Grammatical Errors, Financial Reporting Quality and Audit Engagement Risk*

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Abstract

We examine whether grammatical errors (GEs) in annual financial reports (10-Ks) provide a timely signal of the reliability of firms' financial information. Consistent with the notion that GEs capture the time, effort, and resources devoted to financial filings, we find that GEs are more common when firms have less time to prepare their financial reports and, importantly, that they are positively associated with the likelihood of a future restatement and the discovery of an internal control weakness. We also document a positive association between GEs and auditor effort. Collectively, our findings suggest that GEs provide a timely signal of financial reporting quality and audit engagement risk.

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1. Introduction

Assessing the reliability of firms' financial disclosures is of considerable interest to academics, regulators, investors, and auditors. Although market participants can observe the accuracy of firms' financial information ex post, their investment and contracting decisions depend on ex ante signals of financial statement reliability. Similarly, auditors' risk assessments and corresponding staffing decisions (i.e., effort) largely depend on contemporaneous signals of financial statement quality. Thus, timely signals of financial reporting quality can contribute to more efficient resource allocations for investors, as well as improve audit outcomes.

Across a variety of contexts and academic disciplines, grammatical errors reveal information about the quality and credibility of the information provided. We explore this relation in the corporate setting by investigating the association between grammatical errors in annual financial reports and the quality of the financial statement numbers. We compute a measure of grammatical errors (GEs) that encompasses grammar errors, spelling mistakes, punctuation errors, redundancies, and typos.[1] We then examine whether the grammatical errors in financial filings serve as a reliable and timely signal of financial reporting quality. Additionally, we evaluate whether auditors' attention to this signal impacts audit quality.

Prior literature in linguistics, psychology, and communications documents an association between GEs and the reliability of the information provided. Specifically, these studies find that GEs convey information about the author's competence, conscientiousness, and time constraints.[2] Consequently, GEs reveal the capabilities of the author as well as the time and effort devoted to presenting the information. Extending this intuition to the corporate setting, GEs in annual financial filings likely reveal the capabilities of the financial reporting

[1] We discuss the computation of GEs in detail in Section 4.2.

[2] See, for example, Lea and Spears (1992), Fogg et al. (2001), Jessmer and Anderson (2001), Everard and Galletta (2005), Hargittai (2006), Vignovic and Thompson (2010), and Cox et al. (2017).

system. For example, GEs could convey how carefully or precisely the financial statement numbers were prepared, along with the time invested in ensuring the accuracy of those numbers.

Following this intuition, our first hypothesis is that GEs are a signal of financial reporting quality. We base this hypothesis on the premise that GEs are correlated with the time, effort, and resources a company devotes to financial reporting. If the same internal resources, including human capital and information technology systems, generate both the qualitative and quantitative aspects of financial filings, then GEs in the text may reveal information about the accuracy and precision of the numbers.

Our second hypothesis is that GEs in financial filings serve as a timely signal of auditor engagement risk. Given that audit engagement risk is largely determined by financial reporting quality, the presence of GEs could provide valuable information to auditors when they evaluate client risk and estimate their staffing requirements. Prior literature shows that auditors include qualitative information and textual characteristics in their audit risk assessments (Mayew et al., 2015; Abernathy et al., 2019; De Franco et al., 2020). Therefore, to the extent that auditors encounter GEs in financial disclosures, we expect an association between their attention to such GEs and assessments of engagement risk.

The hypotheses are conceptually intuitive, but whether such GEs exist and whether they convey meaningful information is an empirical question. The widespread availability of proofreading software—an inexpensive way to detect and correct grammatical errors—suggests that such errors may now be random and rare. If the reduction is so great that GEs no longer serve as a reliable signal, the result will be a pooling equilibrium whereby the GEs cannot be used to distinguish between good and poor financial reporting quality. Additionally, the resources that generate the written portion of the financial filing may be largely uncorrelated with the resources that produce the financial information. If this is the case, then GEs most likely lack power in predicting financial reporting quality. Even if the two sets of resources are correlated, it is unclear whether management's dedication of time, effort and resources manifests uniformly across all aspects of financial reporting.

We test our hypotheses by performing empirical analyses in four stages. We begin by calculating the number of grammatical errors across a large sample of annual reports from 2002 to 2023. We find that 49% of 10-Ks contain eight or more grammatical errors. Notably, 40% of firms that provide financial reports with eight or more errors in the current year go on to provide financial reports with eight or more grammatical errors in the following year. Thus, despite the widespread availability of proofreading software, GEs are present and persistent in financial filings.

Next, we validate the assumption that GEs are correlated with the time, effort, and resources devoted to financial reporting. Specifically, using plausibly exogenous, staggered reductions in SEC filing deadlines, we examine whether GEs are correlated with external pressure on firms' financial reporting systems. In the early 2000s, the SEC decreased the number of days in its mandatory filing windows, so firms had less time to file their financial statements. Anecdotal and empirical evidence suggests that these reductions significantly strained firms' financial reporting staff and information systems (Bryant-Kutcher et al., 2013; Doyle and Magilke, 2013; Boland et al., 2015; Lambert et al., 2017). Consequently, we expect the number of GEs to increase following the change in SEC deadlines. Consistent with this, we find that GEs are 5% of a standard deviation higher in the year of a filing window reduction, relative to the unconditional mean.

After validating that GEs vary with the time, effort, and resources devoted to financial reporting, we study their implications for financial reporting quality and audit engagement risk. Specifically, we test whether GEs are associated with future restatements and internal control weaknesses. We find that GEs are positively correlated with the likelihood of a future restatement, consistent with our first hypothesis. Importantly, we find that GEs predict restatements caused by unintentional errors but not ones caused by intentional intervention.

A one standard deviation increase in grammatical errors is associated with a 7.31% (6.72%) increase in the odds of a restatement ("Big R" restatement), relative to the unconditional mean. In contrast, we do not find evidence that grammatical errors predict fraud or future SEC investigations. Our results therefore suggest that GEs capture the resources devoted to financial reporting and the ability of the accounting staff and IT systems to convey financial performance. They appear to be stronger predictors of unintentional errors and the incorrect application of accounting standards than of fraud.

We also find that GEs are positively correlated with the revelation of an internal control weakness. A one standard deviation increase in grammatical errors is associated with a 6.71% increase in the odds of identifying an internal control weakness in the same year, relative to the unconditional mean. Collectively, our results are consistent with the explanation that grammatical quality is associated with the internal resources that drive external financial reporting quality.

Our findings thus far indicate that GEs reflect variation in the internal resources devoted to external financial reporting. Based on these results, our final set of analyses explore whether GEs therefore provide information to auditors that improves their assessments of audit engagement risk and, through these improved assessments, audit quality.

Consistent with our second hypothesis, we document a positive association between GEs and auditor effort (measured using audit fees and audit report lag). Notably, we observe a stronger effect among the auditors who allocate greater resources to examining the MD&A section. We measure auditors' examinations of the MD&A section following the methodology in De Franco et al. (2020), who investigate the similarity of MD&A disclosures among clients of the same auditor. We also observe that the link between GEs and financial reporting quality is weakened when auditors are more attentive to the MD&A. Specifically, the GE-predicted likelihood of a future restatement or material weakness is lower when auditors expend greater effort in reviewing the MD&A. This result is consistent with the explanation that when auditors observe GEs in financial reports, they increase audit effort and improve audit quality accordingly.

We contribute to the accounting literature by providing the first large-sample evidence that grammatical errors convey meaningful information about financial reporting quality and audit engagement risk. Our study shows that GEs not only capture the time, effort, and resources devoted to the written portion of financial filings, but also the time, effort, and resources devoted to the *financial statements*. This result demonstrates an important link between the qualitative and quantitative aspects of financial filings. Consequently, GEs could serve as a novel signal of financial reporting quality and auditor engagement risk. This contribution is particularly important because the internal inputs into the financial reporting process, which play a critical role in determining the quality of external financial reports, are often difficult to observe and quantify.

Our findings also extend the literature on the textual features of financial filings. Our paper is unique in studying a feature of the text that is largely unintentional. In doing so, it answers the call, in Loughran and McDonald (2016), to identify textual artifacts that capture unintended messages conveyed in corporate communications. Prior literature documents that managers have incentives to intentionally increase the complexity of financial filings to obfuscate poor performance (Li, 2008; Lo et al., 2017; Abernathy et al., 2019). GEs, being largely unintentional, are unlikely to be correlated with managerial malfeasance. Consistent with this, we document that grammatical errors are positively related to the likelihood of a restatement as a result of unintentional errors, but are unrelated to the likelihood of a restatement as a result of fraud.

Finally, we contribute to the audit literature. Few studies investigate how qualitative disclosure components affect audit outcomes. Abernathy et al. (2019) examine the readability of financial statement disclosures and find that auditors respond to less readable disclosures by increasing effort and risk premia. Readability, however, captures a combination of management obfuscation and firm complexity. In contrast, our measure is a direct measure of the effort, time, and resources allocated to financial reporting. Our results suggest that GEs in financial filings serve as an informative indicator of audit engagement risk. We document that auditors who are attuned to the signal of GEs in financial reports increase audit effort and improve audit quality. Our findings are valuable to market participants who are interested in assessing audit engagement risk, and to auditors making decisions surrounding audit effort and resource allocation.

Our findings are likely to interest academics, regulators, auditors, and other market participants. Broadly speaking, we show that grammatical errors provide a timely signal of the reliability of financial information. Managers use natural language to communicate their private information to capital markets, so it is possible to assess grammatical quality in almost all financial disclosures, including press releases, management forecasts, and other financial filings. Additionally, the identification of grammatical errors is relatively straightforward and may thus be a more practical heuristic relative to natural language processing techniques using machine learning. Our method for calculating grammatical errors can be performed on a regular basis across a variety of disclosures for large panel data. In sum, we develop a method of capturing grammatical errors in financial filings, and we document that these errors are informative, suggesting that grammatical errors may be useful in a variety of other financial disclosure contexts.

2. Literature Review

2.1. Grammatical Quality

Academic articles in linguistics, communications, and psychology examine the determinants and consequences of writing errors, typically termed "grammatical errors." Collectively, these studies document that grammatical errors reflect the author's characteristics, including the time and effort invested in preparing the document. Consequently, grammatical errors affect readers' perceptions of the author's competence, conscientiousness, and time constraints.

One explanation for grammatical errors is that the author is unaware of grammatical rules and stylistic norms. Readers who accept this notion may attribute GEs to incompetence or variation in the author's ability, intelligence, or education (e.g., Hargittai, 2006; Vignovic and Thompson, 2010). An alternative explanation is that the author knows the rules but does not exert enough effort or care to detect and correct errors. Therefore, GEs are commonly associated with the "Big Five" personality trait of conscientiousness, which can be described as the author's diligence, attention to detail, and carefulness (e.g., Vignovic and Thompson, 2010; Kaplan et al., 2012; Boland and Queen, 2016).[3] Finally, GEs may be explained by time constraints. The author may be both competent and conscientious but under significant time pressure. Consequently, GEs can make readers perceive that less time was invested in preparing the document (e.g., Lea and Spears, 1992; Jessmer and Anderson, 2001; Boland and Queen, 2016).

The presence of writing errors can have significant real effects because readers may use them as signals about characteristics such as competence, conscientiousness, and time constraints, which are difficult to observe and quantify. For example, writing errors on corporate websites reduce consumers' willingness to purchase products from online retailers (Fogg et al., 2001; Everard and Galletta, 2005). Additionally, anecdotal evidence suggests that some employers consider writing errors in their hiring decisions, and that grammatical quality is correlated with professional success (Wiens, 2012; Hoover, 2013).

[3]Prior research examines GEs and conscientiousness outside of financial reporting. Vignovic and Thompson (2010) experimentally examine the association between GEs and the perception of conscientiousness but do not explore actual conscientiousness surrounding GEs and conscientiousness in other areas. Additionally, Kaplan et al. (2012) examine written communication, along with many other factors, in their analysis of how CEO characteristics affect firm performance. However, their results relating specifically to written communication are inconclusive. Our study builds on the prior literature by providing large-sample, archival evidence that GEs signal lower quality in the broader financial reporting environment.

2.2. *Linguistic Characteristics of Disclosure*

Our study adds to the emerging literature that considers the linguistic features of financial disclosure.[4] Historically, the literature has examined whether the quantitative properties of financial filings can help predict future restatements or other measures of financial reporting quality. Quantitative characteristics such as the persistence of earnings, the magnitude of accruals, timely loss recognition, and target beating have all been studied (e.g., Dechow et al., 2010).

A few prior studies, however, have begun examining the characteristics of the language in financial disclosures and whether textual properties contain incremental information about the quality of the numbers. Li (2008) measures the readability of annual reports using the FOG index. He shows that readability is significantly related to performance and the properties of future earnings (i.e., earnings persistence). In large part, the literature interprets readability as a managerial choice and posits that lower readability can be used to obfuscate performance. Consistent with this, Lo et al. (2017) show that the FOG index is higher in periods when managers have managed earnings to meet or beat earnings targets.

Our study also adds to the emerging literature on the linguistic features of written documents other than financial filings. Gao et al. (2018) examine grammatical and syntax errors using the LanguageTool project within the online debt crowdfunding setting. They find that when borrowers make fewer grammatical errors in describing their financial situation, they are more likely to obtain funding and to receive a lower interest rate. Berg et al. (2020) examine consumers' digital footprint, including the consumers' purchasing device (e.g., tablet, laptop, or phone), operating system, time of purchase, email address, whether they write using lower case letters, and whether they make typing errors within their email. The authors argue that these characteristics capture consumers' income, character, and reputation, and

[4]For a review, see Li et al. (2010), Kearney and Liu (2014), and Loughran and McDonald (2016).

find that this digital footprint predicts default and provides incremental information relative to a traditional credit score model.

2.3. Audit Engagement Risk and Qualitative Disclosures

The relationship between audit engagement risk and auditor effort is well-documented in the literature.[5] Furthermore, a line of research examines qualitative disclosures and audit-related outcomes. For example, Brown and Knechel (2016) examine qualitative disclosures in the context of auditor-client matching. Mayew et al. (2015) provide evidence that MD&A disclosures include information predictive of auditor-issued going concern opinions. De Franco et al. (2020) examine the similarity of audit client MD&A disclosures and provide evidence that auditors can exhibit significant influence on these disclosures, particularly when they are more actively engaged in the process. However, research on the specific components of qualitative disclosures and their implications for the audit process is limited. Addressing this gap, Abernathy et al. (2019) examine the readability of financial statement footnotes and its association with audit outcomes, and find that lower readability is indicative of increased audit engagement risk. This risk prompts greater auditor effort, as proxied by audit fees and audit report lag. Instead of readability, which captures a combination of management obfuscation and firm complexity, we consider grammatical errors in financial filings, which are a direct measure of the effort, time, and resources that management allocates to financial reporting. By providing evidence of a new, credible signal of audit engagement risk, our study extends the literature examining the impacts of qualitative disclosure components on the audit process.

[5] For a review, see Simunic (1980), Hay et al. (2006), Knechel and Payne (2001), Simunic and Stein (1996), and Johnstone and Bedard (2004).

3. Hypothesis Development

Our first hypothesis investigates whether grammatical errors (GEs) provide a timely signal of financial reporting quality and audit engagement risk. If GEs reveal how carefully the financial numbers are prepared and the financial reporting system's ability to measure firm performance, then they should be negatively correlated with the reliability of the financial statement numbers. Prior literature in linguistics, communications, psychology, and finance documents that GEs reveal characteristics of the author. In the context of financial disclosure, the "author" of the external financial reports is the financial reporting system—the human capital, hardware, software, business processes, and information technology that generate the firm's external financial reports. We therefore explore whether GEs in financial filings convey information about the quality of the firm's internal financial reporting system.

Our prediction is that if GEs are correlated with the characteristics of the financial reporting system, then they will also be correlated with financial reporting quality. Our intuition is similar to that of Choudhary, Merkley, and Schipper (2021), who provide evidence that immaterial financial reporting errors indicate material financial reporting errors. However, we examine same-period textual disclosures as a signal of financial reporting quality rather than prior-period financial numbers. Although intuitive, our prediction relies on the assumption that the same financial reporting system produces both the qualitative and quantitative aspects of external financial reports. In other words, our prediction requires that the same economic forces affect both the written portion of financial filings and the financial statement numbers. If different economic mechanisms drive the qualitative and quantitative portions, then GEs may not meaningfully signal financial reporting quality. Thus, whether GEs are systematically associated with the characteristics of the financial reporting system and whether they are powerful enough to provide incremental information about financial statement quality is an empirical question.

Our second hypothesis explores the relationship between audit quality, financial reporting quality, and audit risk and examines the potential informativeness of GEs in assessing audit engagement risk. Audit quality can be defined as a greater assurance of high financial reporting quality, though it is not independent of financial reporting quality itself (DeFond and Zhang, 2014). The audit risk model suggests that audit risk (i.e., assurance) is a function of the client's underlying financial reporting quality and the auditor's ability to detect misstatements. Consequently, financial reporting quality is a core determinant of audit engagement risk.

If lower textual quality of disclosures signals poor financial reporting quality, it might also signal heightened audit engagement risk. However, whether auditors can effectively use the textual quality of qualitative disclosures to measure engagement risk remains an open question. Disclosure processing requires investing time and effort in the awareness, acquisition, and processing of the information (Blankespoor et al., 2020). We predict that auditors who incur such costs will be more attuned to the signals in qualitative disclosures, and that they will benefit from incorporating these signals into their assessments of audit engagement risk.

4. Data and GE Computation

4.1. Sample Selection

Table 1 describes the sample selection process. We download all 10-Ks available on the SEC EDGAR website for years 2002 through 2023 for the firms we could link to Compustat (a total of 119,753 10-Ks). We extract the MD&A section and exclude 9,226 observations where the MD&A was not present. We eliminate duplicate 10-Ks in the same fiscal year and 10-Ks belonging to asset-backed securities, REITs, shell companies, blank check companies, non-operational companies, funds, and trusts (as provided by Audit Analytics). We keep the observations for which all variables are available, resulting in a final sample of 83,916 firm-year observations.

We calculate the other variables in our empirical analyses using the following data sources. We obtain financial and internal control weakness data from Compustat; data regarding restatements, audit fees, audit report lag, and staggered reductions in SEC filing deadlines from Audit Analytics; and equity return data from CRSP. We winsorize all continuous variables at the 1% and 99% levels to mitigate the influence of outliers. The number of observations for each test varies according to the data availability in each specification.

4.2. GE Computation

To compute grammatical errors, we use a library provided by the LanguageTool Project.[6] This library can take any text and return a list of grammatical errors based on the order and context of the words. To detect errors, the LanguageTool program matches each phrase in the text against a set of grammatical rules. A key advantage of the program is that it detects errors at the phrase level, as opposed to only at the word level. Moreover, this system allows users to select and create their own rules. We create a Python code that accesses the LanguageTool and extracts the grammatical errors detected by the program for each 10-K.

Following Loughran and McDonald (2011), we adapt the grammatical rules in the program to the language in financial statement text. The result is a Python script that searches each 10-K for errors of 1,114 distinct grammatical rules. For each error, the program extracts the location, names the rule that was violated, and suggests a correction.[7]

Appendix A provides some examples of the grammatical rules and errors in our sample. In our study, grammatical errors involve redundancies, punctuation, grammar, confused words, typos, and other similar errors. Examples of errors in our sample include incorrect subject-verb agreement, inappropriate use of apostrophes, and incorrect choices between

[6] We use version 2.8.1 of the tool, an Open Source grammar project funded by the European Union. For further details, see http://wiki.languagetool.org/.

[7] We distributed 1,000 GEs to research assistants who are currently pursuing degrees in English and Accounting to read and confirm whether the GEs captured by our measure were legitimate GEs or type I errors. The results of this analysis suggest that 85% of GEs are legitimate (i.e., type I error rate). We note, however, that we are unable to verify the Type II error rate (false negatives) with reasonable resources.

homophones (e.g., "affect" versus "effect").[8]

4.3. Descriptive Statistics

We begin by providing descriptive evidence on the characteristics of grammatical errors (GEs) across firms and over time. Figure 1 depicts the number of GEs over time. In Panel A, the raw number of GEs, defined as the sample average in a given year, increases across the sample period from 2002 to 2023. However, the average length of 10-Ks has also increased over time (Dyer et al., 2017), which is likely to raise the number of errors. In Panel B, we plot the average number of GEs scaled by the length of the MD&A section (and multiplied by 1,000). After controlling for the increasing trend in the length of 10-Ks over time, we find that GEs are decreasing over our sample period. This finding is consistent with the notion that grammatical software and online proofreading websites have become more prevalent. The increased use of these grammatical tools may help explain the decreasing trend in grammatical errors during the sample period.[9]

In Figure 1, we plot the average number of GEs (scaled by the length of the MD&A section and multiplied by 1,000) for each of the Fama and French 12-industry classifications across the sample.[10] The plot demonstrates that GEs are pervasive across a variety of industries. They are less frequent in the industries labeled chemical products (5), telecommunications (7), utilities (8), and coal (finance).

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[8] We include characteristics like redundancies (e.g., "add an additional"), as they indicate a lack of text polishing and conciseness. While less obvious than misspellings, these subtle errors can undermine effective writing (Suleiman, 1980). Prior studies show that such features provide insights into writing quality and preparation care (Appelman and Schmierbach, 2018). Although they may be noisy measures due to individual writing styles, they offer a more nuanced perspective on document quality, complementing the more obvious grammatical indicators.

[9] We conjecture that the decline in the quantity of GEs may be offset by an increase in the significance of the remaining errors. The GEs that persist despite the use of advanced correction tools could be more indicative of tighter deadlines for report delivery, providing more meaningful insights into resource constraints. The evolving landscape of grammatical errors in financial reports may offer new perspectives on the quality and circumstances of report preparation. As such, the presence of GEs in modern financial reports may carry more weight in signaling potential issues in the reporting process.

[10] We obtain the 12 industry classifications from Kenneth French's website at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html.

In untabulated analyses, we find that 49% of annual financial reports (10-Ks) contain eight or more grammatical errors. Notably, 40% of the firms whose financial reports contain eight or more errors in a given year provide financial reports with eight or more grammatical errors in the following year. Thus, despite the widespread availability of proofreading software, grammatical errors persist in financial filings.

Table 2 presents the descriptive statistics of the sample. The means of *REST* and *REST BigR* are 0.060 and 0.037, respectively. The averages reflect our restriction of restatements and Big R restatements to the latest year of a restatement period so as to capture only materially misstated financial statements. SEC guidance stipulates that "if the misstatement that exists after recording the adjustment in the current year financial statements is material ... the prior year financial statements should be corrected, even though such revision previously was and continues to be immaterial to the prior year financial statements" (Securities and Exchange Commission, 2006).[11] In our empirical analyses, we scale the raw number of grammatical errors by the length of MD&A section of the 10-K and multiply by 1,000. This scaled measure of grammatical errors (our primary measure), *GE*, has an average value of 0.12. Our program identifies an average (median) of 8.65 (6) total grammatical errors within each 10-K (*untabulated*).

5. Results

5.1. GEs and the Financial Reporting System

After documenting the presence of grammatical errors within financial statements, we explore their determinants and assess whether the errors vary with the time, effort, and resources devoted to financial reporting. Table 3 presents the determinants of grammatical errors. Firm size, firm age, and having a Big 4 auditor are negatively associated with

[11] In untabulated analyses, we find directionally consistent and statistically significant, albeit weaker, results in our main regressions when we include all restatements within a restatement period.

GEs in financial filings. Further, the coefficient on *AuditorSimilarity*—a measure of auditor involvement in client MD&A disclosures following De Franco et al. (2020)—suggests that auditor involvement in the disclosure is associated with a reduction in GEs. We also document a negative association between GEs and readability, measured by the BOG Index following Bonsall IV et al. (2017); however, this association is relatively minor and becomes null after we control for *AuditorSimilarity*. The results are consistent with smaller, more poorly performing firms having weaker financial reporting environments, and they reaffirm our proposition that GEs, as a signal of financial reporting quality, are distinct from other measures, such as readability.

To validate our measure of financial reporting resources, we exploit plausibly exogenous variation generated by changes in SEC filing deadlines. We propose that firms with fewer resources will have to rush to meet the deadline, resulting in more grammatical errors (GEs).

The SEC accelerated its filing deadlines beginning in December 2003, which reduced firms' preparation time for financial statements.[12] The initiative faced pushback due to the burden on firms' resources, particularly for smaller companies (SEC, 2002). The SEC noted variations in firms' technological sophistication and staffing (SEC, 2002, Section IV.A.2) and acknowledged concerns about reduced financial report quality due to the limited review time (SEC, 2002, Section IV.A.2). Prior literature confirms that financial statement quality indeed decreased following these changes (Boland et al., 2015; Bryant-Kutcher et al., 2013; Doyle and Magilke, 2013; Lambert et al., 2017).

We exploit the staggered, plausibly exogenous reductions in filing deadlines using a difference-in-differences analysis. To improve identification, we restrict the sample to small firms in the first period and large firms in the second period. To improve the identification

[12]Prior to December 15, 2003, all firms had 90 days in which to file after the fiscal year-end. From December 15, 2003, to December 15, 2006, large accelerated and accelerated filers had 75 days, while non-accelerated filers still had 90 days. Since December 15, 2006, large accelerated filers have had 60 days, accelerated filers 75 days, and non-accelerated filers 90 days.

of our tests, we restrict the sample to treated and control firms that are similar in size.[13]

We explore whether GEs are related to the time constraints placed on the firm's financial reporting system using a linear model in Eqn. (1) below:

$$\begin{aligned} GE_{it} = {} & \beta_0 + \beta_1 RegChangePeriod_t + \beta_2 Treat_t + \beta_3 RegChangePeriod_t \times Treat_t \\ & + \beta_k' X_k + \alpha_i + \theta_t + \varepsilon. \end{aligned} \tag{1}$$

Where *RegChangePeriod* indicates the periods of mandatory filing window reductions and *Treat* identifies firms affected by the changes. Our primary interest is the interaction term, *RegChangePeriod* × *Treat*. Results in Table 3, column (3) show a positive and significant coefficient on *RegChangePeriod* × *Treat*, indicating that GEs increase following the reduction of SEC filing windows. Our estimates suggest that GEs rise by 5% of a standard deviation relative to the unconditional mean. These findings support our hypothesis that GEs correlate with firms' financial filing time constraints.

5.2. The Relation between GEs and Financial Reporting Quality

Thus far, our results support our prediction that GEs are correlated with characteristics of the financial reporting system—specifically, the time, effort, and resources devoted to external financial reporting. We next explore the implications of this for financial reporting quality.

We examine the relation between financial reporting quality and GEs using the following linear regression (with controls previously applied in research, and defined in Appendix B)

[13]A potential concern is that the small firms that are unaffected by the deadline change are not an appropriate control for the large firms that are. We thus restrict our sample as follows. First, we restrict the treatment group to firms in the lowest market value quartile, both within the accelerated filers group (subject to the first regulatory change) and within the large accelerated filers group (subject to the second regulatory change). Second, we restrict the control group to the highest market value quartile of the firms unaffected by the regulatory change. This approach, which compares the smallest treatment firms to the largest control firms, ensures that the treatment and control samples are similar in size and helps address concerns that differences in size could affect our results.

(Erickson et al., 2006, Burns and Kedia, 2006, Efendi et al., 2007, Lennox and Pittman, 2010, Lobo and Zhao, 2013):

$$FRQ_{it} = \beta_0 + \beta_1 GE_{it} + \beta_k' X_k + \alpha_i + \theta_t + \varepsilon. \tag{2}$$

where the dependent variable, *FRQ*, is one of three variables for restatements and internal control weaknesses. *REST* is an indicator variable equal to one if the annual report used to measure GEs is subsequently restated and zero otherwise.[14] We also estimate equation (2) after replacing *REST* with *REST BigR*, an indicator variable equal to one if the accounting restatement was reported via form 8-K item 4.02 (i.e., a Big R restatement). We next examine whether GEs are related to internal control weaknesses. We do so by replacing the dependent variable with *ICW*, an indicator variable equal to one if there is an internal control weakness in the year in which grammatical errors are measured and zero otherwise. If GEs are a meaningful indicator of financial reporting quality, we expect the coefficient on GE, β_1, to be positive and significant in each test.

The results are presented in Table 4. The coefficients on grammatical errors (*GE*) are positive and significant across all columns.[15] Columns (1) and (2) relate to restatements. In economic terms, a one standard deviation increase in grammatical errors is associated with a 7.31% (6.72%) increase in the odds of a restatement (Big R restatement) due to unintentional errors, relative to the unconditional mean. Notably, in the column (3) results, which focus on restatements that were caused by fraud or that led to an SEC investigation, the coefficient on *GE* is not significant, suggesting that grammatical errors are less powerful in explaining malfeasance or fraud. These findings are consistent with the notion that grammatical errors are largely unintentional and therefore may be correlated with other unintentional errors in the financial numbers.

[14] *REST* denotes a restatement caused by unintentional errors, including accounting errors and the misapplication of GAAP.

[15] We find similar results using firm fixed effects in place of industry fixed effects.

Column (4) relates to internal control weaknesses. The coefficient on grammatical errors is positive and significant. A one standard deviation increase in GEs is associated with a 6.71% increase in the odds of an internal control weakness relative to the unconditional mean. Though ICWs themselves signal financial reporting quality, they do so imperfectly. The positive association between GEs and ICWs validates our finding that GEs signal financial reporting quality and supports our position that GEs provide incremental information on the financial reporting environment. Taken together, our evidence favors our hypothesis that grammatical errors are a timely signal of financial reporting quality because they are correlated with the time, effort, and resources devoted to financial reporting. Our findings indicate that by observing how carefully and competently financial statements are written, one can gain insights into how carefully and competently the financial numbers are prepared.

5.3. Audit Engagement Risk

In the preceding sections, we provided evidence that grammatical errors serve as a timely and credible signal of financial reporting quality. As financial reporting quality is a core determinant of audit engagement risk, it follows that GEs may also signal audit engagement risk. We explore this hypothesis by examining the relationship between GEs and auditor effort and, in subsequent analyses, audit quality.

We examine the relation between auditor effort and GEs in client MD&A disclosures using the following regression:

$$Effort_{it} = \beta_0 + \beta_1 GE_{it-1} + \beta_k' X_k + \alpha_i + \theta_t + \varepsilon. \tag{3}$$

where *Effort* is one of two variables which proxy for auditor effort: audit fees ($AFEE$) and audit report lag (ARL). The audit engagement letter is a fixed-fee contract that is signed well before the auditor receives the MD&A related to the fiscal year under audit. Except when there are significant changes in the extent of audit testing or mutual agreements with clients, audit fees are fixed at the negotiated price (Hackenbrack et al., 2014). Therefore, the signals from the MD&A are likely unavailable to auditors when fees and planned audit procedures are determined. As such, we follow Abernathy et al. (2019) and use GEs relating to the prior year MD&A for tests of auditor effort.

Table 5 presents the results of our tests on auditor effort. The dependent variables in columns (1) and (2) are *ARL* and *AFEE*, respectively. The positive and significant coefficient on *Lag GE* in both columns indicates that GEs reflect financial reporting environments that call for greater auditor effort. Specifically, one standard deviation of GEs represents an increase of 35% (10%) in the audit report lag (audit fee), relative to the unconditional mean.

We next assess whether increased exposure and attention to MD&A disclosures impact auditor response to GEs. For this, we interact *GE* with a variable representing auditors who are likely to be more attuned to potential financial reporting quality signals within the MD&A. De Franco et al. (2020) provide evidence that certain auditors influence client MD&A disclosures such that they become more similar. Their findings suggest that auditors whose clients have higher MD&A similarity are more involved with client MD&A disclosures. Extending this intuition, we consider auditors who are more involved with MD&As to be more attentive to the potential signals within the disclosures. We calculate *AuditorSimilarity*, which measures the similarity of MD&A disclosures among the clients of particular auditors, following a similar process to De Franco et al. (2020).[16] Table 5, columns (3) and (4) present the results. The interaction *Lag GE* $\times$ *Lag AuditorSimilarity* is positive and significant in both columns, suggesting that GEs have an incremental effect on audit effort for the auditors who are most exposed and attentive to them in the MD&A. Taken together, our results support the assertion that grammatical errors reflect audit engagement risk and audit

[16] De Franco et al. (2020) use Stanford University's MOSS plagiarism detection software to calculate similarity. Since November 2022, a policy change has made MOSS unavailable for large-sample research projects. We therefore use SequenceMatcher from the library Difflib, which, like MOSS, indicates direct cases of plagiarism between documents (Vyas et al., 2023). This library is native to Python and available to anyone. We prefer this measure to other similarity measures, such as cosine similarity, as it captures phrasing and copied-and-pasted sentences rather than the frequency of specific words. In untabulated analyses, we obtain similar results using the cosine similarity of trigrams within MD&As.

effort.

We next examine the relation between audit quality and auditor attention and exposure to GEs in client MD&A disclosures with the following regression:

$$\begin{aligned} AQ_{it} = {} & \beta_0 + \beta_1 GE_{it} + \beta_2 AuditorSimilarity_{it} + \beta_3 GE_{it} \times AuditorSimilarity_{it} + \\ & \beta_k' X_k + \alpha_i + \theta_t + \varepsilon. \end{aligned} \tag{4}$$

where AQ is either $REST$ as defined in equation (2) or *REST MISSED ICW*, an indicator variable equal to one if the auditor missed an internal control weakness and that weakness was subsequently identified via a restatement (Rice and Weber, 2012; Beardsley et al., 2021). In our previous analysis, we document a positive and significant relationship between GEs and known proxies of financial statement quality, supporting our first hypothesis that GEs serve as an indicator of financial reporting quality and audit engagement risk. To the extent that auditors can adapt audit processes to address identified engagement risks, we expect auditors who are exposed to and attentive to GEs to more effectively moderate those risks and, therefore, to improve their audit quality. Consistent with this expectation, Table 6 shows that the coefficient on the interaction of *GE* and *AuditorSimilarity* is negative and statistically significant in both models, indicating that the positive relationship between GEs and engagement risk is moderated when auditors are exposed to and attentive to GEs in the MD&A.

Overall, our results provide evidence that GEs in qualitative disclosures serve as an incremental signal of audit engagement risk.[17]

[17] We acknowledge that auditors may not necessarily increase audit effort strictly in response to the presence of grammatical errors. However, our finding that GEs act as a credible signal of audit engagement risk remains robust regardless of whether auditors increase their effort in response to GEs or to financial reporting problems in general.

6. Robustness Tests

Our results are robust to a variety of (untabulated) tests. First we examine the informativeness of errors that occur in one year versus those that are carried over. Our analysis initially finds that 60% of our identified errors are due to new text. Our results, therefore, are mostly driven by new errors. We also adjust our economic significance analysis for fixed effects usage as suggested in Breuer and deHaan (2024). Our models with interactions (e.g., Table 3, column (3)) interact the controls with the more exogenous variable (deHaan et al., 2023).

7. Conclusion

Financial reporting quality affects a wide variety of stakeholders and has important capital market consequences, including effects on market valuation, executive compensation, the cost of raising external capital, and litigation. Consequently, timely signals of financial reporting quality can improve investors' allocation of capital and contracting decisions and aid auditors' assessment of engagement risk. In this paper, we provide evidence on the information content of one such timely signal: grammatical errors (GEs) in financial filings. Using GEs is advantageous because errors are relatively inexpensive to identify and because financial filings are available for all SEC-registered firms on a yearly basis.

We measure the number of GEs, including typos and errors in syntax and punctuation, in the MD&A section of firms' annual financial reports. We document that grammatical errors are positively correlated with the likelihood of a restatement and internal control weakness. Importantly, we find that GEs predict restatements that result from unintentional errors but not restatements associated with intentional misrepresentations or fraud. Consistent with GEs capturing the time, effort, and resources devoted to external financial reporting, we find that GEs are correlated with the characteristics of firms' financial reporting systems. Our results imply that GEs provide meaningful information about how carefully and competently financial statements are prepared, and are therefore useful for inferring the reliability of financial information at the time of the financial filing.

Our findings are likely to interest investors, auditors, academics, regulators, and other market participants. Our results involving GEs in financial disclosures suggest that GEs in other forms of corporate communication, such as management forecasts and press releases, may also serve as useful signals on the reliability of financial information. Future research could investigate whether investors incorporate grammatical errors into their trading decisions. Chordia and Miao (2020) and Jones (2013) suggest that low-latency traders (i.e., high frequency traders) use natural language processing to parse the text in public disclosures and trade on the signals inferred from these algorithms. Our findings suggest that grammatical errors in financial filings are likely a useful signal.

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Appendix A grammatical errors Examples

Rule Name	Sample of Text	Rationale	Replacement
THIS_NNS	...edit insurance for approximately 80% of this licensees accounts receivable balance. ...	Did you mean 'these'?	[these]
EN_A_VS_AN	...king capital increased primarily due to an decrease of $1,597,035 in inventories, ...	Use “a” instead of “an” if the following word doesn't start with a vowel sound, e.g. “a sentence”, “a university”	[a]
ADVERB_WORD_ORDER	...nternal control policies and procedures always will protect us from recklessness, fraudulent behavi...	The adverb 'always' is usually put between 'will' and 'protect'.	[will always]
SHOULD_BE_DO	...adquarters. All such requests should be send to Oncologix Tech, Inc., P.O. Box 8832,...	Did you mean 'sent'?	[sent]
BE_USE_TO_DO	...der this revolving credit facility were use to fund a portion of the Big A Drilling...	Did you mean “used”?	[used]
DOES_YOU	...ort. We are under no obligation to, nor does we intend to, release publicly any upda...	Did you mean “do”? “does” is only used for the third person singular (he/she/it)	[do]
IS_CAUSE_BY	...d in 2016. This inverse relationship is cause by the recognition of certain service r...	Did you mean “caused”?	[caused]
WAS_BEEN	... of the Company on January 24, 2007. He was been employed by AM&M Financial Services, In...	Did you mean “was” or “has been”?	[was, has been]
CONJ_LINK_ADVERB	...th and need for new physical locations. Additionally a payment of $400 was received on the t...	Did you forget a comma after a conjunctive/linking adverb?	[Additionally,]

Appendix B Variable Definitions

Variable	Definition
AuditorSimilarity	Natural logarithm of 1 plus the mean of firm i's *Auditor Similarity* with all other firms' MD&As sharing the same audit firm in the same state. Variable adapted from De Franco et al. (2020).
ARL	The natural log of audit lag for firm i in year t.
AFEE	Natural log of total audit fees.
BIG4	An indicator variable equal to one if the client is audited by one of the Big 4 accounting firms, zero otherwise.
CFF	Cash flow from financing activities scaled by lagged total assets.
CurAccruals	Current accruals, calculated as the change in noncash current assets from year t-1 to t scaled by average total assets.
CurRatio	Current ratio, calculated as current assets scaled by current liabilities.
CiFirm	Client importance to the audit firm, equal to the ratio of the client firm's assets to the sum of the assets of all client firms in the audit firm's portfolio in the fiscal year.
Dividend	An indicator variable that takes the value of one if the firm paid a dividend, zero otherwise.
σ*(Earnings)*	The standard deviation of income before extraordinary items scaled by total assets for the five years prior to the year of the restatement announcement.
LnEmp	Natural logarithm of the number of employees.
ExtFinDemand	An indicator variable that takes the value of one if *FREECASH* $<$ -0.5, zero otherwise. *FREECASH* is cash flows from operations minus average capital expenditure scaled by lagged current assets. Capital expenditures are averaged over the preceding three years (t-3 to t-1) if data *CAPX* are available in each year. Capital expenditures are averaged over the preceding two years (t-2 to t-1) if data *CAPX* are unavailable in year t-3. Capital expenditures are lagged by one year (t-1) if data *CAPX* are unavailable in year t-2.
FCARatio	The ratio of foreign currency adjustment (FCA) to sales, calculated as FCA divided by total sales. It measures the impact of foreign currency fluctuations on a company's sales performance.
FirmAge	The number of years the firm has Compustat data.

Variable	Definition
Fin	An indicator variable equal to one if the sum of new long-term debt plus new equity exceeds 2 percent of lagged total assets, zero otherwise.
GCO	An indicator variable equal to one if the auditor's opinion is modified for going concern, zero otherwise.
GE	The number of grammatical errors in the MD&A, scaled by the MD&A length and multiplied by 1,000.
ICW	An indicator variable equal to one if the internal control opinion by the auditor is either Adverse (Material Weakness Exists) or Disclaimer (Unable to Express Opinion), zero otherwise. ICW equals one if the 10-K used to measure GEs has an ICW, zero otherwise.
InvRatio	The ratio of inventory over total assets.
InvIntCov	Inverse interest expense coverage, measured as interest expense divided by operating income before depreciation. The ratio is capped at 2 and assigned a value of 2 if operating income before depreciation < 0.
Leverage	Calculated as the ratio of total debt (both long-term and short-term) to shareholders' equity.
Loss	An indicator variable equal to one if the firm's current earnings before extraordinary items is negative, zero otherwise.
Litigation	An indicator variable equal to one if the firm operates in a high-litigation-risk industry based on SIC codes (Pharmaceuticals: 2833-2836; Computer Hardware: 3570-3577; Electronics: 3600-3674; Software: 7370-7374), zero otherwise.
M&A	An indicator variable equal to one if there was an acquisition in the financial year.
MTB	Market-to-book ratio, calculated as (market capitalization + book value of debt) divided by total assets.
NegEquity	An indicator variable equal to one if total liabilities are greater than total assets, zero otherwise.
NBSEG	The logarithm of 1 plus the number of business segments.
NGSEG	The logarithm of 1 plus the number of geographical segments.
NonENCountry	An indicator variable equal to one if the company is not incorporated in an English-speaking country, zero otherwise.
NonDec	An indicator variable equal to one if the firm's fiscal year-end is not December, zero otherwise.

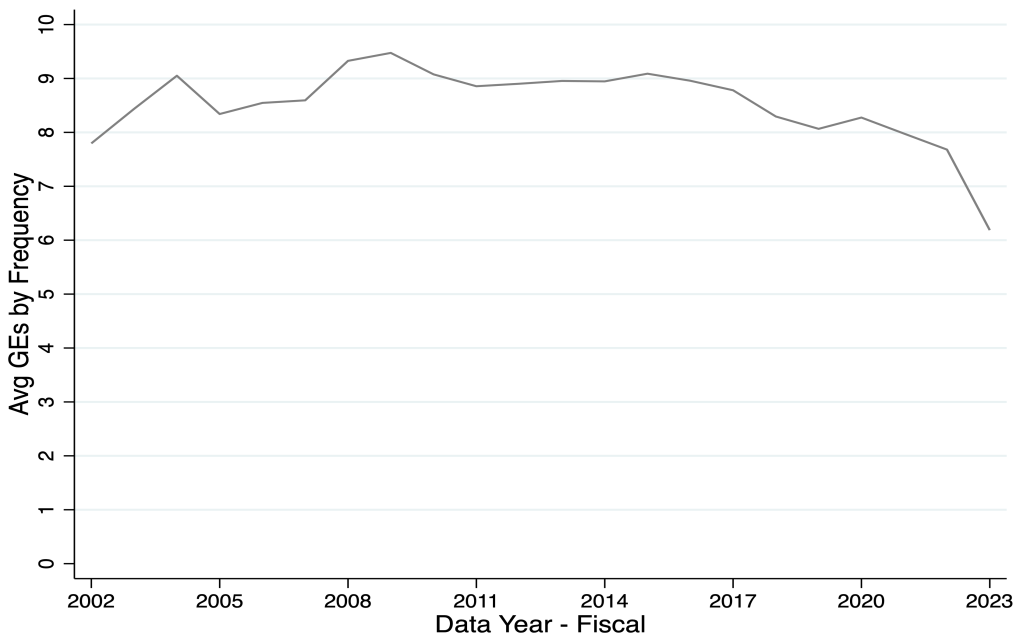
Variable	Definition
OperatingCycle	The log of receivables to sales plus inventory to COGS, multiplied by 360.
Readability	-1 × the BOG Index for firm i's annual report, from **?**. A higher score means higher readability.
RectRatio	The ratio of receivables over total assets.
RegChangePeriod	An indicator variable equal to one during the two periods of mandatory reductions in the filing window (Period 1 = 12/15/2003 - 12/14/2004; Period 2 = 12/15/2006 - 12/14/2007), zero otherwise.
REST	An indicator variable equal to one if the 10-K used to measure GEs is the most recent subsequently restated filing stemming from an accounting error as defined in Audit Analytics, zero otherwise.
REST BigR	An indicator variable equal to one if the 10-K used to measure grammatical errors is subsequently restated with an 8-K disclosure as a result of accounting errors, zero otherwise.
REST MISSED ICW	An indicator variable that takes the value of one if firm i restates its financial statements as a result of accounting errors (as defined in *REST*) and no internal control weakness has been identified (as defined in Audit Analytics), zero otherwise.
ROA	Return on assets, defined as income before extraordinary items scaled by total assets, as reported on the last annual filing before the restatement announcement.
SaleGr	Percentage change in sales from the prior year to the current year.
SdRet	Standard deviation of residuals from the market model, estimated using daily returns during the fiscal year.
Similarity	Difflib-generated score measuring the percentage of content in firm i's MD&A that is considered similar to its peer firm j's MD&A. Variable adapted from De Franco et al. (2020).
Size	Firm size, defined as the log of total assets.
Treat	An indicator variable equal to one for the group of treated firms belonging to the lowest asset value quartile within the accelerated filers group in Period 1 (i.e., subject to the first regulatory change during 12/15/2003 – 12/14/2004) or within the large accelerated filers group in Period 2 (i.e., subject to the second regulatory change during 12/15/2006 – 12/14/2007). TREAT equals zero for control firms in the highest asset value quartile among firms that are not subject to each regulatory change.

Tenure	Natural log of the number of years that the company is audited by the same audit firm (on Compustat).

Figure 1. Grammatical Errors over Time

This figure depicts the number of grammatical errors (GEs) over time. Panel A provides the raw average number of GEs in each year in the sample (2002–2023). Panel B plots the average number of GEs scaled by the length of the MD&A (and multiplied by 1,000) in each year.

Panel A: Average Number of GEs by Year



Panel B: Average Number of GEs Scaled by MD&A Length

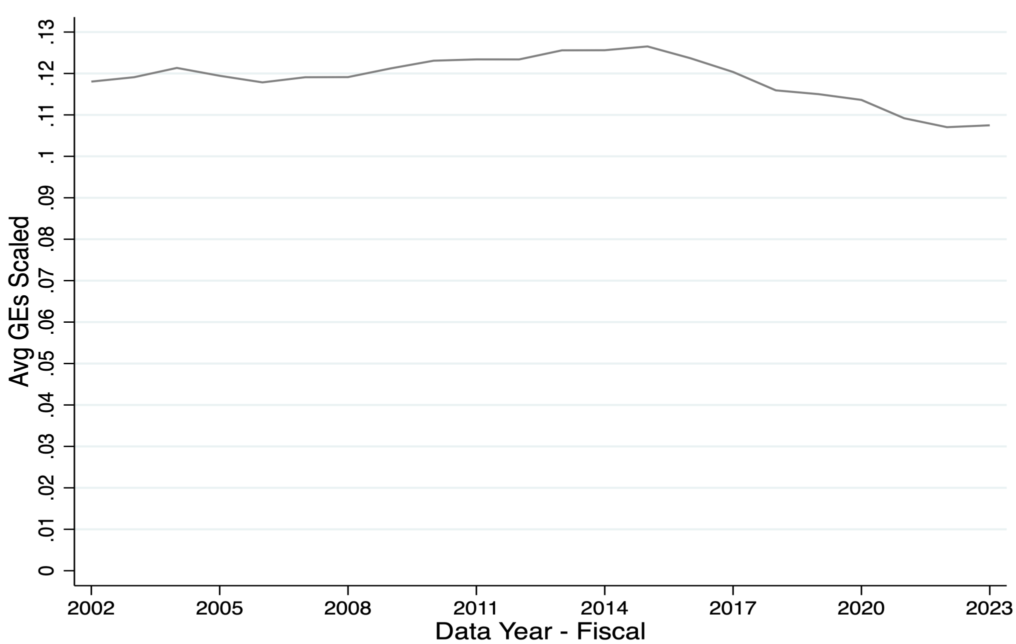


Figure 2. Grammatical Errors by Industry

This figure plots the number of grammatical errors (GEs) by industry. The plot depicts the average number of GEs (scaled by the length of the MD&A and multiplied by 1,000) for the Fama-French 12 industries. The Fama-French 12 industries are defined as follows: (1) Consumer NonDurables – Food, Tobacco, Textiles, Apparel, Leather, Toys, (2) Consumer Durables – Cars, TVs, Furniture, Household Appliances, (3) Manufacturing – Machinery, Trucks, Planes, Off Furn, Paper, Com Printing, (4) Oil, Gas, and Coal Extraction and Products, (5) Chemicals and Allied Products, (6) Business Equipment – Computers, Software, and Electronic Equipment, (7) Telephone and Television Transmission, (8)Utilities, (9) Wholesale, Retail, and Some Services (Laundries, Repair Shops), (10) Healthcare, Medical Equipment, and Drugs, (11) Finance, and (12)Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment.

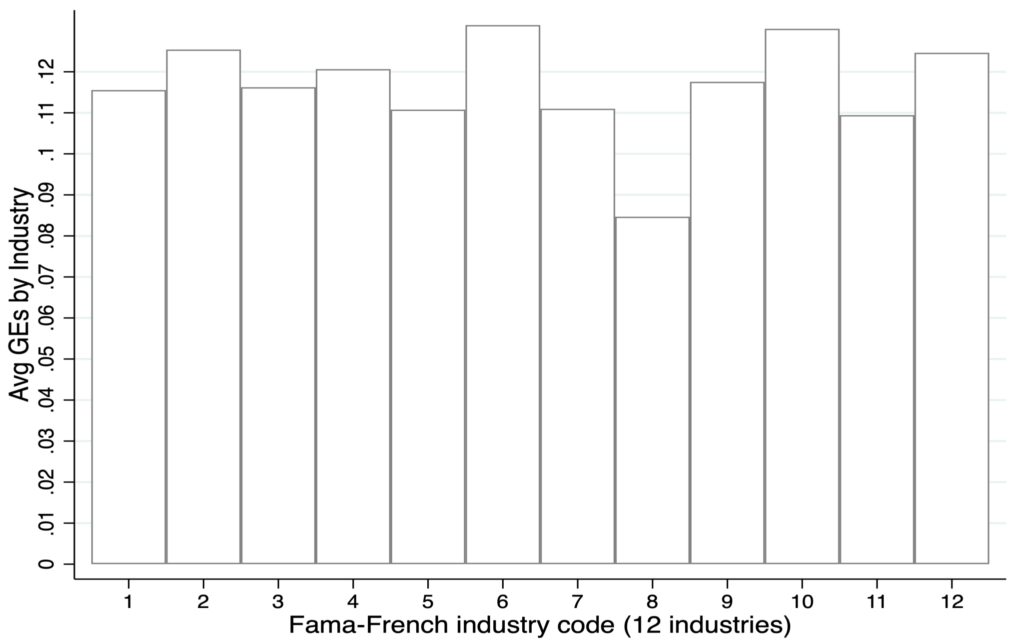


Table 1. Sample Selection

This table reports the sample selection process beginning from the set of 10-Ks available on the SEC EDGAR website. The table provides the number of firm-year observations remaining in the sample after each data requirement. We search for MD&As in 10-K annual reports and count the number of grammatical violations per report. We then merge with Compustat and exclude firms such as ABS, REIT Shell, Blank Check, Non-Operational, Fund or Trust Companies. Finally, we keep all observations with controls, resulting in a final sample of 83,916 firm-year observations.

Sample Selection Procedure	Firm-years
Firm-years from Compustat (with non-missing assets and sales data)	160,915
Downloaded 10Ks	119,753
MD&As Successfully Extracted	110,527
10Ks that are not: ABS, REIT Shell, Blank Check, Non-Operational,	
Fund or Trust Companies	107,497
Years with available controls	83,916
Final Sample (January 2002 and December 2023)	83,916

Table 2. Descriptive Statistics

This table presents descriptive statistics for the variables used in our main analyses. The sample consists of 83,916 firm-year observations for 12,220 unique firms for the calendar year period of 2002 to 2023. *GE*, our main independent variable, is defined as the raw number of grammatical violations in the MD&A, scaled by the length of the MD&A and multiplied by 1,000. See Appendix B for the definitions of the remaining variables.

	N	Mean	Median	S.D.
GE	83,916	0.120	0.109	0.087
Readability	83,916	-86.929	-86.000	8.777
BIG4	83,916	0.637	1.000	0.481
Size	83,916	6.184	6.450	2.705
Dividend	83,916	0.421	0.000	0.494
σ(Earnings)	83,916	0.388	0.038	1.805
FirmAge	83,916	2.263	2.303	0.584
Leverage	83,916	0.767	0.367	2.864
Loss	83,916	0.365	0.000	0.481
NonEnCountry	83,916	0.019	0.000	0.138
AuditorSimilarity	31,740	0.036	0.014	0.115
REST	72,047	0.060	0.000	0.237
REST BigR	72,047	0.037	0.000	0.190
REST FRAUD	72,047	0.004	0.000	0.065
ICW	60,806	0.153	0.000	0.360

Table 3. Determinants of Grammatical Errors

This table estimates the determinants of grammatical errors. The dependent variable, *GE*, is the number of grammatical errors in the MD&A, scaled by the MD&A length and multiplied by 1,000. In Column (1), the variable of interest, *Readability*, is the BOG index multiplied by -1 (i.e., higher levels represent higher readability). Column (2) examines the association between auditor-related MD&A similarity and GEs. *Auditor Similarity* is the natural log of 1 plus the similarity score, which measures the percentage of content in firm i's MD&A that is considered similar to its peer firm j's MD&A. Finally, in Column (3), we examine the relation between grammatical errors and changes in the SEC filing deadlines. *Reg Change Period* is an indicator variable equal to one during the two periods of mandatory reductions in filing windows (i.e., Period 1 = 12/15/2003 - 12/14/2004; Period 2 = 12/15/2006 - 12/14/2007), zero otherwise. *Treat* is an indicator variable equal to one for firms affected by the change in deadlines, zero otherwise. In this test, all variables are interacted with *Reg Change Period* and untabulated for brevity. The definitions of the control variables are provided in Appendix B. Standard errors, clustered by firm, are presented in parentheses under the coefficients. (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var. Columns	GE (1)	GE (2)	GE (3)
Readability	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)
AuditorSimilarity		-0.105***	
		(0.012)	
Treat			-0.012***
			(0.003)
RegChangePeriod			-0.106**
			(0.042)
RegChangePeriod × Treat			0.011**
			(0.006)
BIG4	-0.005***	-0.006**	-0.005**
	(0.002)	(0.003)	(0.002)
Size	-0.005***	-0.004***	-0.005***
	(0.000)	(0.001)	(0.001)
Dividend	-0.007***	-0.007***	-0.006***
	(0.002)	(0.003)	(0.002)
σ(Earnings)	-0.001	-0.000	-0.001
	(0.000)	(0.001)	(0.001)
FirmAge	-0.009***	-0.006***	-0.009***
	(0.001)	(0.002)	(0.002)
Leverage	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Loss	0.007***	0.004*	0.007***
	(0.001)	(0.002)	(0.002)

NonENCountry	0.016**	0.009	0.015*
	(0.006)	(0.006)	(0.008)
Observations	83,916	31,739	37,094
R^2	0.066	0.071	0.053
Time FE	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes

Table 4. Restatements and Grammatical Violations

This table presents the relation between grammatical violations and future restatements and internal control weaknesses. The dependent variable in Column (1), *REST* is an indicator equal to one if the 10-K used to measure grammatical violations is subsequently restated as a result of accounting errors, zero otherwise. In Column (2), *REST BigR*, is an indicator variable equal to one if the 10-K used to measure grammatical violations is subsequently restated with an 8-K disclosure a result of accounting errors, zero otherwise. In Column (3), *REST FRAUD* is an indicator variable equal to one if the 10-K used to measure grammatical violations is subsequently restated due to a fraud or subject to SEC investigation. Finally, in Column (4), *ICW* is an indicator variable equal to one if the internal control opinion by the auditor is either Adverse (Material Weakness Exists) or Disclaimer (Unable to Express Opinion), zero otherwise. The independent variable, *GE*, is the total number of grammatical errors in the MD&A scaled by MD&A length and multiplied by 1,000. The definitions of the control variables are provided in Appendix B. Robust standard errors, clustered by firm, are presented in parentheses under the coefficients. (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	REST	REST BigR	REST FRAUD	ICW
Columns	(1)	(2)	(3)	
GE	0.047***	0.027***	-0.000	0.107***
	(0.012)	(0.009)	(0.003)	(0.026)
BIG4	-0.014***	-0.000	-0.003***	-0.101***
	(0.003)	(0.002)	(0.001)	(0.006)
AFEE	0.005***	0.003**	0.000	0.048***
	(0.002)	(0.001)	(0.000)	(0.004)
Size	0.002**	0.001	0.001**	-0.052***
	(0.001)	(0.001)	(0.000)	(0.003)
FirmAge	-0.004**	-0.001	-0.001**	-0.042***
	(0.002)	(0.001)	(0.000)	(0.004)
Tenure	-0.005***	-0.000	-0.000	-0.019***
	(0.002)	(0.001)	(0.000)	(0.004)
NegEquity	0.010***	0.008***	0.002***	0.079***
	(0.002)	(0.002)	(0.001)	(0.005)
M&A	0.026	0.013	0.004***	-0.073
	(0.032)	(0.032)	(0.001)	(0.058)
Loss	0.005*	0.003*	0.000	0.032***
	(0.002)	(0.002)	(0.001)	(0.004)
MTB	0.000*	0.000***	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
ExtFinDemand	0.008***	0.004	0.000	0.052***
	(0.003)	(0.002)	(0.001)	(0.008)
Fin	0.000	0.000	0.000	-0.001***

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Table 4. *Continued.*

	(0.000)	(0.000)	(0.000)	(0.000)
SaleGr	0.004***	0.000	0.000	0.017***
	(0.001)	(0.001)	(0.000)	(0.003)
Leverage	0.001	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)
CurAccruals	-0.001**	-0.001**	-0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.001)
Dividend	-0.007***	-0.002	-0.001	-0.010**
	(0.003)	(0.002)	(0.001)	(0.004)
Constant	-0.032	-0.034	0.001	-0.012
	(0.037)	(0.035)	(0.005)	(0.074)
Observations	72,047	72,047	72,047	60,806
R^2	0.015	0.011	0.003	0.226
Time FE	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes

Table 5. Grammatical Errors and Restatements

This table presents the relation between grammatical errors and future restatements. The dependent variable, *REST*, is an indicator equal to one if the 10-K used to measure grammatical violations is subsequently restated as a result of unintentional accounting and clerical errors, zero otherwise. The independent variable, *GE*, is the total number of grammatical violations in the MD&A, scaled by the MD&A length and multiplied by 1,000. The definitions of the control variables are provided in Appendix B. Robust standard errors, clustered by firm, are presented in parentheses under the coefficients. (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var. Columns	ARL (1)	AFEE (2)	ARL (3)	AFEE (4)
Lag GE	0.104*** (0.019)	0.103* (0.058)	0.037 (0.030)	0.026 (0.088)
Lag AuditorSimilarity			-0.086* (0.046)	-0.491*** (0.186)
Lag GE × Lag AuditorSimilarity			0.867*** (0.317)	2.675** (1.353)
Size	-0.051*** (0.002)	0.389*** (0.008)	-0.049*** (0.003)	0.347*** (0.010)
BIG4	-0.044*** (0.005)	0.423*** (0.016)	-0.069*** (0.008)	0.540*** (0.023)
NGSEG	-0.019*** (0.005)	0.011 (0.016)	-0.026*** (0.008)	-0.015 (0.024)
NBSEG	-0.005 (0.007)	0.086*** (0.020)	-0.007 (0.012)	0.012 (0.033)
InvRatio	0.074*** (0.025)	0.030 (0.070)	0.209*** (0.043)	-0.116 (0.123)
RectRatio	0.070*** (0.021)	0.286*** (0.065)	0.071** (0.030)	0.285*** (0.097)
CurRatio	-0.004*** (0.001)	-0.009*** (0.002)	-0.002*** (0.001)	-0.010*** (0.002)
FCARatio	-0.151 (0.151)	-1.052*** (0.387)	-0.162 (0.183)	-0.350 (0.403)
M&A	-0.075 (0.072)	0.025 (0.086)	0.013 (0.059)	-0.138 (0.156)
Salegr	0.006*** (0.002)	-0.030*** (0.005)	0.005* (0.003)	-0.021*** (0.006)
MTB	-0.009***	0.009***	-0.011***	0.007***

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Table 5. *Continued.*

	(0.002)	(0.002)	(0.002)	(0.003)
CFF	0.020***	-0.049***	0.011*	-0.048***
	(0.004)	(0.008)	(0.006)	(0.011)
Leverage	0.002***	-0.002	0.002**	-0.002
	(0.000)	(0.001)	(0.001)	(0.002)
ROA	0.018***	-0.092***	0.009	-0.079***
	(0.005)	(0.014)	(0.007)	(0.019)
Loss	0.045***	0.142***	0.030***	0.121***
	(0.004)	(0.008)	(0.006)	(0.012)
L.Loss	0.001	0.150***	-0.009*	0.130***
	(0.003)	(0.007)	(0.005)	(0.011)
SdRet	0.940***	0.982***	0.963***	1.566***
	(0.120)	(0.227)	(0.155)	(0.328)
CiFirm	0.274	-1.562**	-0.718***	2.919***
	(0.249)	(0.673)	(0.278)	(0.979)
REST	0.064***	0.076***	0.061***	0.088***
	(0.006)	(0.011)	(0.010)	(0.019)
LnEmp	-0.006**	0.143***	-0.005	0.176***
	(0.002)	(0.007)	(0.003)	(0.010)
NegEquity	0.037***	0.018	0.041***	0.008
	(0.004)	(0.013)	(0.007)	(0.020)
GCO	0.094***	0.188***	0.065***	0.216***
	(0.011)	(0.024)	(0.013)	(0.032)
NonDec	-0.023***	-0.091***	-0.019**	-0.059***
	(0.005)	(0.015)	(0.009)	(0.023)
Litigation	-0.009	0.065***	-0.002	0.084***
	(0.008)	(0.022)	(0.010)	(0.025)
OperatingCycle	0.015***	-0.040***	0.006*	-0.012
	(0.002)	(0.008)	(0.003)	(0.009)
Observations	56,796	56,686	19,910	19,864
R^2	0.287	0.827	0.312	0.835
Time FE	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes

Table 6. The Relation between Restatements, MD&A Similarity, and Grammatical Errors

This table explores how the likelihood of an auditor reviewing the MD&A can mitigate grammatical errors' informativeness about future restatement. The dependent variable in column (1), *REST*, is an indicator equal to one if the 10-K used to measure grammatical errors is subsequently restated as a result of unintentional accounting error, zero otherwise. In column (2), *REST MISSED ICW* is an indicator variable equal to one if the 10-K used to measure grammatical errors is subsequently restated as a result of an unintentional accounting error and no internal control weakness has been identified, zero otherwise. The independent variable, *GE*, is the total number of grammatical errors in the MD&A, scaled by the MD&A length and multiplied by 1,000. The definitions of the control variables are provided in Appendix B. Robust standard errors, clustered by firm, are presented in parentheses under the coefficients. (***), (**), and (*) denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var. Columns	REST (1)	REST MISSED ICW (2)
GE	0.058***	0.023*
	(0.019)	(0.012)
AuditorSimilarity	0.049	0.032
	(0.047)	(0.027)
GE $\times$ AuditorSimilarity	-0.724**	-0.455**
	(0.363)	(0.192)
BIG4	-0.023***	-0.001
	(0.005)	(0.003)
AFEE	0.003	-0.000
	(0.003)	(0.001)
Size	0.003**	0.003***
	(0.002)	(0.001)
Firm Age	-0.005*	-0.001
	(0.003)	(0.002)
Tenure	-0.001	0.003**
	(0.003)	(0.001)
NegEquity	0.010***	0.003
	(0.004)	(0.002)
M&A	-0.058	0.035***
	(0.109)	(0.007)
Loss	0.001	-0.002
	(0.004)	(0.003)
MTB	0.000**	0.000
	(0.000)	(0.000)
ExtFinDemand	0.005	0.002

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Table 6. *Continued.*

	(0.004)	(0.003)
Fin	0.005	0.001
	(0.004)	(0.002)
SaleGr	0.001	-0.001
	(0.002)	(0.001)
Leverage	0.002***	0.001**
	(0.001)	(0.000)
CurAccruals	-0.000	0.000
	(0.001)	(0.000)
Dividend	-0.004	0.001
	(0.005)	(0.003)
Observations	25,052	25,052
R^2	0.017	0.017
Time FE	Yes	Yes
Ind. FE	Yes	Yes