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Corporate Financial Misconduct and Accounting Reporting Complexity: Evidence from Financial Disclosures in XBRL

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Introduction

Regulators, such as the Financial Accounting Standards Board (FASB) and the Securities and Exchange Commission (SEC), suggest that the complexity inherent in financial reporting can lead to the increased occurrence of financial statement misreporting (Cox, 2005; Peterson, 2012). High levels of financial reporting quality (FRQ) lead firms to have better information environments (e.g., Li, 2008; You and Zhang, 2009; Lehavy et al., 2011; Peterson, 2012) and lower risk of financial misstatements (Filzen and Peterson, 2015). A firm's number of business and geographic segments, existence of foreign operations, and managerial decisions are all determinants of FRQ (e.g., Doyle et al., 2007), which is highly correlated with its accounting reporting complexity (Hoitash and Hoitash, 2018). While corporate financial fraud is a "significant threat to the capital markets" as documented in prior literature (e.g., Amiram et al., 2018), few studies have explored the relationship between firms' fraudulent financial activities and accounting reporting complexity (ARC). In this article, we examine the association between ARC and corporate financial misconduct, which comprehensively covers the irregularities and violations of accounting and business standards (Velte, 2021).

To answer the research question, we construct a sample of 7,687 firm-year observations encompassing 2016 to 2021 and examine how firms' likelihood of financial misconduct affects their accounting reporting outcomes. Following prior literature (e.g., Amiram et al., 2015; Chakrabarty et al., 2020), we capture corporate financial misconduct with Benford Score, a measure proved by the statistical theory of Benford's Law and widely used in forensic accounting studies (e.g., Hill, 1995; Amiram et al., 2015; Golden, 2021; Liu et al., 2025). We use the measure of ARC from Hoitash and Hoitash (2018), based on the number of tags in a firm's XBRL/iXBRL filing, to gauge the accounting reporting complexity. With ordinary least squares (OLS) regression models, our findings show that firms who are more likely to engage in financial misconduct significantly reduce their accounting reporting complexity. This negative association is more pronounced after the firms adopt iXBRL. The results are robust by including year and industry fixed effects in the models. A possible explanation for these findings is that more tagged information (i.e., higher ARC) makes it easier for financial statement users to discover potential misconduct, restraining firms from disclosing accounting data with XBRL tags. Furthermore, when implementing iXBRL, financial statements are more accessible and readable to investors, increasing the restraining effect of corporate financial misconduct on firms' choice of setting iXBRL tags.

We construct a two-stage least squares (2SLS) process to mitigate potential endogeneity issues.[1] Specifically, we use corporate teamwork culture (Li et al., 2021), which is correlated with a firm's financial misconduct possibility (Liu et al., 2023) but not correlated with ARC, as an instrumental variable and generate a predicted Benford Score as the new variable of interest to re-estimate the main OLS regression model as a robustness test. Moreover, we use Beneish M-Score (Beneish, 1999) as an alternative measure of corporate financial misconduct to provide further internal validity. Taken together, the set of analyses with robust results enhances the conclusion we draw from the main hypothesis.

[1] Potential endogeneity problems could be caused by either simultaneous causality, omitted variables, or measurement errors (Roberts and Whited, 2013). Since XBRL/iXBRL documents are usually created after the financial statements are prepared (Plumlee and Plumlee, 2008), we rule out the concern of simultaneous causality. The concerns of omitted variable and measurement error could be addressed by the 2SLS approach (Peel, 2014; Jennings et al., 2020).

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This research contributes to literature in three aspects. First, the study reveals a potential benefit of setting more tags in XBRL/iXBRL structured language, which differs from prior literature findings. Previous research asserts that more tags, especially customized ones, lead to higher reporting complexity and confuse financial statement users by "muddying the water" (e.g., Felo et al., 2018; Hoitash and Hoitash, 2018). Oppositely, our evidence shows that increasing the number of tags in XBRL/iXBRL potentially exposes more clues to stakeholders when a firm conducts financial misbehaviors. Second, our findings have relevance for regulators and policymakers for iXBRL policy setting. Based on survey results, Enofe and Amaria (2011) state that "100% of the respondents believed that XBRL will not reduce financial fraud or have any impact on internal control"; nevertheless, our study shows that increasing tags in XBRL/iXBRL positively influences the quality of financial reporting. If regulators (e.g., the SEC) mandate a minimum number of tags in iXBRL filings, it might significantly reduce fraudulent reporting because firms could have concern about the elevated risk of being detected of misconduct due to detailed information disclosed in tags. Third, this study could be of interest to auditors and forensic accountants that accounting reporting complexity measures may assist them to better assess a firm's financial misconduct likelihood.

The structure of the rest of this article is as follows. In the next section, we review the prior literature and develop the hypotheses. In the third section, we describe the research design, data selection process, and empirical tests. Next, we present the multivariate analysis results and provide the details of additional and robustness tests. Finally, the last section discusses and concludes the study.

Background Literature and Hypothesis Development

Benford's Law and Corporate Financial Misconduct

Benford's Law, also known as the first-digit law, is a statistical principle which describes how frequently each number from one to nine appears as the leading digit in naturally occurring datasets.[2] The principle draws from the observation that the probability of the first digit being a certain number follows a logarithmic distribution (Berger and Hill, 2015). For example, among all naturally generated numbers, the leading digit is more likely to be "1" than "9."[3] This statistical law has practical applications in various fields, such as detecting fraudulent activities in public voting (e.g., Mebane, 2006; Deckert et al., 2011) and identifying errors in scientific datasets (e.g., Dykeman, 2007).

Researchers have proved that Benford's Law is also a powerful tool in accounting and auditing work (Nigrini and Mittermaier, 1997). Relying on the theorem of Benford's Law, Amiram et al. (2015) develop a novel measure, Benford Score, which captures the likelihood of corporate financial misconduct as the Score is highly correlated to proxies of earnings management, report restatement, and financial misstatement. Chakrabarty et al. (2020) support the notion by reporting that audit fees and auditor efforts are negatively associated with the possibility of financial misconduct, measured by Benford Score. Boyle et al. (2021) examine firms' annual reports by using Benford Score as the primary measure of financial statement errors. Moreover, Beneish and Vorst (2022) deploy the Score as an alternative proxy for financial fraud. More recently, Liu et al. (2025) find that the internal audit quality in a firm is negatively associated with its financial misconduct occurrence when using Benford Score as a proxy. In sum, prior literature has demonstrated that Benford Score is reliable to capture corporate financial misconduct.

The Evolution of XBRL and Ixbrl

The SEC mandated the eXtensible Business Reporting Language (XBRL) for financial statement filings for domestic and foreign large-accelerated filers using U.S. Generally Accepted Accounting Principles (GAAP) beginning with fiscal periods ending on or after June 15, 2009 (Hoitash and Hoitash, 2018). Regulators expect that the technology of XBRL will enable financial statement users to search the information more easily, thus reducing information asymmetry between managers and shareholders (Blankespoor et al., 2014). Literature suggests that the adoption of XBRL largely increases firms' investment efficiency (Feng and Kim, 2021), reduces investors' information processing costs (Huang et al., 2021), and significantly constrains earnings management via discretional accrual choices (Kim et al., 2019).

However, financial reports in XBRL format are usually separated from the traditional HTML-based annual report documents (Luo et al., 2023), which increases the inconsistency and calculation errors when investors extract information

[2] "First digit" means the "leading digit" of a number. For example, the first/leading digit of 123.45 is "1".

[3] According to Benford's Law, for all the naturally processed numbers, about 30.1% have leading digit as "1", 17.6% as "2", 12.5% as "3", 9.7% as "4", 7.9% as "5", 6.7% as "6", 5.8% as "7", 5.1% as "8", and 4.6% as "9" (Berger and Hill, 2015).

from XBRL files (Bortiz and No, 2008; Bartley et al., 2011; Du et al., 2013). As a result, the SEC was looking for a new technique which "allows filers to embed XBRL data directly into an HTML document, eliminating the need to tag a copy of the information in a separate XBRL exhibit" (SEC, 2018).

In 2018, the SEC passed an amendment requiring firms to document Inline XBRL (i.e., iXBRL) reports, making the XBRL files more accessible and readable (Hoitash et al., 2021). The new iXBRL system integrates XBRL data into reports formatted in HTML and enhances the accessibility and value of the information disclosed to investors (Luo et al., 2021). In contrast to traditional XBRL documents that require special software to read, iXBRL documents are in the format of HTML that is viewable in any web browser (e.g., Edge or Chrome). Users can click the tagged data points in iXBRL reports and easily obtain detailed information about the tagged accounting items, such as their account definition, reporting period, monetary unit, and related accounting rules.

Reporting Complexity and XBRL/iXBRL

Some researchers consider the impetus behind financial reporting complexity to be primarily rooted in the complex business operation of a company and the applicable accounting rules and regulations. For example, Guay et al. (2016) suggest that managers use reporting complexity strategically; when the financial situation is more complicated, managers increase voluntary disclosure to mitigate the negative impact of the complexity. In an experimental setting, Asay et al. (2018) find that managers write more readable disclosures to lower reporting complexity when good news is available to highlight positive corporate performance. On the other hand, Li (2008) illustrates that managers intentionally increase financial reporting complexity to add the cost of information processing for financial statement users and conceal unfavorable information. Similarly, Lo et al. (2017) find that when firms are close to meet-or-beat earnings targets, their management discussion and analysis sections in annual reports are less readable, and the complexity level in their financial reports is high. In sum, prior literature has a mixed view of the determinants of financial reporting complexity.

In 2009, the SEC instituted a rule that mandates publicly traded firms to faithfully disclose their financial statement information using the XBRL format by 2012 (SEC, 2009). Later, in June 2018, the SEC approved the policy requiring all firms to adopt Inline XBRL (iXBRL). Both XBRL and iXBRL structure financial statements and accompanying notes use a system where every accounting concept is denoted by a unique tag, with each tag linked to relevant accounting standards or regulations. By counting the tags in annual reports, Hoitash and Hoitash (2018) develop a new measure, ARC, to capture the accounting reporting complexity. In contrast to other reporting complexity measures, such as accounting numerical value and textual content, ARC has additional advantages. First, ARC uses the number of tags to calculate the continuous variable, so it's relatively easy to construct. Second, as a variable available for almost every public firm in the U.S., ARC allows researchers to construct samples with more observations (Hoitash et al., 2021). As such, ARC has been widely used in recent literature to proxy for firm reporting complexity (e.g., Huang et al., 2019; Chen et al., 2022; Seavey et al., 2022).

Regulators believe that XBRL reports have high readability and improve the comparability of the financial information in the reports among different firms. Financial statement users thus have more access to managers' customized information (e.g., Debreceny et al., 2005; Valentinetti and Rea, 2012). While the tags in XBRL-structured reports bring benefits such as information transparency and forecast accuracy (Li and Nwaeze, 2018), using a high number of tags in XBRL could also lead to more compounded reporting outcomes (Hoitash et al., 2021). On the one hand, using more tags helps financial statement users to acquire and analyze financial information efficiently (Gunn, 2007; McGuire et al., 2006). Also, with more XBRL tags, investors can acquire more details on the firm's financial performance (Hoitash et al., 2021). Therefore, firms that want to commit fraud and financial misconduct may try to conceal suspicious evidence by using fewer tags in their XBRL reporting to lower the information transparency (Trompeter et al., 2013). On the other hand, a more complex disclosure system provides an opportunity for fraudulent reporting activities because the accounting reporting complexity increases with the number of tags, making financial statement users harder to detect red flags (Hoitash and Hoitash, 2018). Furthermore, Walton et al. (2021) find a negative relation between the total number of XBRL tags in an annual report and tax accrual quality, suggesting that firms could use extra tags to veil important financial information. As a result, it is reasonable to expect that firms may increase XBRL tags to raise the reporting complexity and "muddy the water" when they commit corporate financial misconduct.

XBRL filings happen after the financial statements are finished and audited; therefore, the number of tags in XBRL reports is likely to be the result of financial reporting misbehavior rather than the reason for it.[4] If auditors have not detected the misconduct or fraudulent reporting, firms could either set more XBRL tags to increase the reporting complexity (i.e., ARC) and hide clues of financial misconduct, or set fewer XBRL tags to decrease the reporting complexity and make financial information less transparent to stakeholders. Based on this discussion, we propose a null hypothesis as below:

> ***H1:*** *A firm's likelihood of engaging in financial misconduct has no association with its accounting reporting complexity.*

Since 2018, the SEC has required firms to adopt Inline XBRL (i.e., iXBRL) in financial filings (SEC, 2018). iXBRL is an open standard structured data language that embeds the machine-readable XBRL data into a human-readable HTML document. The switch from XBRL to iXBRL significantly increases the readability and comparability of online financial reports (SEC, 2020). For example, Luo et al. (2021) reveal that iXBRL reduces the information asymmetry between firms and shareholders and lowers stock price volatility following the annual report release. By mimicking some essential features of iXBRL in an experimental setting, Ajayi and Zhang (2022) show that interactive financial reporting significantly improves the effectiveness of conveying information and attracts more investments.

As discussed above, adopting iXBRL makes firms' financial information more accessible to stakeholders. Furthermore, the new search and filter functions in iXBRL allow people to quickly identify customized tags and search-related topics in the document. If a firm is engaged in financial misconduct, it will try to hide any indicative signs in its disclosure. However, the adoption of iXBRL makes hiding misconduct difficult. We conclude that misbehaving firms will be more concerned about financial misconduct exposure due to the clues in the informative iXBRL environment. Therefore, we expect that the implementation of iXBRL leads to a more pronounced relation between financial misconduct and accounting reporting complexity with the hypothesis as below:

> ***H2****: After adopting iXBRL, the association (if any) between a firm's likelihood of engaging in financial misconduct and accounting reporting complexity will be more pronounced.*

Research Design

Measure of Corporate Financial Misconduct

We capture the likelihood of corporate financial misconduct using Benford Score, a measure developed by Amiram et al. (2015), which detects the likelihood of financial misconduct based on the analysis of statistical distribution of leading digits in financial statement numbers. Following prior literature (e.g., Amiram et al., 2015; Chakrabarty et al., 2020; Golden, 2021; Liu et al., 2023), we initiate the calculation of Benford Score by gathering all annual financial statement data from Compustat North America between fiscal year 2016 and 2021. To construct our sample, we exclude all non-numerical variables and remove any data irrelevant to the balance sheet, income statement, or statement of cash flows. Next, we exclude the first non-zero digit of all numerical data in financial statements with an absolute value less than one, set all missing variables to zero, drop any firm-year observations with total negative assets, and eliminate all firm-year observations with fewer than 100 financial statement line items. Finally, with the formula outlined by Amiram et al. (2015), we calculate firm-year Benford Score based on the deviation of the financial data leading digits distribution from the theoretical leading digit distribution recommended by Benford's Law. The higher a firm's Benford Score is, the more likely that firm is engaged in corporate financial misconduct. A detailed calculation process of Benford Score is in Appendix II.

Compared to other measures of financial fraud or misconduct, Benford Score offers several advantages. First, it does not require complete time series or cross-sectional data, and the Score does not rely on stock price information or other unique firm-specific features. These features make it a versatile tool for financial misconduct detection (Golden, 2021; Liu et al., 2023). Second, Benford Score is able to uncover the propensity of financial misconduct that may have gone unnoticed by other methods (e.g., samples reported by Accounting and Auditing Enforcement Releases [AAERs]) because the Score is

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[4] Currently, there are no policies or regulations in the U.S. requiring XBRL or iXBRL reports to be audited by a third party. As a result, financial statement auditors are not responsible for the quality of XBRL/iXBRL reports of their clients. To the best of our knowledge, there is no publicly available data showing the information on whether a firm has its XBRL/iXBRL audited or not (Cheng et al., 2024).

not a result of identified errors or accounting anomalies; it is an overall likelihood of fraud measure that derives from statistical patterns in financial statement data (Golden, 2021).

Measure of Accounting Reporting Complexity

Extant literature has developed several proxies to reflect financial and accounting reporting complexity, which is defined as the difficulty in preparing and understanding financial statements (Hoitash and Hoitash, 2018). For example, Bushman et al. (2004) use firm features such as the number of business segments and product diversity to measure organizational convolution. Guay et al. (2016) measure the number of words in 10-K reports to estimate a firm's reporting complexity. Moreover, Bonsall et al. (2017) leverage the readability of annual reports to assess a firm's financial reporting from a linguistic perspective. In this paper, we focus on corporate accounting reporting behavior in information disclosure and use Arc proposed by Hoitash and Hoitash (2018) as the proxy for firms' accounting reporting complexity.

Compared to other reporting complexity measures, ARC offers several methodological advantages. First, as it is constructed directly from firms' accounting disclosures, ARC provides a more precise proxy for accounting-related outcomes with reduced measurement error. Second, ARC is applicable to all SEC-registered firms, which allows researchers to construct large and representative samples with enhanced statistical power. Third, ARC reflects both cross-sectional and time-series variation, making it effectively track changes in accounting complexity at the firm level (Hoitash and Hoitash, 2018). All these provide more explanatory power and construct validity for the current study of firm-level corporate financial misconduct.

There are several alternatives to constructing ARC. In XBRL/iXBRL, each tag is either a taxonomy (standard) tag or an extension (customized/company-specific) tag. Taxonomy tags are approved by the Financial Accounting Standards Board (FASB) and are in the official XBRL/iXBRL taxonomy book.[5] Extension tags are developed by firms when they consider the pre-approved tags in the taxonomy book are insufficient to show their company-specific economic transactions.[6] Hence, Hoitash and Hoitash (2018) propose three types of ARCs: ARC_TAXONOMY (i.e., the number of taxonomy tags),ARC_EXTENSIONS (i.e., the number of extensions tags), and ARC_ALL (i.e., the sum of taxonomy and extensions tag numbers). We use all three Arc measurements in our analysis to increase the conclusion validity of the current study. According to Hoitash and Hoitash (2018), the more XBRL/iXBRL tags a firm's annual report contains, the more complicated its accounting structure is. As a result, firms have higher ARCs when their accounting reporting complexity increases.

Data and Sample Selection

We initiate the sample selection with 66,419 firm-year observations in Compustat North America from 2016 to 2021. Because Inline XBRL became mandatory for all the U.S. large-accelerated filers since June 2019,[7] our sample starts in 2016 to ensure that we have balanced observations before and after the mandate iXBRL adoption. Next, we eliminate 18,977 firm-year observations not incorporated in the U.S. and drop 28,050 observations without sufficient data to calculate Benford Score. Following Li et al. (2021), we create a control variable, Integrity_Score, to measure a company's integrity culture based on its earnings call transcripts. We exclude 7,103 observations that do not have enough earnings call information. We also eliminate 2,810 firm-year observations without XBRL or iXBRL reporting data in the Calcbench Database and 1,792 observations with missing control variables. The final sample includes 7,687 firm-year observations from 66 different industries. Because we capture corporate internal control quality based on the information reported under the requirement of SOX 404, all the sample firms U.S. listed and most of them are accelerated or large-accelerated filers with annual revenues of $100 million or more. Table 1 summarizes our sample selection process.[8]

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[5] Taxonomy tags are created by the SEC and usually the regular financial statement items. For example, the tag of "us-gaap:OperatingIncomeLoss" showing the operating income or loss is used by almost all our sample firms, and the tag of "us-gaap:InventoryNet" is frequently used by manufacturing companies.

[6] Extension tags are created by the firms for special financial statement items. For example, the tag of "DigitalAssetsNetNonCurrent" are used only by firms with crypto currency assets, etc.

[7] According to the SEC policy, there is a three-year phase-in for U.S. GAAP filers to comply with the Inline XBRL requirements: beginning with fiscal periods ending on or after June 2019 for large-accelerated filers, June 2020 for accelerated filers, and June 2021 for all the other filers (https://www.sec.gov/structureddata/osd-inline-xbrl.html).

[8] As shown in Table 1, we have a large loss in sample size (28,050 firm-year observations) when calculating Benford Score. The main reason for this sample size decrease is that Benford Score is applicable to firms with positive total assets (Compustat item AT) in a given

Table 1: Sample Selection

Firm-year observations available in Compustat North America from 2016 to 2021	66,419
Less:	
Observations of companies incorporated outside the U.S.	18,977
Firm-year observations without enough financial statement data to generate Benford Score	28,050
Firm-year observations without XBRL/iXBRL tags' information	2,810
Firm-year observations without enough earnings call information to generate corporate integrity culture score	7,103
Firm-year observations without enough data for other control variables	1,792
Final sample of firm-year observations	**7,687**

Empirical Models

To test Hypothesis 1, which states there is no association between a firm's likelihood of financial misconduct and accounting reporting complexity, we modify the model in Guo et al. (2021) and Huang et al. (2019) as below:

$$log\_Tags_{i,t} = \alpha_0 + \alpha_1\, Benford\ Score_{i,t} + \alpha_2\, Size_{i,t} + \alpha_3\, Big4_{i,t} + \alpha_4\, Lev_{i,t} + \alpha_5\, Mtb_{i,t} + \alpha_6\, Roa_{i,t} + \alpha_7\, Special\_Item_{i,t} + \alpha_8\, ICMW_{i,t} + \alpha_9\, Bus\_Segment_{i,t} + \alpha_{10}\, Geo\_Segment_{i,t} + \alpha_{11}\, Analyst\_Following_{i,t} + \alpha_{12}\, Loss_{i,t} + \alpha_{13}\, Foreign\_Business_{i,t} + \alpha_{14}\, Extreme\_Sales_{i,t} + \alpha_{15}\, Busy\_Season_{i,t} + \alpha_{16}\, AltmanZ_{i,t} + \alpha_{17}\, Integrity\_Score_{i,t} + Year\ and\ Industry\ Fixed\ Effects + \varepsilon_{i,t}, \quad (1)$$

Where log_Tagsis one of the alternative measures for reporting complexity: the natural logarithm of XBRL or iXBRL total tags (log_All_Tags), extension tags (log_Extension_Tags), and taxonomy tags (log_Taxonomy_Tags).[9] The variable of interest is Benford Score, a continuous variable that captures a firm's likelihood of corporate financial misconduct (Amiran et al. 2015). A higher value of Benford Score indicates a higher likelihood of financial misconduct (Amrian et al., 2015; Charkrabatry et al., 2020; Golden, 2021; Liu et al., 2025). Consistent with the null hypothesis of Hypothesis 1, we do not expect any statistical significance for the estimated coefficient of Benford Score (i.e., α_1) in Eq (1).

We include control variables in the model to mitigate the impact of firm-level factors (other than financial misconduct) on accounting reporting complexity. Following Guo et al. (2021), we control company size (Size), profitability (Roa), business growth and expansion (Mtb), debt burden (Lev), financial distress (AltmanZ), operating loss (Loss), abnormal sales increase (Extreme_Sales), internal control material weakness (ICMW), and international footprint (Foreign_Business). In addition, we use Big4 and Busy_Season to control the influence of auditors on financial reporting (Lopez and Peters 2012). We use a dummy variable, Special_Item, to control situations where firms have specific items to disclose on the reports. Prior studies also document that a firm's business complexity and analyst following are associated with XBRL reporting complexity (Huang et al., 2019). Therefore, we include the firms' number of business segments (Bus_Segment), geographic segments (Geo_Segment), and analyst following (Analyst_Following) in our regression model. We summarize the variable definitions in Appendix I.

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fiscal year (Amiram et al., 2015). When requiring AT>0, about 33.2% observations in our original sample pool were dropped, which is consistent with the results reported in the prior literature (e.g., Golden, 2021; Liu, 2025). In an untabulated test, we run the regression with Benford Score generated without the limitation of AT>0 and still arrive at significant results, though this calculation is likely less accurate than the one used in the literature. Moreover, as documented in the second robustness test, we replaced Benford Score with Beneish M Score (which does not require AT>0) in the model with the full sample and obtained consistent results as well.

[9] log_Tags reflects the natural logarithm value of a firm's XBRL tag number if the firm has not adopted iXBRL during the sample period. We thank Udi Hoitash and Rani Hoitash for sharing firm XBRL/iXBRL tag data at http://www.xbrlresearch.com.

Our second hypothesis (Hypothesis 2) argues that adopting iXBRL leads to a more pronounced association (if any) between a firm's likelihood of corporate financial misconduct and its accounting reporting complexity. To test Hypothesis 2, we estimate the following regression model:

$$\begin{aligned} log\_Tags_{i,t} = {} & \beta_0 + \beta_1\, High\_Benfords_{i,t} + \beta_2\, iXBRL_{i,t} + \beta_3\, High\_Benfords_{i,t} \times iXBRL_{i,t} + \beta_4\, Size_{i,t} + \beta_5\, Big4_{i,t} \\ & + \beta_6\, Lev_{i,t} + \beta_7\, Mtb_{i,t} + \beta_8\, Roa_{i,t} + \beta_9\, Special\_Item_{i,t} + \beta_{10}\, ICMW_{i,t} + \beta_{11}\, Bus\_Segment_{i,t} \\ & + \beta_{12}\, Geo\_Segment_{i,t} + \beta_{13}\, Analyst\_Following_{i,t} + \beta_{14}\, Loss_{i,t} + \beta_{15}\, Foreign\_Business_{i,t} \\ & + \beta_{16}\, Extreme\_Sales_{i,t} + \beta_{17}\, Busy\_Season_{i,t} + \beta_{18}\, AltmanZ_{i,t} + \beta_{19}\, Integrity\_Score_{i,t} \\ & + Year\ and\ Industry\ Fixed\ Effects + \varepsilon_{i,t}, \qquad (2) \end{aligned}$$

Where iXBRL is an indicator variable coded as 1 if a firm's financial statements are in iXBRL format, 0 otherwise. Because our original measure of corporate financial misconduct likelihood (i.e., Benford Score) in Eq (1) is a continuous variable while the proxy of iXBRL adoption (iXBRL) is dichotomous, it is difficult to interpret the coefficient result of the interaction term of these two types of variables (West et al., 1996) in Eq (2). Hence, we construct another indicator variable, High_Benfords, which equals 1 if a firm's Benford Score is among the top 25-percentile by industry and by year, 0 otherwise. We examine the potential effect of iXBRL adoption on the association between ARC and corporate financial misconduct by interacting iXBRL and High_Benfords.

Consistent with Hypothesis 2, if there is an association between accounting reporting complexity and corporate financial misconduct, we expect the estimated coefficient o fHigh_Benfords × iXBRL(i.e., $\beta_3$in Eq 2) to be statistically significant.

Results

Descriptive Statistics

Table 2, Panel A shows the summary statistics of the variables in our main test regressions. For the total 7,687 firm-year observations, the mean of the dependent variable, Benford Score, is close to zero. According to the theorem of Benford's Law, the Score in non-misconduct firms with an ideal financial statement leading digit distribution should be zero.[10] The mean of Benford Score of our sample (0.027) shows that most of our sample firms do not exhibit apparent red flags of financial misconduct, which aligns with the findings that the average Benford Score is about 0.028 – 0.029 for all the U.S. listed firms (Amiram et al., 2015; Golden, 2021; Liu et al., 2025). As discussed in "Data and Sample Selection", our sample consisted of U.S. listed firms with a certain size, the calculation of Benford Score is not affected by the outliers such as small firms or underperforming firms.

The means of the variables of interest, log_All_Tags, log_Extension_Tags, and log_Taxonomy_Tags are 5.982, 3.881, and 5.835, which are also consistent with the values in accounting literature (e.g., Hoitash and Hoitash, 2018). The mean of iXBRL is 0.478, indicating that slightly less than half of the whole firm-year observations adopted iXBRL from 2016 to 2021. Because the SEC requires firms to gradually adopt iXBRL since 2019 (the middle of our sample period), this iXBRL data summary matches the expectation. Our sample includes popular firms in healthcare and information technology featured by high growth potential, as well as firms in traditional manufacturing and retailing industries that are well-developed and with wide-spread business locations; therefore, the variances of Size, Mtb (market-to-book ratio), and Geo_Segment (the number of geographic segments in a firm) are high. The descriptive statistics of other variables such as Loss, ICMW, and Big 4are also consistent with the findings in prior studies of forensic and accounting information systems (e.g., Zhang et al., 2021), suggesting most U.S. listed firms are profitable, report no material internal control weaknesses, and use Big 4 accounting firms as auditors.

[10] One example to illustrate why a Benford Score larger than zero may reflect possible financial misconducts: a firm inflates its net income during some years may show more of its revenue balances with leading digits larger than expected (i.e., revenue balances with large leading digits such as "6", "7", "8", or "9" instead of small digits such as "1", "2", "3", or "4"), which violates Benford's Law. Another example is that for a firm having a stable annual sales growth rate of 3%, it will take more years to increase its revenues from one million to two million than from eight million to nine million (because with the same growth rate, sales increase faster when the basis/foundation is larger). In other words, for an entity with stable business without financial misconduct, it should have more revenue balances with smaller leading digits than large digits. Hence, a larger Benford Score means a stronger deviation between the actual leading digits distribution and the theoretical leading digits distribution of financial data, serving as a proxy of potential financial misconduct.

Table 2, Panel B reports the Pearson Correlation statistics of the variables in the main test. The correlation between Benford Score and the three measures of accounting reporting complexity (log_All_Tags, log_Extension_Tags, and log_Taxonomy_Tags) are all negative and strongly significant, providing the initial support for Hypothesis 1. Size, Special_Item, Bus_Segment, and Geo_Segment are all positively correlated with the ARC measures, showing that the larger the firm is, the more complicated its accounting reporting will be. AltmanZ and Loss are both negatively correlated with the ARC measures. This result matches our expectation since firms under the pressure of financial distress are more likely to commit fraud (Kassem, 2024), thus leading to fewer accounting information disclosures. To mitigate the impact of sample outliers, we winsorized all the continuous variables at the 1st and 99th percentiles. The variance inflation factors (VIFs) for all variables in our models are less than ten, suggesting that collinearity is not distorting our analytical results.

Table 2 Panel A: Descriptive Statistics

Variable	Mean	Std Dev	25th Pctl	Median	75th Pctl
log_All_Tags	5.982	0.336	5.756	5.971	6.213
log_Extension_Tags	3.881	0.653	3.466	3.892	4.317
log_Taxonomy_Tags	5.835	0.319	5.620	5.835	6.059
Benford Score	0.027	0.008	0.021	0.026	0.032
High_Benfords	0.500	0.389	0.000	1.000	1.000
iXBRL	0.478	0.500	0.000	0.000	1.000
Size	8.213	1.672	7.037	8.087	9.300
Big4	0.865	0.342	1.000	1.000	1.000
Lev	0.281	0.219	0.093	0.264	0.411
Mtb	3.754	5.847	1.307	2.294	4.474
Roa	0.016	0.124	0.002	0.029	0.067
Special_Item	0.846	0.361	1.000	1.000	1.000
ICMW	0.039	0.192	0.000	0.000	0.000
Bus_Segment	6.566	4.728	3.000	5.000	9.000
Geo_Segment	4.478	6.587	0.000	3.000	6.000
Analyst_Following	10.030	7.526	4.000	8.000	14.000
Loss	0.240	0.427	0.000	0.000	0.000
Foreign_Business	0.620	0.486	0.000	1.000	1.000
Extreme_Sales	0.260	0.439	0.000	0.000	1.000
Busy_Season	0.769	0.422	1.000	1.000	1.000
AltmanZ	3.691	5.280	1.521	2.802	4.380
Integrity_Score	2.328	1.102	1.550	2.126	2.864

Table 2 Panel B: Correlation Table for Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) log_All_Tags	1.000						
(2) log_Extension_Tags	0.755***	1.000					
(3) log_Taxonomy_Tags	0.979***	0.619***	1.000				
(4) Benfords_Score	-0.170***	-0.023**	-0.203***	1.000			
(5) High_Benfords	-0.153***	-0.084***	-0.162***	0.713***	1.000		
(6) iXBRL	0.098***	0.079***	0.096***	0.001	-0.012	1.000	

(7) Size	0.601***	0.451***	0.586***	-0.116***	-0.140***	0.147***	1.000
(8) Big4	0.086***	0.058***	0.088***	-0.070***	-0.041***	0.066***	0.266***
(9) Lev	0.044***	0.082***	0.031***	-0.040***	-0.018	0.076***	0.054***
(10) Mtb	-0.177***	-0.155***	-0.166***	0.021*	0.022*	0.044***	-0.050***
(11) Roa	0.068***	-0.093***	0.110***	-0.161***	-0.082***	-0.016	0.244***
(12) Special_Item	0.200***	0.097***	0.217***	-0.206***	-0.104***	0.025**	0.064***
(13) ICMW	0.025**	0.015	0.026**	-0.017	-0.008	-0.036***	-0.079***
(14) Bus_Segment	0.356***	0.189***	0.370***	-0.154***	-0.091***	-0.107***	0.284***
(15) Geo_Segment	0.047***	-0.099***	0.092***	-0.176***	-0.080***	-0.083***	-0.037***
(16) Analyst_Following	0.108***	0.027**	0.126***	-0.083***	-0.072***	0.043***	0.564***
(17) Loss	-0.126***	-0.009	-0.146***	0.091***	0.058***	0.048***	-0.282***
(18) Foreign_Business	-0.015	-0.187***	0.046***	-0.245***	-0.101***	0.007	-0.026**
(19) Extreme_Sales	-0.093***	-0.020*	-0.104***	0.072***	0.030***	-0.109***	-0.070***
(20) Busy_Season	0.142***	0.213***	0.107***	0.102***	0.026**	0.079***	0.070***
(21) AltmanZ	-0.305***	-0.282***	-0.282***	0.069***	0.043***	0.001	-0.097***
(22) Integrity_Score	0.072***	0.154***	0.038***	0.066***	0.014	0.044***	0.111***

Table 2 Panel B: Correlation Table for Variables (Continued)

Variables	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(8) Big4	1.000						
(9) Lev	0.121***	1.000					
(10) Mtb	0.070***	-0.047***	1.000				
(11) Roa	0.052***	-0.088***	0.048***	1.000			
(12) Special_Item	0.051***	0.132***	-0.054***	0.001	1.000		
(13) ICMW	-0.050***	0.024**	-0.033***	-0.075***	0.026**	1.000	
(14) Bus_Segment	0.093***	0.004	-0.106***	0.148***	0.105***	-0.011	1.000
(15) Geo_Segment	0.065***	-0.042***	0.022*	0.095***	0.135***	0.074***	0.169***
(16) Analyst_Following	0.250***	0.038***	0.228***	0.155***	0.051***	-0.094***	0.079***
(17) Loss	-0.037***	0.114***	0.018	-0.630***	0.048***	0.073***	-0.156***

(18) Foreign_Business	0.127***	0.009	0.130***	0.119***	0.199***	0.020*	0.080***
(19) Extreme_Sales	-0.061***	-0.041***	0.123***	-0.043***	-0.022*	-0.003	-0.079***
(20) Busy_Season	-0.029**	0.061***	-0.059***	-0.117***	-0.057***	-0.004	0.001
(21) AltmanZ	-0.016	-0.391***	0.236***	0.301***	-0.152***	-0.040***	-0.089***
(22) Integrity_Score	0.048***	0.003	0.004	-0.127***	-0.059***	0.001	-0.017

Table 2 Panel B: Correlation Table for Variables (Continued)

Variables	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(15) Geo_Segment	1.000						
(16) Analyst_Following	0.082***	1.000					
(17) Loss	-0.007	-0.104***	1.000				
(18) Foreign_Business	0.452***	0.183***	0.021*	1.000			
(19) Extreme_Sales	-0.011	0.059***	0.031***	-0.050***	1.000		
(20) Busy_Season	-0.085***	-0.080***	0.052***	-0.168***	0.055***	1.000	
(21) AltmanZ	0.003	0.091***	-0.157***	0.056***	0.106***	-0.077***	1.000
(22) Integrity_Score	-0.120***	0.034***	0.097***	-0.091***	0.001	0.101***	-0.012

Multivariate Analysis for Corporate Financial Misconduct and Accounting Reporting Complexity (Hypothesis 1)

Table 3 shows the results of Hypothesis 1 test, examining the possible relationship between the likelihood of corporate financial misconduct (measured by Benford Score) and accounting reporting complexity (measured by log_All_Tags, log_Extension_Tags, and log_Taxonomy_Tags). In Column 1 of Table 3, the estimated coefficient of Benford_Score is negative and statistically significant (-3.914, p-value < 0.001). This result means that firms with a higher likelihood of engaging in financial misconduct are also more likely to reduce their overall tag disclosure in XBRL/iXBRL reports. The results are robust when we use the alternative measures of extension tags (log_Extension_Tags) and taxonomy tags (log_Taxonomy_Tags). Consistent with the outcome in Table 3 Column 1, the estimated coefficient of log_Extension_Tags is negative (-4.613, p-value < 0.001) in Column 2 as well as in Column 3 (-3.835, p-value < 0.001). Extreme_Sales (Roa) is negatively (positively) associated with log_Taxonomy_Tags, but positively (negatively) associated log_Extension_Tags. These findings further support the notion that firms adjust the transparency of XBRL disclosure when they are subject to manipulating the financial numbers of sales growth rate and return on assets; they may not avoid the required standard XBRL tags (i.e., taxonomy tags), but they are more likely to reduce the XBRL tags that they can control (i.e., extension tags).

All these results suggest that firms reduce the reporting complexity when potentially involved in financial misconduct. In sum, our findings in Table 3 reject Hypothesis 1 by showing a strong negative association between the likelihood of corporate financial misconduct and accounting reporting complexity.

Table 3: Multivariate Analysis for Hypothesis 1 (Financial Misconduct Has No Impact on Accounting Reporting Complexity)

	Dependent Variables		
Independent Variables	(1) **log_All_Tags** Coefficients (p-value) n=7,687	(2) **log_Extension_Tags** Coefficients (p-value) n=7,687	(3) **log_Taxonomy_Tags** Coefficients (p-value) n=7,687
Constant	5.353*** (0.000)	2.889*** (0.000)	5.272*** (0.000)
Benford Score	-3.914*** (0.000)	-4.613*** (0.000)	-3.835*** (0.000)
Size	0.094*** (0.000)	0.131*** (0.000)	0.089*** (0.000)
Big4	0.004 (0.780)	0.038 (0.344)	-0.001 (0.960)
Lev	0.146*** (0.000)	0.137** (0.030)	0.151*** (0.000)
Mtb	-0.001 (0.764)	-0.001 (0.848)	-0.001 (0.761)
Roa	0.082* (0.072)	-0.303*** (0.003)	0.144*** (0.000)
Special_Item	0.145*** (0.000)	0.211*** (0.000)	0.137*** (0.000)
ICMW	0.059*** (0.001)	0.077* (0.064)	0.056*** (0.002)
Bus_Segment	0.007*** (0.000)	0.005 (0.110)	0.007*** (0.000)
Geo_Segment	0.003*** (0.003)	0.003 (0.265)	0.003*** (0.001)
Analyst_Following	-0.007*** (0.000)	-0.009*** (0.000)	-0.006*** (0.000)
Loss	0.036*** (0.000)	0.087*** (0.000)	0.030*** (0.002)
Foreign_Business	0.059*** (0.000)	-0.004 (0.891)	0.069*** (0.000)
Extreme_Sales	-0.013* (0.071)	0.049*** (0.008)	-0.021*** (0.002)
Busy_Season	0.038*** (0.002)	0.092*** (0.003)	0.031*** (0.006)
AltmanZ	-0.007*** (0.000)	-0.012*** (0.000)	-0.006*** (0.000)
Integrity_Score	0.002 (0.611)	0.028*** (0.003)	-0.002 (0.605)
Year Fixed Effect	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes
R^2	57.70%	43.33%	58.60%

*,**, and *** indicate significance at p < 0.10, p < 0.05, and p < 0.01 levels, respectively.

Multivariate Analysis for the Moderating Effect of Ixbrl on Corporate Financial Misconduct and Accounting Reporting Complexity (Hypothesis 2)

Table 4 shows the test results for Hypothesis 2. In Column 1, the coefficient of High_Benfords is -0.040 (p-value < 0.001), consistent with Hypothesis 1 test results, and suggests that a higher likelihood of financial misconduct reduces financial reporting complexity. Moreover, the estimated coefficient of the interaction High_Benfords × iXBRL is negative and statistically significant (-0.015, p-value = 0.006). This incremental effect of corporate financial misconduct on reporting complexity due to iXBRL adoption provides evidence to support Hypothesis 2.

In Table 3, we present the regression results in Column 2 and 3 using alternative dependent variables of ARC: number of extensions (log_Extension_Tags) and taxonomy (log_Taxonomy_Tags) tags. The estimated coefficients of High_Benfords × iXBRL are -0.014 (p-value = 0.018) and -0.019 (p-value = 0.004) in Column 2 and 3, respectively.

Taken together, our results imply that firms reduce customized and standard tags in financial reporting with iXBRL format when they are more likely to engage in corporate financial misconduct. Although our study does not propose a causal relationship between iXBRL adoption and financial reporting complexity, a possible reason for our finding is that firms are concerned about the potential effect of iXBRL on information conveyance. iXBRL can potentially help financial statement users acquire and analyze in-depth accounting information at a low cost of time and effort, and firms are seeking to hide clues of financial misconduct in the environment of iXBRL.[11]

Table 4: Multivariate Analysis for Hypothesis 2 (Moderating Effect of iXBRL on Financial Misconduct and Accounting Reporting Complexity)

	Dependent Variables		
Independent Variables	(1) **log_All_Tags** Coefficients (p-value) n=7,687	(2) **log_Extension_Tags** Coefficients (p-value) n=7,687	(3) **log_Taxonomy_Tags** Coefficients (p-value) n=7,687
Constant	5.286***	2.798***	5.207***
	(0.000)	(0.000)	(0.000)
High_Benfords	-0.040***	-0.043**	-0.038***
	(0.000)	(0.041)	(0.000)
iXBRL	0.020**	0.028*	0.025**
	(0.042)	(0.060)	(0.047)
High_Benfords × iXBRL	-0.015***	-0.014**	-0.019***
	(0.006)	(0.018)	(0.004)
Size	0.096***	0.133***	0.090***
	(0.000)	(0.000)	(0.000)
Big4	0.003	0.039	-0.003
	(0.867)	(0.333)	(0.839)
Lev	0.146***	0.137**	0.151***
	(0.000)	(0.030)	(0.000)
Mtb	-0.000	-0.000	-0.000
	(0.668)	(0.797)	(0.662)
Roa	0.101**	-0.282***	0.164***
	(0.027)	(0.006)	(0.000)
Special_Item	0.151***	0.219***	0.144***
	(0.000)	(0.000)	(0.000)
ICMW	0.061***	0.077*	0.058***
	(0.001)	(0.063)	(0.001)
Bus_Segment	0.007***	0.005	0.007***

[11] In and untabulated test, we run the model of Eq (2) by further including firm fixed effect. We obtained results consistent with those in Table 3.

	(0.000)	(0.101)	(0.000)
Geo_Segment	0.003***	0.003	0.003***
	(0.002)	(0.245)	(0.001)
Analyst_Following	-0.007***	-0.010***	-0.006***
	(0.000)	(0.000)	(0.000)
Loss	0.036***	0.086***	0.030***
	(0.001)	(0.001)	(0.002)
Foreign_Business	0.062***	-0.001	0.071***
	(0.000)	(0.966)	(0.000)
Extreme_Sales	-0.014*	-0.048***	-0.022***
	(0.058)	(0.010)	(0.002)
Busy_Season	0.034***	0.092***	0.026**
	(0.006)	(0.003)	(0.025)
AltmanZ	-0.007***	-0.012***	-0.007***
	(0.000)	(0.000)	(0.000)
Integrity_Score	0.002	0.028**	-0.002
	(0.641)	(0.013)	(0.581)
Year Fixed Effect	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes
R^2	57.21%	43.27%	58.10%

*,**, and *** indicate significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Additional Analyses and Robustness Tests

Corporate Financial Misconduct and XBRL/iXBRL Reporting Errors

Our hypothesis testing results show that when firms are engaged in financial misconduct, they will reduce the tags created in XBRL/iXBRL to decrease information disclosure. In other words, companies with flaws actively minimize their exposure to the public. Researchers find that firms with errors in XBRL are more likely to be scrutinized by both regulators and investors (Du et al., 2013; Markelevich, 2017); hence, if a firm has misconduct issues, it is reasonable to expect that the firm will pay efforts to reduce errors in its XBRL or iXBRL files, which helps the firm stay low and not be exposed to additional scrutiny from stakeholders.

Following Guo et al. (2021), we conduct an additional test using the following model to examine whether a firm's likelihood of corporate financial misconduct has an impact on its XBRL or iXBRL reporting errors:

$$\begin{aligned} logit\ (Error_{i,t}) = {} & \lambda_0 + \lambda_1\ Benford\ Score_{i,t} + \lambda_2\ Size_{i,t} + \lambda_3\ Lev_{i,t} + \lambda_4\ Mtb_{i,t} + \lambda_5\ Roa_{i,t} + \lambda_6\ ICMW_{i,t} \\ & + \lambda_7\ Foreign\_Business_{i,t} + \lambda_8\ Analyst\_Following_{i,t} + \lambda_9\ Total\_Accrual_{i,t} + \lambda_{10}\ Loss_{i,t} \\ & + \lambda_{11}\ Extension\%_{i,t} + \lambda_{12}\ Extreme\_Sales_{i,t} + \lambda_{13}\ Restructuring_{i,t} \\ & + Year\ and\ Industry\ Fixed\ Effects + \varepsilon_{i,t}, \end{aligned} \quad (3)$$

Where Error is an indicator variable equals 1 if a firm has an XBRL or iXBRL 10-K filing error each year, 0 otherwise.[12] The control variables in the model are defined the same as those in Eq (1) and (2).

Table 5 Panel A reports the regression results. The estimated coefficient of Benford Score is -14.624 with a p-value of 0.011, meaning that the higher likelihood a firm has for corporate financial misconduct, the less likely it will have errors in the XBRL or iXBRL annual report files.[13] This finding is consistent with our expectation based on Risk Perception Theory that when a firm shows no or few mistakes in XBRL/iXBRL filings, it does not necessarily indicate high financial reporting quality; instead, investors should read the filing with more caveats because there might be severe financial performance issues that are intentionally covered up.

[12] Following the prior literature (e.g., Guo et al., 2021), a firm's XBRL/iXBRL filing error data are obtained from XBRL Cloud EDGAR Dashboard (https://edgardashboard.xbrlcloud.com/).

[13] As shown in Table 5 Panel A, the sample size in the additional test is 5,742, less than the sample size in the main hypotheses' tests. The reason is that we obtained the XBRL/iXBRL filling error data form XBRL Cloud EDGAR Dashboard, which reduced the sample size when we merge it with Compustat for this additional test.

Table 5 Panel A: Additional Test of Financial Misconduct and Reporting Errors

	Dependent Variable: Error = 1 if error(s) in a firm's XBRL/iXBRL reporting in a certain fiscal year	
Independent Variables	**Coefficients** n=5,742	**P-values**
Constant	-1.168**	(0.017)
Benford Score	-14.624**	(0.011)
Size	0.296***	(0.000)
Lev	0.162	(0.513)
Mtb	-0.002	(0.764)
Roa	-1.238**	(0.035)
ICMW	-0.377*	(0.054)
Foreign_Business	-0.091	(0.469)
Analyst_Following	-0.013	(0.149)
Total_Accrual	1.990***	(0.005)
Loss	-0.037	(0.762)
Extension%	-2.497***	(0.009)
Extreme_Sales	0.004	(0.972)
Restructuring	0.289	(0.537)
Year and Industry Fixed Effects	Yes	
Pseudo R^2	21.08%	

*,**, and *** indicate significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$ levels, respectively.

The SEC mandates iXBRL framework because it increases the accessibility of financial reports to non-technical and non-professional financial data users (Chang et al., 2021). With iXBRL, more people can access online accounting data, which increases financial statements exposure. Based on the Risk Perception Theory, a firm's perception of risk may increase if it committed misconduct in the past. As such, the mandate of iXBRL also encourages firms to reduce reporting errors and attention from investors. In our next analysis, we examine whether the adoption of iXBRL has an incremental effect on the association between corporate financial misconduct and accounting reporting errors. We estimate the following regression model:

$$\begin{aligned} logit\ (Error_{i,t}) = {} & \mu_0 + \mu_1\ High\_Benfords_{i,t} \times iXBRL_{i,t} + \mu_2\ High\_Benfords_{i,t} + \mu_3\ iXBRL_{i,t} \\ & + \mu_4\ Size_{i,t} + \mu_5\ Lev_{i,t} + \mu_6\ Mtb_{i,t} + \mu_7\ Roa_{i,t} + \mu_8\ ICMW_{i,t} + \mu_9\ Foreign\_Business_{i,t} \\ & + \mu_{10}\ Analyst\_Following_{i,t} + \mu_{11}\ Total\_Accrual_{i,t} + \mu_{12}\ Loss_{i,t} + \mu_{13}\ Extension\%_{i,t} \\ & + \mu_{14}\ Extreme\_Sales_{i,t} + \mu_{15}\ Restructuring_{i,t} + Year\ and\ Industry\ Fixed\ Effects + \varepsilon_{i,t}, \end{aligned} \quad (4)$$

Where High_Benfords is an indicator variable coded as 1 if a firm's Benford Score is among the top 25-percentile by industry and year, 0 otherwise. iXBRL is also an indicator variable, coded as 1 when a firm's online financial reporting has adopted the format of iXBRL in a fiscal year, 0 otherwise. If iXBRL adoption leads to an incremental effect of financial misconduct on a firm's tag errors, the estimated coefficient of High_Benfords × iXBRL(i.e.,μ_1) will be negative and significant.

Table 5 Panel B shows the results. The coefficient of High_Benfords × iXBRL is negative (-0.067) but not significant (p-value = 0.162), indicating that there is no significant effect of iXBRL adoption as we expected. However, we noticed that the coefficient of High_Benfords is negative (-0.141, p-value = 0.095), supporting the findings in the main test that higher propensity for financial misconduct reduces the likelihood of iXBRL errors. The coefficient estimate of iXBRL is 0.376 (p-value = 0.028), suggesting it is possible that firms have more tag errors during the first few years of adopting iXBRL before they become familiar with the new technology.

In sum, with the additional tests, we find a negative association between a firm's likelihood of corporate financial misconduct and its financial reporting errors, but the adoption of iXBRL does not show a significant interfering effect.

Table 5 Panel B: Additional Test of iXBRL's Effect on Financial Misconduct and Reporting Errors

Independent Variables	Dependent Variable Error = 1 if error(s) in a firm's XBRL/iXBRL reporting in a certain fiscal year	
	Coefficients n=5,742	P-values
Constant	-1.474***	(0.001)
High_Benfords × iXBRL	-0.067	(0.162)
High_Benfords	-0.141*	(0.095)
iXBRL	0.376**	(0.028)
Size	0.289***	(0.000)
Lev	0.159	(0.519)
Mtb	-0.002	(0.807)
Roa	-1.209**	(0.041)
ICMW	-0.369*	(0.061)
Foreign_Business	-0.078	(0.538)
Analyst_Following	-0.013	(0.154)
Total_Accrual	2.027***	(0.005)
Loss	-0.024	(0.846)
Extension%	-2.405**	(0.012)
Extreme_Sales	0.004	(0.971)
Restructuring	-0.301	(0.541)
Year and Industry Fixed Effects	Yes	
Pseudo R^2	18.15%	

*,**, and *** indicate significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Robustness Test for the Main Hypothesis Analysis with Two-Stage Least Squares (2SLS) Approach

To mitigate the concern of endogeneity and alternative explanation issues, we use the 2SLS approach to conduct a robustness test by following the prior literature (e.g., Wooldridge, 2005). Liu et al. (2023) find that teamwork culture highly correlates with the propensity of a firm's financial misconduct. However, there is no evidence supports a firm's teamwork culture correlates with its accounting reporting complexity. Therefore, we use the measure of corporate teamwork culture (IV_Teamwork) as the instrumental variable in 2SLS process.[14] Specifically, in stage one, we regress the potential endogenous variable (i.e., Benford Score) on the instrumental variable (IV_Teamwork) and generate a predicted valuable of Benford Score. Next, in stage two, we re-estimate Eq (1) using the predicted Benford Score as the variable of interest to check the robustness of our main test results.

Table 6 reports the regression results. The outcomes of the first stage show that the estimated coefficient of IV_Teamwork is positive and statistically significant (0.246, p-value = 0.019), suggesting that teamwork culture correlates with the likelihood of corporate financial misconduct. The results of the second stage regression show that the estimated coefficient of Benford Score(predicted) is significantly negative (-0.013, p-value = 0.046). With log_All_Tags as the dependent variable in the second stage, the results confirm the findings we obtained in the main hypothesis test that the likelihood of corporate financial misconduct is negatively associated with firms' accounting reporting complexity.[15]

[14] Using a word embedding model in machine learning, Li et al. (2021) analyze the culture highlights frequently mentioned in SandP 500 firms, covering the cultural dimensions of innovation, integrity, quality, respect, and teamwork. With the analysis, the authors create a neural network model to quantitatively measure corporate culture by capturing the meanings of phrases in earnings calls. For example, the model identifies phrases such as "shoulder to shoulder" or "hand in glove" as a reflection of teamwork. A company's teamwork culture score is then generated based on the weighted frequency of these reflections in earnings call transcripts. Since the publication in 2021, the corporate culture measure has been used in a lot of accounting studies and available in Wharton Research Data Services (WRDS) at https://wrds-www.wharton.upenn.edu/login/?next=/pages/get-data/contributed-data-forms/corporate-culture/. We also appreciate the authors of Li et al. (2021) for sharing their corporate culture measures and the related Python codes at https://www.dropbox.com/scl/fo/7g859c9h96cnwzb5uxvbe/h?rlkey=gtjua3yik96szjlob7833lng7&e=1&dl=0.

[15] In untabulated tests, we also change the dependent variable to be log_Extesnsion_Tags and log_Taxonomy_Tags. The estimated coefficients of IV_Teamwork are all statistically significant.

Table 6: Robustness Test with 2SLS

	Dependent Variables			
	First Stage DV: Benford Score		Second Stage DV: log_All_Tags	
Independent Variables	Coefficients n=7,687	P-values	Coefficients n=7,687	P-values
Constant	31.943***	(0.000)	5.661***	(0.000)
Benford Score (predicted)			-0.013**	(0.046)
IV_Teamwork	0.246**	(0.019)		
Size	-1.009***	(0.000)	0.084***	(0.000)
Big4	0.060	(0.880)	0.005	(0.594)
Lev	0.599	(0.413)	0.151***	(0.000)
Mtb	0.019	(0.404)	-0.001	(0.997)
Roa	-7.149***	(0.000)	0.008	(0.920)
Special_Item	-2.709***	(0.000)	0.119***	(0.000)
ICMW	-0.887	(0.104)	0.051***	(0.002)
Bus_Segment	-0.038	(0.164)	0.006***	(0.000)
Geo_Segment	-0.045**	(0.013)	0.002***	(0.001)
Analyst_Following	0.105***	(0.000)	-0.006***	(0.000)
Loss	0.008	(0.980)	0.036**	(0.035)
Foreign_Business	-1.511***	(0.000)	0.045***	(0.007)
Extreme_Sales	0.380	(0.159)	-0.009	(0.244)
Busy_Season	0.248	(0.405)	0.040***	(0.000)
AltmanZ	0.104***	(0.001)	-0.006***	(0.000)
Integrity_Score	0.068	(0.591)	0.004	(0.269)
Year Fixed Effect	Yes		Yes	
Industry Fixed Effect	Yes		Yes	
R^2	35.66%		56.79%	

*,**, and *** indicate significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Robustness Test with Alternative Corporate Financial Misconduct Measure

Prior literature demonstrates that firms engaged in fraudulent financial reporting are also more likely to have earnings manipulation (Rosner, 2003). To further investigate the robustness of our results, we use Beneish M-score to capture the likelihood of earnings manipulation and re-estimate Eq (1).[16] Created by Beneish (1999), M-score is based on selected financial ratios deviate of a firm and increases with the likelihood of a firm's engagement in earnings manipulation. If M-score is greater than -1.78, the firm is likely to be a manipulator of earnings numbers (Beneish, 1999; Beneish et al., 2013). We estimate the following regression model for the robustness test:

$$log\_All\_Tags_{i,t} = \gamma_0 + \gamma_1 Beneish\_M_{i,t} + \gamma_2 Size_{i,t} + \gamma_3 Big4_{i,t} + \gamma_4 Lev_{i,t} + \gamma_5 Mtb_{i,t} + \gamma_6 Roa_{i,t} + \gamma_7 Special\_Item_{i,t} + \gamma_8 ICMW_{i,t} + \gamma_9 Bus\_Segment_{i,t} + \gamma_{10} Geo\_Segment_{i,t} + \gamma_{11} Analyst\_Following_{i,t} + \gamma_{12} Loss_{i,t} + \gamma_{13} Foreign\_Business_{i,t} + \gamma_{14} Extreme\_Sales_{i,t} + \gamma_{15} Busy\_Season_{i,t} + \gamma_{16} AltmanZ_{i,t}$$

[16] The Dechow F-score(Dechow et al., 2011) is also a widely used proxy for earnings manipulation. However, F-score includes the impacts of a firm's nonfinancial, off-balance-sheet, and market-based activities, and the XBRL/iXBRL reporting complexity in the current study may not directly reflect these factors. Therefore, we use M-score instead of F-score in the robustness test.

$$+ \gamma_{17}\ Integrity\_Score + Year\ and\ Industry\ Fixed\ Effects + \varepsilon_{i,t}, \qquad (5)$$

where the variable of interest, Beneish_M, is an indicator variable coded as 1 if a firm's M-score is greater than -1.78, 0 otherwise.

The results in Table 7 show that Beneish_M is negatively (-0.040, p-value < 0.01) associated with log_All_Tags, suggesting that a higher possibility of earnings manipulation leads to lower accounting reporting complexity. Overall, this test supports our findings in the main hypothesis analysis from the perspective of corporate earnings manipulation.

Table 7: Robustness Test with Beneish M-Score Measure

	Dependent Variable log_All_Tags	
Independent Variables	**Coefficients** n=7,687	**P-values**
Constant	5.259***	(0.000)
Beneish_M	-0.040***	(0.000)
Size	0.100***	(0.000)
Big4	0.005	(0.727)
Lev	0.140***	(0.000)
Mtb	-0.000	(0.757)
Roa	0.096**	(0.035)
Special_Item	0.152***	(0.000)
ICMW	0.061***	(0.001)
Bus_Segment	0.007***	(0.000)
Geo_Segment	0.003***	(0.003)
Analyst_Following	-0.007***	(0.000)
Loss	0.037***	(0.000)
Foreign_Business	0.060***	(0.000)
Extreme_Sales	-0.011	(0.128)
Busy_Season	0.036***	(0.003)
AltmanZ	-0.007***	(0.000)
Integrity_Score	0.002	(0.682)
Year Fixed Effect	Yes	
Industry Fixed Effect	Yes	
R^2	57.09%	

*,**, and *** indicate significance at p < 0.10, p < 0.05, and p < 0.01 levels, respectively.

Change Analysis

To increase the internal validity, we also conduct a change analysis by testing the impact of corporate financial misconduct likelihood change on a firm's change in accounting reporting complexity based on Eq (1). This change analysis also helps to mitigate the concern of potential endogeneity issues as the time-invariant omitted variables can be controlled by the change model (Wang, 2023).

Table 8 reports the results of the change analysis. In Column 1, the estimated coefficient of ΔBenfords_High is negative and significant (-4.494, p-value = 0.041), meaning that when a firm's Benford Score increased in year t (compared with that in year t-1), that firm is less likely to increase (or more likely to decrease) its accounting reporting complexity compared with the previous year. This result supports our findings in Hypothesis 1 test. In Column 2 of Table 8, the estimated coefficient of ΔBenfords_High × iXBRL is negative and statistically significant (-0.109, p-value = 0.036), which is consistent with the results in our test of Hypothesis 2, showing that a firm's adoption of iXBRL moderates the impact of financial misconduct likelihood on accounting reporting complexity. In sum, the outcomes of the change analysis enhance our conclusions from our main hypothesis analysis.

Table 8: Change Analysis Supplementing the Main Hypothesis Tests

	Dependent Variables	
Independent Variables	(1) **∆log_All_Tags** Coefficients (p-value) n=5,174	(2) **∆log_All_Tags** Coefficients (p-value) n=5,174
Constant	3.328***	3.352***
	(0.000)	(0.000)
∆Benford Score	-4.494**	
	(0.041)	
∆Benford_High		-0.019*
		(0.082)
iXBRL		0.194**
		(0.026)
∆Benford_High × iXBRL		-0.109**
		(0.036)
∆Size	0.665***	0.663**
	(0.000)	(0.000)
Big4	0.075	0.050
	(0.314)	(0.512)
∆Lev	0.275	0.282
	(0.221)	(0.210)
∆Mtb	-0.000	0.000
	(0.982)	(0.993)
∆Roa	-0.082	-0.042
	(0.783)	(0.888)
Special_Item	0.497***	0.492***
	(0.000)	(0.000)
ICMW	0.386***	0.396***
	(0.002)	(0.002)
∆Bus_Segment	0.030	0.030
	(0.127)	(0.134)
∆Geo_Segment	-0.003	-0.003
	(0.838)	(0.841)
∆Analyst_Following	-0.026***	-0.026***
	(0.005)	(0.004)
Loss	0.111*	0.119**
	(0.060)	(0.046)
Foreign_Business	0.015	0.008
	(0.811)	(0.896)
Extreme_Sales	0.058	0.065
	(0.368)	(0.317)
Busy_Season	-0.040	-0.076
	(0.512)	(0.233)
∆AltmanZ	-0.008	-0.009
	(0.258)	(0.212)
∆Integrity_Score	0.036	0.040

	(0.204)	(0.159)
Year Fixed Effect	Yes	Yes
Industry Fixed Effect	Yes	Yes
R^2	12.01%	12.21%

*,**, and *** indicate significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$ levels, respectively.

Discussion and Conclusion

In this research, we document a negative association between corporate financial misconduct and a firm's accounting reporting complexity (ARC). We also show that the adoption of iXBRL has an incremental effect on the negative association. Our evidence indicates that firms deem the accounting data in XBRL/iXBRL as important information disclosed to the public and can be scrutinized by financial statement users. Thus, firms with fraudulent activities are more likely to hide misbehaviors and disclose less information in XBRL and iXBRL. Additional analyses suggest that firms with a higher likelihood of financial misconduct have fewer XBRL/iXBRL filing errors, suggesting that firms seek to reduce attention from the public when they have potential financial problems.

This research contributes to accounting practice and literature in three aspects. First, different from the prior literature which states that a firm exhibits higher accounting reporting complexity (ARC) can confuse financial statement users by having more tags in XBRL/iXBRL reporting (e.g., Felo et al., 2018; Hoitash and Hoitash, 2018), our research demonstrates that firms engage in corporate financial misconduct may set less tags to avoid sufficient information disclosure and hide their problems; in other words, less tags in XBRL/iXBRL leads to a lower ARC, which also has negative impacts. Second, our evidence suggests that a detailed information disclosure in XBRL/iXBRL constitutes a major concern to firms with financial misconduct. This finding could be of interest to policymakers as if future policy mandates firms to include a minimum amount of financial information in iXBRL (as indicated by tags), such a policy might be an effective approach to refrain firms from accounting misbehaviors. Finally, our paper has helpful implications for practitioners; forensic accountants and auditors can use accounting reporting complexity measures to better assess a client's financial statement fraud risk. Overall, we extend the research of accounting reporting complexity to the area of corporate financial misconduct, one of the most important research topics related to the public interest (Karpoff et al., 2017; Klimczak et al., 2022).

We acknowledge that the current study has some limitations. First, we do not measure the expertise of the personnel implementing transactions and XBRL/iXBRL reporting in each sample firm, which might be an omitted variable in our model. Second, our findings could be biased because the type of information systems used for accounting input may be the origins of red flags instead of human errors (e.g., Du et al., 2013; Guo et al., 2021), and organizations' operational performance also impacts their reporting quality (Habib and Jiang, 2015). Finally, due to the lack of information availability, we do not check the association between isolation of specific tagged financial statements and subsequent stakeholder perception. Future research could extend the paper to investigating the relationship between accounting reporting complexity and more corporate financial behaviors based on stakeholder's reaction to the perceived iXBRL tag issues.

References

Ajayi, O., and Zhang, J. (2022). The joint effects of argument quality and interactivity on nonprofessional investors' perceptions of disclosure credibility and investment decisions. *Journal of Information Systems* 36(3): 1–26.

Altman, E. I. (2018). A fifty-year retrospective on credit risk models, the Altman Z-score family of models and their applications to financial markets and managerial strategies. *Journal of Credit Risk* 14(4).

Amiram, D., Bozanic, Z., and Rouen, E. (2015). Financial statement errors: Evidence from the distributional properties of financial statement numbers. *Review of Accounting Studies* 20(4): 1540–1593.

Amiram, D., Bozanic, Z., Cox, J. D., Dupont, Q., Karpoff, J. M., and Sloan, R. (2018). Financial reporting fraud and other forms of misconduct: A multidisciplinary review of the literature. *Review of Accounting Studies* 23: 732–783.

Asay, H. S., Libby, R., and Rennekamp, K. (2018). Firm performance, reporting goals, and language choices in narrative disclosures. *Journal of Accounting and Economics* 65(2–3): 380–398.

Bartley, J., Chen, A. Y. S., and Taylor, E. Z. (2011). A comparison of XBRL filings to corporate 10-Ks—Evidence from the voluntary filing program. *Accounting Horizons* 25(2): 227–245.

Beneish, M. D. (1999). The detection of earnings manipulation. *Financial Analysts Journal* 55(5): 24–36.

Beneish, M. D., Lee, C. M., and Nichols, D. C. (2013). Earnings manipulation and expected returns. *Financial Analysts Journal* 69(2): 57–82.

Beneish, M. D., and Vorst, P. (2022). The cost of fraud prediction errors. *The Accounting Review* 97(6): 91–121.

Berger, A., and Hill, T. P. (2015). An introduction to Benford's law. Princeton University Press.

Blankespoor, E., Miller, B. P., and White, H. D. (2014). Initial evidence on the market impact of the XBRL mandate. *Review of Accounting Studies* 19: 1468–1503.

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

Boritz, J. E., and No, W. G. (2008). The SEC's XBRL voluntary filing program on EDGAR: A case for quality assurance. *Current Issues in Auditing* 2(2): A36–A50.

Boyle, E. S., Lewis-Western, M. F., and Seidel, T. A. (2021). Do quarterly and annual financial statements reflect similar financial statement error in the post-SOX era? *Journal of Financial Reporting* 6(1): 1–31.

Bushman, R., Chen, Q., Engel, E., and Smith, A. (2004). Financial accounting information, organizational complexity and corporate governance systems. *Journal of Accounting and Economics* 37(2): 167–201.

Calcbench. (2014). The quality of XBRL filings. Available at: https://www.calcbench.com/xbrldataquality

Chakrabarty, B., Duellman, S., and Hyman, M. A. (2020). A new approach to estimating the relation between audit fees and financial misconduct. *Accounting Horizons* 34(2): 41–61.

Chang, H. W., Kaszak, S., Kipp, P., and Robertson, J. C. (2021). The effect of iXBRL formatted financial statements on the effectiveness of managers' decisions when making inter-firm comparisons. *Journal of Information Systems* 35(2): 149–177.

Chen, C., Jia, H., Xu, Y., and Ziebart, D. (2022). The effect of audit firm attributes on audit delay in the presence of financial reporting complexity. *Managerial Auditing Journal* 37(2): 283–302.

Cheng, X., Masli, A., Walton, S., Wang, M., and Zhang, Y. (2024). iXBRL adoption and the pricing of audit services. *Journal of Information Systems* 38(3): 23–50.

Cox, C. (2008). Speech by SEC chairman: Remarks before the 2005 AICPA National Conference on current SEC and PCAOB developments. *U.S. Securities and Exchange Commission.* www.sec.gov/news/speech/spch120505cc.htm, 24-04.

Debreceny, R. S., Chandra, A., Cheh, J. J., Guithues-Amrhein, D., Hannon, N. J., Hutchison, P. D., Janvrin, D., Jones, R. A., Lamberton, B., Lymer, A., and Mascha, M. (2005). Financial reporting in XBRL on the SEC's EDGAR system: A critique and evaluation. *Journal of Information Systems* 19(2): 191–210.

Deckert, J., Myagkov, M., and Ordeshook, P. C. (2011). Benford's law and the detection of election fraud. *Political Analysis* 19(3): 245–268.

Dechow, P. M., Ge, W., Larson, C. R., and Sloan, R. G. (2011). Predicting material accounting misstatements. *Contemporary Accounting Research* 28(1): 17–82.

Doyle, J., Ge, W., and McVay, S. (2007). Determinants of weaknesses in internal control over financial reporting. *Journal of Accounting and Economics* 44(1–2): 193–223.

Du, H., Vasarhelyi, M. A., and Zheng, X. (2013). XBRL mandate: Thousands of filing errors and so what? *Journal of Information Systems* 27(1): 61–78.

Enofe, A., and Amaria, P. (2011). Extensible Business Reporting Language (XBRL): A new dimension in financial reporting. *International Journal of Business, Accounting and Finance* 5(1): 78–91.

Felo, A. J., Kim, J. W., and Lim, J. H. (2018). Can XBRL detailed tagging of footnotes improve financial analysts' information environment? *International Journal of Accounting Information Systems* 28: 45–58.

Feng, C., and Kim, C. (2021). Information processing costs and firms' investment efficiency: An examination of channels of the XBRL effect. *Journal of Information Systems* 35(3): 53–75.

Filzen, J. J., and Peterson, K. (2015). Financial statement complexity and meeting analysts' expectations. *Contemporary Accounting Research* 32(4): 1560–1594.

Golden, J. (2021). Local crime environment and corporate financial misconduct using Benford's law. *Journal of Forensic Accounting Research* 6(1): 436–460.

Guay, W., Samuels, D., and Taylor, D. (2016). Guiding through the fog: Financial statement complexity and voluntary disclosure. *Journal of Accounting and Economics* 62(2–3): 234–269.

Gunn, J. (2007). XBRL: Opportunities and challenges in enhancing financial reporting and assurance processes. *Current Issues in Auditing* 1(1): A36–A43.

Guo, F., Luo, X., Wheeler, P. R., Yang, L., Zhao, X., and Zhang, Y. (2021). Enterprise resource planning systems and XBRL reporting quality. *Journal of Information Systems* 35(3): 77–106.

Habib, A., and Jiang, H. (2015). Corporate governance and financial reporting quality in China: A survey of recent evidence. *Journal of International Accounting, Auditing and Taxation* 24: 29–45.

Hill, T. P. (1995). Base-invariance implies Benford's law. *Proceedings of the American Mathematical Society* 123(3): 887–895.

Hoitash, R., and Hoitash, U. (2018). Measuring accounting reporting complexity with XBRL. *The Accounting Review* 93(1): 259–287.

Hoitash, R., Hoitash, U., and Morris, L. (2021). eXtensible Business Reporting Language (XBRL): A review and implications for future research. *Auditing: A Journal of Practice and Theory* 40(2): 107–132.

Huang, F., No, W., and Vasarhelyi, M. (2019). Do managers use extension elements strategically in the SEC's tagged data for financial statements? Evidence from XBRL complexity. *Journal of Information Systems* 33(3): 61–74.

Huang, Y., Shan, Y. G., and Yang, J. W. (2021). Information processing costs and stock price informativeness: Evidence from the XBRL mandate. *Australian Journal of Management* 46(1): 110–131.

Jennings, J. N., Kim, J. M., Lee, J. A., and Taylor, D. J. (2020). Measurement error and bias in causal models in accounting research. *Available at SSRN* 3731197.

Karpoff, J. M., Koester, A., Lee, D. S., and Martin, G. S. (2017). Proxies and databases in financial misconduct research. *The Accounting Review* 92(6): 129–163.

Kassem, R. (2024). Beyond the numbers: Assessing the risk of management motives for fraud in external audits. *Journal of Accounting Literature.*

Kim, J. B., Kim, J. W., and Lim, J. H. (2019). Does XBRL adoption constrain earnings management? Early evidence from mandated US filers. *Contemporary Accounting Research* 36(4): 2610–2634.

Klimczak, K. M., Sison, A. J. G., Prats, M., and Torres, M. B. (2022). How to deter financial misconduct if crime pays? *Journal of Business Ethics* 179(1): 205–222.

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

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

Li, K., Mai, F., Shen, R., and Yan, X. (2021). Measuring corporate culture using machine learning. *The Review of Financial Studies* 34(7): 3265–3315.

Li, S., and Nwaeze, E. T. (2018). Impact of extensions in XBRL disclosure on analysts' forecast behavior. *Accounting Horizons* 32(2): 57–79.

Liu, C., Dai, H., and Lu, L. (2025). The watchful eye: How does the prominence of chief audit executives curb financial misconduct? *Journal of Forensic Accounting Research* 1–29.

Liu, C., Ryan, D., Lin, G., and Xu, C. (2023). No rose without a thorn: Corporate teamwork culture and financial statement misconduct. *Journal of Behavioral and Experimental Finance* 100786.

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

Lopez, D. M., and Peters, G. F. (2012). The effect of workload compression on audit quality. Auditing: A *Journal of Practice and Theory* 31(4): 139–165.

Luo, X., Wang, T., Yang, L., Zhao, X., and Zhang, Y. (2023). Initial evidence on the market impact of the iXBRL adoption. *Accounting Horizons* 37(1): 143–171.

McGuire, B. L., Okesson, S. J., and Watson, L. A. (2006). Second-wave benefits of XBRL. *Strategic Finance* 88(6): 43.

Mebane Jr, W. R. (2006, July). Election forensics: Vote counts and Benford's law. *In Summer Meeting of the Political Methodology Society*, UC-Davis, July (Vol. 17).

Nigrini, M. J. (1996). A taxpayer compliance application of Benford's law. *The Journal of the American Taxation Association* 18(1): 72.

Nigrini, M. J., and Mittermaier, L. J. (1997). The use of Benford's law as an aid in analytical procedures. *Auditing* 16(2): 52.

Peel, M. J. (2014). Addressing unobserved endogeneity bias in accounting studies: Control and sensitivity methods by variable type. *Accounting and Business Research* 44(5): 545–571.

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

Roberts, M. R., and Whited, T. M. (2013). Endogeneity in empirical corporate finance. In G. M. Constantinides, M. Harris, and R. M. Stulz (Eds.), *Handbook of the Economics of Finance* Vol. 2, pp. 493–572. Elsevier.

Rosner, R. L. (2003). Earnings manipulation in failing firms. *Contemporary Accounting Research* 20(2): 361–408.

Seavey, S. E., Whitworth, J. D., and Imhof, M. J. (2022). Early earnings releases and the role of accounting quality. *Auditing: A Journal of Practice and Theory* 41(3): 175–203.

Securities and Exchange Commission (SEC). (2009). Interactive data to improve financial reporting. Available at: http://www.sec.gov/rules/final/2009/33-9002.pdf

Securities and Exchange Commission (SEC). (2018). Inline XBRL filing of tagged data. Release Nos. 33-10514; 34-83551; IC-33139. Washington, DC: SEC. Available at: https://www.sec.gov/rules/final/2018/33-10514.pdf

Securities and Exchange Commission (SEC). (2020). Inline XBRL. Available at: https://www.sec.gov/structureddata/osd-inline-xbrl.html

Trompeter, G. M., Carpenter, T. D., Desai, N., Jones, K. L., and Riley, R. A. (2013). A synthesis of fraud-related research. *Auditing: A Journal of Practice and Theory* 32(Supplement 1): 287–321.

Valentinetti, D., and Rea, M. A. (2012). IFRS taxonomy and financial reporting practices: The case of Italian listed companies. *International Journal of Accounting Information Systems* 13(2): 163–180.

Velte, P. (2021). The link between corporate governance and corporate financial misconduct. A review of archival studies and implications for future research. *Management Review Quarterly* pp. 1–59.

Walton, S., Yang, L., and Zhang, X. (2021). XBRL tag extensions and tax accrual quality. *Journal of Information Systems* 35(2): 91–114.

Wang, S. (2023). Top management team functional diversity and management forecast accuracy. *Accounting Horizons* 37(3): 1–36.

West, S. G., Aiken, L. S., and Krull, J. L. (1996). Experimental personality designs: Analyzing categorical by continuous variable interactions. *Journal of Personality* 64(1): 1–48.

Wooldridge, J. M. (2005). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics* 20(1): 39–54.

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

Appendix I: Variable Definitions

AltmanZ	The Altman Z score calculated by following Altman (2018).
Benford_Score	The Benford's Score calculated by following Amiram et al. (2015). An illustration of the Score calculation is in Appendix II of this study.
Big4	Indicator variable equals to 1 if a firm used one of the Big 4 accounting firms (Compustat AU = 4/5/6/7) as auditor in a fiscal year, 0 otherwise.
Busy_Season	Indicator variable equals to 1 if a firm's fiscal year-end is December 31st, 0 otherwise.
iXBRL	Indicator variable equals to 1 if a firm had adopted the iXBRL format to report its financial statement online in a fiscal year, 0 otherwise.
Special_Item	Indicator variable equals to 1 if a company included a special item transaction (Compustat SPI) in its financial statement, 0 otherwise.
Foreign_Business	Indicator variable equals to 1 if a firm had any income generated by business outside the U.S. in a fiscal year, 0 otherwise.
ICMW	Indicator variable equals to 1 if a firm had an internal control material weakness disclosed in its audit report under SOX 404 (b), 0 otherwise.
Beneish_M	Indicator variable equals to 1 if a firm is identified to be financially distressed with a risk in committing financial misconduct (i.e., Beneish M-Score > -1.78), 0 otherwise.
Bus_Segment	Number of the total business segments a firm had in a fiscal year. Data from Compustat Historitical Segments.
Lev	Total long-term debt (Compustat DLTT) scaled by total assets of a firm at the end of a fiscal year.
Mtb	Market-to-book ratio calculated as the market value of a company's common equity (Compustat PRCC_F×CSHO) scaled by the book value of common equity (Compustat CEQ) at the end of a fiscal year.
Geo_Segment	Number of the total geographic segments a firm had in a fiscal year. Data from Compustat Historitical Segments.
Roa	A company's income before extraordinary items (Compustat IB) scaled by its total assets at the end of a fiscal year.
Extreme_Sales	Indicator variable if a firm's sales growth (based on Compustat Sale) is among the top 25-percentile of an industry in a certain fiscal year, 0 otherwise.
Size	The natural logarithm value of total assets (Compustat AT).
Analyst_Following	Number of the analysts following a firm at the end of a fiscal year. Data from I/B/E/S.
Loss	Indicator variable equals to 1 if a firm reported a loss (Compustat NI < 0) in a fiscal year, 0 otherwise.

Integrity_Score	A continuous variable developed by Li et al. (2021), measuring the level of a firm's integrity culture.
High_Benford	Indicator variable equals to 1 if a firm's Benford's Score is among the top 25-percentile of an industry in a fiscal year, 0 otherwise.
Restructuring	A firm's restructuring charge (Compustat RCP) scaled by its market capitalization (Compustat CSHO×PRCC_F) at the end of a fiscal year.
Total_Accrual	A firm's total accrual in a fiscal year based on the cash-flow method.
Extension%	The percentage of a firm's XBRL or iXBRL filing extension tags in a fiscal year's annual report.
Error	An indicator variable equals to 1 if a firm's XBRL or iXBRL filing of annual report includes one or more errors in a fiscal year, 0 otherwise.
log_All_Tags	The natural logarithm of the number of all tags set in a firm's XBRL or iXBRL annual report filling in a certain year.
log_Extension_Tags	The natural logarithm of the number of extension tags (the tags created by companies) set in a firm's XBRL or iXBRL annual report filling in a certain year.
log_Taxonomy_Tags	The natural logarithm of the number of taxonomy tags (the standard tags approved by FASB) set in a firm's XBRL or iXBRL annual report filling in a certain year.
IV_Teamwork	The score used as an instrumental variable in the 2SLS to measure corporate teamwork culture by following Li et al. (2021).
Benford_Score (predicted)	The predicted Benfords_Score in the 2SLS based on the instrumental variable of IV_Teamwork.

Appendix II: Calculation of Benford Score

Following Liu et al. (2025), we set Benford Score as the proxy of corporate financial misconduct. The Score reflects the deviation of financial statement data's leading digit distribution from the digits' theoretical distribution suggested by Benford's Law.

To obtain the digits' theoretical distribution of Benford's Law, we use the equation as below:

$P(d) = \log_{10}(1 + 1/d)$,
where d = 1, 2, …, 9, respectively. By applying the equation, the probability for "1" to serve as a leading digit in naturally generated datasets is about 30.10%, "2" is about 17.61%, …, and "9" is about 4.58%.

To obtain the Benford Score, we use the equation as below (Golden 2021):

$\text{Benford\_Score} = (\sum_{i=1}^{9} |AD - BD|i) / 9$,
where AD is the actual financial statements' leading digit distribution and BD is the theoretical leading digit distribution expected based on Benford's Law. The higher a firm's *Benford Score* is, the more likely that firm is engaged in financial misconduct.

For example, if 20% of a firm's financial statement leading digits are "1", 18% of the leading digits are "2", 15% are "3", 12% are "4", 10% are "5", 9% are "6", 7% are "7", 5% are "8", and 4% are "9". Because the theoretical distribution of leading digits of 1, 2, 3, …, 9 under Benford's Law are 30.1%, 17.6%, 12.5%, 9.7%, 7.9%, 6.7%, 5.8%, 5.1%, and 4.6%, this firm's *Benford Score* is 0.024; that is, (|20% – 30.1%| + |18% –17.6%| + |15% – 12.5%| + |12% – 9.7%| + |10% – 7.9%| + |9% – 6.7%| + |7% – 5.8%| + |5% – 5.1%| + |4% – 4.6%|) / 9.