DO MACHINE-READABLE DISCLOSURES FACILITATE REGULATORY SCRUTINY? EVIDENCE FROM SEC COMMENT LETTERS

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____ (Signed)

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ABSTRACT

This paper examines whether machine-readable disclosures facilitate Securities and Exchange Commission (SEC) scrutiny. Using firms' mandatory adoption of Inline XBRL (iXBRL), which significantly increases the machine readability of firms' financial reports, I find that the SEC is more likely to issue comment letters to firms mandated to adopt iXBRL compared to those not mandated following the adoption. Such an increase is greater when the SEC is in its busy season and under high workload pressure, suggesting that machine-readable filings improve the SEC's reviewing efficiency. Furthermore, I find that the comment letters sent to adoption firms cover more topics and that the SEC spends less time responding compared to those sent to non-adoption firms after the mandate. Collectively, my findings provide evidence that machine-readable disclosures enhance the SEC's efficiency in reviewing mandatory filings and facilitate regulatory scrutiny activities.

Keywords: Machine-readable disclosure; regulatory scrutiny; Inline XBRL; SEC comment letter
JEL Classifications: G14; G18; M41

1. INTRODUCTION

To facilitate its role in overseeing public firms' compliance with disclosure regulations, the Security and Exchange Commission's (SEC) Division of Corporate Finance (DCF) regularly reviews the filings of public firms and provides feedback and guidance to them in the form of comment letters. Prior studies find that the comment letter process plays a crucial role in ensuring a high-quality information environment for investors (e.g., Bens, Cheng, and Neamtiu 2016; Wang 2016; Ahn, Hoitash, and Hoitash 2020; Cunningham and Leidner 2022). However, the SEC has long been criticized for an inefficient compliance review process due to resource constraints (e.g., Richards 2009; Kedia and Rajgopal 2011; Gunny and Hermis 2020). With rapid developments in machine learning and the increasing use of machine-readable data in the recent decade, the SEC has implemented rules to transform some certain filings to be machine readable. The primary objective of machine-readable disclosure mandates is to improve the usefulness, timeliness, and quality of financial information to benefit investors and other market participants (SEC 2018). In this paper, I examine whether and how the SEC utilizes the recent surge of machine-readable disclosures to improve review efficiency.

I focus on SEC comment letters because they are one of the important scrutiny activities. Several studies document the benefits of SEC comment letters for scrutiny purposes. Johnston and Petacchi (2017) find that after firms receive SEC comment letters, these firms' information asymmetry is reduced. Cunningham, Johnson, Johnson, and Lisic (2020) provide evidence that the comment letter process improves firms' accounting quality by effectively constraining accrual-based earnings management. In addition, comment letters can mitigate firms' tax avoidance behavior (Kubick, Lynch, Mayberry, and Omer 2016). Given its importance in terms of regulatory scrutiny, the reviewing efficiency of the SEC has always caught attention (e.g., Ackerman 2011).[1] Prior studies find that the resource constraints of the SEC heavily impact regulatory efficiency (Kedia and Rajgopal 2011; Gunny and Hermis 2020).

With the rising importance of machine-readable data in recent years, I expect that the use of machine-readable data will allow for greater efficiency in conducting the filing review process and relieve SEC resource constraints, ultimately improving regulatory scrutiny. In its 2021 Examination Priorities Report, the SEC claims that the use of machines and machine-readable data will increase the efficiency of compliance staff and reduce manual processes (SEC 2021). In its

[1] For details, see https://www.wsj.com/articles/SB10001424053111904265504576566902841796640.

semi-annual report to Congress in June 2023, the SEC further illustrates the use of machine-readable data to lessen the burden of regulatory supervision, especially when making preliminary compliance assessments and issuing comment letters in connection with the reviews (SEC 2023a).

Given the growing importance of machine-readable disclosures, on June 28, 2018, the SEC adopted a new disclosure regulation called "Inline XBRL Filing of Tagged Data." This regulation mandates the use of the Inline eXtensible Business Reporting Language (Inline XBRL or iXBRL) format for public firms in the submission of financial statement information, including annual and quarterly financial reports (i.e., 10-K and 10-Q filings). The iXBRL format embeds machine-readable XBRL tags directly into HyperText Markup Language (HTML) documents. The utilization of a single-document reporting format simplifies the processing of financial reports for machine readers, requiring minimal efforts in data cleansing and restructuring.

Prior to the implementation of iXBRL, in April 2009, the SEC initiated the *Interactive Data to Improve Financial Reporting Rule*, which mandates that companies file XBRL documents in addition to their current filings. The XBRL mandate requires firms to tag financial statement elements. Tagging is the process of identifying each financial statement element and linking it to descriptive information (Blankespoor, Miller, and White 2014). Compared to the 2009 XBRL mandate, iXBRL is more suitable for my research setting for several reasons. First, iXBRL improves the overall machine readability of financial disclosures. The XBRL mandate primarily makes numbers in financial statements more machine-readable (Blankespoor 2019), while the iXBRL mandate makes both quantitative and qualitative information more machine-readable (Workiva 2023; Bas Groenveld 2024) and improves the overall machine readability of financial reports (Call, Wang, Weng, and Wu 2023).[2]

Second, the iXBRL mandate improves the data quality by reducing the XBRL tagging and filing errors that impair machine readability (Allee, DeAngelis, and Moon 2018). Thirdly, the unique and unprecedented function of iXBRL, the topic search function, helps the users identify all items related to disclosure topics of interest. This may reduce search time for DCF when they conduct the filing review process. Lastly, big data and machine learning technologies have developed explosively in the recent decade. Machine readers have become much more common

[2] Reference link: https://www.youtube.com/watch?v=dE_LQRUDdGM and https://support.workiva.com/hc/en-us/community/posts/15797032475028-Insider-Trading-Arrangements-Quarterly-Disclosure-and-Tagging-Requirements-Are-you-Ready.

and impactful in the 2020s, with the implementation of iXBRL, than they were in 2009, when XBRL was implemented.

Given that the iXBRL provides an exogenous shock to the machine-readable financial reports, I utilize it as my identification strategy. The iXBRL mandate was implemented gradually over three dates, each one year apart. My treatment group consists of large accelerated filers and control group consists of other domestic filers, including accelerated filers and other filers.[3] The large accelerated filers are mandated to adopt iXBRL in the first phase-in date (i.e., June 15, 2019) while the other filers are mandated in the following years (i.e., accelerated filers on June 15, 2020 and other filers on June 15, 2021). My sample spans four quarters before and four quarters after the first phase-in date. I find that the SEC is more likely to issue comment letters to treatment firms whose corporate disclosures are more machine-readable due to iXBRL, relative to control firms that are not subject to iXBRL in my sample period. Compared to control firms, the probability of the SEC issuing a comment letter to treatment firms increases by 52% following iXBRL adoption. My parallel trend analysis confirms that this effect is not driven by any differences in pre-treatment trends between treatment and control firms. My results are robust to an alternative regression model, alternative measures of SEC scrutiny, and a regression discontinuity design (RDD). My findings indicate that machine-readable disclosures increase the SEC's likelihood of issuing comment letters.

I argue that machine-readable data improves the SEC's review efficiency by relieving the resource constraints of the SEC. To validate this argument, I provide further cross-sectional analyses using two proxies for SEC efficiency. My first measure is an indicator variable for the SEC's busyness if the firm has a December fiscal year end (Gunny and Hermis 2020; Lerman, Steffen, and Zhang 2022). The SEC experiences a significant surge in workload after December, as December is the fiscal year-end for most firms. The seasonally compressed working schedule puts the SEC under high workload pressure, making it less efficient with limited resources (Ege, Glenn, and Robinson 2020; Gunny and Hermis 2020). Secondly, I use the number of firms allocated to each SEC industry office as another proxy for SEC efficiency (Ege et al. 2020; Pan 2023). As companies are allocated to each SEC industry office based on their four-digit standard

[3] Large accelerated files are defined as those large firms with an aggregate worldwide public float of at least $700 million, while Accelerated files are defined as those firms with an aggregate worldwide public float between $75 million and $700 million.

industrial classification (SIC) code, some offices have more firms to review than others. The imbalance in firm distribution further exacerbates the problem of resource constraints. I conjecture that, after iXBRL adoption, SEC staff can utilize machine-readable disclosures to automate information processing (e.g., information extraction and preliminary assessments) and leverage reviewing efficiency. Consistent with my expectations, I find that the machine-readable disclosures offer greater benefits to the SEC regulatory process when the SEC is busier and when the firms are reviewed by busier industry offices.

I further explore comment letter characteristics to shed light on the improved efficiency of the comment letter review process after the iXBRL mandate. I find that the SEC issues more comment letters, raises more issues in each comment letter, and mentions more accounting and non-accounting topics for treatment firms after the regulation. In addition, it takes less time for the SEC to initiate comment letters after treatment firms file their financial reports. These results indicate that machine-readable disclosures help the SEC expand the scope of its filing reviews, allowing the SEC to identify more deficiencies and instances of non-compliance, thus increasing overall review efficiency.

One may argue that the machine-readable disclosure mandate affects financial reporting quality, which consequently affects the probability of issuing a comment letter. I provide further tests to examine the plausibility of this alternative explanation. Using the absolute value of total accruals as a measure of financial reporting quality, I find that financial reporting quality does not change significantly after the iXBRL mandate. I also provide a cross-sectional test by partitioning the sample into high and low financial reporting quality groups. I find that my main finding holds for both groups, with no statistical differences between the two groups. Overall, I do not find supportive evidence for this alternative explanation. I also rule out the impact of financial statement comparability and reduced human readability explanations in the analysis.

This paper contributes to the literature in two ways. First, it contributes to the literature on the determinants of comment letter issuance. Previous literature mainly focuses on two streams of determinants. One stream investigates firm characteristics, corporate governance characteristics, and accounting disclosure characteristics (Ertimur and Nondorf 2006; Cassell, Dreher, and Myers 2013; Heese, Khan, and Ramanna 2017; Nam and Thompson 2023). Another stream focuses on the SEC, finding that the SEC resource constraint is an important factor negatively affecting the efficiency of SEC scrutiny (Kedia and Rajgopal 2011; Gunny and Hermis 2020). My paper is closely related to the second stream of studies. I show that machine-readable data significantly facilitates the SEC review process and increases its scrutiny efficiency. My paper provides empirical evidence that machine-readable disclosures have the potential to improve SEC regulatory efficiency and benefit enforcement activities (Stein 2018; Azevedo 2024).[4]

Second, this paper contributes to the emerging literature on machine-readable reporting. Prior literature finds that machine-readable disclosures benefit investors, markets, and issuers. Machine-readable data reduces information asymmetry (Luo, Wang, Yang, Zhao, and Zhang 2023), improves information efficiency (Barbopoulos, Dai, Putniņš, and Saunders 2023), and improves managers' decision making (Chang, Kaszak, Kipp, and Robertson 2021). All these papers consider SEC as the providers and regulators of machine-readable disclosures, while less papers investigate how the SEC uses the machine-readable data to facilitate their regulatory activities. My paper provides fresh evidence that machine-readable data increases the efficiency of the SEC's scrutiny. Different from Deng (2023), which examines the effect of the SEC regional office's use of data analytics on the success rate of investigations, I focus on the effect of machine-readable disclosures. I argue that machine-readable data provides more opportunities for data analytics talent to incorporate their skills into the filing review process. My study has important practical and policy implications for the SEC's continuing efforts to improve regulatory scrutiny effectiveness and achievement of the objective of the filing review process.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Institutional Background

In response to the public urge for high-quality disclosures after the Enron accounting fraud, the U.S. SEC requires that companies' periodic filings (e.g., 10-K and 10-Q) be reviewed at least once every three years (Cunningham and Leidner 2022). The DCF is responsible for overseeing the filing review process (SEC 2015). Comprising nine industry offices as of September 9, 2022,

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[4] Reference link: https://www.sec.gov/news/public-statement/statement-stein-xbrl-062818 and https://news.bloomberglaw.com/bloomberg-law-analysis/analysis-secs-data-tagging-will-ensnare-companies-next-year.

each DCF unit is responsible for reviewing firms in a specific industry, as classified by their four-digit SIC codes.

As a part of its budget-making process, the DCF establishes a schedule at the start of each year, detailing which companies will undergo review and the timing of review. The SEC sets priority for the selection of filing reviews with discretion. Section 408, paragraph (b), of the Sarbanes-Oxley (SOX) Act of 2002 identifies five specific criteria and one catch-all provision to consider if scheduling reviews more frequently than once every three years. In addition to the risk factors explicitly stated in Section 408 of the SOX Act, firms with lower profitability, higher complexity, that engage a small audit firm, and have weakness in governance are to be reviewed more frequently (Cassell et al. 2013). Transactional filings (e.g. Form 8-K) undergo selective review, but the determinants of said reviews remain undisclosed by the SEC.

The review process comprises screening and examination phases. During the screening phase, SEC staff determines the scope of the filing review with discretion. The scope of a review may be (i) a full cover-to-cover review in which the SEC staff examines the entire filing in detail; (ii) a financial statement reviews in which the SEC staff examines financial statements and related disclosures; or (iii) a targeted issue review in which the SEC staff examines the filing for one or more specific items of disclosure (Barron, Kile, and O'keefe 1999; SEC 2007). During the examination phase, the SEC staff evaluates the disclosure from the perspective of a potential investor (SEC 2019). If a filing review reveals any potential accounting violations or material deficiencies, the DCF will issue a comment letter requesting additional information, recommending a disclosure revision to the current filings, or requesting an amendment to change disclosures or accounting applications in future filings. Firms are required to respond to comments and questions posed by the regulators within ten business days of receiving the initial comment letter. The comment letter process can span several rounds of communication between the SEC and the company to sufficiently address concerns and ensure compliance.

During the comment letter process, the firm is expected to address and remediate the issues raised by the SEC. Management often works with lawyers and auditors to provide one of the following responses: (i) the company provides supplementary information required by the SEC to clarify or justify their disclosure choice or accounting methods; (ii) the company commits to implementing future changes to its disclosures or accounting applications on a prospective basis, often providing the precious language or applications that will be used when filing the related amendment in the response letter; or (iii) the company agrees to amend a previous filing(s), providing the exact language that will be used in the related amendment in the response letter. If the SEC is unsatisfied with the firm's response, it can issue a follow-up comment letter to the firm, and the company will again be asked to respond within ten business days or to provide an alternative timeframe. Once the DCF is satisfied with the company's responses, they will issue a no-further-comment letter to indicate the closure of the filing review process. All filing review-related correspondence is publicly available on EDGAR.

2.2. Literature Review

The SEC's DCF reviews corporate disclosures filed with the SEC to facilitate the Commission's role in regulating U.S. capital markets. Upon identifying accounting, disclosure, or legal concerns in these filings, SEC reviewers send firms a comment letter requesting additional information or adjustments to their current or future filings. Therefore, the comment letter process is an important mechanism through which the SEC carries out its oversight activities.

Prior literature examines the determinants of issuing a comment letter from various perspectives. Many studies suggest that the issuance of a comment letter is associated with specific firm characteristics, such as operational risks, profitability, corporate governance, and senior management. Ertimur and Nondorf (2006) find that firms with highly skilled CFOs are less likely to receive a comment letter because managers who hold a higher level of financial reporting expertise are able to better anticipate comments and have an improved ability to negotiate with the SEC. Johnston and Petacchi (2017) build a model comprising the criteria in SOX Section 408 to investigate factors affecting the probability of issuing a comment letter on a 10-K/10-Q filing. Larger, older, and more volatile companies, and those making restatements or amendments, issuing new securities, or engaging non-Big4 auditing firms, are more likely to receive a comment letter. By adding additional factors, Cassell et al. (2013) find that firms with low profitability, high operating complexity, and weaknesses in corporate governance, as well as those who engage small audit firms, are more likely to receive a comment letter. Heese et al. (2017) reveal that political connections positively predict comment letter reviews and the intensity of the reviews, suggesting that the DCF staff may actively target politically connected firms in the filing review process.

Moreover, Nam and Thompson (2023) find that the SEC's ex-ante knowledge about the comparability of financial statements increases the likelihood of issuing a comment letter.

In addition to firm characteristics, the resources and abilities of the SEC staff also affect the issuance of the comment letters. Kedia and Rajgopal (2011) find that the SEC is more likely to investigate firms located near its regional offices because of the reduced travel time and greater familiarity with and knowledge about nearby firms. In using SEC office case backlog as a proxy for resource constraints, Bonsall, Holzman, and Miller (2023) find that a high office case backlog decreases the likelihood of investigating a restating firm. Ege et al. (2020) find that comment letters for periodic reports (i.e., 10-K and 10-Q) are of lower quality when the SEC has an abnormally high quantity of transactional filings to review. Furthermore, Gunny and Hermis (2020) find that the SEC issues fewer comment letters during busy periods. When resources are limited such as when they are seasonably compressed, the SEC focuses on the most severe noncompliance cases. These studies suggest an association between SEC resource constraints and the issuance and quality of comment letters.

With the advancement of machine learning technology and the widely use of machine-readable data, the SEC has started to utilize machine technology and machine-readable data to increase the efficiency of reviewing filings (SEC 2023a). As suggested by organizational theory, organizational adoption represents changes made to cope with new environments (Thompson 1967). As filings awaiting review become increasingly machine-readable, it is reasonable that the SEC changes its workflow. For example, the SEC documents how the DCF staff uses machine-readable data to make preliminary compliance assessments and issues comment letters in connection with the reviews, accessing certain key data points, such as financial data, audit-related information, and other non-financial data for filling firms (SEC 2023a). This streamlined approach enables SEC staff to extract and analyze data more efficiently, reducing the time and effort required for data validation. Secondly, the first appearance of the topic search function of iXBRL reduces the searching time of SEC staff. Staffs can use the topic search function to identify all items that relate to certain disclosure topics. Lastly, the application of the iView tool largely increases working efficiency. iView leverages the open-source, freely and publicly available Inline XBRL Viewer. iView includes various filters and query capabilities, such as the identification of disclosures with custom tags (i.e., filers creating tags instead of using standard tags) and the sorting of machine-readable data by scale (e.g., amounts in thousands, millions, or billions). These evidences collectively suggest that machine-readable disclosures are used by the SEC to assist its regulatory activities. In my paper, I aim to investigate how the SEC utilizes machine-readable data to improve its workflow and scrutiny efficiency. I specifically examine how the application of the machine-readable requirements for periodic filings impacts comment letter issuance.

2.3. Hypothesis Development

I focus primarily on two aspects of SEC scrutiny efficiency: busyness and workload pressure. Several studies suggest that busyness, or workload compression, has a detrimental effect on the outcomes of financial professionals. López and Peters (2012) find that audit quality is lower when auditors are busy because busy auditors often have dysfunctional outcomes, such as impaired professional judgments. Tanyi and Smith (2015) find that a board member's capacity to oversee financial reporting decisions is compromised due to the demanding workload resulting from serving on multiple audit committees, meaning that firms with busy audit committee chairs or busy financial experts have significantly lower financial reporting quality. These studies suggest that busyness can lead to potential dysfunctional outcomes and impair professional oversight.

The problem also exists in the filing review process. Due to resource constraints, the SEC staff is under high workload pressure. While the DCF's budget rose from $145,755,000 to $156,611,000 from 2018 to 2020, the budget decreased as a proportion of total market capitalization, from 0.032% to 0.026%, meaning that the DCF budget cannot fully support its efforts in the filing review process. In addition to monetary resource constraints, the DCF also faces human capacity constraints. The total number of filings received by the SEC increased from 652,265 in 2018 to 732,995 in 2020.[5] However, the number of DCF staff remained around 400, meaning filings per staff member increased from 1,631 to 1,832 over the three years. The resulting resource constraints impose significant workload pressure upon DCF staff (Ramonas 2022), worsening during the SEC's busy season. These constraints can lead to dysfunctional outcomes, such as an inability to thoroughly investigate potential violations, decreasing the reviewing efficiency and quality of the DCF (Ege et al. 2020).

[5] I obtain the DCF budget data from data from the SEC's periodic budget reports available on the website https://www.sec.gov/reports?field_article_sub_type_secart_value=Reports+and+Publications-BudgetReports. In addition, I obtain the filings review data from https://www.sec.gov/dera/data/dera_edgarfilingcounts.

Prior studies find that machine-readable data is useful for lightening workloads and leveraging working efficiencies. Coderre (2009) finds that data analysis techniques improve internal audit efficiencies by reducing overall SOX Act compliance costs and expanding the scope and reliability of audit tests. In addition, machine-readable data enhances efficiency and accessibility, enabling financial analysts to incorporate more data into their analysis and follow more companies (Liu, Wang, and Yao 2014). Improved accessibility and quality make information acquisition less costly and thus stimulate the analyst forecast (Roulstone 2003).

The SEC is driving forward the adoption of machine-readable financial disclosures given its potential to improve regulatory efficiency. Machine-readable data is driving the emergence of "RegTech," making compliance and regulatory-related activities easier, faster, and more efficient (Bauguess 2017). The SEC's 2021 Examination Priorities Report indicates that the Division of Examinations uses data analytics to prioritize examination candidates and further analyze information collected during inspections. In June 2023, the SEC's semi-annual report to Congress further illustrated the use of machine-readable data to lessen the burden of regulatory supervision, especially when making preliminary compliance assessments. The DCF staff, for example, uses several items of machine-readable data that appear on the cover pages of registrants' annual reports (Forms 10-K, 20-F, and 40-F) to identify, count, sort, compare, and analyze registrants and their disclosures (e.g., to more readily and accurately identify issuers that are listed on a specific exchange or that have identified themselves as well-known seasoned issuers). In addition, the groundbreaking topic search function in iXBRL reduces the searching time for relevant contents for a specific topic (SEC 2024).[6] The filtering function allows users to quickly identify all amounts that are tagged as negative in XBRL. When the SEC staff combine different filters, they will be able to quickly find potential data errors. This evidence indicates that the use of machine-readable disclosures is helpful for optimizing the SEC's limited resources and developing more effective and efficient enforcement programs (Clayton 2019; White 2016).

In my study, I anticipate a positive relationship between machine-readable disclosures and the likelihood of the issuance of a comment letter. I expect that the SEC will utilize the machine-

[6] Reference link: https://www.sec.gov/structureddata/osd-inline-xbrl.html, accessed in March 2024.

readable financial disclosure information to relieve resource constraints and improve review efficiency by the SEC staff in two ways.

First, machine-readable data relieves the seasonally compressed workload. Gunny and Hermis (2020) find that firms' fiscal year-ends tend to cluster around December; by extension, the SEC DCF offices are at their busiest when firms file their periodic reports. The seasonality of fiscal year-ends could motivate the DCF offices to review fewer filings or reduce the extent of their review. If the filings are more machine-readable, however, the DCF staff can use automated processes to facilitate faster data extraction, analysis, and identification of potential compliance issues (SEC 2023a), thus enhancing the efficiency of the review process during the busy season. Second, machine-readable filings relieve the resource constraints that affect the SEC's filing review process. Blackburne (2014) finds that when the SEC allocates greater financial resources (i.e., budgetary dollars) to a specific DCF office, the financial reporting quality of firms assigned to that office improves. In a recent study, Ege et al. (2020) use an influx of initial public offering (IPO) and acquisition transactional filings as a proxy for resource constraints to investigate their impact on periodic filing reviews. Unexpected resource limitations are found to diminish the overall quality of comment letters for periodic reports. These studies collectively indicate that resource constraints significantly influence the SEC's filing review process and enforcement activities. Machine-readable corporate filings have the potential to alleviate the resource burden of regulatory oversight by enabling preliminary compliance assessments (SEC 2023a). This largely releases the resource constraints of the DCF staff, who can then further assess filings based on the preliminary assessment results. Based on the SEC efficiency mechanism, I make the following prediction:

> ***Hypothesis:*** *There is a positive relation between machine-readable level of corporate filings and the likelihood of receiving comment letters from the SEC.*

Although I expect a positive relationship between machine-readable disclosures and the issuance of comment letters, I acknowledge that the iXBRL adoption has the potential to improve financial reporting quality, thus decreasing the likelihood of comment letter issuance. Basoglu and White (2015) argue that iXBRL is a technical solution for improving the quality of SEC filings, including enhanced data quality and usefulness. In the UK, for instance, firms submit tax returns, which consist of financial accounts and calculations, in the machine-readable iXBRL format, enhancing the quality and usefulness of the filings. It is possible that, following the adoption of the iXBRL format in the US, firms will receive fewer comment letters from the SEC due to the increased financial reporting quality brought by the increase in machine-readable disclosures. Moreover, I further rule out financial statement comparability and reduced human readability in later analysis. These opposite prediction makes my research question an empirical question.

3. METHODOLOGY AND DATA

3.1. Inline XBRL Adoption

To examine the effects of enhancements in the machine-readable disclosures to the issuance of comment letters, I utilize the setting of adoption of Inline XBRL Filing of Tagged Data regulation. The regulation was adopted on June 28, 2018, and creates an exogenous increase in the machine readability of annual and quarterly financial reports (i.e., 10-K and 10-Q filings). The regulation requires the use of the iXBRL format, which integrates machine-readable XBRL data tags directly into HyperText Markup Language (HTML) documents. The adoption of a single-document approach makes HTML-based main filings easier for machine readers to process in three ways. First, iXBRL requires firms to transform their HTML-based filings into a stricter and more standardized XHTML format. XHTML's predictable structure and simplified machine parsing reduce errors and ambiguity during the parsing process. Second, unlike XBRL exhibits, which only offer isolated data items with tags chosen at firms' discretion, iXBRL tags are surrounded by supporting XHTML tags and context. This allows machine readers to utilize information from custom tags more effectively and process the context accurately. Third, iXBRL mitigates errors in reading numbers in two separate filings by creating a single, consistent file. Therefore, the SEC’s iXBRL regulation introduces a positive shock to the machine readability of financial reports.

The regulation phased in compliance for firms based on their filer category, which is primarily determined by the market value of shares (i.e., public float) of common equity held by non-affiliates. U.S. filers were phased in over a three-year period. Large accelerated filers with a worldwide public float of at least $700 million were obligated to comply by the fiscal period ending on June 15, 2019. Accelerated filers with a worldwide public float between $75 million and $700 million, had a compliance deadline of June 15, 2020. Other filers were required to comply by June

15, 2021. In Figure 1, Panel A provides a timeline illustrating the compliance dates for these different categories of firms.

[Insert Figure 1 here]

3.2. Model and Variables

To examine the effect of machine-readable disclosures on the issuance of comment letters, I estimate the following difference-in-differences (DiD) regression model using the iXBRL regulation:

$$\Pr(Comment\_Letter_{it}) = \alpha + \beta Treat \times Post + \theta Controls_{it} + Firm\ FE + Time\ FE + \varepsilon. \quad (1)$$

Following prior literature, *Comment_Letter* is an indicator variable set equal to one if a firm *i* received a comment letter related to its 10-K/Q filings with fiscal quarter ending at time period *t*. *Treat* equals one if the firm is a large accelerated filer (i.e., public float ≥ $700 million) and zero otherwise. *Post* equals one if the fiscal quarter end is after June 15, 2019, and zero otherwise.

Controls is a vector that includes a set of variables associated with the issuance of a comment letter following prior literatures. Firstly, I include several factors related to SOX Section 408. I set *Internal_Control_Weakness* (*Restatement*) equal to one if the firm has ever reported a material weakness (issued a restatement) in recent three fiscal years. I also set an indicator variable equal to one if a firm is in the highest quartile of the distribution of volatility of abnormal stock returns, denoted *High_Volatility*. Secondly, prior research finds that probability of receipt of comment letter is higher for larger, older, and more profitable firms (Doyle, Ge, and McVay 2007; Cassell et al. 2013). Thus, I include firm size *Ln(MarketCap),* a firm's age *(Firm_Age)*, a loss indicator *(Loss).* I also include an indicator proxy for financial distress *(BankruptcyRank),* as financially distressed companies are more likely to violate GAAP (Dechow, Sloan, and Sweeney 1996; Brazel, Jones, and Zimbelman 2009). Cassell et al. (2013) find that the complexity of a company increases the likelihood of being reviewed. I therefore include sales growth *(SalesGrowth),* the number of reported operating segments *(Segments),* an indicator for merger and acquisition activity *(M&A),* an indicator for restructuring chargers *(Restructuring),* a proxy for management's plans to issue new equity or debt securities *(ExtFinancing),* and an indicator variable for companies in highly litigious industries (*Litigation_industry*).

Thirdly*,* I include an indicator variable if a firm is audited by a Big 4 firm (*Big4*) or a second-tier audit firm (*Second_Tier*), as Big 4 firms and second-tier audit firms are more likely to provide high-quality audits due to higher reputation concerns (DeAngelo 1981). As an additional auditor characteristic, I include the number of consecutive years during which the auditor has audited the company *(Audit_Tenure),* which could impact the financial reporting quality due to auditor learning impaired independence (Geiger and Raghunandan 2002; Myers, Myers, and Omer 2003). Fourthly, I include an indicator if the CEO is the chairman of the board of directors (*CEO_Chair*), as firms with weaker corporate governance will have a higher probability to receive a comment letter (Cassell et al. 2013). In addition, I include the number of analysts following the firm (*Analyst*), as Zang (2012) finds that firms will have higher earnings management incentives when they face pressure from analysts. Lastly, I include a natural logarithm of the net file size in bytes of the SEC EDGAR "complete submission text file" for the 10-K/Q filing (*Ln(NetFileSize)*) as a proxy for information communication effectiveness and the extent of information processing effort (Loughran and Mcdonald 2014). All continuous variables are winsorized at the 1st and 99th percentiles. Appendix A contains the variable definitions.

Since the DiD design does not necessitate the treatment and control groups to possess similar characteristics, in addition to controlling for firm size, I also control for firm fixed effect to control for any time-invariant effects. These controls are important given that the first mandate of iXBRL applies only to larger firms. In addition, I control for time fixed effects. Since the mandating date of iXBRL happened at the last month of second quarter (i.e., June), I define time fixed effects as equal-length time periods (i.e., 3-month) before and after the adoption date instead of the natural quarter. Specifically, I define firms with fiscal quarter end in June, July, and August of 2018 as *Pre4*, firms with fiscal quarter end in September, October, and November of 2018 as *Pre3,* firms with fiscal quarter end in December 2018, January, and February of 2019 *as Pre2,* and firms with fiscal quarter end in March, April, and May of 2019 *as Pre1.*Similarly, I define firms with fiscal quarter end in June, July, and August of 2019 as *Post1,* firms with fiscal quarter end in September, October, and November of 2019 as *Post2,* firms with fiscal quarter end in December 2019, January, and February of 2020 *as Post3,* and firms with fiscal quarter end in March, April, and May of 2020 *as Post4*.[7] I use conditional logistics regression in my analysis. I do not use conventional logistic regressions due to the incidental parameters problem after including firm fixed effects (Allison, 2005, 2009; Kim, Li, and Zhang 2011; Useche, Miguelez, and Lissoni 2020).

The unit of my analysis is the firm-fiscal quarter level. I examine both quarterly and annual financial reports, namely 10-Q and 10-K filings. The coefficient of *Treat* and *Post* are subsumed by firm fixed effects and time fixed effects. Therefore, I report only the coefficient on *Treat*×*Post*. I correct the standard errors by clustering at the firm level.

3.3. Data, Sample, and Summary Statistics

I obtain 10-K/Q filings and firms' public float values from EDGAR.[8] The comment letter data is from Audit Analytics. Financial statement information is from Compustat. The analyst following data is from I/B/E/S, while corporate governance data is from ExecuComp. I begin identifying my sample by selecting all firm-quarter observations in Compustat with valid PERMNO-GVKEY-CIK identifiers from June 2018 to May 2020. I delete firms that change their filer categories during the sample period (e.g., from large accelerated filers to accelerated filers or vice versa) because I cannot know exactly when they were mandated to adopt iXBRL. Next, I delete firms that voluntarily adopt iXBRL (i.e., large accelerated filers that adopt iXBRL before June 15, 2019, and accelerated filers and other filers that adopt before June 15, 2020). In addition, I delete observations without sufficient data for calculating variables in my main analysis. Appendix B shows the sample selection process.

My final sample contains 19,904 firm-quarter observations. Table 1 presents the summary statistics for the variables described above. About 45 percent of the firms in my sample are treatment firms. On average, 2.5 percent of the firm-quarter observations have received a comment letter related to its 10-K/Q filings from the SEC in time period *t*.[9] The values of most of the control variables are comparable to those reported in Heese et al. (2017).

[7] In untabulated test, I define the time fixed effects using the natural quarters and include *Post* in my main analysis. The result remains.

[8] Specifically, I search the following regular expression in 10-K/Q filings to get the public float: r'\<dei\:entitypublicfloat.*?dei\:entitypublicfloat'.

[9] Previous literature finds that 10% to 30% of firms' 10-K or 10KSB received comment letters. In my setting, the quarterly percentage of 10-K/Q received comment letters is 2.5%. If I aggregate at the fiscal year level, I get 2.5%×4=10%.

[Insert Table 1 here]

4. EMPIRICAL ANALYSES AND RESULTS

4.1. Main Analyses

Table 2 shows the results of estimating Equation (1). In Column (1), I include control variables but do not include firm fixed effects and time fixed effects, and in Column (2), I include control variables and firm fixed effects and time fixed effects. I find that in Column (1), the coefficient estimates on *Treat×Post* is significantly positive with a *z-statistic* of 3.45. In terms of control variables, I find that firms with weak financial health, have previous restructuring charges, and operate in litigated industries will have a higher probability of receiving a comment letter.

[Insert Table 2 here]

Consistent with my hypothesis, the coefficient on *Treat×Post* in Column (2), my baseline specification, is 1.074 and significant at the 1 percent level, which means that the probability of treatment firms receiving a comment letter increases by 52% after the adoption of iXBRL.[10] Regarding the control variables, I find that older firms may be subject to increased scrutiny in the review process due to their large size. *Ln(NetFileSize)* are significant and positive in both columns, indicating that length of 10-K/Q filings represents effort in processing the filings. The use of machine-readable data helps the DCF staff detect material deficiencies in financial reporting, indicating the SEC's investment in machine-readable disclosures benefits the regulatory scrutiny process.

My DiD design assumes that the treatment and control firms have parallel trends of *Comment_Letter* if the adoption of iXBRL does not occur. To test the validity of my empirical strategy, I incorporate several time indicators for quarters before and after the compliance date in my DiD design. Specifically, in Table 3, *Pre3+, Pre2*, *Pre1*, *Post1*, *Post2*, *Post3+* equal one if the fiscal quarter ends in November 2018 or before, February 2019, May 2019, August 2019, November 2019, February 2020 or after, respectively, and zero otherwise. Due to my limited sample in the *Pre4* and *Post4* periods, I aggregate *Pre3* and *Pre4* into *Pre3+*, and *Post3* and *Post4*

[10] I calculate the 52% following the instructions from Stata. Available at: https://www.stata.com/features/overview/marginal-analysis/. The command calculates the absolute marginal changes after the iXBRL adoption.

into *Post3+*. *Pre3+* is the benchmark, so it is omitted in the regressions.[11] All other specifications remain the same.

In Table 3, Column (1), I add indicators only for the pre-treatment period. In Column (2), I add indicators for both the pre-treatment and post-treatment periods. For both Column (1) and Column (2), the coefficients on *Treat*×*Pre2*, and *Treat*×*Pre1* are insignificant, indicating that the parallel trend assumption is satisfied. In Column (1), the coefficient on *Treat*×*Post* is significantly positive at the 5 percent level (*z-statistic*=2.23). In Column (2), coefficients on *Treat*×*Post2* and *Treat*×*Post3+* are positive and significant at the 10 percent and 5 percent level, suggesting that machine-readable data starts to help the DCF staff in reviewing the corporate filings one period after the adoption of iXBRL. The coefficient on *Treat*×*Post1* is insignificant, probably due to the time-lag effect. After the adoption of iXBRL, the DCF staff needs some time to adjust into a new workflow method that utilize the machine-readable disclosures.

[Insert Table 3 here]

4.2. Mechanisms

4.2.1. SEC Busyness

I argue that machine-readable corporate filings enable the DCF staff to review more filings within the same timeframe, hence significantly enhancing their efficiency in conducting the review process during the peak time. I use a binary variable set equal to one if the firm has a December fiscal year end and zero otherwise (Gunny and Hermis 2020). I find that 80 percent of firms in my sample have a December fiscal year end. I define a *High* group if the firm has a December fiscal year end, and a *Low* group if the firm has a fiscal year end in any other month. As shown in Columns (1) and (2) of Table 4, the coefficient on the variable of interest for the high-busyness group is positively significant at the 5 percent level (coefficient=0.953, *z-statistic*s=2.11) while the one for the low-busyness group is insignificant (coefficient=0.664, *z-statistic*s=0.87). Importantly, the difference is statistically significant at the 10 percent level (*p*-value=0.052), indicating that machine-readable data is more helpful for SEC staff to identify noncompliance concerns during busy season when the SEC faces more resource constraints.

[Insert Table 4 here]

[11] My inferences remain the same if I use another pre-treatment period, *Pre1*, as a benchmark.

4.2.2. SEC Workload

Apart from the clustered filings review, the SEC also faces an overload arising from more and more corporate filings every year (GAO 2002; SEC 2023b; SEC 2024). The efficacy of enforcement and comment letter quality are highly deteriorated by the high workload. I expect that machine-readable disclosures are more helpful for staff in DCF offices confronted by heavy workloads than staff occupying less burdened offices. I use the number of firms assigned to each DCF office as a proxy for the workload (Ege et al. 2020; Pan 2023).[12] The more firms assigned to one office, the higher the workload for that office. Since each DCF office is responsible for discrete industries, I define firm *i* is in *High* workload group if its industry corresponds to a DCF office overseeing a filing volume exceeding the median for all such offices in *Pre1*. The coefficient for firms in the *High* workload group (1.650) in Column (3) of Table 4 is larger than for firms in the *Low* workload group (0.394) in Column (4), and the difference is significant at the 10 percent level. This indicates that the beneficial effect of machine reading is more clustered in the SEC staff who have higher workloads.

In sum, the machine-readable disclosures assist the DCF staff by enhancing their productivity during busy periods and freeing up human resources when workloads are heavier. This improves the efficiency of SEC and enhances the likelihood of identifying material deficiencies.

4.2.3. Comment Letter Characteristics

I further explore detailed comment letter characteristics to shed more light on the nature of the reviewing process and examine whether the machine-readable filings improve the review process. I include several comment letter characteristics variables following previous literature (Cassell et al. 2013; Cassell, Cunningham, and Lisic 2019). I first examine the number of comment letters issued by the SEC for each 10-K/Q filing. In addition, I explore whether the SEC uses machines to help them expand the scope of deficiencies in financial reporting. Finally, I investigate if the response time of the SEC staff will be shorter with the help of machine-readable disclosure.

[12] I acknowledge that I should scale the number of filings allocated to each DCF office by the number of staffs in each office as a stricter measure of SEC workload. Due to data limitations from FOIA from SEC, I cannot do this in this version.

First, I include the number of comment letters issued (*Num_Comment_Letter*), defined as the number of comment letters (Form UPLOAD) in a comment letter conversation to its 10-K/Q filings in fiscal quarter *t*.[13] I argue that the number of comment letters proxy for the efficiency that SEC staff identify and communicate firms' financial and reporting problems. Consistent with my prediction, in Column (1) of Table 5, the coefficient on *Treat*×*Post* is significant and positive. The result indicates that the SEC will issue more comment letters when the filings become more machine-readable.

[Insert Table 5 here]

Second, Ballestero and Schmidt (2022) argue that the SEC initial comment letter always contain more than one accounting and disclosure topics. Therefore, I test how machine-readable disclosures help the SEC identify more deficiencies in various topics. I measure the scope of deficiencies using the number of issue codes assigned by Audit Analytics (*Topics*) mentioned in the first issuance of comment letter. The more topics in an initial comment letter, the more severe it is and will arise the short-term interest of investors (Lee, Ling, and Rezaee 2023). As shown in Column (2), I find that machine-readable disclosures are positively related to the number of topics the SEC mentioned in a comment letter. This indicates that the DCF staff identify more deficiencies in a variety of topics with the facility of machine-readable disclosures.

In Columns (3) and (4), I separate the number of topics into: (1) the number of Accounting Rule and Disclosure Issues comment topics (*NumAccounting*); and (2) the number of non-accounting topics (*NumNonAccounting*). Baldwin, Blankley, Hurtt, and MacGregor (2023) find that the more accounting-related issues addressed in the comment letter, the more likely it is that the firm will dismiss the current auditor. I find that the coefficients on *Treat*×*Post* in both columns are significantly positive, meaning that machine-readable data helps in identifying issues about both accounting topics and non-accounting topics.

Lastly, I examine whether the SEC issue comment letter in a timelier manner when the corporate filings become more machine-readable. I define the *Response_Time* as the number of days between the corporate filing date and the first comment letter date. Consistent with my predictions, in Column (5), I find the coefficient on the interested variable is significantly negative.

[13] I use the Poisson model in Column (1) to (4) since the dependent variables used here are countable variables (Cohn, Liu, and Wardlaw 2022). I use Cox Regression model in Column (5) since the dependent variable used here is the amount of days until the 10-K/Q filing receives the comment letter (Cleves 2008). results remain the same if I use the OLS regression.

This indicates that the DCF staff use the machine to read the filings, and largely reduce the processing time and response time.

Overall, my results on detailed comment letter characteristics further indicate that machine-readable disclosures assist the SEC in filing review process by expanding the scope of their review and shortening the response time to firms.

5. ROBUSTNESS ANALYSES

5.1. Alternative Research Designs

5.1.1. Regression Discontinuity Design (RDD)

One concern in my DiD approach is that treatment and control firms are fundamentally different because the iXBRL regulation applies only to firms with at least $700 million in public float. To mitigate this concern, I directly control for firm size and include firm fixed effects in my previous analyses. In this subsection, I try to use RD design to further release the concern. In my setting, the likelihood of iXBRL treatment increases at the cut-off point but does not go from zero to one in a deterministic manner. Thus, following the suggestion of Roberts and Whited (2013) and Blankespoor (2019), I employ a fuzzy regression discontinuity (RD) design utilizing two-stage least squares (2SLS) for the first phase of iXBRL adoption in 2019. The instrument is an indicator variable set equal to one for firms having a market float above the cutoff ($700 million). As expected, the instrument in Table 6 Panel A, is strongly predictive of iXBRL adoption, with a first stage Pesudo R^2 of 0.957. I validate the first stage results using link test to examine whether the logistic model is properly specified, and find that there is no significant specification error. The coefficient on the instrumental variable is positively correlated with the adoption of iXBRL.

[Insert Table 6 here]

In the second stage of regression, I follow the suggestion by Lee and Lemieux (2010) and estimate the issuance of comment letters (*Comment_Letter)*. This allows me to absorb the time-series correlation and predictable variation. Following Roberts and Whited (2013), I regress *Comment_Letter* on polynomials of market float, estimating unique coefficients for the difference and squared difference between the firm's market float and the treatment cutoff value, both above and below the cutoff. The method models the relationship between the market float and the issuance of a comment letter, focusing completely on the discontinuity to estimate the causal impact of the treatment. As shown in Table 6 Panel B, the coefficient on *Treat_estimate* is significant and positive at the 5 percent level. I continue to find a positive relation between machine-readable filings and the issuance of a comment letter in the first phase of adoption.

5.1.2. Additional Tests

In this subsection, I conduct several additional tests. In the first test, I change the regression model from Logit model to OLS. In the second test, I change from firm and time fixed effects to SEC industry office fixed effects and time fixed effects. Thirdly, I add a proxy for human readability (*Fog_Index*) as an additional control variable due to the concerns that machine-readable disclosure may impact the human readability (Call et al. 2023). Lastly, I expand my sample period into four years (i.e., from 2016 Q2 to 2020 Q2).

In my main test, I use conditional logistic regression to satisfy the high-dimensional fixed effect. In Table 7, Column (1), I change to OLS regression for estimating equation (1) to ensure my results are not sensitive to the estimation method (Wooldridge 2010). The coefficient on *Treat*×*Post* is positive and significant at the 5 percent level, indicating my main finding is robust.

[Insert Table 7 here]

Secondly, following previous research (Heese et al. 2017; Nam and Thompson 2023), I perform conditional logistics regression with SEC industry office fixed effects and time fixed effects to ensure my results are not driven by specific fixed effect combination. The SEC industry office fixed effect is indicator variables for each SEC DCF represented in my sample. DCF offices are assigned based on the four-digit industry code.[14] I include *Treat* in the regression as the new set of fixed effects does not absorb the coefficient on *Treat*. In Table 7, Column (2), I find that the coefficient on the interested variable is positive and significant at the 5 percent level. This indicates that my result is not driven by selective fixed effects.

In my third test, I add *Fog_Index* as an additional variable to rule out the impact of machine readability on human readability (Call et al. 2023). In Table 7, Column (3), I find that the coefficient on the interested variable is still positive and significant at the one percent level after I control the human readability, indicating that the negative interaction between machine readability and human readability documented in the previous paper is not a concern in my paper.

[14] I match a firm's SIC code to the DCF's SIC Code List, which shows the DCF's allocation of SIC codes to each office. The code list is found at https://www.sec.gov/corpfin/division-of-corporation-finance-standard-industrial-classification-sic-code-list.

In my last set of tests, I expand the sample period to four years (i.e., from 2016Q2 to 2020Q2). I extend the pre-treatment period as I expect the results will not change with a longer sample period. *Treat* and *Post* are defined the same as in my main regression. In Table 7, Column (4), I continue to find a positive and significant coefficient on *Treat*×*Post* at the 5 percent level. In sum, these robustness tests indicate that my main result is not due to specific model specification or coincidence.

5.2. Placebo Tests

To further enhance the reliability of my results, I conduct two placebo tests. The first is based on a placebo treatment date. In Table 8 Column (1), *Treat* is defined the same as in my main analysis, but *Post_Placebo* is set equal to one if the fiscal quarter is after June 15, 2017, which is a placebo treatment date two years before the actual treatment date, and zero otherwise. The sample spans from 2016 Q2 to 2018 Q1, which does not cover any treatment period and does not overlap with the sample period in my main analysis. In Column (1), I do not find any significant coefficients on *Treat*×*Post_Placebo*.

[Insert Table 8 here]

In Column (2), I perform a placebo test using a placebo treatment group. I define *Treat_Placebo* as one if the firm has a public float between $75 million and $700 million (i.e., firms not subject to the June 15, 2019 mandate) and zero if the firm has a public float less than $75 million. In this analysis, I employ the same sample period as in my main analysis, such that the post-period does not capture a mandated increase in machine-readable disclosures for placebo-treatment or placebo-control firms. As reported in Column (2), I do not find any significant results. This placebo test provides additional evidence consistent with the notion that machine-readable disclosures increase the issuance of comment letters, rather than a result of market float or other effects.

5.3. Alternative Explanation Test

One may argue that the increased probability of issuing comment letters is due to the change of financial reporting quality while adopting iXBRL. For example, Li, Zhu, and Zuo (2021) argues that adopting reporting technologies is time-consuming and distracts managers' attention on maintaining high quality of financial report. To rule out this alternative explanation, I first test whether financial reporting quality is changed after the iXBRL mandate. In Panel A of Table 9, I use the absolute value of total accruals as a proxy for financial reporting quality (Sloan 1996). In Panel A, I find that the coefficient on *Treat×Post* is insignificant, suggesting that there's no evidence that the machine-readable disclosures affect the financial reporting quality.

[Insert Table 9 here]

To further rule out this alternative explanation, I partition the sample into *High* and *Low* groups based on the median value of *Financial_Reporting_Quality* within the quarter and industry and rerun the analysis for the subsamples. In Panel B, I find that the coefficients for both the high and low financial reporting groups are statistically significant. More importantly, the high and low financial reporting quality groups do not have significant difference in coefficients, suggesting that the facilitating effect of machine-readable disclosures is not conditional on the financial reporting quality of investigated firms.[15]

Apart from the improved financial reporting quality argument, I further test financial statement comparability and reduced human readability arguments. One may argue that machine-readable data improves structural similarity and financial statement surface comparability by leveraging the search-facilitating functionality of XBRL within the HTML-formatted financial statements, lowering the effort necessary to associate and reconcile the XBRL information with the associated line item in the financial statements, and providing enhanced context regarding the tagged financial statement line item (Chang et al. 2021). If the financial statement comparability increases after the adoption of iXBRL, the SEC staff could utilize the similarity of the financial reporting line items to identify deficiencies. In table 10, I report the results on this alternative explanation. In Panel A of Table 10, I use the firm benchmarking measurement (*FSB*) (Hoitash, Hoitash, Kurt, and Verdi 2023). In Panel A, I find that the coefficient on *Treat×Post* is insignificant, suggesting that there's no evidence that the machine-readable disclosures affect the financial statement comparability. In Panel B, I partition the sample into *High* and *Low* groups based on the median value of *Financial_Statement_Comparability* within the quarter and industry and rerun the analysis for the subsamples. I find that the coefficients for both the high and low financial reporting groups are insignificant. More importantly, the high and low financial reporting quality groups do

[15] My results remain similar if I use discretionary accruals per Larcher-Richardson model and discretionary accruals per Teoh-Welch-Wong model.

not have significant differences in coefficients, suggesting that the facilitating effect of machine-readable disclosures is not conditional on the financial statement similarity of investigated firms.

Lastly, I rule out the alternative explanations for the reduced human readability. I acknowledge that fewer top tier publications investigate the impact of 10-K/Q readability on the issuance of comment letters. However, intuitively, if the human readability of filings is reduced after the adoption of iXBRL (Call et al. 2023), I should expect that the SEC will issue more comment letters due to the perception of the reduced truthfulness of disclosures (Cassell et al. 2019). In table 11, I report the results on the reduced human readability explanations. In Panel A of Table 11, I use the reduction of human readability (*Fog_Index_Reduct*). In Panel A, I find that the coefficient on *Treat*×*Post* is statistically significant, suggesting that the human readability does not reduced significantly after the machine-readable disclosures. In Panel B, I partition the sample into *High* and *Low* groups based on the median value of *Fog_Index_Reduct* within the quarter and industry and rerun the analysis for the subsamples. I find that the coefficients for both the high and low financial reporting groups are insignificant. More importantly, the high and low financial reporting quality groups do not have significant difference in coefficients, suggesting that the facilitating effect of machine-readable disclosures is not conditional on reduced human readability.

In sum, I am confident that the increased probability of SEC comment letter issuance is more likely to be originated from the increased regulatory efficiency rather than deteriorating financial reporting quality, feasible financial statement comparability, and reduced human readability.

6. CONCLUSION

The SEC has long highlighted the need for utilizing machine-readable data, which is increasingly valuable for investors, markets, and issuers. However, little is known about whether the SEC also benefits from machine-readable disclosures in terms of its scrutiny effectiveness. Using the adoption of iXBRL as an identification strategy, I find that the machine-readable filings increase the likelihood of the SEC issuing a comment letter. In the cross-sectional analysis, I find that the effect is more pronounced when the SEC is under busy seasons and periods of high workload. I also find that the comment letters cover more topics, and the SEC's response time is shorter after the adoption of iXBRL. Overall, my results demonstrate a positive effect of machine-readable disclosures on SEC reviewing efficiencies. By leveraging the advantages of machine-readable data, the SEC can enhance its oversight ability. This aligns with the SEC's ongoing efforts to promote information quality and protect investors.

The findings of this paper contribute to the literature on the determinants of comment letters. Prior studies find that SEC resource constraints are a detrimental factor that impedes its effectiveness of scrutiny. My findings provide a plausible solution to relieve the SEC resource constraints. Thus, my findings are important to understand the continuing efforts of the SEC to improve regulatory scrutiny's effectiveness.

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Appendix A. Variable Definitions

Variables	Descriptions
Dependent Variables	
Comment_Letter	An indicator variable set equal to one if a firm has received a comment letter related to its 10-K/Q filings from the SEC in fiscal quarter *t* as reported in Audit Analytics, and zero otherwise. (Source: Audit Analytics)
Comment Letter Characteristics	
Num_Comment_Letter	The number of comment letters (Form UPLOAD) in a comment letter conversation to its 10-K/Q filings in fiscal quarter *t*. (Source: Audit Analytics)
Topics	The total number of issue codes, assigned by Audit Analytics, in the first comment letter to its 10-K/Q filings from the SEC in fiscal quarter *t* (LIST_CL_ISSUE_TAXGROUP). (Source: Audit Analytics)
NumnonAccounting	The total number of Accounting Rule and Disclosure Issue comment topics in 10-K/Q filings as reported by Audit Analytics in fiscal quarter *t*. (Source: Audit Analytics)
NumAccounting	The total number of non-accounting comment topics, equal to the sum of comment topics in Internal Control Disclosure Issues, MD&A, Regulatory Filing Issues, Risk Factors, and other, in 10-K/Q as reported by Audit Analytics in fiscal quarter *t*. (Source: Audit Analytics)
Response_Time	The response time (in days) from the filing date to the first SEC comment letter, as reported by Audit Analytics in fiscal quarter *t*. (Source: Audit Analytics &SEC EDGAR)
Independent Variables	
Treat	An indicator variable set equal to one if the firm is a large accelerated filer (i.e., public float ⩾$700 million) and zero otherwise. (Source: SEC EDGAR)

Post	An indicator variable set equal to one if the fiscal quarter is after June 15, 2019, and zero otherwise.
Treat_Placebo (in Placebo Test)	An indicator variable set equal to one if the firm has public float between $75 million and $700 million (i.e., firms not subject to the June 15, 2019 mandate), and zero if the firm has public float less than $75 million. (Source: SEC EDGAR)
Post_Placebo (in Placebo Test)	An indicator variable set equal to one if the fiscal quarter is after June 15, 2017 (two years before the actual treatment date), and zero otherwise.
Control Variables	
Internal_Control _Weakness	An indicator variable set equal to one if the internal control audit opinion (under SOX Section 404) or the management certification (under SOX Section 302) as reported in Audit Analytics is qualified for a material weakness in year *t, t-1,* or *t-2*, and zero otherwise. (Source: Audit Analytics)
Restatement	An indicator variable set equal to one if firm files a 10-K restatement in year *t, t-1 or t-2* and zero otherwise. (Source: Audit Analytics)
High_Volatility	An indicator variable set equal to one if the volatility of abnormal monthly stock returns (equal to the monthly return (*RET*) minus the value weighted return (*VWRTD*)) is in the highest quartile in a given fiscal quarter, and zero otherwise. Return volatility is calculated as the standard deviation of monthly stock returns for the 36-month period ending in the last month of the fiscal year. (Source: CRSP and Compustat)
Ln(MarketCap)	The natural logarithm of market capitalization, calculated as shares outstanding at fiscal quarter-end (*CSHOQ*) times the share price at fiscal quarter-end (*PRCC_Q*). (Source: Compustat)
Firm_Age	The current year less the first-time appearance year in Compustat. (Source: Compustat)

Loss	An indicator variable set equal to one if earnings before extraordinary items (*IBQ*) is negative in fiscal quarter *t*, and zero otherwise. (Source: Compustat)
BankruptcyRank	The decile rank of the company's Altman's Z-score at fiscal quarter *t*. Companies in the decile having the poorest financial health are assigned a value of ten and so on down to one for the highest financial health. Altman's Z-score is measured following Cassell et al (2013). (Source: Compustat)
SalesGrowth	The percentage change in quarterly sales (*REVTQ*) from fiscal quarter *t-1* to *t*. (Source: Compustat)
Segments	Number of reported operating segments. (Source: Compustat)
M&A	An indicator variable set equal to one if there are reported acquisitions (AQPQ) in quarter *t*. (Source: Compustat)
Restructuring	An indicator variable set equal to one if there is reporting restructuring (RCPQ) in quarter *t.* (Source: Compustat)
ExtFinancing	The sum of equity financing and debt financing scaled by total assets in quarter *t*. Equity financing equals sales of common and preferred stock (SSTK) minus the purchases of common and preferred stock (PRSTKC) minus dividends (DV)). Debt financing equals long-term debt issued (DLTIS) minus long-term debt reduction (DLTR) minus the change in current debt (DLCCH)). (Source: Compustat)
Litigation_industry	An indicator variable set equal to one if the company is in a highly litigious industry (four-digit SIC industry codes 2833–2836, 3570–3577, 3600–3674, 5200–5961, 7370–7374, and zero otherwise. (Source: Compustat)
Big4	An indicator variable set equal to one if a firm's auditor is a Big 4 auditor, and zero otherwise. (Source: Compustat)
Second_Tier	An indicator variable set equal to one if the firm has a second-tier auditor, and zero otherwise. (Source: Compustat)
Audit_Tenure	The number of consecutive years (through year t) during which the auditor has audited the company. (Source: Compustat)

CEO_Chair	An indicator variable set equals to one if the CEO is also the chairman of the board of directors, and zero otherwise. (Source: ExecuComp)
Analyst	The number of analysts following the firms in quarter *t*. (Source: I/B/E/S)
Ln(NetFileSize)	The natural logarithm of the net file size in bytes of the SEC EDGAR "complete submission text file" for the 10-K/Q filing. (Source: SEC EDGAR)
Other Variables	
Instrument (in RD Design)	An indicator variable set equal to one if the firm has a public float above the cutoff ($700 million) and zero otherwise.
Treat_estimated (in RD Design)	The estimated value of *Treat* from the first stage of the 2SLS in the RD design.
Fog_Index	The Gunning Fog index of annual and quarterly reports, measured as 0.4 * ((number of words / number of sentences) + 100 * (number of words with more than two syllables / number of words)). (Source: SEC EDGAR)
SEC_Busyness	An indicator variable set equal to one for firms with a fiscal year-end in December, and zero otherwise. (Source: Compustat)
SEC_Workload	The number of firms assigned to each SEC industry office. (Source: SEC Website)
Financial_Reporting _Quality	Absolute value of total accruals based on balance-sheet method (Sloan 1996), calculated as change of current asset – change of current liability – change of cash + change of short-term debt – depreciation expense. (Source: Compustat)
FSB	A pairwise financial statement benchmarking measure that captures the degree of overlap in the financial statement line items reported by two public firms in fiscal year *t*.
Fog_Index_Reduct	The reduction of human readability measure from fiscal quarter *t* to *t-1*.

Appendix B. Sample Construction and Selection

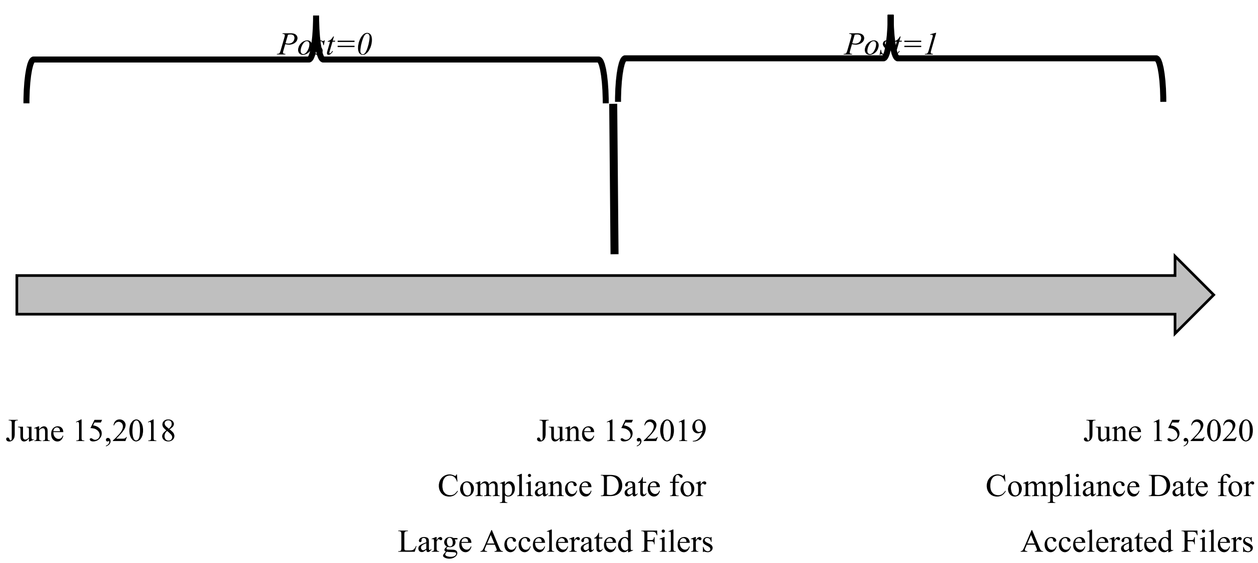
Description	**Observations**
Firm-quarter observations with valid PERMNO-GVKEY-CIK identifier and comment letter data	**31,379**
Delete: Observations in firms who change filer category during the sample period	(2,722)
Delete: Observations in firms that voluntarily adopted iXBRL	(7,595)
Delete: Observations in firms that lack sufficient data for calculating variables in main analysis	(1,158)
Final sample	**19,904**

Figure 1

Timeline of Inline XBRL Regulation

Panel A. Timeline of Inline XBRL Compliance

Panel B. Timeline in Difference-in-Differences Design



Notes: Panel A illustrates the timeline of the Inline XBRL compliance. Panel B shows the timeline in our difference-in-differences design. *Post* equals 1 if the fiscal quarter end is after June 15, 2019, and 0 otherwise.

Table 1

Summary Statistics

Variables	N	Mean	SD	P25	P50	P75
Comment_Letter	19,904	0.025	0.156	0	0	0
Treat	19,904	0.450	0.498	0	0	1
Post	19,904	0.499	0.500	0	0	1
Internal_Control_Weakness	19,904	0.174	0.379	0	0	0
Restatement	19,904	0.020	0.139	0	0	0
High_Volatility	19,904	0.264	0.441	0	0	1
Ln(MarketCap)	19,904	6.388	2.285	4.655	6.323	8.060
Firm_Age	19,904	22.070	17.143	7.501	19.014	30.019
Loss	19,904	0.398	0.489	0	0	1
BankruptcyRank	19,904	5.633	2.650	3	6	8
SalesGrowth	19,904	0.039	0.383	-0.047	0	0.066
ExtFinancing	19,904	0.054	0.216	-0.025	-0.001	0.036
M&A	19,904	0.030	0.170	0	0	0
Restructuring	19,904	0.031	0.174	0	0	0
Litigation_Industry	19,904	0.312	0.463	0	0	1
Big4	19,904	0.591	0.492	0	1	1
Second_Tier	19,904	0.165	0.371	0	0	0
Audit_Tenure	19,904	17.578	9.511	7.753	19.014	27.767
CEO_Chair	19,904	0.027	0.163	0	0	0
Segments	19,904	2.153	1.583	1	1	3
Analyst	19,904	3.911	4.472	0	2	6
Ln(NetFileSize)	19,904	12.272	0.659	11.771	12.198	12.761

Notes: This table provides descriptive statistics for the sample used in the main analyses. The variables are as defined in Appendix A, and all continuous variables are winsorized at 1 percent and 99 percent.

Table 2

Effects of Machine-Readable Disclosures on Issuance of Comment Letters

	Dependent Variable: Issuance of Comment Letters (*Comment_Letter*)	
	(1)	(2)
Treat×Post	**0.402*** **	**1.074*** **
	(3.45)	**(3.09)**
Internal_Control_Weakness	0.163	-0.799
	(1.19)	(-1.56)
Restatement	-0.317	-0.367
	(-0.82)	(-0.44)
High_Volatility	-0.148	0.004
	(-0.97)	(0.01)
Ln(MarketCap)	-0.042	-0.081
	(-1.04)	(-0.23)
Firm_Age	-0.000	2.391*
	(-0.07)	(1.72)
Loss	-0.097	0.097
	(-0.75)	(0.35)
BankruptcyRank	0.113***	0.203
	(5.17)	(1.60)
SalesGrowth	-0.056	0.016
	(-0.42)	(0.06)
ExtFinancing	-0.621*	-0.362
	(-1.94)	(-0.53)
M&A	0.390*	0.129
	(1.90)	(0.31)
Restructuring	0.426**	0.37
	(2.03)	(0.84)
Litigation_Industry	0.254**	53.371

	(2.03)	(1.03)
Big4	-0.026	-1.748
	(-0.16)	(-1.18)
Second_Tier	-0.141	-1.389
	(-0.75)	(-0.95)
Audit_Tenure	0.013	-2.487
	(1.31)	(-1.41)
CEO_Chair	0.152	0.838
	(0.63)	(0.73)
Segments	0.042	0.262
	(1.36)	(0.90)
Analyst	0.011	-0.013
	(0.84)	(-0.25)
Ln(NetFileSize)	1.662***	2.517***
	(26.41)	(13.77)
Firm FE	No	Yes
Time FE	No	Yes
No. of Obs.	19,904	19,904
Pseudo R^2	0.136	0.614

Notes: This table provides difference-in-differences estimates of the effect of machine-readable disclosures on the issuance of a comment letter (*Comment_Letter*) using a conditional logistic regression model. *Treat* equals 1 if the firm is a large firm (i.e., public float ≥ $700 million) and 0 otherwise. *Post* equals 1 if the quarter is after June 15, 2019, and 0 otherwise. Since the mandate date of iXBRL happened at the last month of second quarter (i.e., June), I define time fixed effects as equal-length time periods (i.e., 3-month) before and after the adoption date instead of the natural quarter. Specifically, I define firms with fiscal quarter end in June, July, and August of 2018 as *Pre4*, firms with fiscal quarter end in September, October, and November of 2018 as *Pre3*, and so on. The coefficients for *Treat* and *Post* are subsumed by the firm and time-fixed effects. Coefficients are provided with *z-statistics* in parentheses below. The sample consists of 19,904 firm-quarter 10-K/Q filings for fiscal quarters from 2018Q2 to 2020Q2. Standard errors are corrected by clustering at the firm level. Variables are defined in Appendix A. Continuous variables are winsorized at the 1% and 99% levels. Constants are not tabulated because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed *t*-test.

Table 3

Parallel Trend Analysis

	Dependent Variable: Issuance of Comment Letters (*Comment_Letter*)	
	(1)	(2)
Treat×Pre2	0.351	0.327
	(0.64)	(0.69)
Treat×Pre1	-0.284	-0.279
	(-0.42)	(-0.41)
Treat×Post	1.250**	
	(2.23)	
Treat×Post1		0.395
		(0.44)
Treat×Post2		1.425*
		(1.82)
Treat×Post3+		1.332**
		(2.35)
Control Variables	Included	Included
Firm FE	Yes	Yes
Time FE	Yes	Yes
No. of Obs.	19,904	19,904
Pseudo R^2	0.615	0.615

Notes: This table provides dynamic difference-in-differences estimates of the effect of machine-readable disclosures on the issuance of comment letters. *Treat* equals 1 if the firm is a large firm (i.e., public float ≥ $700 million), and 0 otherwise. *Post* equals 1 if the quarter is after June 15, 2019, and 0 otherwise. *Pre3−, Pre2, Pre1, Post1, Post2, Post3+* equal one if the fiscal quarter ends in August 2018 or November 2018, February 2019, May 2019, August 2019, November 2019, February 2020, or May 2020, respectively, and zero otherwise. *Pre3−* is the benchmark, so it is omitted in the regression. Coefficients for *Treat, Post, Pre2*, *Pre1*, *Post1*, *Post2*, and *Post3+* are subsumed by the firm and time fixed effects, respectively. Column (1) presents dynamic estimates for the pre-treatment period, and Column (2) presents dynamic estimates for both the pre- and post-treatment periods. The coefficients are provided with *z-statistic*s in parentheses below. The sample consists of 19,904 firm-quarter 10-K/Q filings for fiscal quarters from 2018Q2 to 2020Q2. Standard errors are corrected by clustering at the firm level. Variables are defined in Appendix

A. Continuous variables are winsorized at the 1% and 99% levels. Constants are not tabulated because of fixed effects.

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed *t*-test.

Table 4

Cross-Sectional Variation in Effects of Machine-Readable Disclosures on Issuance of Comment Letters: SEC Efficiency

	Dependent Variable: Issuance of Comment Letters (*Comment_Letter*)			
	(1)	(2)	(3)	(4)
	SEC_Busyness		*SEC_Workload*	
	High	Low	High	Low
Treat×Post	**0.953****	**0.664**	**1.650*****	**0.394**
	(2.11)	**(0.87)**	**(3.20)**	**(0.72)**
Difference in Coefficients	**0.289***		**1.256***	
P-Value	0.052		0.077	
Control Variables	Included	Included	Included	Included
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
No. of Obs.	15,922	3,982	10,104	9,432
Pseudo R^2	0.565	0.674	0.630	0.638

Notes: This table presents results of the effect of machine-readable disclosures on the issuance of a comment letter conditional on SEC efficiency. In Columns (1) and (2), I partition the sample based on whether the SEC is in the busy season, i.e., if the firm has a December fiscal year-end. In Columns (3) and (4), I partition the sample based on the workload of the SEC using the number of firms assigned to each SEC industry office that exceeds the industry-quarter mean. Difference-in-differences estimates are provided with *z-statistics* in parentheses below. Standard errors are corrected by clustering at the firm level. The empirical *p*-value for the difference in coefficients is estimated through a bootstrapping procedure with 500 repetitions. Variables are defined in Appendix A. Continuous variables are winsorized at the 1% and 99% levels. Constants are not tabulated because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed *t*-test.

Table 5

Alternative Measurements: Comment Letter Characteristics

Dependent Variables	*Num_ Comment_ Letter*	*Topics*	*Num Accounting*	*Num nonAccounting*	*Response_ Time*
	(1)	(2)	(3)	(4)	(5)
Treat×Post	**0.735*** **	**0.807*** **	**1.122*** **	**0.930*** **	**-0.513*** **
	(3.34)	**(3.43)**	**(2.62)**	**(3.03)**	**(-3.26)**
Control Variables	Included	Included	Included	Included	Included
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
No. of Obs.	3,572	3,572	1,283	1,283	481
Pseudo R^2/Wald	0.352	0.332	0.411	0.411	70.45

Notes: This table provides the results of comment letter characteristics from increased machine-readable disclosures using the Poisson regression model in Column (1) to (4) and the Cox regression model in Column (5). *Num_Comment_Letter* is the number of SEC letters (Form UPLOAD) in a comment letter conversation. *Topics* is the total number of issue codes assigned by Audit Analytics, in the first comment letter from the SEC. *NumAccounting* is the total number of Accounting Rule and Disclosure Issue comment topics as reported by Audit Analytics. *NumnonAccounting* is the total number of non-accounting comment topics as reported by Audit Analytics. *Response_Time* is the number of days from the filing date to the first SEC comment letter, as reported by Audit Analytics. Control variables are included following Cassell et al. (2013). Standard errors are corrected by clustering at the firm level. Variables are defined in Appendix A. Continuous variables are winsorized at the 1% and 99% levels. Constants are not tabulated because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed *t*-test.

Table 6

Effects of Machine-Readable Disclosures on Issuance of Comment Letters: RD design

Panel A: Impact on issuance of comment letters first-stage results	
	Dependent Variable: *Treat*
Instrument	**6.497***** **(11.51)**
No. of Obs.	18,607
Pesudo R^2	0.957

Panel B: Impact on issuance of comment letters second-stage results	
	Dependent Variable: *(Comment_Letter)*
Treat_estimated	**0.365**** **(2.14)**
Market float Polynomials	Yes
No. of Obs.	18,533
Pesudo R^2	0.147

Notes: This table reports the regression discontinuity parametric estimates. The goal of an RD design is to use the discontinuity in treatment to estimate the impact of treatment. Following Blankespoor (2019), I implement a parametric fuzzy RD design using 2SLS for the first phase of iXBRL adoption in 2019, using an indicator variable that influences the probability of treatment as an exogenous instrument in the first stage, i.e., an indicator of having a market float above $700 million. In Panel A, the instrumental variable *Instrument* is strongly predictive of iXBRL adoption, with a first-stage Pesudo R^2 of 0.957. The linktest results in Stata validate my results. The coefficient on the cut-off indicator is positively correlated with adoption. For the second stage, I regress the issuance of a comment letter *(Comment_Letter)* on polynomials of market float, estimating unique coefficients for the difference and squared difference betIen firms' market float and the treatment cutoff value, both above and below the cutoff. *Comment_Letter* is an indicator variable set equal to one if a firm has received a comment letter related to its 10-K/Q filings from the SEC in fiscal quarter *t*. Market float polynomials include the firm's market float less than the $700 million cutoff value (separately for values above and below the cutoff), and the squares of those two differences. The results are reported in Panel B. The model has firm-clustered, robust standard errors. Variables are defined in Appendix A. Continuous variables are winsorized at the 1% and 99% levels. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed *t*-test.

Table 7

Robustness Tests

	Dependent Variable: Issuance of Comment Letters (*Comment_Letter*)			
	(1)	(2)	(3)	(4)
	OLS Model	SEC Industry-Office FE	Additional Controls	Expanded Sample
Treat×Post	**0.015*****	**0.476****	**1.491*****	**0.535****
	(3.15)	**(2.36)**	**(4.16)**	**(2.21)**
Treat		0.039		
		(-1.24)		
Control Variables	Included	Included	Included	Included
Firm FE	Yes	No	Yes	Yes
SEC industry-office FE	No	Yes	No	No
Time FE	Yes	Yes	Yes	Yes
No. of Obs.	19,855	19,536	19,767	36,751
Adj./Pseudo R^2	0.176	0.204	0.631	0.477

Notes: This table provides the results of robustness tests. Column (1) presents difference-in-differences estimates of the effect of machine-readable disclosures on the issuance of a comment letter using the OLS regression. Column (2) presents difference-in-differences estimates of the effect of machine readability on the issuance of comment letter using SEC industry-office and time fixed effects. Column (3) adds the *Fog_Index* as an additional control variable to rule out the concerns that machine readability and human readability interact with each other. Column (4) expands the sample period into four years (i.e., from 2016Q2 to 2020Q2) using conditional logistic regression. Standard errors are corrected by clustering at the firm level. Variables are defined in Appendix A. Continuous variables are winsorized at the 1% and 99% levels. Constants are not tabulated because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed *t*-test.

Table 8

Placebo Tests

	Dependent Variable: Issuance of Comment Letters (*Comment_Letter*)	
	(1)	(2)
Treat×Post_Placebo	0.124	
	(0.13)	
Treat_Placebo×Post		0.78
		(1.44)
Control Variables	Included	Included
Firm FE	Yes	Yes
Time FE	Yes	Yes
No. of Obs.	13,738	10,951
Pseudo R^2	0.648	0.636

Notes: This table reports the results of two falsification tests based on a placebo treatment date and a placebo treatment group. In Column (1), the sample consists of 13,738 10-K/Q filings for fiscal quarters from 2016Q2 to 2018Q1. *Treat* equals 1 if the firm is a large firm (i.e., public float ≥ \$700 million), and 0 otherwise, which is the same as *Treat* used in the main analysis. *Post_Placebo* equals 1 if the fiscal quarter is after June 15, 2017 (two years before the actual treatment date) and 0 otherwise. In Column (2), the sample consists of 10,951 10-K/Q filings for fiscal quarters from 2018Q2 to 2020Q2. *Treat_Placebo* equals 1 if the firm is a small firm that does not receive treatment during the sample period, and 0 otherwise. I exclude large accelerated filers, who receive treatment during the sample period. In Column (2). *Post* equals 1 if the quarter is after June 15, 2019, and 0 otherwise, which is the same as *Post* used in the main analysis. Coefficients for *Treat, Treat_Placebo, Post*, and *Post_Placebo* are subsumed by the firm and time-fixed effects, respectively. Coefficients are provided with *z-statistic*s in parentheses below. Standard errors are corrected by clustering at the firm level. Variables are defined in Appendix A. Continuous variables are winsorized at the 1% and 99% levels. Constants are not tabulated because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed *t*-test.

Table 9

Alternative Explanations: Financial Reporting Quality

Panel A: The effect of machine-readable disclosures on financial reporting quality

	Dependent Variable: *Financial_Reporting_Quality*
Treat×Post	**0.003**
	(1.02)
Control Variables	Included
Firm FE	Yes
Time FE	Yes
No. of Obs.	14,889
Adjusted R^2	0.603

Panel B: The effect of machine-readable disclosures on comment letters conditional on financial reporting quality

	Dependent Variable: Issuance of Comment Letters (*Comment_Letter*)	
	(1)	(2)
	Financial_Reporting_Quality	
	Low	High
Treat×Post	**2.607*****	**1.579****
	(2.74)	**(2.40)**
Difference in Coefficients	1.028	
P-Value	0.403	
Control Variables	Included	Included
Firm FE	Yes	Yes
Time FE	Yes	Yes
No. of Obs.	7,448	7,480
Pseudo R^2	0.688	0.749

Notes: This table presents the results of the effect of machine-readable disclosures on the issuance of a comment letter conditional on financial reporting quality. I use the absolute value of total accruals based on the balance-sheet method as a proxy for financial reporting quality. In Panel A, I use OLS regression. Standard errors are corrected by clustering at the firm level. In Panel B, I partition the sample based on whether the firm's financial reporting quality exceeds the industry-quarter median of *Financial_Reporting_Quality*. Difference-in-differences estimates are provided with *t-statistics* in Panel A and *z-statistics* in Panel B in parentheses below. Standard errors are corrected by clustering at the firm level. The empirical *p*-value for the difference in coefficients is estimated through a bootstrapping procedure with 500 repetitions. Variables are defined in Appendix A. Continuous variables are winsorized at the 1% and 99% levels. Constants are not tabulated because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed *t*-test.

Table 10

Alternative Explanations: Financial Statement Comparability

Panel A: The effect of machine-readable disclosures on financial statement comparability

	Dependent Variable: *FSB*
Treat×Post	**0.0006**
	(0.65)
Control Variables	Included
Firm FE	Yes
Time FE	Yes
No. of Obs.	11,596
Adjusted R^2	0.912

Panel B: The effect of machine-readable disclosures on comment letters conditional on financial statement comparability

	Dependent Variable: Issuance of Comment Letters (*Comment_Letter*)	
	(1)	(2)
	FSB	
	Low	High
Treat×Post	**1.038**	**0.584**
	(1.40)	(0.76)
Difference in Coefficients	0.455	
P-Value	0.912	
Control Variables	Included	Included
Firm FE	Yes	Yes
Time FE	Yes	Yes
No. of Obs.	5,894	5,753
Pseudo R^2	0.676	0.682

Notes: This table presents the results of the effect of machine-readable disclosures on the issuance of a comment letter conditional on financial statement comparability. In Panel A, I use OLS regression. Standard errors are corrected by clustering at the firm level. In Panel B, I partition the sample based on whether the firm's financial statement comparability (*FSB*) exceeds the industry-quarter median. Difference-in-differences estimates are provided with *t-statistics* in Panel A and *z-statistics* in Panel B in parentheses below. Standard errors are corrected by clustering at the firm level. The empirical *p*-value for the difference in coefficients is estimated through a bootstrapping procedure with 500 repetitions. Variables are defined in Appendix A. Continuous variables are winsorized at the 1% and 99% levels. Constants are not tabulated because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed *t*-test.

Table 11

Alternative Explanations: Reduced Human Readability

Panel A: The effect of machine-readable disclosures on reduced human readability

	Dependent Variable: *Fog_Index_Reduct*
Treat×Post	**-0.251*****
	(-6.70)
Control Variables	Included
Firm FE	Yes
Time FE	Yes
No. of Obs.	16,957
Adjusted R^2	0.178

Panel B: The effect of machine-readable disclosures on comment letters conditional on reduced human readability

	Dependent Variable: Issuance of Comment Letters (*Comment_Letter*)	
	(1)	(2)
	Fog_Index_Reduct	
	Low	High
Treat×Post	**0.626**	**1.499**
	(0.545)	(0.963)
Difference in Coefficients	0.873	
P-Value	0.225	
Control Variables	Included	Included
Firm FE	Yes	Yes
Time FE	Yes	Yes
No. of Obs.	8,668	8,350
Pseudo R^2	0.840	0.700

Notes: This table presents the results of the effect of machine-readable disclosures on the issuance of a comment letter conditional on reduction of human readability. In Panel A, I use OLS regression. Standard errors are corrected by clustering at the firm level. In Panel B, I partition the sample based on whether the firm's reduced human readability (*Fog_Index_Reduct*) exceeds the industry-quarter median. Difference-in-differences estimates are provided with *t-statistics* in Panel A and *z-statistics* in Panel B in parentheses below. Standard errors are corrected by clustering at the firm level. The empirical *p*-value for the difference in coefficients is estimated through a bootstrapping procedure with 500 repetitions. Variables are defined in Appendix A. Continuous variables are winsorized at the 1% and 99% levels. Constants are not tabulated because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed *t*-test.