Review of Accounting Studies
https://doi.org/10.1007/s11142-024-09822-y

Does automation improve financial reporting? Evidence from internal controls

Musaib Ashraf[1]

Accepted: 25 March 2024

Abstract
Automation—such as machine learning, robotic process automation, and artificial intelligence—is the next major technological leap in accounting and financial reporting, and I empirically study whether public firms' use of automation technology improves their financial reporting, specifically focusing on the internal control environment. I document two critical inferences. First, I find evidence which suggests that automation improves financial reporting quality. Specifically, firms' use of automation in the financial reporting process is associated with a reduction in internal control material weaknesses. This association is consistent in a levels analysis with firm and year fixed effects, in a changes analysis, and in a propensity score matched difference-in-differences analysis. Second, I find evidence which suggests that monitoring of the financial reporting process decreases after automation, likely because of a perception that automation reduces the need for monitoring vis-à-vis stronger internal controls. Specifically, automation is associated with higher external audit fees and audit committee meetings in the initial years after a firm implements automation but associated with lower external audit fees and audit committee meetings in subsequent years. I also find evidence which suggests that this decreased monitoring may be costly: when internal control failures *do* happen for firms with automation, the failures are more material, as proxied by stronger negative market reactions. In aggregate, my evidence provides nuanced insights regarding whether automation technology improves financial reporting.

Keywords Automation · Robotic process automation · Artificial intelligence · Financial reporting · Internal controls · Information technology

JEL classification G34 · M40 · M41 · O30 · O33

✉ Musaib Ashraf
musaib@msu.edu

[1] Michigan State University, Business Complex 632 Bogue St Rm N270, East Lansing, MI 48824, USA

Published online: 23 April 2024

1 Introduction

Automation—such as machine learning, robotic process automation, and artificial intelligence—is hailed as the next frontier in accounting and financial reporting. Deloitte (2018a, p. 3) argues that accounting is "prime for automation" and "a significant number of [accounting] roles have the potential to be automated." PwC (2021, p. 1) agrees, asserting that automation is "the future" of financial reporting. AICPA (2020, p. 1) also contends that automation is "especially important" for accountants. Regulators too have taken notice, with an ongoing debate about whether and how to modify standards because of automation (PCAOB 2020; PCAOB 2021). At the same time, EY (2021) reports that close to two-thirds of chief financial officers are concerned about the financial reporting risks posed by automation, and Gartner finds that concerns about removing human judgment from the financial reporting process has made (at least some) accounting executives reluctant to adopt automation (McCann 2019). Indeed, the robots may be "coming for Phil in accounting" (Roose 2021, p. 1), but empirical evidence is extremely limited on the effect these robots have on financial reporting. To that end, in this study, I analyze whether public firms' use of automation improves their financial reporting, specifically focusing on the internal control environment.

Broadly defined, accounting automation encompasses a wide range of technologies that enable firms to automate accounting processes, including but not limited to technologies that enable artificial intelligence, machine learning, and robotic process automation (Wang 2022). While these technologies differ in their scope and how they function, they all share the common ability to enable technology to automate otherwise manual processes.[1] For example, Vic.ai is an "autonomous accounting" platform that uses artificial intelligence to automate various accounting functions like invoice processing and expense approvals (Vic.ai 2021). Likewise, SolveXia allows firms to "automate hundreds of processes for your company, including reconciliations, revenue and expense reporting, regulatory compliance, rebate management, and much more" (SolveXia 2023). Similarly, BlackLine provides firms the ability to "automate accounting workflows," such as reconciliations, accounts receivables, and consolidations (BlackLine 2017).

The concerns raised by practitioners (e.g., McCann 2019; EY 2021) about automation harming internal controls and financial reporting are based on the notion that automation injects a new source of complexity into the financial reporting process. This complexity results from automation's reliance on imperfect technologies (e.g., optical character recognition and fuzzy logic), the fact that data inputs are not always well structured (which automation can struggle with), and the rise of shadow information technology—which is the notion that often automation implementations are siloed within business units, giving rise to potential frictions

[1] Artificial intelligence and machine learning are relatively more sophisticated forms of automation in which the software has (at least some) built-in ability to make decisions, whereas robotic process automation is relatively less sophisticated where software repeats the tasks it is programmed to do but with no decision-making (Deloitte 2017).

with the firm's other information technology and internal control infrastructure (Deloitte 2018a; Whitehouse 2019; PwC 2019; Commerford et al. 2022; Plattfaut and Borghoff 2022).[2] As Gartner (2020, p. 5) notes, one of the top modern trends that chief financial officers must address is how automation is "putting internal controls at risk." It should therefore come as no surprise that the Association of Chartered Certified Accountants (2015) reports that chief financial officers are reluctant to trust automation.

In contrast to concerns raised by practitioners, I argue that automation improves internal controls and, by association, financial reporting because a significant source of internal control problems is humans—people who fail to properly execute a firm's internal control policies or blatantly disregard those policies, whether for fraudulent purposes, due to agency conflicts, or because of poor training and low skill (Ashraf 2022). For example, PCAOB (2007, p. 58) notes that "internal control over financial reporting is a process that involves human diligence and compliance and is subject to lapses in judgment and breakdowns resulting from human failures." The value proposition of automation is to remove (or minimize) the human element and thereby prevent weaknesses that result from forgetfulness, mistakes, discretion, and collusion or fraud (Lanza 2007; Blue Lance 2012; Deloitte 2015; Deloitte 2018b; WNS 2020). Given that humans are a major source of failure in the internal control environment, conceptually, the benefits of replacing human labor with automation should arguably outweigh any additional complexity automation injects into the financial reporting process.

I identify firms that introduce automation in their financial reporting process based on textual analysis of the Controls and Procedures section of 10-K and 10-Q filings. In this section of periodic accounting reports, firms are *required* to disclose all the material changes made to a firm's internal control environment—regardless of whether the changes were made in response to an existing weakness or whether the changes were made as a routine part of business rather than to address existing problems (EY 2020). Although disclosure of new accounting automation in the Controls and Procedure section of SEC filings does not mean that a firm has completely automated financial reporting, I am able to cleanly identify a comprehensive set of firms that introduce material automation in at least some parts of their financial reporting process. Further, because disclosures in the Controls and Procedure section are mandatory, voluntary disclosure incentives are less likely to threaten my inferences, and analyzing the Controls and Procedures section ensures that I am focused on firms' implementation of *material* accounting automation.

Empirically, I search in the Controls and Procedure section for automation-related terms, such as "machine learning", "artificial intelligence", and "automation" (Chen and Srinivasan 2023). For example, MicroStrategy notes in its 10-Q

[2] The complexity also varies depending on the type of automation technology. For example, artificial intelligence and machine learning depend on models that must be trained on and learn from data, while robotic process automation is rules-based and completes repetitive tasks with little to no training or learning from data. Thus, the source of risk for artificial intelligence and machine learning stems from training on or learning from poor quality or unapplicable data whereas the source of risk for robotic process automation stems from being confined to pre-defined rules that are unable to adapt to potentially changing scenarios.

filing for 2017 that "we implemented a new professional service automation system to track billable time used to invoice customers"; LL Flooring discloses in its 10-K filing for 2016 that "[we] implemented automated alert controls to monitor privileged access activities"; and Solo Cup states in its 10-Q filing for 2011 that it implemented a "software [which] automates the vendor, purchase order, and overall spending review and approval processes." I discuss my textual analysis process in more detail in Sect. 4.

In my main analysis, I find *AUTOMATION* (an indicator variable for whether the firm has introduced automation in its financial reporting process before the beginning of the firm-year) is *negatively* associated with *MATERIAL_WEAKNESS* (an indicator variable for whether a firm-year possesses a material weakness in internal control over financial reporting), with the data suggesting that firms who introduce automation in their financial reporting process exhibit 61.80 percent lower odds of experiencing a material weakness. This association is consistent in (i) a levels analysis with firm and year fixed effects, (ii) a changes analysis, and (iii) a propensity score matched difference-in-differences analysis. Further, I drill down to identify the specific area of accounting where automation is introduced and document a reduction in material weaknesses for the same area of accounting that is automated. My findings in aggregate suggest that automation improves financial reporting quality for the average firm.

There are six potential concerns with my main analysis. One concern is whether *AUTOMATION* is noisily proxying for firms that address existing material weaknesses rather than the effect of automation per se. Another concern is whether I am capturing the effect of automation specifically or the effect of overall upgrades to a firm's information technology that may be unrelated to automation. A third concern is whether *AUTOMATION* is noisily proxying for firms that make changes to their internal controls. Although I am studying automation use by public firms and not external audit firms, a fourth concern is whether *AUTOMATION* is confounded with the effect of automation use by external auditors. The fifth concern is whether my results are driven by my choice to study SOX 404b material weaknesses rather than SOX 404a. Finally, there is a concern whether my results hold only in the later years of my sample. I address all six of these concerns using robustness analyses. Inferences remain consistent.

Having provided evidence which supports the notion that automation improves financial reporting quality, I next explore in additional analyses how *AUTOMATION* impacts monitoring of the financial reporting process. If automation benefits financial reporting quality, then it is possible that the firm scales back oversight over financial reporting, due to a perception that automation reduces the likelihood of errors or fraud and therefore financial reporting requires less monitoring. I focus on two monitors: auditors (i.e., an external monitor) and the audit committee (i.e., an internal monitor). I find *AUTOMATION* is associated with an *increase* in audit fees and audit committee meetings during the initial years of automation but a *decrease* in audit fees and audit committee meetings in subsequent years. The former is consistent with the external auditor and the audit committee increasing oversight initially to gain comfort over new automation in the financial reporting process. The latter is consistent with both the external auditor and the audit committee scaling back oversight once they perceive automation is leading to stronger financial reporting quality.

Further, while my evidence suggests that automation overall benefits internal controls, automation cannot perfectly prevent weaknesses. Consequently, a byproduct of less oversight may be that internal control weaknesses are more material when they *do* happen. Consistent with this notion, I find *AUTOMATION* is associated with more negative market reactions around the disclosure of internal control weakness—but this association exists only in the later years after automation, rather than during the initial years after automation, which comports with the just-documented decrease in monitoring by the external auditor and the audit committee.

Finally, I conduct four more additional analyses. First, to ensure that my findings are not driven by my choice of studying internal controls, in additional analysis, I study the association of *AUTOMATION* with another proxy of financial reporting quality—restatements (e.g., Dechow et al. 2010). Consistent with my main analysis, *AUTOMATION* is significantly negatively associated with restatements (i.e., less likely to possess an error in financial statements). I also document some evidence that the reduction in restatements is in the specific area of accounting that was automated. Second, I study whether *AUTOMATION* is associated with securities class action lawsuits by investors (e.g., Kim and Skinner 2012). I find a significant and negative association with these lawsuits, suggesting that investors view firms with automation relatively more favorably. Third, I study another component of financial reporting: timeliness (e.g., Ashraf et al. 2020). I find that *AUTOMATION* is significantly associated with earlier disclosure of annual financial statements. This finding is consistent with arguments that automation increases efficiencies (e.g., Cooper et al. 2019). Fourth, I document that *AUTOMATION* is associated with a smaller audit committee, suggesting that there is lower demand for audit committee directors after a firm introduces automation during the financial reporting process.

Overall, my findings contribute to our understanding of how automation impacts financial reporting. The use of automation in accounting and financial reporting is forecasted to increase going forward (Deloitte 2018a; AICPA 2020; PwC 2021). At the same time, there is practitioner concern about whether removing human judgment will harm the financial reporting process (McCann 2019; Gartner 2020; EY 2021). My evidence indicates that the effect of automation on financial reporting is more nuanced than one may expect. My results suggest that automation improves financial reporting overall through a stronger internal control environment; I also provide some evidence of increased reporting efficiencies. With the caveat that I am unable to observe the investment costs that firms must undertake in order to implement automation, my analyses provide empirical support for the push by firms to increase reliance on automation of their financial reporting process. At the same time, my evidence suggests that this automation is associated with decreased oversight over the financial reporting process, perhaps due to the perception that less oversight is needed because automation decreases the likelihood of errors or fraud; this has an unintended consequence of more material internal control weaknesses when they *do* happen.

My manuscript is related to recent literature that studies the effect of automation use by external auditors. Fedyk et al. (2022) find that use of artificial intelligence by external auditors *improves* audit quality and decreases demand for auditor jobs. In contrast, Commerford et al. (2022) show that use of artificial intelligence by external auditors *harms* audit quality, and concurrent work by Law and Shen (2022) finds audit firm use of artificial intelligence does *not* decrease demand for auditor jobs. I build upon this literature in four ways.

First, I study public firms' use of automation in their own financial reporting processes rather than external audit firm use of automation during the audit of clients. The two are related but distinct constructs. Second, I document that a possible negative externality of automation is that oversight of the financial reporting process decreases and, as a result, financial reporting failures are more material when they do happen—an important inference not documented by prior literature. Third, empirically, extant research uses either job postings or résumés of employees to proxy for auditor use of automation. In contrast, I study the effect of automation actually implemented by public firms, based on textual analysis of periodic accounting filings, rather than whether a firm has hired or is trying to hire automation-skilled employees. In that regard, my manuscript resembles the work of Chen and Srinivasan (2023), who use textual analysis of periodic accounting filings to document higher firm value for firms that adopt digital technologies, and Schoenfeld (2022), who identifies firms that conduct voluntary cybersecurity audits based on 10-K disclosures. Fourth, the literature disagrees on the effect that automation has on demand for rank-and-file (auditor) employees (e.g., Fedyk et al. 2022; Law and Shen 2022). I contribute to this debate by focusing on demand for board directors at public firms, specifically the audit committee.

To my knowledge, I am the first to empirically document the role automation plays in financial reporting and oversight thereof.[3] Given the increasing relevance of automation in accounting and financial reporting, empirical evidence is warranted on whether firms' use of automation improves their financial reporting—especially as regulators debate adapting regulations and standards to accommodate automation use by firms (e.g., PCAOB 2020; PCAOB 2021). Taken in aggregate, my evidence should be informative to regulators, boards, and shareholders regarding practitioner concerns about removal of human judgment in the financial reporting process (e.g., McCann 2019; Gartner 2020; EY 2021).

[3] Concurrent work by Awyong et al. (2022) finds that firms' digitalization improves financial reporting quality. However, like other manuscripts, Awyong et al. (2022) study the effect of job postings that require candidates to have digital skills, whereas I study the effect of implemented automation. Aside from being different empirical proxies, conceptually digitalization (which is related to information technology more generally) is a different construct than automation (which tends to focus on specifically on technologies like machine learning, artificial intelligence, and robotic process automation). Awyong et al. (2022) also do not document the same nuanced implications that I do (i.e., stronger overall financial reporting but decreased oversight).

2 Related literature

2.1 Related literature on the role of accounting automation

There is a nascent but growing accounting literature on the effects of accounting automation, and this literature generally focuses on the external audit setting. Commerford et al. (2022) study auditor use of artificial intelligence in an experimental setting, finding that auditors exhibit algorithm aversion wherein they tend to advise more audit adjustments to management when suggested by a human specialist compared to a machine-suggested adjustment, ultimately *harming* audit quality. In contrast, Fedyk et al. (2022) find that the use of artificial intelligence technology by external auditors *improves* audit quality. They also find *lower* demand for human auditors, although Law and Shen (2022) find that auditor use of artificial intelligence does *not* decrease jobs for human auditors. Finally, Cooper et al. (2019) survey partners at Big 4 firms, who report that the firms continue to implement robotic process automation across their service lines and claim that the use of automation has enhanced work quality and efficiency, and Cooper et al. (2022) find in a survey that both Big 4 partners and lower-level employees positively view robotic process automation. While these manuscripts are not about financial reporting quality or internal controls per se and they focus on external auditors, the manuscripts collectively highlight the growing importance of automation in accounting and signify the need for large sample, generalizable empirical evidence on whether automation use by firms during their own financial reporting process is beneficial.

2.2 Related literature on the role of accounting information technology

Beyond the literature that focuses on various forms of automation, a large literature studies firms' use of information technology generally (rather than automation specifically) in a variety of accounting settings. For example, Kobelsky et al. (2008) study the determinants and consequences of information technology budgets; Chen and Srinivasan (2023) find that non-technology firms that implement digitalization exhibit higher market-to-book ratios; and Schoenfeld (2022) studies the determinants and outcomes of firm's that opt for cybersecurity audits. However, more relevant to my research question is the literature that studies the effect of information technology (although not automation specifically) on financial reporting and disclosure.

In particular, Dorantes et al. (2013) study the effect of information technology on a firm's internal information environment, finding that enterprise systems are associated with more accurate management forecasts. Next, Ashraf et al. (2020) find that possessing an information technology expert on audit committees is associated with higher financial reporting quality. Further, Masli et al. (2010) study firms that implement SOX-related information technology during 2004 to 2006, the years that immediately follow the passage of SOX; they find firms that implement such technology exhibit better internal controls, smaller increases in audit fees, and smaller increases in audit delay. However, in sharp contrast, concurrent work by Choudhary et al. (2023) provide evidence that complex information technology can harm financial reporting quality, as proxied by a higher likelihood of restatements.

3 Is automation synonymous with information technology?

While automation is undoubtedly a component of information technology, disagreement in the literature and the unique attributes of automation make it ex ante unclear whether automation improves internal controls and financial reporting. First, empirically, the literature appears to disagree on whether better information technology is associated with stronger or weaker financial reporting (e.g., Masli et al. 2010; Choudhary et al. 2023. Second, conceptually, information technology can benefit internal controls through several channels that are distinct from automation (e.g., enabling the implementation of internal controls, facilitating testing and evaluation of controls, transforming internal information environment and communication, improving compliance, and enhancing risk assessment and mitigation). In other words, even if the literature was in agreement on the effect information technology has on financial reporting, it is not clear whether it is the automation or the non-automation aspect of information technology that drives this (possible) benefit. Consequently, it remains an open question whether automation in particular (rather than information technology in general) benefits financial reporting quality—especially given the apparent disagreement in the literature regarding the effects of automation in the setting of external auditors (Fedyk et al. 2022; Commerford et al. 2022) and the lack of extant empirical evidence on this topic (Plattfaut and Borghoff 2022).

4 Empirically identifying firms' use of automation during their own financial reporting process

Firms are required to disclose material changes to internal control over financial reporting in the Controls and Procedures section of 10-K and 10-Q filings (usually Item 9a in 10-Ks and Item 4 in 10-Qs) (SEC 2008). This disclosure must be made every quarter, even though assessment of the effectiveness of internal control over financial reporting is on an annual basis, and the disclosure requirement is triggered regardless of the underlying reason for the internal control changes (EY 2020).[4] For example, a firm that is making changes to address existing material weaknesses must disclose the changes to investors; so too must a firm that does not possess existing material weaknesses but is still making changes as a routine part of business.

[4] According to SEC (2008, p.19), "a company must disclose any change in its internal control over financial reporting that occurred during the fiscal quarter covered by the quarterly report, or the last fiscal quarter in the case of an annual report, that has materially affected, or is reasonably likely to materially affect, the company's internal control over financial reporting.".

I use CALCBENCH to analyze the content of the Controls and Procedures section of 10-K and 10-Q filings, thereby allowing me to identify firms that introduce automation in their financial reporting process.[5] Following Chen and Srinivasan (2023), I search for the following automation-related words in the Controls and Procedures section: "artificial intelligence", "ai tech", "ai related", "conversational ai", "evolutionary ai", "evolutionary computing", "intelligent system", "computer vision", "neural network", "virtual agent", "virtual assistant", "cognitive computing", "biometric", "deep learning", "machine learning", "natural language processing", "image recognition", "facial recognition", "speech recognition", "automation solutions", "intelligent automation", "marketing automation", "process automation", "robotic process automation", "autonomous tech", "autonomous", and the catchall root word of "automat" (which captures the words "automation", "automate", and "automatically").[6] I then manually read each Controls and Procedures section that contains such a word to ensure construct validity.

For example, in its 10-K filing for the year that ended December 31, 2012, Novus Robotics note: "The bookkeeping system has been modified so that all sales of extended warranties are automatically recorded as deferred revenue and that the amount of revenue that is ultimately recognized as warranty revenue is as the result of an analysis of the significant aspects of the warranty such as coverage and period." Further, in its 10-Q filing for the quarter that ended June 30, 2010, Jetblue Airways state: "We significantly strengthened our internal controls over our customer loyalty program by implementing and leveraging the enhanced automated controls of the new customer loyalty system." Moreover, in its 10-K filing for the year that ended September 30, 2015, Wesco Aircraft Holdings reveal: "[We] purchased and began implementation of new software that will help automate and improve certain elements of our financial close and reporting process, including our consolidations process." Finally, in its 10-Q filing for the quarter that ended September 30, 2018, Quintana Energy Services declare: "[We] designed, implemented and tested an automated process that eliminated the ability for the same individual to Create and Post

[5] CALCBENCH is a data aggregator that extracts data directly from SEC filings (Hoitash and Hoitash 2018). CALCBENCH is similar to traditional data sources such as Compustat, except CALCBENCH extracts more than just financial statements from SEC filings. Specifically relevant to my research design, CALCBENCH gathers and allows textual analysis on the individual sections of 10-K and 10-Q filings – such as the Controls and Procedures section (Calcbench 2023).

[6] Chen and Srinivasan (2023) search for seven types of words in their analyses: analytics-related, automation-related, artificial intelligence-related, big data-related, cloud-related, digitization-related, and machine learning-related (see their Appendix A). Given that my construct of interest is automation (which tends to focus specifically on things like machine learning, artificial intelligence, and robotic process automation) and not Chen and Srinivasan's (2023) construct of digitalization (which is related to information technology more generally), I focus on their words that are related to automation, artificial intelligence, and machine learning.

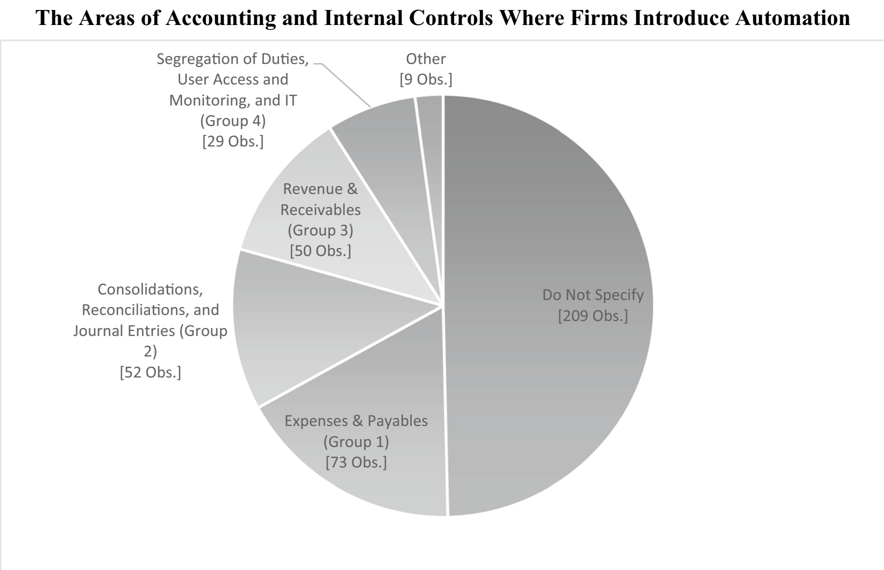

Fig. 1 The Areas of Accounting and Internal Controls Where Firms Introduce Automation

journal entries into the general ledger, thus resulting in the proper segregation of duties."

I ultimately identify 422 unique firms in my sample period that make material changes to internal controls which involve automation.[7] I use this data to calculate my test variable, as I describe in Sect. 5. As shown in Fig. 1, roughly half of the 422 firms do not specify the area of accounting that was automated. Of the ones that do specify, 73 firms introduce automation in expenses and payables; 52 in consolidations, reconciliations, and journal entries; 50 in revenue and receivables; 29 in segregation of duties, user access and monitoring, and information technology; and nine in miscellaneous areas that could not be easily grouped together.

Given that the Controls and Procedures section disclosures are required, arguably I am able to cleanly identify a comprehensive set of firms that introduce material automation in their financial reporting process. However, although my bag of words contains a broad range of automation-related words, a limitation of the data is that firms usually do not explain in detail the automation technology they use; some, but not all, firms detail the task the automation technology will accomplish (see Fig. 1), but they still do not describe the underlying technology that will be used to accomplish said task. So, for example, when a firm discloses that it has introduced

[7] It is possible that some firms introduce accounting automation that they do not discuss in the Controls and Procedures section. However, firms are required to disclose *material* changes to their financial reporting process in this section of 10-K and 10-Q filings (SEC 2008), filings that the CEO and CFO personally attest to the validity of. Consequently, any automation that a firm has introduced but has not disclosed in the Controls and Procedures section is likely to be *not* material. Empirically, this noise in my test variable should *not* bias toward statistical significance.

automation in its financial reporting process, it typically discusses the technology broadly as automation rather than specifically mentioning artificial intelligence or machine learning. Conceptually, I am focused on firms' implementation of material accounting automation and am agnostic to the form that it takes.

5 Research design, data, and sample selection

5.1 Research design

I use the following linear probability model to test my research question:

$$\begin{gathered} MATERIAL\_WEAKNESS_{it} = \alpha_i + \alpha_t + \beta 1 AUTOMATION_{it} \\ +\beta 2 IT\_COMMITTEE_{it} + \beta 3 AC\_IT\_EXPERTISE_{it} + \beta 4 NEW\_IT_{it} \\ +\beta 5 SIZE_{it} + \beta 6 SEGMENTS_{it} + \beta 7 FOREIGN_{it} \\ +\beta 8 ACQUISITION_{it} + \beta 9 RESTRUCTURE_{it} + \beta 10 FIRM\_AGE_{it} \\ +\beta 11 SALES\_GROWTH_{it} + \beta 12 INV_{it} + \beta 13 LOSS_{it} + \beta 14 Z\_SCORE_{it} \\ +\beta 15 AUDITOR\_RESIGN_{it} + \beta 16 ANNOUNCE\_RESTATEMENT_{it} \\ +\beta 17 INST\_OWNERSHIP_{it} + \beta 18 BIG4_{it} + e_{it}, \end{gathered} \tag{1}$$

where i indexes firm and t indexes years.[8] The dependent variable, *MATERIAL_WEAKNESS*, equals one if firm i has a SOX 404b material weakness in internal controls for year t (zero otherwise). My test variable is *AUTOMATION*, which equals one if firm i has introduced automation in its financial reporting process before the beginning of year t (zero otherwise). I identify the use of automation via textual analysis of the Controls and Procedures section of 10-K and 10-Q filings, as described in Sect. 4. A negative coefficient on *AUTOMATION* indicates that accounting automation enhances the internal control environment and, thus, financial reporting.

My model includes firm fixed effects to help control for time-invariant unobservable firm characteristics and year fixed effects to mitigate the effect of time-correlated factors, such as year-specific shocks or time trends. I also cluster robust standard errors at the firm level to account for heteroskedasticity and correlated standard errors. Further, I control for *IT_COMMITTEE*, *AC_IT_EXPERTISE*, and *NEW_IT* to ensure the effect of *AUTOMATION* is orthogonal to IT-related effects documented by extant research (e.g., Masli et al. 2010; Ashraf et al. 2020). Finally, I follow prior literature and control for a vector of firm-year characteristics that have been shown to affect a firm's internal controls; following Ashbaugh-Skaife et al. (2007), Doyle et al. (2007), and Ashraf (2022), I control for the variables *SIZE*, *SEGMENTS*, *FOREIGN*, *ACQUISITION*, *RESTRUCTURE*, *FIRM_AGE*, *SALES_GROWTH*, *INV*, *LOSS*, *Z_SCORE*, *AUDITOR_RESIGN*, *ANNOUNCE_RESTATEMENT*,

[8] I employ a linear probability model, instead of a logistic regression, because of the incidental parameters problem that can arise from complex fixed effect structures in nonlinear models (Greene 2004) and because interactions can be difficult to interpret in nonlinear models (Ai and Norton 2003). Results are consistent in an analogous fixed effects logistic regression (see Table OA.2 in the online appendix).

Table 1 Sample Selection

Main Internal Controls Sample	
Firm-years observations from 2009 – 2019 that have data on CIK and possess a SOX 404b internal control over financial reporting opinion (Compustat; Audit Analytics)	39,888
Less: Observations with data missing on the Controls and Procedures section (CALCBENCH)	(7,203)
Less: Missing data to calculate required control variables (BoardEx; Compustat; Audit Analytics; Thomson Reuters) or are singleton observations (Correia 2015)	(7,081)
Final main internal controls sample of firm-year observations	25,604

INST_OWNERSHIP, and *BIG4* in my regression model. These firm-year variables are defined in Appendix A.

5.2 Data and sample selection

I present my sample selection in Table 1. I begin with 39,888 Compustat firm-year observations between 2009 and 2019 that possess data on CIK and have data on the effectiveness of SOX 404b internal control over financial reporting.[9] I then exclude 7,203 observations that are missing data on the Controls and Procedures section and 7,081 observations that have data missing to calculate control variables or are singleton observations (Correia 2015). This results in a main sample of 25,604 firm-year observations.

6 Results

6.1 Descriptive statistics and Pearson correlations

The descriptive statistics for my main sample are presented in Table 2. Three percent of observations in my sample have introduced accounting automation before the beginning of the firm-year. Further, five percent of firm-years exhibit an internal control material weakness, consistent with the literature (e.g., Ashraf 2022). All control variables are also generally consistent with the literature (e.g., Ashbaugh-Skaife et al. 2007; Doyle et al. 2007).

I plot my test variable *AUTOMATON* by Fama–French 12 industries in Fig. 2. While *AUTOMATION* does, understandably, vary by industry, there does not appear to be significant outliers relative to the sample mean—industry averages range between a low of 1.28 percent in the chemicals and allied products industry and a high of 4.78 percent for manufacturing firms. Importantly, firm fixed effects in my analyses mitigate concerns about the potentially confounding effect of industry-level characteristics on my inferences.

[9] My sample begins in 2009 because CALCBENCH coverage starts in 2008 and I require at least one prior period to calculate my test variable.

Table 2 Descriptive Statistics for Internal Controls Sample (N = 25,604)

Variable	Mean	Std. Dev	25%	Median	75%
Test Variable					
AUTOMATION (binary)	0.03	0.17	0.00	0.00	0.00
Dependent Variable					
MATERIAL_WEAKNESS (binary)	0.05	0.22	0.00	0.00	0.00
Control Variables					
AC_IT_EXPERTISE (binary)	0.08	0.28	0.00	0.00	0.00
ACQUISITION (binary)	0.11	0.32	0.00	0.00	0.00
ANNOUNCE_RESTATEMENT (binary)	0.02	0.12	0.00	0.00	0.00
AUDITOR_RESIGN (binary)	0.00	0.07	0.00	0.00	0.00
BIG4 (binary)	0.83	0.37	1.00	1.00	1.00
FIRM_AGE	26.50	16.87	14.00	21.00	35.00
FOREIGN (binary)	0.56	0.50	0.00	1.00	1.00
INST_OWNERSHIP	0.71	0.29	0.54	0.79	0.92
INV	0.09	0.12	0.00	0.04	0.14
LOSS	0.26	0.44	0.00	0.00	1.00
NEW_IT (binary)	0.12	0.33	0.00	0.00	0.00
RESTRUCTURE (binary)	0.37	0.48	0.00	0.00	1.00
SALES_GROWTH	0.13	0.56	-0.03	0.05	0.16
SEGMENTS	1.92	1.57	1.00	1.00	3.00
SIZE (logged)	7.31	1.72	6.05	7.25	8.43
IT_COMMITTEE (binary)	0.04	0.21	0.00	0.00	0.00
Z_SCORE	1.52	3.33	0.75	1.64	2.66

This table presents descriptive statistics for the internal controls sample. Continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in Appendix A.

Pearson correlations for my main sample are presented in Table 3. *AUTOMATION* is positively and significantly (p-value ≤ 0.01) correlated with *MATERIAL_WEAKNESS*, suggesting that automation harms financial reporting vis-à-vis a weaker internal control environment. However, this univariate correlation is likely affected by confounds that muddy inferences, particularly time: as show in Fig. 3, there is a clear positive time trend in both *AUTOMATION* and *MATERIAL_WEAKNESS* in my sample. I further explore the relation between my test and dependent variables in subsequent multivariate analyses that allow me to control for confounding factors, such as time. I also graph the yearly percentage of firms that newly introduce automation in their financial reporting process in Fig. 4.

6.2 Main analysis

I present the results of my main analysis in Panel A of Table 4. The coefficient on *AUTOMATION* is negative and significant (p-value ≤ 0.01), and the coefficient remains negative and significant (p-value ≤ 0.01) if I calculate all my control

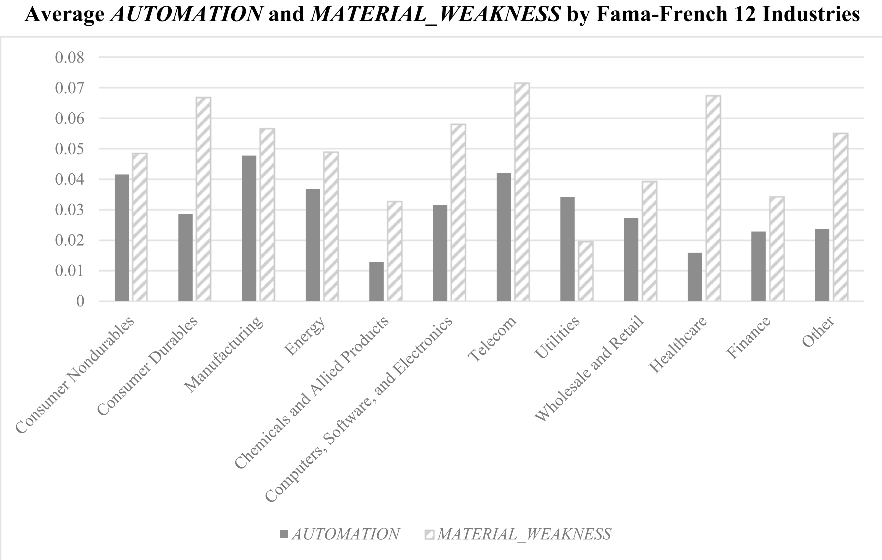

Fig. 2 Average *AUTOMATION* and *MATERIAL_WEAKNESS* by Fama–French 12 Industries

variables in year *t*-1 instead of year *t* (see Table OA.3 in the online appendix). The data suggests that firms who introduce automation in their financial reporting process subsequently possess 61.80 percent lower odds of experiencing a material weakness in internal control over financial reporting.[10] Inferences remain consistent when I rerun the analysis using an analogous changes model in Panel B of Table 4 (p-value ≤ 0.01) rather than the levels analysis in Panel A.

I further conduct a propensity score matched difference-in-differences analysis in Panel C of Table 4. I regress *BEGIN_AUTOMATION* (equals one if firm *i* has introduced automation in its financial reporting process during year *t*; zero otherwise) on all the control variables from Eq. (1), consistent with the recommendations of Shipman et al. (2017). I then match the propensity score of treated firms (i.e., *BEGIN_AUTOMATION* = 1) to control firms (i.e., firms that never automated during my sample) within the same year of treatment, the same industry of treatment, and a caliper distance of 0.01 (without replacement). As noted in Table OA.4 in the online appendix, the covariates are perfectly balanced between these treatment and control firms.

I graph in Fig. 5 the trends in *MATERIAL_WEAKNESS* for the treatment and control groups in a window of [*t*-5, *t* + 2] around year *t*, where year *t* is either the year that the treatment firm has introduced automation or the year where the control firm's matched treatment firm has introduced automation. Visually, the incidence rate of *MATERIAL_WEAKNESS* clearly drops for the treatment group after treatment. I confirm this inference in a difference-in-differences regression analysis

[10] I calculate economic significance by re-estimating Eq. (1) in an analogous fixed effects logistic regression and then calculating the odds ratio for the coefficient on *AUTOMATION* (odds ratio = 0.3820) (see Table OA.2 in the online appendix).

Table 3 Pearson Correlations for Internal Controls Sample

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	AUTOMATION										
(2)	MATERIAL_WEAKNESS	**0.06**									
(3)	AC_IT_EXPERTISE	**0.04**	0.00								
(4)	ACQUISITION	0.01	**0.02**	0.00							
(5)	ANNOUNCE_RESTATEMENT	**0.02**	**0.18**	0.00	-0.01						
(6)	AUDITOR_RESIGN	0.01	**0.08**	-0.01	0.00	**0.08**					
(7)	BIG4	0.00	**-0.08**	**0.05**	-0.01	**-0.04**	**-0.08**				
(8)	FIRM_AGE	**0.03**	**-0.06**	**0.05**	**-0.03**	**-0.04**	-0.01	**0.08**			
(9)	FOREIGN	**0.04**	0.00	**0.07**	**0.08**	-0.02	**-0.02**	**0.13**	**0.10**		
(10)	INST_OWNERSHIP	-0.01	**-0.08**	**0.06**	**0.04**	**-0.04**	**-0.04**	**0.24**	**0.02**	**0.14**	
(11)	INV	0.00	0.00	0.00	**-0.03**	-0.01	0.00	-0.01	**0.12**	**0.12**	**0.04**
(12)	LOSS	0.01	**0.11**	**-0.03**	**-0.02**	**0.05**	**0.02**	**-0.11**	**-0.19**	**-0.03**	**-0.18**
(13)	NEW_IT	**0.26**	**0.07**	**0.05**	0.01	0.01	0.01	**0.05**	**0.12**	**0.09**	**0.04**
(14)	RESTRUCTURE	**0.04**	0.02	**0.06**	**0.04**	0.00	**-0.02**	**0.14**	**0.13**	**0.32**	**0.10**
(15)	SALES_GROWTH	-0.01	**0.02**	-0.01	**0.07**	0.01	0.01	**-0.05**	**-0.13**	**-0.07**	**-0.05**
(16)	SEGMENTS	**0.07**	0.01	**0.04**	**0.05**	**-0.02**	**-0.02**	**0.07**	**0.25**	**0.13**	**0.06**
(17)	SIZE	**0.04**	**-0.13**	**0.11**	**0.02**	**-0.07**	**-0.05**	**0.38**	**0.30**	**0.21**	**0.31**
(18)	IT_COMMITTEE	0.00	-0.01	**0.02**	0.00	0.00	-0.01	**0.04**	**0.08**	**0.09**	**0.04**
(19)	Z_SCORE	0.00	**-0.06**	**0.02**	0.02	**-0.04**	-0.01	**0.04**	**0.08**	**0.09**	**0.18**

		(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	AUTOMATION								
(2)	MATERIAL_WEAKNESS								
(3)	AC_IT_EXPERTISE								
(4)	ACQUISITION								
(5)	ANNOUNCE_RESTATEMENT								

Table 3 (continued)

		(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(6)	AUDITOR_RESIGN								
(7)	BIG4								
(8)	FIRM_AGE								
(9)	FOREIGN								
(10)	INST_OWNERSHIP								
(11)	INV								
(12)	LOSS	**-0.06**							
(13)	NEW_IT	**0.02**	0.00						
(14)	RESTRUCTURE	**0.07**	**0.06**	**0.10**					
(15)	SALES_GROWTH	**-0.06**	**0.04**	**-0.02**	**-0.09**				
(16)	SEGMENTS	**0.03**	**-0.08**	**0.18**	**0.12**	**-0.06**			
(17)	SIZE	**-0.10**	**-0.37**	**0.10**	**0.09**	**-0.02**	**0.24**		
(18)	IT_COMMITTEE	0.00	0.00	**0.04**	**0.08**	0.00	**0.04**	**0.11**	
(19)	Z_SCORE	**0.19**	**-0.30**	-0.01	0.00	**-0.06**	**0.02**	**0.12**	0.00

This table presents Pearson correlations for the internal controls sample. Bold values indicate significance at the 0.10 level or lower.

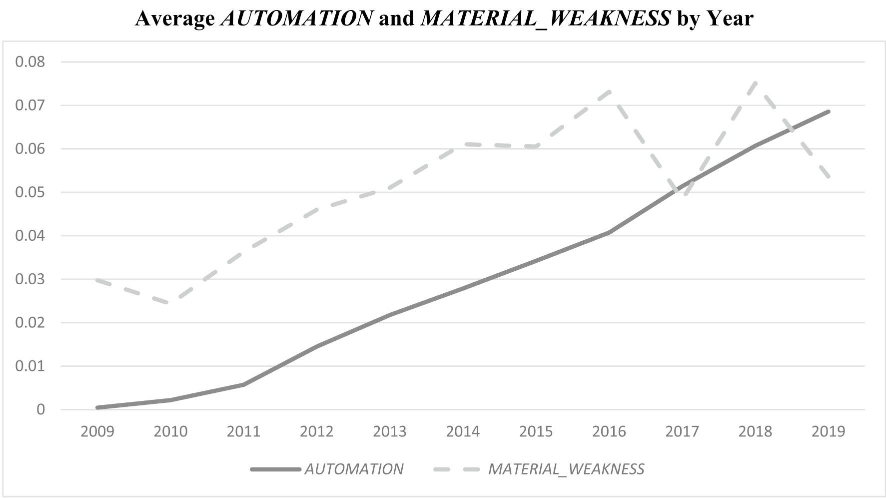

Fig. 3 Average *AUTOMATION* and *MATERIAL_WEAKNESS* by Year

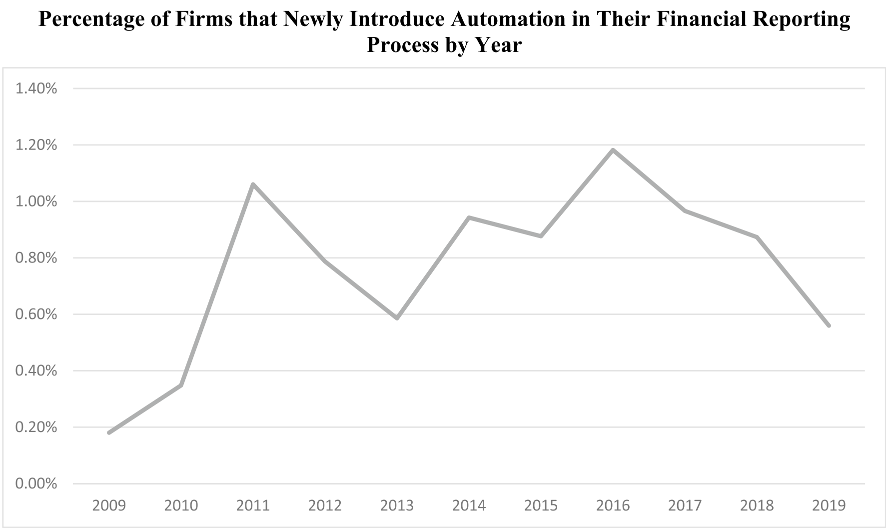

Fig. 4 Percentage of Firms that Newly Introduce Automation in Their Financial Reporting Process by Year

Table 4 The Association Between Accounting Automation and Internal Controls

Panel A: Levels Analysis

Independent Variables	Pr.	Dependent Variable: *MATERIAL_WEAKNESS*	
		(1)	
Test Variable:			
AUTOMATION	-	**-0.0745**	***
[t-stat] (p-value)		[-3.30]	(≤0.01)
Control Variables:			
IT_COMMITTEE	-	-0.0335	**
AC_IT_EXPERTISE	-	-0.0043	
NEW_IT	-	-0.0153	**
SIZE	-	-0.0130	***
SEGMENTS	+	-0.0003	
FOREIGN	+	0.0068	
ACQUISITION	+	0.0104	**
RESTRUCTURE	+	0.0010	
FIRM_AGE	-	0.0002	
SALES_GROWTH	+	0.0046	*
INV	+	-0.0848	
LOSS	+	0.0271	***
Z_SCORE	-	-0.0030	**
AUDITOR_RESIGNED	+	0.1411	***
ANNOUNCE_RESTATEMENT	+	0.1657	***
INST_OWNERSHIP	-	-0.0115	*
BIG4	?	0.0346	**
Firm Fixed Effects		YES	
Year Fixed Effects		YES	
N		25,604	
Adjusted R-squared		22.24%	

Panel B: Changes Analysis

Independent Variables	Pr.	Dependent Variable: Δ*MATERIAL_WEAKNESS*	
		(1)	
Test Variable:			
ΔAUTOMATION	-	**-0.0971**	***
[t-stat] (p-value)		[-2.64]	(≤0.01)
Control Variables:			
ΔIT_COMMITTEE	-	-0.0334	*
ΔAC_IT_EXPERTISE	-	-0.0072	
ΔNEW_IT	-	-0.0993	***
ΔSIZE	-	-0.0044	
ΔSEGMENTS	+	-0.0021	

Table 4 (continued)

Panel B: Changes Analysis

Independent Variables	Pr.	Dependent Variable: Δ*MATERIAL_WEAKNESS*	
		(1)	
ΔFOREIGN	+	0.0152	
ΔACQUISITION	+	0.0120	**
ΔRESTRUCTURE	+	-0.0086	*
ΔFIRM_AGE	-	-0.0169	***
ΔSALES_GROWTH	+	0.0031	
ΔINV	+	0.0360	
ΔLOSS	+	0.0241	***
ΔZ_SCORE	-	-0.0023	*
ΔAUDITOR_RESIGNED	+	0.0373	
ΔANNOUNCE_RESTATEMENT	+	-0.0672	***
ΔINST_OWNERSHIP	-	-0.0179	*
ΔBIG4	?	0.0666	**
Firm Fixed Effects		NO	
Year Fixed Effects		YES	
N		21,905	
Adjusted R-squared		1.48%	

Panel C: Propensity Score Matched Difference-in-Differences

Independent Variables	Pr.	Dependent Variable: *MATERIAL_WEAKNESS*	
		(1)	
Test Variable:			
POST*TREAT	-	**-0.1718**	***
[t-stat] (p-value)		[-5.01]	(≤0.01)
Control Variables:			
TREAT	?	0.2176	***
POST	?	0.0088	
IT_COMMITTEE	-	-0.0670	*
AC_IT_EXPERTISE	-	0.0069	
NEW_IT	-	0.1006	***
SIZE	-	-0.0274	***
SEGMENTS	+	0.0104	**
FOREIGN	+	0.0136	
ACQUISITION	+	0.0080	
RESTRUCTURE	+	-0.0103	
FIRM_AGE	-	-0.0013	**
SALES_GROWTH	+	0.0288	*
INV	+	-0.0884	
LOSS	+	0.0643	***

Table 4 (continued)

Panel C: Propensity Score Matched Difference-in-Differences

Independent Variables	Pr.	Dependent Variable: *MATERIAL_WEAKNESS* (1)	
Z_SCORE	-	0.0011	
AUDITOR_RESIGNED	+	0.3894	***
ANNOUNCE_RESTATEMENT	+	0.4638	***
INST_OWNERSHIP	-	-0.0813	*
BIG4	?	-0.0251	
Firm Fixed Effects		NO	
Year Fixed Effects		NO	
N		1,623	
Adjusted R-squared		19.08%	

This table presents the analysis of the association between accounting automation and internal control material weaknesses. Panel A is a levels analysis. Panel B is a changes analysis. Panel C is a propensity score matched difference-in-differences analysis, where treatment observations are matched within treatment industry and within treatment year to the nearest control neighbor within a caliper distance of 0.01; the sample in Panel C consists of years *t*-2 to years *t*+2, where year *t* is the year that the treatment observation introduces automation. All variables are defined in Appendix A. The models in Panels A and C are linear probability models with robust standard errors clustered by firm. The model in Panel B is an ordinary least squares regression model with robust standard errors clustered by firm. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests if the coefficient sign is consistent with the predicted direction (if a directional prediction is made) and two-tailed tests otherwise.

Pre-Treatment and Post-Treatment Trends in *MATERIAL_WEAKNESS* for Treatment and Control Groups in Table 4 Panel C's Propensity Score Matched Difference-in-Differences Analysis (Year *t* = Year of Treatment)

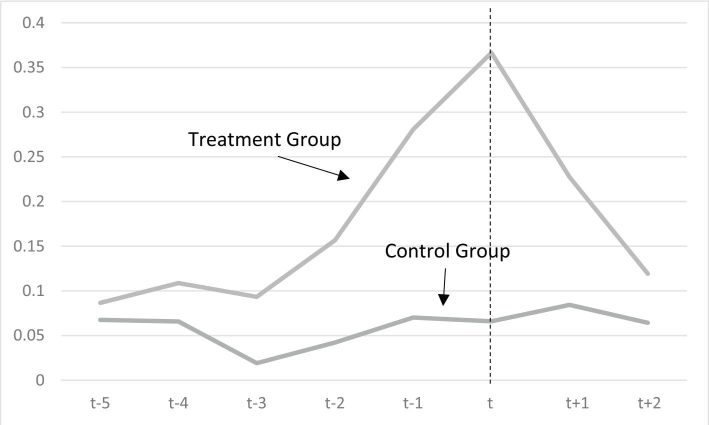

Fig. 5 Pre-Treatment and Post-Treatment Trends in *MATERIAL_WEAKNESS* for Treatment and Control Groups in Table 4 Panel C's Propensity Score Matched Difference-in-Differences Analysis (Year *t* = Year of Treatment)

using a window of [*t*-2, *t*+2]. Tabulated in Panel C of Table 4, the coefficient on *POST*TREAT* is negative and significant (*p*-value ≤ 0.01).[11]

Taken together, the results of Table 4 suggest accounting automation improves the internal control environment and, by association, financial reporting. However, to reinforce my inferences, I go a step further and identify the specific areas of accounting that are being automated by firms. I then study the association between automation of a specific area of accounting and internal control material weaknesses in that same specific area. Using the categorizations shown in Fig. 1, I create five new test variables: *AUTOMATION_GROUP_1*, *AUTOMATION_GROUP_2*, *AUTOMATION_GROUP_3*, *AUTOMATION_GROUP_4*, and *AUTOMATION_GROUP_1&2&3&4*.[12] I also create five new analogous dependent variables: *MATERIAL_WEAKNESS_GROUP_1*, *MATERIAL_WEAKNESS_GROUP_2*, *MATERIAL_WEAKNESS_GROUP_3*, *MATERIAL_WEAKNESS_GROUP_4*, and *MATERIAL_WEAKNESS_GROUP_1&2&3&4*.[13] The association between my test and dependent variables remain generally negative and significant (*p*-values ≤ 0.10 or lower) in Table 5.[14]

[11] *TREAT* equals one if firm *i* is part of the treatment group and zero if firm *i* is part of the control group. *POST* equals one if year *t* is after the year that firm *i* is treated (for treatment observations) or after the year that firm *i*'s matched treatment firm is treated (for control observations) (zero otherwise).

[12] *AUTOMATION_GROUP_1* equals one when *AUTOMATION* equals one but only for observations that introduced automation into the {expenses & payables} area of accounting; equals zero when *AUTOMATION* equals zero; and all other observations are discarded. *AUTOMATION_GROUP_2*, *AUTOMATION_GROUP_3*, and *AUTOMATION_GROUP_4* are calculated similarly except for the {consolidations, reconciliations, and journal entries}, {revenue & receivables}, and {segregation of duties, user access and monitoring, and IT} areas of accounting, respectively. *AUTOMATION_GROUP_1&2&3&4* equals one when either of *AUTOMATION_GROUP_1*, *AUTOMATION_GROUP_2*, *AUTOMATION_GROUP_3*, or *AUTOMATION_GROUP_4* equals one; equals zero when *AUTOMATION* equals zero; and all other observations are discarded.

[13] *MATERIAL_WEAKNESS_GROUP_1* equals one when *MATERIAL_WEAKNESS* equals one but only for observations that Audit Analytics categorizes as {code 29 [expense recording (payroll, SG&A) issues], code 14 [capitalization of expenditures issues], code 32 [inventory, vendor and cost of sales issues], code 27 [deferred, stock-based or executive comp issues], code 33 [liabilities, payables, reserves and accrual estimation failure issues], code 80 [pension and other post-retirement benefit issues], or code 41 [tax expense/benefit/deferral/other (FAS 109) issues]}; equals zero when *MATERIAL_WEAKNESS* equals zero; and all other observations are discarded. *MATERIAL_WEAKNESS_GROUP_2*, *MATERIAL_WEAKNESS_GROUP_3*, and *MATERIAL_WEAKNESS_GROUP_4* are calculated similarly except for observations that Audit Analytics categorizes as {code 76 [journal entry control issues], code 24 [consolidation, (Fin46r/Off BS) & foreign currency translation issues], code 8 [intercompany/investment w/ subsidiary/affiliate issues], code 12 [untimely or inadequate account reconciliations], or code 38 [foreign, related party, affiliated and/or subsid issues]}, {code 39 [revenue recognition issues] or code 15 [accounts/loans receivable, investments & cash issues]}, and {code 42 [segregations of duties/design of controls issue] or code 22 [information technology, software, security & access issue]}, respectively. *MATERIAL_WEAKNESS_GROUP_1&2&3&4* equals one when either of *MATERIAL_WEAKNESS_GROUP_1*, *MATERIAL_WEAKNESS_GROUP_2*, *MATERIAL_WEAKNESS_GROUP_3*, or *MATERIAL_WEAKNESS_GROUP_4* equals one; equals zero when *MATERIAL_WEAKNESS* equals zero; and all other observations are discarded.

[14] The sample size varies between columns in Table 5 because in each column I exclude (i) observations that automated but did not specify the area of accounting that the automation was introduced in, (ii) observations that automated an area of accounting that is different than the focal area being studied, and (ii) observations that have a material weakness but in an area that is other than the focal accounting area being studied. In other words, the zeroes for each test variable are observations that did not introduce automation, and the zeroes for each dependent variable are observations that do not possess any material weaknesses.

Table 5 The Association Between Automation in Particular Areas of Accounting and Internal Controls in those Same Areas

Independent Variables	Pr	Dependent Variable: *MATERIAL_WEAKNESS_GROUP_1* (1)		Dependent Variable: *MATERIAL_WEAKNESS_GROUP_2* (2)		Dependent Variable: *MATERIAL_WEAKNESS_GROUP_3* (3)		Dependent Variable: *MATERIAL_WEAKNESS_GROUP_4* (4)		Dependent Variable: *MATERIAL_WEAKNESS_GROUP_1&2&3&4* (5)		Dependent Variable: *MATERIAL_WEAKNESS_GROUP_1&2&3&4* (6)	
Test Variables:													
AUTOMATION_GROUP_1	-	**-0.2206**	***									**-0.1763**	***
[t-stat] (p-value)		[-3.14]	(≤0.01)									[-2.43]	(≤0.01)
AUTOMATION_GROUP_2	-			**-0.1296**	***							**-0.1491**	***
[t-stat] (p-value)				[-2.72]	(≤0.01)							[-3.26]	(≤0.01)
AUTOMATION_GROUP_3	-					**-0.1786**	***					**-0.1210**	*
[t-stat] (p-value)						[-2.38]	(≤0.01)					[-1.34]	(0.091)
AUTOMATION_GROUP_4	-							**-0.3128**	***			**-0.0785**	
[t-stat] (p-value)								[-2.79]	(≤0.01)			[-0.44]	(0.329)
AUTOMATION_GROUP_1&2&3&4	-									**-0.1703**	***		
[t-stat] (p-value)										[-4.47]	(≤0.01)		
Control Variables:													
IT_COMMITTEE	-	-0.0108		-0.0236	**	-0.0136	**	-0.0197	**	-0.0329	**	-0.0327	**
AC_IT_EXPERTISE	-	-0.0069		0.0014		-0.0063		-0.0028		-0.0017		-0.0016	
NEW_IT	-	-0.0140	**	-0.0077		-0.0011		-0.0196	***	-0.0196	**	-0.0206	***
SIZE	-	-0.0074	***	-0.0056	***	-0.0043	**	-0.0066	***	-0.0113	***	-0.0113	***
SEGMENTS	+	-0.0002		-0.0008		-0.0008		-0.0011		-0.0013		-0.0012	
FOREIGN	+	0.0173	**	0.0133	***	0.0122	**	0.0119	**	0.0186	**	0.0188	**
ACQUISITION	+	0.0025		0.0000		0.0011		0.0030		0.0050		0.0049	
RESTRUCTURE	+	0.0029		0.0004		-0.0009		0.0017		0.0023		0.0023	
FIRM_AGE	-	0.0017		0.0001		-0.0013		0.0048	**	0.0000		0.0000	
SALES_GROWTH	+	0.0026		0.0015		0.0022		0.0026		0.0041	*	0.0041	*

Table 5 (continued)

Independent Variables	Pr	Dependent Variable: *MATERIAL_WEAKNESS_GROUP_1* (1)		Dependent Variable: *MATERIAL_WEAKNESS_GROUP_2* (2)		Dependent Variable: *MATERIAL_WEAKNESS_GROUP_3* (3)		Dependent Variable: *MATERIAL_WEAKNESS_GROUP_4* (4)		Dependent Variable: *MATERIAL_WEAKNESS_GROUP_1&2&3&4* (5)		Dependent Variable: *MATERIAL_WEAKNESS_GROUP_1&2&3&4* (6)	
INV	+	-0.0190		-0.0422		-0.0858		-0.0968	*	-0.0822		-0.0831	
LOSS	+	0.0197	***	0.0091	***	0.0112	***	0.0103	***	0.0254	***	0.0255	***
Z_SCORE	-	-0.0002		-0.0009	*	-0.0004		-0.0014	*	-0.0013		-0.0013	
AUDITOR_RESIGNED	+	0.1034	***	0.0951	***	0.0889	***	0.0929	***	0.1411	***	0.1401	***
ANNOUNCE_RESTATEMENT	+	0.1408	***	0.1152	***	0.1384	***	0.1273	***	0.1668	***	0.1667	***
INST_OWNERSHIP	-	-0.0037		-0.0086	*	-0.0078	*	-0.0153	***	-0.0152	**	-0.0148	**
BIG4	?	0.0273	**	0.0251	**	0.0183		0.0169		0.0399	***	0.0398	***
Firm Fixed Effects		YES		YES		YES		YES		YES		YES	
Year Fixed Effects		YES		YES		YES		YES		YES		YES	
N		24,347		24,083		24,110		24,099		24,956		24,956	
Adjusted R-squared		18.42%		22.27%		21.54%		25.71%		21.87%		21.82%	

This table presents the analysis of the association between automation in particular areas of accounting and internal controls in those same areas. All variables are defined in Appendix Table 14. The model in all columns is a linear probability model with robust standard errors clustered by firm. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests if the coefficient sign is consistent with the predicted direction (if a directional prediction is made) and two-tailed tests otherwise.

6.3 Sensitivity analyses

I next address six concerns with my main analysis. One concern is that firms may only introduce automation when they have existing internal control material weaknesses, and thus my test variable *AUTOMATION* may be noisily proxying for firms that are correcting existing weaknesses. The second concern is whether *AUTOMATION* is capturing the effect of a firm's upgrades to its information technology that involve non-automation changes rather than the effect of automation per se. A third concern with my inferences is whether *AUTOMATION* is capturing the effect of firms that make changes to their internal controls rather than the effect of automation per se. The fourth concern with my main analysis is whether *AUTOMATION* is capturing the effect of automation use by external audit firms (e.g., Commerford et al. 2022; Fedyk et al. 2022; Law and Shen 2022) rather than automation use by public firms. The fifth concern with my inferences is whether my inferences are driven by my choice to study SOX 404b internal control material weaknesses rather than SOX 404a. The sixth concern with my main analysis is whether my observed effect is concentrated in the later years in my sample, given the surge in adoption of automation-related technologies during that time.I address all six concerns with empirical analyses tabulated and discussed in the online appendix. Inferences remain consistent.

7 Additional analyses

For my final set of tests, I conduct six additional analyses. First, I study how a firm's use of automation impacts monitoring over the financial reporting process, focusing on the auditor (an external monitor) and the audit committee (an internal monitor). These analyses are motivated by the fact that the effect automation has on monitoring is ex ante ambiguous. On one hand, monitoring may increase because automation is new information technology used by the firm and enhances a firm's information technology complexity—and this requires oversight. On the other hand, the primary argument in favor of automation is that it helps prevent human-driven errors and fraud—a notion that is borne out in the data (see main analysis in Sect. 6). Consequently, oversight over the financial reporting process may decrease if monitors perceive there is less of a need for monitoring, given the lower risk of errors and fraud vis-à-vis automation.

I empirically test these assertions by studying the association of *AUTOMATION* with *AUDIT_FEES* (log of audit fees paid by firm *i* to its external auditor in year *t*) as a proxy for external auditor monitoring and with *AC_MEETINGS* (log of the number of meetings held by firm *i*'s audit committee in year *t*) as a proxy for audit committee monitoring. For these tests, *AUTOMATION* is interacted with *YEARS_SINCE_AUTOMATION* (a count variable that represents the number of years since firm *i* introduced accounting automation, where zero represents the first year where *AUTOMATION* = 1; this variable is always zero for observations where *AUTOMATION* = 0). For ease of interpretation of the interaction term, I normalize

Table 6 The Association Between Accounting Automation and External Audit Fees

Independent Variables	Pr	Dependent Variable: *AUDIT_FEES*	
		(1)	
Test Variables:			
AUTOMATION	?	**0.0464**	*
[t-stat] (p-value)		[1.83]	(0.068)
AUTOMATION*YEARS_SINCE_AUTOMATION	?	**-0.2245**	***
[t-stat] (p-value)		[-3.06]	(≤0.01)
Control Variables:			
IT_COMMITTEE	?	0.0251	
AC_IT_EXPERTISE	?	0.0136	
NEW_IT	?	0.0770	***
SIZE	+	0.3120	***
LEVERAGE	+	0.0791	***
LOSS	+	0.0516	***
ROA	-	-0.0282	***
CURRENT_ASSETS	?	0.0379	
QUICK_RATIO	?	-0.0110	***
FOREIGN	+	0.0890	***
SEGMENTS	+	0.0110	***
DECEMBER	+	0.0874	*
GOING_CONCERN	+	0.0984	***
BIG4	+	0.4348	***
Firm Fixed Effects		YES	
Year Fixed Effects		YES	
N		36,315	
Adjusted R-squared		96.12%	
AUTOMATION + AUTOMATION*YEARS_SINCE_AUTOMATION = 0	?	**-0.1781**	***
[t-stat] (p-value)		[-2.58]	(≤0.01)

This table presents the analysis of the association between accounting automation and external audit fees. All variables are defined in Appendix Table 14. The model is an ordinary least squares regression with robust standard errors clustered by firm. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests if the coefficient sign is consistent with the predicted direction (if a directional prediction is made) and two-tailed tests otherwise.

YEARS_SINCE_AUTOMATION so that the variable ranges between 0 and 1 (inclusive), where 1 represents observations that are in their 11th year of automation (which is the maximum that is possible in my sample). The main effect of *AUTOMATION* captures the association for the first year where *AUTOMATION* = 1 and the interaction term *AUTOMATION*YEARS_SINCE_AUTOMATION* captures the incremental association for each year thereafter.

Table 7 The Association Between Accounting Automation and Audit Committee Meetings

Independent Variables	Pr	Dependent Variable: *AC_MEETINGS*	
		(1)	
Test Variables:			
AUTOMATION	?	**0.0639**	**
[t-stat] (p-value)		[2.06]	(0.039)
AUTOMATION*YEARS_SINCE_AUTOMATION	?	**-0.2612**	**
[t-stat] (p-value)		[-2.32]	(0.020)
Control Variables:			
IT_COMMITTEE	?	-0.0057	
AC_IT_EXPERTISE	?	0.0252	
NEW_IT	?	0.0343	**
SIZE	+	-0.0041	
SEGMENTS	-	0.0002	
FOREIGN	-	0.0161	
ACQUISITION	-	-0.0201	**
RESTRUCTURE	-	0.0250	***
FIRM_AGE	+	0.0241	**
SALES_GROWTH	-	-0.0072	**
INV	-	0.0649	
LOSS	-	0.0250	***
Z_SCORE	+	0.0006	**
AUDITOR_RESIGNED	-	0.0489	*
ANNOUNCE_RESTATEMENT	-	0.2161	***
INST_OWNERSHIP	+	0.0758	***
BIG4	?	0.0671	***
Firm Fixed Effects		YES	
Year Fixed Effects		YES	
N		13,583	
Adjusted R-squared		68.05%	
AUTOMATION + AUTOMATION*YEARS_SINCE_AUTOMATION = 0	?	**-0.1973**	**
[t-stat] (p-value)		[-1.96]	(0.050)

This table presents the analysis of the association between accounting automation and audit committee meetings. All variables are defined in Appendix Table 14. The model is an ordinary least squares regression with robust standard errors clustered by firm. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests if the coefficient sign is consistent with the predicted direction (if a directional prediction is made) and two-tailed tests otherwise.

As shown in Table 6 and 7 respectively, the coefficient on *AUTOMATION* for both *AUDIT_FEES* and *AC_MEETINGS* is *positive* and significant (p-value ≤ 0.10 or lower) in the initial years after a firm introduces automation in its financial reporting process.[15] This suggests that both monitors enhance oversight when automation is new to the firm. However, this relation flips as the auditors and audit committees become more comfortable with the technology, as evidenced by the *negative* and significant (p-value ≤ 0.05 or lower) coefficient on *AUTOMATION*YEARS_SINCE_AUTOMATION*.[16] This suggests that both monitors decrease their oversight over the financial reporting process as they observe stronger internal control environment after automation, and the significantly (p-value ≤ 0.05 or lower) negative 'total effect' of *AUTOMATION + AUTOMATION*YEARS_SINCE_AUTOMATION* suggests that the monitoring is overall lower after automation compared to before.

Second, an extensive extant literature has documented the financial reporting benefits of greater monitoring by the audit committee and external auditor (see DeFond and Zhang 2014). Also, although my evidence suggests that overall internal control environment is stronger after automation, automation cannot perfectly prevent weaknesses in internal controls. Given that auditor and audit committee oversight is beneficial and that automation is not perfect, a byproduct of less oversight by the auditor and the audit committee may be that internal control weaknesses are more material when they *do* happen. I test this assertion by studying the association between *AUTOMATION* and *CAR* (which captures a firm's cumulative abnormal market return in the [-1,1] window around the disclosure date of its internal control material weakness; this variable represents the percent return in decimal form) in a subsample of observations that disclose internal control material weaknesses in their 10-K filings. Tabulated in Table 8, there is no significant association between *AUTOMATION* and *CAR* in the initial years a firm introduces automation (p-value = 0.37). However, the association of *AUTOMATION* with *CAR* is *negative* and significant in the later years (p-value ≤ 0.05). Taken together, these results suggest that internal control material weaknesses are more material for firms with *AUTOMATION*—but only in the later years after automation, which is consistent with the pattern of lower monitoring documented in Table 6 and 7.

Third, one concern with my main analysis is that my findings may be driven by my research design choice to study material weaknesses in internal controls. Therefore, as my next additional analysis, I reinforce my main inferences by studying an alternative proxy of financial reporting quality: *RESTATEMENT* (equals one if firm i restates the financial statements for year t [zero otherwise]) (e.g., Dechow et al. 2010). I present the results in Table 9. While controlling for firm and year fixed effects and other documented determinants of restatements following Badolato et al.

[15] I obtain data on audit committee meetings from Ashraf, Deore, and Krishnan (2024), who programmatically extract data on audit committee meetings from firms' proxy statement filings (firms are required to make such disclosures, see 17 CFR §229.407(b)). The sample size in Table 7 is relatively smaller than other analyses due to the fact that the audit committee meetings data is unstructured in proxy filings and therefore it is not possible to programmatically extract meetings data from every proxy filing. Observations with missing data on *AC_MEETINGS* are excluded from the analysis.

[16] The 'main effect' of *YEARS_SINCE_AUTOMATION* is omitted from Table 6 and 7 due to collinearity: *AUTOMATION*YEARS_SINCE_AUTOMATION* and *YEARS_SINCE_AUTOMATION* are effectively the same variables and therefore both cannot be included in the same regression analysis.

Table 8 The Association Between Accounting Automation and Materiality of Internal Control Material Weaknesses

Independent Variables	Pr	Dependent Variable: *CAR* (1)	
Test Variables:			
AUTOMATION	?	**-0.0196**	
[t-stat] (p-value)		[-0.89]	(0.372)
AUTOMATION*YEARS_SINCE_AUTOMATION	?	**-0.1741**	**
[t-stat] (p-value)		[-2.17]	(0.031)
Control Variables:			
IT_COMMITTEE	?	-0.0162	
AC_IT_EXPERTISE	?	0.0014	
NEW_IT	?	0.0094	
SIZE	?	-0.0167	*
SEGMENTS	?	-0.0022	
FOREIGN	?	0.0206	
ACQUISITION	?	0.0000	
RESTRUCTURE	?	-0.0001	
FIRM_AGE	?	0.0424	
SALES_GROWTH	?	0.0002	
INV	?	-0.0151	
LOSS	?	-0.0096	
Z_SCORE	?	0.0004	
AUDITOR_RESIGNED	?	-0.0373	
ANNOUNCE_RESTATEMENT	?	0.0015	
INST_OWNERSHIP	?	0.0028	
BIG4	?	-0.0049	
Firm Fixed Effects		YES	
Year Fixed Effects		YES	
N		731	
Adjusted R-squared		12.42%	
AUTOMATION + AUTOMATION*YEARS_SINCE_AUTOMATION = 0	?	**-0.1937**	**
[t-stat] (p-value)		[-2.52]	(0.012)

This table presents the analysis of the association between accounting automation and abnormal returns around the disclosure date of internal control material weaknesses. The sample is restricted to observations that disclose an internal control material weakness in their 10-K filing. All variables are defined in Appendix Table 14. The model is an ordinary least squares regression with robust standard errors clustered by firm. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests if the coefficient sign is consistent with the predicted direction (if a directional prediction is made) and two-tailed tests otherwise.

(2014) restatements model, I find *AUTOMATION* is significantly negatively associated with *RESTATEMENT* (p-value ≤ 0.05). As fewer restatements is representative of stronger financial reporting quality similar to fewer internal control material

Table 9 The Association Between Accounting Automation and Restatements

Independent Variables	Pr	Dependent Variable: *RESTATEMENT*	
		(1)	
Test Variable:			
AUTOMATION	-	**-0.0332**	**
[t-stat] (p-value)		[-2.16]	(0.016)
Control Variables:			
IT_COMMITTEE	-	0.0030	
AC_IT_EXPERTISE	-	0.0067	
NEW_IT	-	-0.0124	**
AUDIT_COMM_SIZE	-	0.0029	*
BOARD_INDEPENDENCE	-	-0.0429	**
BOARD_SIZE	-	-0.0017	*
CEO_CHAIRMAN	+	0.0087	***
SIZE	-	0.0062	***
MTB	?	0.0000	
ROA	?	-0.0001	
LEVERAGE	-	0.0086	
ISSUANCE	?	0.0011	
INST_OWNERSHIP	-	-0.0147	**
MATERIAL_WEAKNESS	+	0.0552	***
Firm Fixed Effects		YES	
Year Fixed Effects		YES	
N		27,236	
Adjusted R-squared		36.76%	

This table presents the analysis of the association between accounting automation and restatements. All variables are defined in Appendix Table 14. The model is a linear probability model with robust standard errors clustered by firm. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests if the coefficient sign is consistent with the predicted direction (if a directional prediction is made) and two-tailed tests otherwise.

weaknesses, this analysis provides reassurance that my findings are not driven by my choice of dependent variable.

I also conduct an analysis similar to Table 5 (where I study the effects of automation in specific areas of accounting), except I now focus on restatements instead of material weaknesses.[17] The results of this analysis are tabulated in Table 10. The

[17] *RESTATEMENT_GROUP_1* equals one when *RESTATEMENT* equals one but only for observations that Audit Analytics categorizes as {code 7 [expense (payroll, SGA, other) recording issues], code 12 [liabilities, payables, reserves and accrual estimate failures], code 23 [capitalization of expenditures issues], code 20 [inventory, vendor and/or cost of sales issues], code 17 [deferred, stock-based and/or executive comp issues], code 48 [deferred, stock-based options backdating only], code 39 [deferred, stock-based SFAS 123 only], code 69 [pension and other post-retirement benefit issues], or code 18 [tax expense/benefit/deferral/other (FAS 109) issues]}; equals zero when *RESTATEMENT* equals zero; and all other observations are discarded. *RESTATEMENT_GROUP_2* and *RESTATEMENT_GROUP_3* are calculated similarly except for observations that Audit Analytics categorizes as {code 13 [consolidation

aggregate evidence is consistent with lower restatements, albeit the evidence is weaker than previously—likely due to lack of statistical power, as the variation in the test and dependent variables is very low in Table 10.

As my fourth additional analysis, I focus on an external indicator of financial reporting quality—securities class action lawsuits by investors. These lawsuits are allegations by investors that firms violated federal securities laws, and the allegations are usually centered on improper financial reporting or disclosure (Kim and Skinner 2012). This analysis allows me to study whether investors perceive the financial reporting for firms has improved after automation, as there should be fewer allegations of misconduct in such a scenario. Empirically, I regress *SUED*, which equals one if firm *i* is sued for year *t* in a securities class action lawsuit by investors (zero otherwise), on *AUTOMATION* while controlling for firm and year fixed effects and other common control variables, which are based on Kim and Skinner (2012). The results, presented in Table 11, are consistent with my prior findings: the coefficient on *AUTOMATION* is negative and significant (p-value ≤ 0.01).

Fifth, I study whether automation impacts another aspect of financial reporting—timeliness (e.g., FASB 1980; Ashraf et al. 2020). I proxy for timeliness with the time it takes for a firm to disclose its annual 10-K filing, which I capture with the variable *DAYS_TO_10K* (log of one plus the number of days between firm *i*'s year *t*'s fiscal-year end date and the date of 10-K filing for the same firm-year). The results of this analysis are presented in Table 12. I find a negative and significant association between *AUTOMATION* and *DAYS_TO_10K* (p-value ≤ 0.01).[18] This suggests that automation enables reporting efficiencies, which is one of the proposed benefits of automation (e.g., Cooper et al. 2019).

Finally, I study the association of *AUTOMATION* with demand for audit committee directors. This analysis is important because the literature disagrees on the effect that automation has on demand for rank-and-file auditor employees (e.g., Fedyk et al. 2022; Law and Shen 2022). Studying the effect on the board is a different—but important—perspective on how automation affects demand for accounting jobs. The results of this analysis, tabulated in Table 13, suggest that audit committees shrink after a firm introduces automation in its financial reporting process: the coefficient on *AUTOMATION* is negative and significant (p-value ≤ 0.05) when the dependent variable is *AUDIT_COMM_SIZE* (the number of directors on firm *i*'s audit committee in year *t*).

Footnote 17 (continued)

issues incl Fin 46 variable interest & off-B/S], code 37 [consolidation, foreign currency/inflation issue], code 24 [intercompany, investment in subs./affiliate issues], code 43 [intercompany, only—accounting issues], code 11 [foreign, related party, affiliated, or subsidiary issues], or code 44 [foreign, subsidiary only issues]} and {code 6 [revenue recognition issues] or code 14 [accounts/loans receivable, investments & cash issues]}, respectively. *RESTATEMENT_GROUP_1&2&3* equals one when either of *RESTATEMENT_GROUP_1*, *RESTATEMENT_GROUP_2*, or *RESTATEMENT_GROUP_3*; equals zero when *RESTATEMENT* equals zero; and all other observations are discarded. I do not conduct any analysis of *AUTOMATION_GROUP_4* for restatements because there are no analogous restatement categories.

[18] Following the advice of extant literature (e.g., Chan, Chen, Chen, and Yu 2012; Jha and Chen 2015; Ashraf et al. 2020), the control variables in Table 12 are based on DeFond and Zhang's (2014) audit fees model.

Table 10 The Association Between Automation in Particular Areas of Accounting and Restatements in those Same Areas

Independent Variables	Pr	Dependent Variable: *RESTATEMENT_GROUP_1*		Dependent Variable: *RESTATEMENT_GROUP_2*		Dependent Variable: *RESTATEMENT_GROUP_3*		Dependent Variable: *RESTATEMENT_GROUP_1&2&3*		Dependent Variable: *RESTATEMENT_GROUP_1&2&3*	
		(1)		**(2)**		**(3)**		**(4)**		**(5)**	
Test Variables:											
AUTOMATION_GROUP_1	-	**-0.0408**								**-0.0672**	**
[t-stat] (p-value)		[-0.97]	(0.167)							[-1.72]	(0.043)
AUTOMATION_GROUP_2	-			**-0.0485**						**-0.0820**	*
[t-stat] (p-value)				[-0.98]	(0.164)					[-1.28]	(0.100)
AUTOMATION_GROUP_3	-					**-0.1740**	**			**-0.1442**	**
[t-stat] (p-value)						[-2.15]	(0.016)			[-2.06]	(0.020)
AUTOMATION_GROUP_1&2&3	-							**-0.0781**	***		
[t-stat] (p-value)								[-2.35]	($\leq$0.01)		
Control Variables:											
IT_COMMITTEE	-	0.0020		0.0013		-0.0003		0.0015		0.0014	
AC_IT_EXPERTISE	-	0.0007		0.0017		0.0017		0.0035		0.0034	
NEW_IT	-	-0.0136	**	-0.0069	**	-0.0100	**	-0.0130	**	-0.0125	**
AUDIT_COMM_SIZE	-	0.0016		0.0013		0.0018	*	0.0017		0.0017	
BOARD_INDEPENDENCE	-	-0.0112		-0.0089		-0.0169	*	-0.0345	**	-0.0342	**
BOARD_SIZE	-	-0.0011	*	-0.0003		-0.0007		-0.0008		-0.0008	
CEO_CHAIRMAN	+	0.0040	*	0.0038	**	0.0059	***	0.0086	***	0.0087	***
SIZE	-	0.0042	**	0.0020		0.0052	***	0.0062	***	0.0063	***
MTB	?	0.0000		0.0000		0.0000		0.0000		0.0000	
ROA	?	0.0004		0.0005		0.0011		0.0014		0.0013	
LEVERAGE	-	0.0022		0.0014		0.0104		0.0081		0.0085	
ISSUANCE	?	0.0001		0.0020	*	0.0004		-0.0001		-0.0001	

Table 10 (continued)

Independent Variables	Pr	Dependent Variable: *RESTATEMENT_GROUP_1*		Dependent Variable: *RESTATEMENT_GROUP_2*		Dependent Variable: *RESTATEMENT_GROUP_3*		Dependent Variable: *RESTATEMENT_GROUP_1&2&3*		Dependent Variable: *RESTATEMENT_GROUP_1&2&3*	
		(1)		**(2)**		**(3)**		**(4)**		**(5)**	
INST_OWNERSHIP	-	-0.0091	*	-0.0070	*	-0.0110	**	-0.0136	**	-0.0136	**
MATERIAL_WEAKNESS	+	0.0275	***	-0.0024		0.0001		0.0264	***	0.0260	**
Firm Fixed Effects		YES		YES		YES		YES		YES	
Year Fixed Effects		YES		YES		YES		YES		YES	
N		26,246		26,087		26,184		26,586		26,586	
Adjusted R-squared		38.98%		38.48%		38.37%		36.91%		37.00%	

This table presents the analysis of the association between automation in particular areas of accounting and restatements in those same areas. All variables are defined in Appendix Table 14. The model in all columns is a linear probability model with robust standard errors clustered by firm. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests if the coefficient sign is consistent with the predicted direction (if a directional prediction is made) and two-tailed tests otherwise.

Table 11 The Association Between Accounting Automation and Securities Class Action Lawsuits by Investors

Independent Variables	Pr	Dependent Variable: *SUED*	
		(1)	
Test Variable:			
AUTOMATION	-	**-0.0343**	***
[t-stat] (p-value)		[-3.06]	(≤0.01)
Control Variables:			
IT_COMMITTEE	-	-0.0114	
AC_IT_EXPERTISE	-	-0.0118	**
NEW_IT	-	-0.0029	
FPS	+	0.0172	*
SIZE	+	0.0314	***
SALES_GROWTH	+	0.0023	
STOCK_RETURN	-	0.0109	***
RET_SKEW	-	0.0027	***
RET_STD	+	-0.4979	***
TURNOVER	+	0.0000	*
Firm Fixed Effects		YES	
Year Fixed Effects		YES	
N		39,058	
Adjusted R-squared		22.68%	

This table presents the analysis of the association between accounting automation and securities class action lawsuits by investors. All variables are defined in Appendix Table 14. The model is a linear probability model with robust standard errors clustered by firm. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests if the coefficient sign is consistent with the predicted direction (if a directional prediction is made) and two-tailed tests otherwise.

8 Conclusion

In this study, I investigate whether automation improves financial reporting, specifically focusing on the internal control environment. This research question is motivated by the fact that both practitioners and regulators argue that automation will play a material role in accounting and financial reporting going forward (Deloitte 2018a; AICPA 2020; PCAOB 2020; PCAOB 2021; PwC 2021; Roose 2021)—but there is practitioner concern that automation may harm internal controls and financial reporting (McCann 2019; Gartner 2020; EY 2021). However, I argue that automation will improve financial reporting by preventing human-related reporting errors or fraudulent behavior (Lanza 2007; Blue Lance 2012; Deloitte 2015; Deloitte 2018b; WNS 2020).

Table 12 The Association Between Accounting Automation and the Number of Days Needed to File the 10-K

Independent Variables	Pr	Dependent Variable: *DAYS_TO_10K*	
		(1)	
Test Variable:			
AUTOMATION	-	**-0.0366**	***
[t-stat] (p-value)		[-3.08]	(≤0.01)
Control Variables:			
IT_COMMITTEE	-	-0.0131	*
AC_IT_EXPERTISE	-	-0.0042	
NEW_IT	-	-0.0077	*
SIZE	-	-0.0288	***
LEVERAGE	+	-0.0073	
LOSS	+	0.0332	***
ROA	?	-0.0006	
CURRENT_ASSETS	?	-0.0550	***
QUICK_RATIO	?	0.0003	
FOREIGN	+	-0.0028	
SEGMENTS	+	0.0029	***
DECEMBER	?	0.0406	**
GOING_CONCERN	+	0.0896	***
BIG4	-	-0.0009	
Firm Fixed Effects		YES	
Year Fixed Effects		YES	
N		36,214	
Adjusted R-squared		74.19%	

This table presents the analysis of the association between accounting automation and the number of days needed to file the 10-K after year-end. All variables are defined in Appendix Table 14. The model is an ordinary least squares regression with robust standard errors clustered by firm. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests if the coefficient sign is consistent with the predicted direction (if a directional prediction is made) and two-tailed tests otherwise.

I identify firms that introduce automation in their financial reporting process through textual analysis of mandated disclosures in periodic accounting SEC filings. I find that automation is significantly associated with a lower incidence rate of internal control material weaknesses, suggesting that firms that introduce automation benefit from higher quality financial reporting due to a stronger internal control environment. This association holds in (i) a levels analysis with firm and year fixed effects, (ii) a changes analysis, and (iii) a propensity score matched difference-in-differences analysis. Inferences are consistent when focusing on the specific area of accounting that is automated, and results are robust to a battery of sensitivity

Table 13 The Association Between Accounting Automation and Size of the Audit Committee

Independent Variables	Pr	Dependent Variable: *AUDIT_COMM_SIZE*	
		(1)	
Test Variable:			
AUTOMATION	?	**-0.1155**	**
[t-stat] (p-value)		[-2.30]	(0.022)
Control Variables:			
IT_COMMITTEE	?	-0.1035	**
AC_IT_EXPERTISE	?	0.3661	***
NEW_IT	?	0.0197	
SIZE	+	0.0531	***
SEGMENTS	-	0.0079	
FOREIGN	-	-0.0467	*
ACQUISITION	-	0.0162	
RESTRUCTURE	-	0.0246	*
FIRM_AGE	+	0.0168	
SALES_GROWTH	-	-0.0095	**
INV	-	0.2720	**
LOSS	-	0.0323	**
Z_SCORE	+	0.0008	**
AUDITOR_RESIGNED	-	0.0318	
ANNOUNCE_RESTATEMENT	-	0.0598	*
INST_OWNERSHIP	+	-0.0046	
BIG4	?	0.0273	
Firm Fixed Effects		YES	
Year Fixed Effects		YES	
N		32,025	
Adjusted R-squared		60.78%	

This table presents the analysis of the association between accounting automation and the size of the audit committee. All variables are defined in Appendix Table 14. The model is an ordinary least squares regression with robust standard errors clustered by firm. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, using one-tailed tests if the coefficient sign is consistent with the predicted direction (if a directional prediction is made) and two-tailed tests otherwise.

analyses. I further find that automation is associated with decreased monitoring over the financial reporting process and with more material weaknesses when they do happen. Finally, I find that inferences remain consistent when studying restatements and securities class action lawsuits by investors (instead of internal control material weaknesses); firms with accounting automation are associated with more timely financial reporting; and automation appears to be associated with weaker demand for audit committee directors.

Overall, my evidence furthers the literature on how automation affects financial reporting, and I provide empirical support for the push by firms to introduce automation in their financial reporting process. However, my analyses also provide nuanced inferences in that firms appear to decrease oversight of the financial reporting process after they introduce automation, which can be costly when failures do happen. My study is related to but distinct from extant and concurrent research (e.g., Chen and Srinivasan 2023; Schoenfeld 2022; Fedyk et al. 2022; Commerford et al. 2022; Law and Shen 2022; Choudhary, Ramadas, and Sigler 2023), and it is unclear from extant and concurrent evidence whether automation improves financial reporting and internal controls. My aggregate findings should be informative to the myriad of stakeholders (including academics, managers, shareholders, board members, practitioners, and regulators) that are interested in how the use of accounting automation impacts financial reporting.

My findings should be taken within the context of two caveats. First, automation is not costless. Due to data limitations, I am unable to observe how much firms invest in automation. I speak only to the financial reporting benefits of automation and cannot speak to the whether automation is beneficial overall when considering both costs and benefits. Second, my textual methodology for identifying firms that introduce automation is designed to capture the wide range of technologies that firms may use when adding automation to their financial reporting process. However, while firms disclose when they introduce automation, they typically do not specify in their disclosures the specific type of automation technology they use. Thus, I speak to the effects of automation, but I am unable to differentiate between the different types of automation technologies—such as artificial intelligence, machine learning, and robotic process automation.

Appendix A

See Table 14

Table 14 Variable Definitions

Variable		Definition [Data Source]
AC_IT_EXPERTISE	=	one if firm *i*'s audit committee has an information technology expert on the audit committee in year *t* (zero otherwise) [BoardEx]
AC_MEETINGS	=	log of the number of meetings held by firm *i*'s audit committee during year *t* [EDGAR]
ACQUISITION	=	one if there is an acquisition by firm *i* in year *t* that contributes to sales or net income (zero otherwise) [Compustat]
ANNOUNCE_RESTATEMENT	=	one if firm *i* announces a restatement in year *t* (zero otherwise) [Audit Analytics]
AUDIT_COMM_SIZE	=	total number of audit committee directors for firm *i*'s year *t* [BoardEx]
AUDIT_FEES	=	log of audit fees paid by firm *i* to its external auditor in year *t* [Audit Analytics]
AUDITOR_RESIGN	=	one if the external auditor for firm *i* resigned between nine months prior to the fiscal-year end to three months after fiscal year-end (zero otherwise) (Ashbaugh-Skaife et al. 2007; Ashraf et al. 2020) [Audit Analytics]
AUTOMATION	=	one if firm *i* has introduced automation in its financial reporting process before the beginning of year *t* (zero otherwise), where introduction of automation in the financial reporting process is identified by searching the Controls and Procedures section of periodic accounting filings for the following words: "artificial intelligence", "ai tech", "ai related", "conversational ai", "evolutionary ai", "evolutionary computing", "intelligent system", "computer vision", "neural network", "virtual agent", "virtual assistant", "cognitive computing", "biometric", "deep learning", "machine learning", "natural language processing", "image recognition", "facial recognition", "speech recognition", "automation solutions", "intelligent automation", "marketing automation", "process automation", "robotic process automation", "autonomous tech", "autonomous", and the catchall root word of "automat" (which captures the words "automation", "automate", and "automatically") [CALCBENCH]
AUTOMATION_GROUP_1	=	equals one when *AUTOMATION* equals one but only for observations that introduced automation into the expenses & payables area of accounting; equals zero when *AUTOMATION* equals zero [CALCBENCH]
AUTOMATION_GROUP_1&2&3&4	=	equals one when either of *AUTOMATION_GROUP_1*, *AUTOMATION_GROUP_2*, *AUTOMATION_GROUP_3*, or *AUTOMATION_GROUP_4* equals one; equals zero when *AUTOMATION* equals zero [CALCBENCH]
AUTOMATION_GROUP_2	=	equals one when *AUTOMATION* equals one but only for observations that introduced automation into the consolidations, reconciliations, and journal entries area of accounting; equals zero when *AUTOMATION* equals zero [CALCBENCH]

Table 14 (continued)

Variable		Definition [Data Source]
AUTOMATION_GROUP_3	=	equals one when *AUTOMATION* equals one but only for observations that introduced automation into the revenue & receivables area of accounting; equals zero when *AUTOMATION* equals zero [CALCBENCH]
AUTOMATION_GROUP_4	=	equals one when *AUTOMATION* equals one but only for observations that introduced automation into the segregation of duties, user access and monitoring, and IT area of accounting; equals zero when *AUTOMATION* equals zero [CALCBENCH]
BIG4	=	one if firm *i*'s external auditor for year *t* is a Big 4 auditor (zero otherwise) [Audit Analytics]
BOARD_INDEPENDENCE	=	total number of independent directors for firm *i*'s year *t* scaled by total number of board directors for the same firm-year [BoardEx]
BOARD_SIZE	=	total number of board directors for firm *i*'s year *t* [BoardEx]
CAR	=	firm *i*'s raw return on day *t* minus the CRSP value-weighted index on day *t*, aggregated over the [-1,1] window where day 0 is the date of firm *i*'s 10-K filing for year *t*; this variable represents the percent return in decimal form [CRSP]
CEO_CHAIRMAN	=	one if firm *i*'s CEO in year *t* is also the chairman of the board for the same firm-year (zero otherwise) [BoardEx]
CURRENT_ASSETS	=	current assets for firm *i*'s year *t* scaled by total assets for the same firm-year [Compustat]
DAYS_TO_10K	=	log of one plus the number of days between firm *i*'s year *t*'s fiscal-year end date and the date of 10-K filing for the same firm-year [Audit Analytics]
DECEMBER	=	one if firm *i*'s year *t*'s fiscal year ends in December (zero otherwise) [Compustat]
FIRM_AGE	=	age of firm *i* in years as of year *t* [Compustat]
FOREIGN	=	one is firm *i* exhibits nonzero pre-tax foreign income in year *t* (zero otherwise) [Compustat]
FPS	=	one if firm *i* is in the for biotech (SIC 2833 to 2836 and 8731 to 8734), computer (SIC 3570 to 3577 and 7370 to 7374), electronics (SIC 3600 to 3674), or retail (SIC 5200 to 5961) industries in year t (zero otherwise) (Kim and Skinner 2012) [Compustat]
GOING_CONCERN	=	one if firm *i*'s external auditor issues a going concern option for year *t* (zero otherwise) [Audit Analytics]
INST_OWNERSHIP	=	the percentage of firm *i* owned by institutional investors in year *t* [Thomson Reuters]
INV	=	total inventory for firm *i*'s year *t* scaled by total assets for the same firm-year [Compustat]
ISSUANCE	=	one if firm *i* issues equity or debt in year *t* equal to or more than 10 percent of the total assets of the same firm-year (zero otherwise) [Compustat]

Table 14 (continued)

Variable		Definition [Data Source]
IT_COMMITTEE	=	one if firm *i* has a technology-related committee in year *t* (zero otherwise) [BoardEx]
LEVERAGE	=	long-term debt for firm *i*'s year *t* scaled by total assets for the same firm-year [Compustat]
LOSS	=	one if firm *i* exhibits net income less than zero in year *t* (zero otherwise) [Compustat]
MATERIAL_WEAKNESS	=	one if firm *i* has a SOX 404b material weakness in internal controls for year *t* (zero otherwise) [Audit Analytics]
MATERIAL_WEAKNESS_GROUP_1	=	equals one when *MATERIAL_WEAKNESS* equals one but only for observations that Audit Analytics categorizes as code 29 [expense recording (payroll, SG&A) issues], code 14 [capitalization of expenditures issues], code 32 [inventory, vendor and cost of sales issues], code 27 [deferred, stock-based or executive comp issues], code 33 [liabilities, payables, reserves and accrual estimation failure issues], code 80 [pension and other post-retirement benefit issues], or code 41 [tax expense/benefit/deferral/other (FAS 109) issues]; equals zero when *MATERIAL_WEAKNESS* equals zero [Audit Analytics]
MATERIAL_WEAKNESS_GROUP_1&2&3&4	=	equals one when either of *MATERIAL_WEAKNESS_GROUP_1*, *MATERIAL_WEAKNESS_GROUP_2*, *MATERIAL_WEAKNESS_GROUP_3*, or *MATERIAL_WEAKNESS_GROUP_4* equals one; equals zero when *MATERIAL_WEAKNESS* equals zero [Audit Analytics]
MATERIAL_WEAKNESS_GROUP_2	=	equals one when *MATERIAL_WEAKNESS* equals one but only for observations that Audit Analytics categorizes as code 76 [journal entry control issues], code 24 [consolidation, (Fin46r/Off BS) & foreign currency translation issues], code 8 [intercompany/investment w/ subsidiary/affiliate issues], code 12 [untimely or inadequate account reconciliations], or code 38 [foreign, related party, affiliated and/or subsid issues]; equals zero when *MATERIAL_WEAKNESS* equals zero [Audit Analytics]
MATERIAL_WEAKNESS_GROUP_3	=	equals one when *MATERIAL_WEAKNESS* equals one but only for observations that Audit Analytics categorizes as code 39 [revenue recognition issues] or code 15 [accounts/loans receivable, investments & cash issues]; equals zero when *MATERIAL_WEAKNESS* equals zero [Audit Analytics]
MATERIAL_WEAKNESS_GROUP_4	=	equals one when *MATERIAL_WEAKNESS* equals one but only for observations that Audit Analytics categorizes as code 42 [segregations of duties/design of controls issue] or code 22 [information technology, software, security & access issue]; equals zero when *MATERIAL_WEAKNESS* equals zero [Audit Analytics]
MATERIAL_WEAKNESS_SOX404A	=	one if firm *i* has a SOX 404a material weakness in internal controls for year *t* (zero otherwise) [Audit Analytics]
MTB	=	market value of equity for firm *i*'s year *t* scaled by book value of equity for the same firm-year [Compustat]

Table 14 (continued)

Variable		Definition [Data Source]
NEW_IT	=	one if firm *i* has upgraded information technology in its financial reporting process before the beginning of year *t* (zero otherwise), where upgraded information technology in the financial reporting process is identified by searching the Controls and Procedures section of periodic accounting filings for the following terms: "information technology", "information system", "enterprise resource planning", "ERP", and "accounting system" [CALCBENCH]
POST	=	one if year *t* is after the year that firm *i* is treated (for treatment observations) or after the year that firm *i*'s matched treatment firm is treated (for control observations) (zero otherwise) [Compustat]
QUICK_RATIO	=	current assets for firm *i*'s year *t* minus inventory for the same firm-year, all scaled by current liabilities for the same firm-year [Compustat]
RESTATEMENT	=	one if firm *i* restates the financial statements for year *t* (zero otherwise) [Audit Analytics]
RESTATEMENT_GROUP_1	=	equals one when *RESTATEMENT* equals one but only for observations that Audit Analytics categorizes as code 7 [expense (payroll, SGA, other) recording issues], code 12 [liabilities, payables, reserves and accrual estimate failures], code 23 [capitalization of expenditures issues], code 20 [inventory, vendor and/or cost of sales issues], code 17 [deferred, stock-based and/or executive comp issues], code 48 [deferred, stock-based options backdating only], code 39 [deferred, stock-based SFAS 123 only], code 69 [pension and other post-retirement benefit issues], or code 18 [tax expense/benefit/deferral/other (FAS 109) issues]; equals zero when *RESTATEMENT* equals zero [Audit Analytics]
RESTATEMENT_GROUP_1&2&3	=	equals one when either of *RESTATEMENT_GROUP_1*, *RESTATEMENT_GROUP_2*, or *RESTATEMENT_GROUP_3* equals one; equals zero when *RESTATEMENT* equals zero [Audit Analytics]
RESTATEMENT_GROUP_2	=	equals one when *RESTATEMENT* equals one but only for observations that Audit Analytics categorizes as code 13 [consolidation issues incl Fin 46 variable interest & off-B/S], code 37 [consolidation, foreign currency/inflation issue], code 24 [intercompany, investment in subs./affiliate issues], code 43 [intercompany, only—accounting issues], code 11 [foreign, related party, affiliated, or subsidiary issues], or code 44 [foreign, subsidiary only issues]; equals zero when *RESTATEMENT* equals zero [Audit Analytics]
RESTATEMENT_GROUP_3	=	equals one when *RESTATEMENT* equals one but only for observations that Audit Analytics categorizes as code 6 [revenue recognition issues] or code 14 [accounts/loans receivable, investments & cash issues]; equals zero when *RESTATEMENT* equals zero [Audit Analytics]
RESTRUCTURE	=	one if firm *i* exhibits nonzero restructuring costs in year *t* (zero otherwise) [Compustat]
RET_SKEW	=	skewness of firm *i*'s daily stock return during year *t* [CRSP]

Table 14 (continued)

Variable		Definition [Data Source]
RET_STD	=	standard deviation of firm *i*'s daily stock return during year *t* [CRSP]
ROA	=	net income for firm *i*'s year *t* scaled by total assets for the same firm-year [Compustat]
SALES_GROWTH	=	sales for firm *i*'s year *t* minus sales for firm *i*'s year *t*-1, all scaled by sales for firm *i*'s year *t* [Compustat]
SEGMENTS	=	number of segments for firm *i*'s year *t* [Compustat Segments]
SIZE	=	log of market value for firm *i*'s year *t* (for all analyses except audit fees, securities class action lawsuits, and days to 10-K filing) or log of total assets for firm *i*'s year *t* (for audit fees, securities class action lawsuits, and days to 10-K filing analyses) [Compustat]
STOCK_RETURN	=	buy-and-hold abnormal stock return for firm *i* over year *t* [CRSP]
SUED	=	one if firm *i* is sued by investors in a securities class action lawsuit for year *t* (zero otherwise) [Stanford Securities Class Action Clearinghouse]
TREAT	=	one if firm *i* is part of the treatment group and zero if firm *i* is part of the control group [CALCBENCH]
TURNOVER	=	trading volume for firm *i* over year *t* [CRSP]
YEARS_SINCE_AUTOMATION	=	number of years since firm *i* introduced accounting automation, where zero represents the first year; for ease of interpretation of the interaction term, *YEARS_SINCE_AUTOMATION* is normalized so that the variable ranges between 0 and 1 (inclusive) [CALCBENCH]
Z_SCORE	=	0.717 * [(current assets—current liabilities) / total assets] + 0.847 * [retained earnings / total assets] + 3.107 * [earnings before interest and taxes / total Assets] + 0.42 * [book value of equity / total liabilities] + 0.998 * [sales / total assets], where all terms are calculated for firm *i*'s year *t* (Altman 1983)

Supplementary information The online version contains supplementary material available at https://doi.org/10.1007/s11142-024-09822-y.

Acknowledgements I thank Lakshmanan Shivakumar (editor), two anonymous reviewers, Preeti Choudhary, Ranjani Krishnan, Adi Masli, Vernon Richardson, Juan Manuel Sanchez, David Wood, and the workshop participants at University of Connecticut for their feedback. I also thank the Eli Broad College of Business at Michigan State University for funding that enabled this study. Any errors are my own.

References

Ai, C., and E.C. Norton. 2003. Interaction terms in logit and probit models. *Economics Letters* 80 (1): 123–129. https://doi.org/10.1016/S0165-1765(03)00032-6.

Altman, E. I. (1983). *Corporate Financial Distress: A Complete Guide to Predicting, Avoiding, and Dealing with Bankruptcy* (1st ed.). John Wiley and Sons.

American Institute of Certified Public Accountants (AICPA). (2020). Why CPAs should care about RPA. https://blog.aicpa.org/2020/08/why-cpas-should-care-about-rpa.html

Ashbaugh-Skaife, H., D.W. Collins, and W.R. Kinney. 2007. The discovery and reporting of internal control deficiencies prior to SOX-mandated audits. *Journal of Accounting and Economics* 44 (1–2): 166–192. https://doi.org/10.1016/j.jacceco.2006.10.001.

Ashraf, M. 2022. The Role of Peer Events in Corporate Governance: Evidence from Data Breaches. *The Accounting Review* 97 (2): 1–24. https://doi.org/10.2308/TAR-2019-1033.

Ashraf, M., P.N. Michas, and D. Russomanno. 2020. The Impact of Audit Committee Information Technology Expertise on the Reliability and Timeliness of Financial Reporting. *The Accounting Review* 95 (5): 23–56. https://doi.org/10.2308/accr-52622.

Ashraf, M., Deore, A., and Krishnan, R. (2024). The Role of Identity in Corporate Governance: Evidence from Gender Differences in the Audit Committee Chair-Chief Financial Officer Dyad. *Working Paper*.

Association of Chartered Certified Accountants. (2015). The robots are coming? Implications for finance shared services. https://www.accaglobal.com/content/dam/ACCA_Global/Technical/fin/ea-robots-finance-shared-services-0909.pdf

Awyong, A., Cheng, Q., Deng, T., & Wang, R. (2022). Awyong et al. - 2022 - Digitalization, Accounting Jobs, and Financial Reporting Quality.pdf. *Working Paper*. https://abfer.org/component/edocman/main-annual-conference/digitalization-accounting-jobs-and-financial-reporting-quality?Itemid≡

Badolato, P.G., D.C. Donelson, and M. Ege. 2014. Audit committee financial expertise and earnings management: The role of status. *Journal of Accounting and Economics* 58 (2–3): 208–230. https://doi.org/10.1016/j.jacceco.2014.08.006.

BlackLine. (2017). BlackLine The Unified Cloud for Finance and Accounting Automation. https://www.blackline.com/

Blue Lance. (2012). Sarbanes-Oxley Control Transformation Through Automation. https://bluelance.com/wp-content/uploads/2015/02/SOX_ControlTransformation.pdf

Calcbench. (2023). Interactive Disclosures & Footnotes. https://www.calcbench.com/home/InteractiveDisclosures

Chan, L.H., K.C.W. Chen, T.-Y. Chen, and Y. Yu. 2012. The effects of firm-initiated clawback provisions on earnings quality and auditor behavior. *Journal of Accounting and Economics* 54 (2–3): 180–196. https://doi.org/10.1016/j.jacceco.2012.05.001.

Chen, W., and S. Srinivasan. 2023. Going digital: Implications for firm value and performance. *Review of Accounting Studies*. https://doi.org/10.1007/s11142-023-09753-0.

Choudhary, P., Ramadas, V., and Sigler, J. (2023). The Implications of IT Sophistication on Audit Effort and Effectiveness. *Working Paper*.

Commerford, B.P., S.A. Dennis, J.R. Joe, and J.W. Ulla. 2022. Man Versus Machine: Complex Estimates and Auditor Reliance on Artificial Intelligence. *Journal of Accounting Research* 60 (1): 171–201. https://doi.org/10.1111/1475-679X.12407.

Cooper, L.A., D.K. Holderness, T.L. Sorensen, and D.A. Wood. 2019. Robotic Process Automation in Public Accounting. *Accounting Horizons* 33 (4): 15–35. https://doi.org/10.2308/acch-52466.

Cooper, L.A., D.K. Holderness, T.L. Sorensen, and D.A. Wood. 2022. Perceptions of Robotic Process Automation in Big 4 Public Accounting Firms: Do Firm Leaders and Lower-Level Employees Agree? *Journal of Emerging Technologies in Accounting* 19 (1): 33–51. https://doi.org/10.2308/JETA-2020-085.

Correia, S. (2015). Singletons, Cluster-Robust Standard Errors and Fixed Effects: A Bad Mix. *Working Paper*. http://scorreia.com/research/singletons.pdf

Dechow, P., W. Ge, and C. Schrand. 2010. Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics* 50 (2–3): 344–401. https://doi.org/10.1016/j.jacceco.2010.09.001.

DeFond, M., and J. Zhang. 2014. A review of archival auditing research. *Journal of Accounting and Economics* 58 (2–3): 275–326. https://doi.org/10.1016/j.jacceco.2014.09.002.

Deloitte. (2015). Financial Reporting Automation. https://www2.deloitte.com/content/dam/Deloitte/ng/Documents/audit/Financial Reporting/ng-financial-reporting-automation-1.pdf

Deloitte. (2017). Automate this: The business leader's guide to robotic process automation. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/process-and-operations/us-sdt-process-automation.pdf

Deloitte. (2018a). Internal Controls Over Financial Reporting Considerations for Developing and Implementing Bots. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/audit/us-audit-internal-controls-over-financial-reporting-considerations-for-developing-and-implementing-bots.pdf

Deloitte. (2018b). The Future of IT Internal Controls - Automation A Game Changer. https://www2.deloitte.com/content/dam/Deloitte/in/Documents/risk/in-risk-future-of-it-internal-controls-noexp.pdf

Dorantes, C., C. Li, G.F. Peters, and V.J. Richardson. 2013. The Effect of Enterprise Systems Implementation on the Firm Information Environment. *Contemporary Accounting Research* 30 (4): 1427–1461. https://doi.org/10.1111/1911-3846.12001.

Doyle, J., W. Ge, and S. McVay. 2007. Determinants of weaknesses in internal control over financial reporting. *Journal of Accounting and Economics* 44 (1–2): 193–223. https://doi.org/10.1016/j.jacceco.2006.10.003.

Ernst & Young (EY). (2020). 2020 SEC annual reports — Form 10-K. https://assets.ey.com/content/dam/ey-sites/ey-com/en_us/topics/assurance/accountinglink/ey-sec11376-201us-12-16-2020v2.pdf

Ernst & Young (EY). (2021). Finance leaders rethink roles and responsibilities as new operating reality sets in. https://www.ey.com/en_gl/news/2021/02/finance-leaders-rethink-roles-and-responsibilities-as-new-operating-reality-sets-in

Fedyk, A., J. Hodson, N. Khimich, and T. Fedyk. 2022. Is artificial intelligence improving the audit process? *Review of Accounting Studies* 27 (3): 938–985. https://doi.org/10.1007/s11142-022-09697-x.

Financial Accounting Standards Board (FASB). (1980). Statement of Financial Accounting Concepts No. 2. https://www.fasb.org/page/ShowPdf?path=con2.pdf&title=CON%202%20(AS%20ISSUED)

Gartner. (2020). 10 Trends for Finance to Navigate Now. https://www.gartner.com/smarterwithgartner/10-trends-for-finance-to-navigate-now

Greene, W. 2004. The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. *The Econometrics Journal* 7 (1): 98–119.

Hoitash, R., and U. Hoitash. 2018. Measuring Accounting Reporting Complexity with XBRL. *The Accounting Review* 93 (1): 259–287. https://doi.org/10.2308/accr-51762.

Jha, A., and Y. Chen. 2015. Audit Fees and Social Capital. *The Accounting Review* 90 (2): 611–639. https://doi.org/10.2308/accr-50878.

Kim, I., and D.J. Skinner. 2012. Measuring securities litigation risk. *Journal of Accounting and Economics* 53 (1–2): 290–310. https://doi.org/10.1016/j.jacceco.2011.09.005.

Kobelsky, K.W., V.J. Richardson, R.E. Smith, and R.W. Zmud. 2008. Determinants and Consequences of Firm Information Technology Budgets. *The Accounting Review* 83 (4): 957–995.

Lanza, R. B. (2007). Automate Your Internal Controls. *Journal of Accountancy*. https://www.journalofaccountancy.com/issues/2007/feb/automateyourinternalcontrols.html

Law, K., and Shen, M. (2022). How Does Artificial Intelligence Shape Audit Firms? *Working Paper*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3718343

Masli, A., G.F. Peters, V.J. Richardson, and J.M. Sanchez. 2010. Examining the Potential Benefits of Internal Control Monitoring Technology. *The Accounting Review* 85 (3): 1001–1034.

McCann, D. (2019). Finance Avoids RPA for Financial Reporting. https://www.cfo.com/financial-reporting-2/2019/10/finance-avoids-rpa-for-financial-reporting/

Plattfaut, R., and V. Borghoff. 2022. Robotic Process Automation: A Literature-Based Research Agenda. *Journal of Information Systems* 36 (2): 173–191. https://doi.org/10.2308/ISYS-2020-033.

PricewaterhouseCoopers (PwC). (2019). Re-inventing Internal Controls in the Digital Age. https://www.pwc.com/sg/en/publications/assets/reinventing-internal-controls-in-the-digital-age-201904.pdf
PricewaterhouseCoopers (PwC). (2021). The future of finance: Leveraging automation to deliver undiscovered value. https://www.pwc.com/sg/en/risk-assurance/intelligent-automation-in-financial-reporting.html
Public Company Accounting Oversight Board (PCAOB). (2007). Auditing Standard No. 5 An Audit of Internal Control Over Financial Reporting. http://pcaobus.org/Rules/Rulemaking/Docket 021/2007–06–12_Release_No_2007–005A.pdf
Public Company Accounting Oversight Board (PCAOB). (2020). Data and Technology Research Project Update Spotlight. https://pcaob-assets.azureedge.net/pcaob-dev/docs/default-source/documents/data-technology-project-spotlight.pdf
Public Company Accounting Oversight Board (PCAOB). (2021). Changes in the Use of Data and Technology in the Conduct of Audits. https://pcaobus.org/oversight/standards/research-standard-setting-projects/changes-use-data-technology-conduct-audits
Roose, K. (2021). The Robots Are Coming for Phil in Accounting. *The New York Times*. https://www.nytimes.com/2021/03/06/business/the-robots-are-coming-for-phil-in-accounting.html
Schoenfeld, J. 2022. Cyber risk and voluntary Service Organization Control (SOC) audits. *Review of Accounting Studies*. https://doi.org/10.1007/s11142-022-09713-0.
Securities and Exchange Commission (SEC). (2019). SEC Charges Four Public Companies With Long-standing ICFR Failures. https://www.sec.gov/news/press-release/2019-6
Securities and Exchange Commission (SEC). (2008). Final Rule: Management's Report on Internal Control Over Financial Reporting and Certification of Disclosure in Exchange Act Periodic Reports; Rel. No. 33–8238. https://www.sec.gov/rules/final/33-8238.htm
Shipman, J.E., Q.T. Swanquist, and R.L. Whited. 2017. Propensity Score Matching in Accounting Research. *The Accounting Review* 92 (1): 213–244. https://doi.org/10.2308/accr-51449.
SolveXia. (2023). SolveXia for Accountants. https://www.solvexia.com/role/solvexia-for-accountants
Vic.ai. (2021). Automate your accounting to save time and money. https://www.vic.ai/
Wang, F. (2022). Accounting Automation: What Is It & Will It Replace Accountants. *Tipalti*. https://tipalti.com/accounting-automation/
Whitehouse, T. (2019). Automating Keep Controls in Step With Technology. *The Wall Street Journal*. https://deloitte.wsj.com/articles/automating-keep-controls-in-step-with-technology-01576529105
WNS. (2020). Use Automated Controls the Right Way to Mitigate Process Risks in F&A. https://www.wns.com/insights/articles/articledetail/18/use-automated-controls-the-right-way-to-mitigate-process-risks-in-fna