 | 0.045 | 0.024 |

This table presents the results for the OLS regressions of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ and the logistic regression of $CRASH_{t+1}$ on our readability measure $MODFOG_t$, controlling for accounting conservatism (*CSCORE*), tax avoidance (*LRETR*), stock liquidity (*LIQ*), CEO overconfidence (*OC*), and accounting comparability (*ACCTCOMP*). The variable $NCSKEW_{t+1}$ is the negative skewness of *W* over fiscal year *t*+1; $DUVOL_{t+1}$ is the natural logarithm of the ratio of the standard deviation of *W* on *down* weeks to the standard deviation of *W* on *up* weeks, where the down and up weeks are, respectively, those with *W* below and above the mean over fiscal year *t*+1; $CRASH_{t+1}$ is an indicator variable that takes the value of one if at least one of the values of *W* over the fiscal year *t*+1 falls 3.09 or more standard deviations below the mean *W* for the fiscal year and zero otherwise; and *W* is the firm-specific weekly return, defined as the natural logarithm of one plus the residual return from estimating an expanded index model including lead and lag terms for the market and industry indexes. We define a fiscal year as the 12-month period ending three months after the fiscal year-end to avoid look-ahead bias. The variable $MODFOG_t$ is the modified version of the Fog Index for the 10-K report filed for fiscal year *t*. The Fog Index is calculated as (words per sentence + percentage of complex words) × 0.4. To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as simple words in calculating *MODFOG*. *CSCORE* is the conservatism measure developed by Khan and Watts (2009). *LRETR* is the sum of income taxes paid (#*txpd*) over the past five years divided by the sum of pretax income (#*pi*) minus special items (#*spi*) over the same five-year period. Higher values of *LRETR* indicate lower levels of tax avoidance. *LIQ* is −1 times Amihud's (2002) measure of illiquidity. *OC* is the firm-level measure of overconfidence developed by Schrand and Zechman (2012). Specifically, *OC* is an indicator variable that takes the value of one if the firm satisfies at least three of the following five criteria and zero otherwise: (i) the firm's excess investment is above the industry–year median, where excess investment is the residual from estimating a regression of asset growth (#*at*) on sales growth (#*sale*) for each fiscal year; (ii) the firm's acquisition expenditure (#*aqc*) scaled by total assets (#*at*) is above the the industry–year median; (iii) debt-to-equity ratio is above the industry–year median, where debt-to-equity ratio is long-term debt (#*dltt*) divided by market value of equity (#*csho* × #*prcc_f*); (iv) the firm makes no dividend payment (#*dv* and #*dvc*); and (v) the firm has a positive value of convertible debt and preferred stock (#*dcpstk*). *ACCTCOMP* is the yearly decile ranking (standardized to the range of 0 to 1) of the average of the firm's top 4 comparability scores during the year (De Franco et al. 2011). *LOGASSET* is the natural logarithm of total assets (#*at*). We use *LOGASSET* rather than *LOGMV* in this table to minimize the multicollinearity problem because the latter is used to construct *CSCORE*. See the Appendix for the definitions of the control variables. All the models also include an unreported intercept. The *t*- and *z*-statistics reported in parentheses are based on standard errors clustered by firm. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

TABLE D.6
Alternative proxies for readability

**Panel A:** *$NCSKEW_{t+1}$* as the dependent variable

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *$MODFOG_t$* | | | | | 0.008*** | | |
| | | | | | (3.43) | | |
| *$MODFLESCH_t$* | 0.003*** | | | | | 0.003*** | |
| | (3.00) | | | | | (2.78) | |
| *$RAWFOG_t$* | | 0.007*** | | | | | 0.007** |
| | | (2.60) | | | | | (2.41) |
| *$LENGTH_t$* | | | 0.021*** | | | | |
| | | | (3.16) | | | | |
| *$FILESIZE_t$* | | | | 0.007 | −0.000 | 0.003 | 0.004 |
| | | | | (1.19) | (−0.00) | (0.49) | (0.68) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 52,879 | 52,879 | 52,879 | 52,879 | 52,879 | 52,879 | 52,879 |
| Adjusted $R^2$ | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 |

**Panel B:** *$DUVOL_{t+1}$* as the dependent variable

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *$MODFOG_t$* | | | | | 0.003*** | | |
| | | | | | (2.76) | | |
| *$MODFLESCH_t$* | 0.001** | | | | | 0.001** | |
| | (2.14) | | | | | (2.02) | |
| *$RAWFOG_t$* | | 0.002** | | | | | 0.002* |
| | | (1.96) | | | | | (1.86) |
| *$LENGTH_t$* | | | 0.006** | | | | |
| | | | (2.15) | | | | |
| *$FILESIZE_t$* | | | | 0.002 | −0.001 | 0.001 | 0.001 |
| | | | | (0.69) | (−0.25) | (0.19) | (0.30) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 52,879 | 52,879 | 52,879 | 52,879 | 52,879 | 52,879 | 52,879 |
| Adjusted $R^2$ | 0.054 | 0.054 | 0.054 | 0.054 | 0.054 | 0.054 | 0.054 |

**Panel C:** *$CRASH_{t+1}$* as the dependent variable

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $MODFOG_t$ | | | | | 0.018** | | |
| | | | | | (2.44) | | |
| $MODFLESCH_t$ | 0.008** | | | | | 0.007** | |
| | (2.44) | | | | | (2.25) | |
| $RAWFOG_t$ | | 0.012 | | | | | 0.010 |
| | | (1.38) | | | | | (1.21) |
| $LENGTH_t$ | | | 0.056*** | | | | |
| | | | (2.77) | | | | |
| $FILESIZE_t$ | | | | 0.019 | 0.004 | 0.009 | 0.014 |
| | | | | (1.05) | (0.24) | (0.52) | (0.80) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 52,879 | 52,879 | 52,879 | 52,879 | 52,879 | 52,879 | 52,879 |
| Pseudo-$R^2$ | 0.021 | 0.021 | 0.021 | 0.021 | 0.021 | 0.021 | 0.021 |

This table presents the results for the OLS regressions of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ and the logistic regression of $CRASH_{t+1}$ on 10-K readability using alternative readability measures. The variables $MODFOG_t$ and $MODFLESCH_t$ are the modified versions of the Fog Index and the Flesch Reading Ease Score, respectively, for the 10-K report filed for fiscal year *t*. The Fog Index is calculated as (words per sentence + percentage of complex words) × 0.4, while the Flesch Reading Ease Score is calculated as 206.835 − (1.015 × words per sentence) − (84.6 × syllables per word). To capture readability in the financial (versus general) context, we identify a list of 2,028 words that exceed three syllables but which are not difficult to understand in the financial context and reclassify them as simple words (two-syllable words) in calculating *MODFOG* (*MODFLESCH*). We take the negative value of the Flesch Reading Ease Score to make it directionally consistent with the other two readability measures. The variable $RAWFOG_t$ is the raw Fog Index for the 10-K report filed for fiscal year *t*, $LENGTH_t$ is the natural logarithm of the total number of words in the 10-K report filed for fiscal year *t*, and $FILESIZE_t$ is the natural logarithm of the file size (in megabytes) of the 10-K report filed for fiscal year *t*. All the models include the determinants of crash risk as control variables, which are not tabulated in detail here for brevity. See the Appendix for the definitions of the control variables. See the Appendix of the paper for the definitions of the other variables. All the models also include an unreported intercept. The *t*- and *z*-statistics reported in parentheses are based on standard errors clustered by firm. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

## Online Appendix E. Using a term-weighting scheme to modify the Fog Index

We express the percentage of complex words component of the raw Fog Index as follows:

$$Percent\ of\ complex\ words = 100 \times \frac{\sum_{j=1}^{J} n_j}{\sum_{i=1}^{I} n_i}, \tag{E.1}$$

where *i* denotes words (including both complex and simple words) and *j* denotes complex words and *n* is the word count. The underlying assumption for the raw Fog Index is that each complex word *j* carries the same weight in determining the readability of a document. This is easy to implement but ignores the fact that so-called complex words that appear in a larger proportion of documents become familiar or easy to the readers. The words *financial*, *company*, and *director* are of this class if we look at all SEC filers, while the word *telecommunications* can also be of this class if we focus on the telecommunications industry. To incorporate this complication, we modify the percentage of complex words as follows:

$$Percent\ of\ complex\ words = 100 \times \frac{\sum_{j=1}^{J} n_j w_j}{\sum_{i=1}^{I} n_i}, \tag{E.2}$$

$$\text{where } w_j = \frac{\log(\frac{N}{df_j})}{\log(N)}, \tag{E.3}$$

with $N$ the total number of documents in the population and $df_j$ the number of documents with the word *j* appearing at least once. The term $\log(N/df_j)$ comes from one of the most common term-weighting schemes in the information retrieval literature and is used by Loughran and McDonald (2011) to adjust the relative importance of tonal words. We scale $\log(N/df_j)$ by $\log(N)$ to make the weight fall in the range [0,1]. This is an important step, because we have to make the modified Fog Index directly interpretable. The new modified Fog Index can thus be interpreted as the number of years of formal education needed to understand a 10-K report on the first reading for a reader who has experience in reading 10-K reports and is thus already familiar with this context.

We design two ways of defining the document population. First, we use all 10-K reports filed from 1994 to 2015 as the population. Second, we use 10-K reports filed in this period by all firms that operate in the same two-digit SIC industry as the population. While the first way treats words such as *financial* and *director* as easier to understand than words such as *telecommunications*, the second way treats them similarly. Both ways are reasonable, and their relative accuracy depends on whether the reader focuses on an individual industry or follows all firms.

Arguably, the modification method based on a term-weighting scheme is more objective, because the discounting factors assigned to each individual word are solely determined by a machine that reads all 10-K reports in the population. However, this method is applicable to the Fog Index but may not work well for other readability indices (e.g., the Flesch Reading Ease Score and the Kincaid Index) because these normally consider the number of syllables per word rather than the proportion of multisyllabic words. In this case, any term-weighting scheme could result in a non-integer number of syllables, which makes no sense. To illustrate, if we assign 0.5 as the discounting factor for the seven-syllable word *telecommunications*, it would be considered to have 3.5 syllables in constructing the modified Flesch Reading Ease Score or the modified Kincaid Index. Therefore, the modification method based on term weighting is good for categorizing complex words but not for counting syllables. Our main modification method based on a self-constructed word list is applicable to any readability indices with a syllable-based complex word component, be it the number of multisyllabic words or the number of syllables per word. We thus recommend the word list method used in our main test for future research in financial disclosure readability.

## References


Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets* 5 (1): 31–56.

Dechow, P. M., and I. D. Dichev. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (Suppl.): 35–59.

De Franco, G., S. P. Kothari, and R. S. Verdi. 2011. The benefits of financial statement comparability. *Journal of Accounting Research* 49 (4): 895–931.

Francis, J., R. LaFond, P. Olsson, and K. Schipper. 2005. The market pricing of accruals quality. *Journal of Accounting and Economics* 39 (2): 295–327.

Khan, M., and R. L. Watts. 2009. Estimation and empirical properties of a firm-year measure of conservatism. *Journal of Accounting and Economics* 48 (2–3): 132–150.

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

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

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

Schrand, C. M., and S. L. C. Zechman. 2012. Executive overconfidence and the slippery slope to financial misreporting. *Journal of Accounting and Economics* 53 (1–2): 311–329.