Audit Quality Under Remote Working Arrangement: The Role of Workforce Technology Competency

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SUMMARY: Using comprehensive labor market data to measure client firms' workforce technology competency, this study investigates how companies' workforce technology competency may mitigate the deterioration of audit quality under the remote working arrangement following COVID-19. Our results suggest that after the COVID-19 outbreak, companies' accrual quality has decreased, indicating a deterioration of audit quality. The negative impact of remote audits during COVID-19 on audit quality is less pronounced in companies with greater workforce technology competency. Our results are robust to various alternative measures, local versus non-local client analysis, and non-high-technology industry analysis. Our study provides important implications for regulatory bodies and industry professionals to understand the importance of technological human capital in improving audit quality in remote auditing contexts.

Data Availability: Data is obtained from the sources specified in the paper.

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I. INTRODUCTION

COVID-19 has substantially disrupted the way people communicate and reshaped the working environment (i.e., remote work arrangements), imposing challenges on almost all businesses and services (e.g., Buchanan et al. 2021; Galanti et al. 2021; Wang et al. 2021). For the auditing profession, COVID-19 has catalyzed a rapid transition to remote auditing and a deeper integration of technology in audit processes. Meanwhile, economic turbulences and market uncertainty have significantly affected audit quality, as auditee companies face incentives to manage or misreport earnings (KPMG, 2020). Access to client firms' original documentation to support transactions has become very difficult due to social distancing practices during the COVID-19 outbreak (Altiero, Baudot, and Hazgui 2024). Although some survey-based studies (e.g., Eulerich, Wagener, and Wood 2022; Li, Goel, and Williams 2023) suggest that remote auditing can still be effective with sufficient support from auditees and audit firms, the adverse impact of COVID-19 on several aspects - including audit quality, audit fees, audit risks, and audit delays - has been well documented by a growing body of literature (e.g., Kend and Nguyen 2022; Gong et al. 2023; Gong et al. 2022; Morris, Hoitash, and Hoitash 2023; Harjoto and Laksmana 2023).

The adverse impact can vary substantially across firms and auditors. Baatwah, Al-Ansi, Almoataz, and Salleh (2023) and Gong et al. (2022) note that challenges can arise particularly in resource-intensive areas, where non-Big 4 auditors and auditors without remote audit proficiency struggled more significantly with audit quality under remote conditions. Remote auditing, by its nature, involves using information and communication technology tools to access, review, and analyze digital accounting data, via email or cloud-based SharePoint. Audit client firms lacking workforce technology competency may struggle to transition to remote auditing, and inappropriately prepared or questionable digital evidence can eventually lead to lower audit quality (KPMG 2020; Albitar et al. 2020; Altiero, Baudot, and Hazgui 2024). Hence, firms that are more technology-savvy and familiar with digital evidence should be less affected (Jin et al. 2022). Considering the sustained trend of remote auditing practice following COVID-19, our study aims to extend Baatwah et al. (2023) and Gong et al. (2022) to investigate whether and how the technological competency of client firms' workforce contributes to more effective auditing services in a remote working setting and thus moderate the impact of COVID-19 on audit quality.

Our study draws on the discussion of the importance of technological competency in accounting information systems. Prior studies suggest that employees' technology competency may promote knowledge sharing and enhance social relationships within and across firms (Peng, Zhang, and Dubinsky 2016). It may also improve quality management and reduce business risks (Pérez-Aróstegui, Bustinza-Sánchez, and Barrales-Molina 2015). The information technology competency of firms' audit committees may also affect the reliability and timeliness of financial reporting (Ashraf, Michas, and Russomanno 2020). Efficient use of technology systems in a client firm may facilitate more effective record-keeping and data transfer to assist auditors in collecting sufficient and reliable digital evidence (Jin et al. 2022). Thus, we hypothesize that the decrease in engagement-level audit quality during COVID-19 is less pronounced for audit client firms with greater workforce technology competency.

To empirically evaluate our hypothesis, we adopt the Emsi Burning Glass Technology's (BGT) historical job posting database from 2017 to 2020 and follow Darendeli, Law, and Shen (2022) to construct a firm-level workforce technology competency measure using the total number of software-related job skills divided by the total number of job skills required in a firm's job postings in a fiscal year. The BGT software has been extensively used in management studies to measure job skill competency at the firm level (Alekseeva et al. 2021; Darendeli, Law, and Shen 2022; Babina et al. 2024). For example, Babina et al. (2024) utilize the BGT database to identify job postings related to Artificial Intelligence (AI) using a data-driven approach and classify jobs into AI-skilled and non-AI-skilled to investigate whether companies focus more on AI is more innovative. Audit quality is measured with discretionary accruals, a widely used measure for audit quality in the auditing literature (e.g., Aobdia 2019). In support of our hypothesis, we find a significant interaction effect between remote auditing and firms' workforce technology competency. We further find that this relationship is more pronounced among non-local clients and the clients of Big 4 auditors. Collectively, our findings suggest that technology mitigates the negative effect of remote auditing on audit quality. As a result, the engagement-level audit quality for client firms with stronger workforce technology competency is less impacted by COVID-19.

Using the COVID-19 outbreak as a quasi-experiment, our study provides significant contributions to the developing literature on remote auditing by documenting the necessity of audit clients' technology competency for effective remote audit engagements, which is the direction of future audits (Bierstaker, Burnaby, and Thibodeau 2001; Deloitte 2021). Our findings provide important and timely insight for investors, managers, and policymakers concerning public companies' reporting quality, emphasizing the importance of technology in developing sustainable post-Covid business practices with remote working arrangements; in this regard, the study extends recent work by Baatwah et al. (2023) and Gong et al. (2022) on factors that can moderate the impact of COVID-19 on audit quality. Our study also makes important methodological contributions by proposing a novel measure of workforce technology competency that complements existing measures of firm IT capabilities. Prior studies investigating the effects of audit client firms' technology often focus on managerial IT background (Ashraf, Michas, and Russomanno 2020) or external evaluation such as the InformationWeek 500 (Chen, Smith, Cao, and Xia 2014; Hoffman, Sellers, and Skomra 2018; (Banker, Frost, and Tripathi 2022). While these are plausible measures of a firm's overall IT competency and the depth of technological capabilities, they do not directly capture the breadth of employees' IT competency which is important in remote auditing. In this regard, our measure of workforce IT competency provides a useful addition to the literature and can be particularly important to future research in remote auditing (Teeter, Alles, and Vasarhelyi 2010).

The rest of the paper is organized as follows. Section 2 discusses related literature, background, and hypothesis development. Section 3 describes the research method used, and the empirical findings are provided in Section 4. Section 5 concludes with a summary and discussion.

II. Literature Review and Hypotheses

Audit Quality in Remote Work Setting

Capital markets need reliable financial reports that are audited effectively and in a timely manner. To ensure audit quality, the U.S. Public Companies Accounting Oversight Board and Center for Audit Quality emphasize the importance of extensive interactions and communications among companies' audit committees and their audit engagement teams (CAQ 2016; PCAOB 2013). Similarly, the global auditing standard-setter IAASB (2014) requires audit partners and audit engagement teams to effectively perform "on-site" audit work to ensure that the engagement team is accessible to client management and those charged with governance. Thus, effective interactions of all parties involved in audit engagements, including the audit firms and the client firms, play a key role in audit quality. However, the recent COVID-19 outbreak severely hindered face-to-face interactions for auditors to effectively evaluate client firms' audit risks and collect supporting documents.

Since the declaration of a COVID-19 emergency in each state, the way people interact and communicate has been drastically disrupted and remote working arrangements have been prevalent in almost all non-essential business sectors (e.g., Buchanan et al. 2021; Galanti et al. 2021; Wang et al. 2021; Gallup 2020). In the public accounting sector, audit firms also identify the transition to remote working as substantial and permanent and are making plans to transform their workforce for the future remote auditing service (e.g., Deloitte 2021; CNBC 2021). Due to the enactment of the widely adopted remote work arrangements, KPMG (2020) argues that the COVID-19 pandemic makes it very difficult to use client firms' original documentation to support the payments and accounts receivable collection transactions and the remote auditing arrangement induced by the COVID-19 outbreak may generate a negative impact on audit quality.

Recent studies have also documented consistent evidence suggesting the deterioration of audit quality after the COVID-19 outbreak. For example, Albitar et al. (2020) adopt a desk study method to analyze how COVID-19 affects audit quality. They find that the remote working arrangement caused by COVID-19 challenges audit firms' human capital and affects audit procedures and auditor efforts, resulting in lower audit quality. Gong et al. (2022) utilize the stay-at-home orders to study the impact of COVID-19 on audit quality and provide empirical support for the contention that remote audits interrupt auditors' judgment on key resource-intensive accounts, such as inventory and R&D expenditures, especially for non-Big 4 auditors, due to their limited experience with remote working arrangements. Similarly, Morris, Hoitash, and Hoitash (2023) find a decline in audit quality and an increase in delayed filings in the initial months of

COVID-19. Baatwah et al. (2023) and Hsu and Yang (2022) document the impact of COVID-19 on audit quality and discuss several determinants of such impact, including self-efficacy, remote audit proficiency, and corporate governance. In addition, to address the negative impact of COVID-19, Kend and Nguyen (2022) conduct a textual analysis of over 3,000 Australian statutory audit reports and document that auditors specifically designed audit procedures to tackle audit risks that arose due to the COVID-19 pandemic. Given the sustained trend towards remote working in public accounting following COVID-19, there is an urgent need to identify factors that could mitigate this negative impact and maintain market confidence in the audited financial data supplied by public companies.

The Role of Technology in Remote Auditing

Prior studies often find that information technology affects firm performance (Bharadwaj, Bharadwaj, and Konsynski 1999; Mithas, Ramasubbu, and Sambamurthy 2011; Zhang, Zhao, and Kumar 2016), management earnings forecast accuracy (Huang, Li, and Wang 2018), tax risks (Hamilton and Stekelberg 2017), internal control, and audit risks (Chen et al. 2014; Hoffman, Sellers, and Skomra 2018). Employees' technology skills are one of the critical dimensions of human technology resources because they allow firms to communicate and work with business units more efficiently (e.g., Bharadwaj 2000; Giotopoulos et al. 2017; Lucchetti and Sterlacchini 2004). Employees' technology competency may promote knowledge sharing and enhance communication and social relationships within and across firms (Peng, Zhang, and Dubinsky 2016), especially in remote working situations which can bring significant disruptions to communication and collaboration efficiency (Blaskovich 2008).

Some recent studies have specifically examined how technology affects audit services, especially remote auditing, which heavily relies on information and communication technology tools. For example, Farcane et al. (2023) find that auditors perceive their work efficiency in remote audits to be significantly influenced by the degree of technology utilization in audit services. On the client firm side, Ismanidar et al. (2022) and Castka and Searcy (2023) argue that, in addition to the rudimentary technologies that are currently in auditing practice, high-tech audit support including more digitalization and automation tools need to be adopted by client employees to enhance remote auditing services and assist the transition from traditional auditing to the new paradigm of remote auditing. Altiero, Baudot, and Hazgui (2024) interview 30 auditors in non-Big4 firms in the U.S. and find that the readiness and security of clients' technology systems present significant barriers for auditors to gather audit evidence and maintain audit quality during the post-COVID era. In a more general setting, Ashraf, Michas, and Russomanno (2020) find that information technology expertise on audit committees impacts the reliability and timeliness of financial reporting. To summarize, firms with higher workforce technology competency are likely to adapt to remote communications more effectively and interact with auditors more efficiently in a remote setting. Thus, we hypothesize that firms' workforce technology competency may positively affect audit quality in a remote audit setting. We state our hypothesis in an alternative form:

Hypothesis. The negative impact of remote auditing on audit quality is less pronounced for client firms with greater workforce technology competency, relative to client firms with lower workforce technology competency.

III. Research Design and Sample

Measures of Workforce Technology Competency

To measure firms' workforce technology competency, we adopt the Emsi BGT historical online job postings database[1] to calculate firms' demands of the workforce requiring software skills. The BGT job postings database has been widely used in management studies to measure job skill competency at the firm level (e.g., Alekseeva et al. 2020; Darendeli, Law, and Shen 2022; Babina et al. 2024). We use the job postings data to proxy firms' workforce technology competency because job seekers and employers often rely on online job advertisements posted by employers on firms' websites and various popular employment websites as primary sources to get employment information (Faberman and Kudlyak 2016). Thus, online job postings may serve as an important tool to understand firms' most recent workforce demands for occupations and various skills that should be prepared by job applicants. Moreover, BGT software skills cover all jobs that require job owners to use computer software[2] infused with modern technology and could be applied to all job functions and across all industries. More job postings requiring software skills relative to other types of skills may indicate a higher preparedness for modern technologies by a firm. Lastly, prior studies suggest that larger firms and firms with more R&D activities tend to have a stronger workforce on technologies (e.g., Lucchetti and Sterlacchini 2004; Giotopoulos et al. 2017; Giunta and Trivieri 2007; Haller and Siedschlag 2011), we thus examine the relationships between firm specific factors and *TECH* to evaluate its validity. Our results, untabulated for brevity, suggest that *TECH* is positively associated with firm size and R&D spending, which are

[1] Emsi BGT job postings data is extracted globally from over 45,000 websites, including companies' career sites, national and local job boards and job posting aggregators. BGT also identifies job posting duplicates using a 60-day rule to avoid double counting a posting. The BGT job postings database contains detailed information about a job posting, including the time a job is first posted, employer name, employer geographic location, description of occupation, skill set requirements, etc. Detailed information about the database is available at Emsi Burning Glass Data Basic Overview – Knowledge Base (emsidata.com).

[2] Examples of software-related skills include operating systems, C and C++, office and productivity software, science software, databases, IT management, Web design, Project Management, Query Languages, Cloud Solutions, etc. These skills are required in multiple job fields such as administration, information technology, design, engineering, business, science, and research, etc.

consistent with this line of literature. Hence, our *TECH* measure is able to capture firm-level workforce technology competency, controlling for industry, year, and firm characteristics. Thus, software-related job postings data may reasonably represent the workforce technology competency of a firm.

We first drop BGT firms that are not covered in Compustat using the BGT-Compustat linkage GVKEY, which is provided by BGT, to generate a job postings database that contains only firms available on Compustat. We then extract the fiscal year-end dates for the sample firms from Compustat to identify the fiscal year of each job posting. We follow Darendeli, Law, and Shen (2022) to construct the measure for the workforce technology competency (*TECH*) of a firm by calculating a software job ratio using the number of software skills required in job postings from a firm, scaled by the total number of skills required in job postings from the firm in a given month. We then average monthly software job ratios for a given firm in a fiscal year to generate an annual measure of *TECH*[3], which indicates a firm's workforce technology competency cultivated by employees with software skills in a year.

Measuring COVID-19-Induced Remote Auditing

To capture the periods of traditional auditing services versus remote auditing services, we construct a quasi-experiment using the COVID-19 emergency declaration in each state. A state declaration of the COVID emergency typically comes with other measures to curb the pandemic such as stay-at-home orders, travel restrictions, bans of large-group gatherings[4], and forced closures of non-essential services. All of the 50 US states declared emergencies, most of which

[3] Since the number of job postings requiring software skills might vary across industries (i.e., high-tech industry versus agriculture industry), we also construct an industry-adjusted *TECH* measure for robustness tests. we construct an industry-adjusted *TECH_IND*, which is formulated as the difference between a firm's *TECH* and the mean value of *TECH* for its industry based on the two-digit SIC code.

[4] Most of the states banned gatherings of 10 or more people, and some (like the states of New York and California) banned all gatherings in public.

occurred in March (NASHP 2023) when panic and psychological stress peaked, and clear scientific guidance was lacking. States started to gradually reopen after April 2020, but normal business operations took years to recover. Virtually all firms were forced to transition to remote working arrangements in 2020. With little guidance from authorities, auditors, like all individuals in society, resorted to restricting their mobility to help flatten the curve and transitioned to remote auditing (Badr et al. 2020; Zhou et al. 2020). Even after the reopening, many firms decided to keep remote working and remote or hybrid auditing arrangements for the years to come (Almodovar, Graves, and Victoravich 2023).

To identify the COVID-19-induced remote auditing arrangement, we follow Gong et al. (2022) to gather the specific date of the emergency declaration made by each state in the U.S. from the state government website and construct a binary measure *COVID*, which equals 1 if a firm's fiscal year ended after the declaration of COVID emergency in the firm's headquarters state, and 0 otherwise. Thus, *COVID* represents the firm-year observations that were affected by the sudden shift to remote auditing services. We adopt a different approach from Gong et al. (2022)[5] in defining the post-COVID stage by focusing on the fiscal year-end dates rather than the 10-K filing dates because auditors generally begin their fieldwork for year-end audit engagement immediately after their client firms' fiscal year-end (Whitmire 2020).

Model Specification

[5] Gong et al. (2022) define the post-COVID filings as 10-K filings with the SEC at least seven days later than the issuance date of stay-at-home order in its auditor's state.

We adopt the following model to evaluate how firms' workforce technology competency (*TECH*) affects audit quality (*AQ*) under the remote working arrangement induced by the COVID-19 outbreak (*COVID*):

$$
\begin{aligned}
AQ_{i,t} = {} & \alpha_0 + \alpha_1 COVID_{i,t} + \alpha_2 COVID_{i,t} \times TECH_{i,t} + \alpha_3 TECH_{i,t} + \alpha_4 GENDER_{i,t} + \\
& \alpha_5 TOT_{ACC_{i,t}} + \alpha_6 ASSET_{i,t} + \alpha_7 FOREIGN_{i,t} + \alpha_8 INV_{REC_{i,t}} + \alpha_9 LOSS_{i,t} + \\
& \alpha_{10} MTB_{i,t} + \alpha_{11} LEV_{i,t} + \alpha_{12} FYR_{i,t} + \alpha_{13} CFO_{i,t} + \alpha_{14} SALE_{i,t} + \alpha_{15} BIG4_{i,t} + \\
& \alpha_{16} ACCEL_{i,t} + \alpha_{17} SCI_{i,t} + \alpha_{18} ACCELERATED_{i,t} + \sum State + \\
& \sum Industry + \varepsilon_{i,t} \qquad (1)
\end{aligned}
$$

Since audit quality is closely related to financial reporting quality, we follow prior studies (e.g., Becker et al. 1998; Krishnan 2003) to use two accrual quality measures to measure audit quality (*AQ*): (1) *Dechow1995* refers to the absolute value of discretionary accruals calculated using the modified Jones model by Dechow, Sloan, and Sweeney (1995); (2) *Kothari2005* refers to the absolute value of performance-matched discretionary accruals as in Kothari, Leone, and Wasley (2005). To test our hypothesis, we include an interaction term between *COVID* and *TECH* with a negative expected coefficient because firms with higher workforce technology competency are able to provide better digital evidence for remote auditing and thus, produce better *AQ* (lower *Dechow1995* and *Kothari2005*), relative to firms with lower workforce technology competency.

We also follow prior literature to include a series of control variables in the model. We control for the audit partner's gender (*GENDER*) since prior studies suggest that the audit partner's gender may significantly affect audit quality (Lee, Nagy, and Zimmerman 2019; Lee and Levine 2020; Chi et al. 2017). We also follow the literature to control for a vector of firm factors that affect audit quality (*AQ*), such as total accrual (*TOT_ACC*), firm size (*ASSET*), audit complexity as of foreign operations (*FOREIGN*)[6], inherent risk (*INV_REC*), profitability (*LOSS* and *CFO*),

[6] In our main analysis, we define *Foreign* as a binary variable that equals 1 if a firm reports foreign income in a given year, and 0 otherwise. Additionally, we use an alternative measure for *Foreign*, which is foreign income scaled by income before extraordinary items. Our findings remain consistent when using this alternative measure.

market-to-book ratio (*MTB*), financial leverage (*LEV*), seasonal effect (*FYR*), sales growth (*SALE*), auditor type (*BIG4*), and SEC accelerated filer (*ACCEL*) (e.g., Lobo and Zhou 2001; Degeorge, Patel, and Zeckhauser 1999; DeAngelo 1981). We include social capital (*SCI*) since previous studies suggest that firms located in high social capital regions tend to have high financial reporting quality (e.g., Jha 2019). We include state and industry fixed effects in the regression model to mitigate the unobservable heterogeneity problem. All variables are defined in Appendix A.

Sample Selection

To evaluate the effects of a remote working environment on audit quality, we first obtain the full sample of 33,251 firm-year observations of U.S. public companies' financial information from 2017 to 2020 from Compustat. Since some companies started to return to the workplace in early 2021 after the administration of COVID-19 vaccines, we restrict our primary sample period from 2017 to 2020 for a cleaner analysis of the traditional working versus remote working arrangements. Compared with Gong et al. (2022) that limit their sample to fiscal year 2019 only, our study uses a significantly increased post-COVID sample size for more powerful tests. We then follow Matsumoto (2002) to remove the regulated industries and reduce our sample to 27,585 firm-year observations.

We extract partners' attributes from PCAOB's audit engagement database for the U.S. public companies and obtained firms' online job posting data from the historical job posting database provided by BGT and then merge the two datasets with Compustat. This merging process renders a sample of 8,077 firm-year observations. After removing observations with missing values, our final sample contains 5,853 (or 5,743) firm-year observations when using discretionary accruals evaluated using the *Dechow1995* model (or *Kothari2005* model). Table 1 outlines our sample reduction process.

Sample Descriptive Statistics

Table 2 and Table 3 present the descriptive statistics of our sample. As shown in Table 2, which presents the sampling frequency across years, we observe similar numbers of firm observations across the four sample years. About 73 percent (4,299 or 4,219) of the firm-year observations are in the pre-COVID period, while the remaining 27 percent (1,554 or 1,524) are under the remote auditing arrangement. Interestingly, Table 2 also shows a slight decreasing trend in *TECH* over the years. Since we follow Darendeli, Law, and Shen (2022) to calculate *TECH* using the number of software skills divided by the total number of skills required in all job postings from a firm within a given year, the observed decreasing trend is attributed to disproportionate changes in the number of required skills in job postings over the years due to industry trends and demand.

Table 3 shows the descriptive statistics and the pre- to post-*COVID* changes of our sample with all continuous variables winsorized at the 1 and 99 percent levels. As shown in Panel A of Table 3, the discretionary accruals measure *Dechow1995* shows a significant difference in the pre- and post-*COVID* periods (Pre-*COVID* Mean = 0.520, post-*COVID* Mean = 2.418, Mean value changes = 1.898, P-value < 0.001), suggesting that firms' discretionary accruals have significantly increased since the prevalence of the remote working arrangement. Panel B of Table 3 shows the same pattern of changes in discretionary accruals using the *Kothari2005* Model (pre-*COVID* mean = 0.509, post-*COVID* mean = 0.900, Mean difference = 0.391, P-value < 0.001). Our sample contains 74 percent of male audit partners, and this gender distribution is consistent across different sample periods. Moreover, about 85 percent of firms in our sample are SEC accelerated filers, and about 75 percent of firms in our sample are audited by one of the Big 4 audit firms. The descriptive statistics of other control variables are largely consistent with those reported in prior studies (e.g., Hsieh, Wang, and Abdolmohammadi 2019).

Table 4 shows the correlation matrix for the variables. We observe a significant positive correlation between *COVID* and *AQ* measured by both *Dechow1995* and *Kothari2005*, indicating that audit quality has deteriorated since the COVID outbreak due to the remote auditing arrangement. We also observe significant correlations among the variables in our model due to our large sample size; however, the magnitudes of the correlations are mostly weak or moderate and should not cause multicollinearity issues.[7]

IV. RESULTS

Main Analysis for Hypothesis Testing

We report our baseline analysis results in Table 5. The dependent variable is the accounting quality; in Panel A, accounting quality is measured using *Dechow1995*, while in Panel B using *Kothari2005*. Each panel consists of three models: in model (1), we regress discretionary accruals on *COVID* and *TECH* along with industry and state fixed effects, but not including other control variables; in model (2), we add control variables defined in the previous section on top of model (1); and in model (3), we adopt the full regression model by including the interaction of *COVID* and *TECH*.

Models (1) and (2) in both Panels A and B suggest that discretionary accrual levels increase substantially after the declaration of the COVID-19 emergency. Specifically in Panel A, discretionary accruals increase by approximately two times its mean of 1.024 after state-level emergency declarations, and the increase is statistically significant at the one percent level. Panel B shows similar results. The main effect results of *COVID* are consistent with Gong et al. (2022)

[7] The VIF values of the variable in our regression model are below 10, suggesting that multicollinearity should not be a concern for our regression analysis.

in terms of the notion that the travel restrictions and other safety precautions following the declaration of the COVID-19 emergency negatively affected accounting quality. In models (1) and (2), *TECH* is not statistically significant; however, when it is interacted with *COVID* in model (3), the interaction term shows a significant and negative sign in both panels: while audit client firms, in general, have lower accounting quality after the COVID outbreak, those firms with greater workforce IT competency are much less affected. Table 3 results support our hypothesis that workforce IT competency allows firms to better adapt to an effective remote working environment with auditors, especially during the COVID-19 pandemic when traditional means of communication were severely affected, and face-to-face interactions were suspended.

To better illustrate the interaction effects of *COVID* and *TECH*, we adopt the 10 percent and 90 percent *TECH* values to represent the Low-*TECH* and High-*TECH* situations to plot the average accounting quality measures by pre-/post-*COVID* and high-/low- *TECH* in Figure 1. The dashed line and the solid line represent the pre- vs. post-*COVID* comparison for low-*TECH* and high-*TECH* audit client firms, respectively. Regardless of the measure of accounting quality, the dashed line exhibits a steeper slope. When the *Dechow1995* Model is used, discretionary accruals increase from -0.33 to 2.27 for low-*TECH* firms, in clear contrast to a much smaller increase from -0.02 to 1.04 for high-*TECH* firms. When the *Kothari2005* model is used, discretionary accruals increase from 4.44 to 5.23 for low-*TECH* firms but decrease slightly from 4.61 to 4.60 for high-*TECH* firms. The message from Figure 1 is consistent with that from Table 5: Low-technology firms see their accounting quality deteriorate by a greater extent after the outbreak of COVID-19, whilst high-technology firms are much less affected.

Robustness Tests

To evaluate the robustness of our testing results, we perform a series of sensitivity tests. First, the presumption for our study is that firms demonstrate greater hiring needs for employees with software-related skills because they emphasize technological infrastructure and development. It is also possible for certain subcategories of software skills, such as software development skills or coding skills, to reflect a current deficiency in these skills due to shifting strategic goals or employee turnover. In some cases, a lagged *TECH* measure may better reflect workforce technology competency. To capture this delayed impact, we create a one-year lagged *TECH* measure which is *Lag_TECH*. We first note that *Lag_TECH* has a very large autocorrelation coefficient of approximately 0.8 with *TECH*, suggesting that the firm-level demand for software-related skills tends to be stable over time. We then replace *TECH* with *Lag_TECH* in our regression models to examine our hypothesis to determine whether there is also a lagged effect of technology on audit quality. As shown in Table 6, we observe consistent findings: the coefficient estimate of *COVID* × *Lag_TECH* is negative and significant at the ten percent and one percent levels in Panels A and B, respectively, suggesting that firms with stronger workforce technology competency tend to be less affected by COVID-19.

Moreover, we employ two alternative cash-flow-based measures of audit quality. Specifically, we follow Dechow and Dichev (2002) (*DD2002*) and McNichols (2002) (*MN2002*) to measure cash-flow-based discretionary accruals and use them as dependent variables in our main model. The results, as shown in Table 7, are consistent with those in Table 5. We conclude that audit quality deteriorates substantially after COVID-19 emergency declarations, but the deterioration is significantly less pronounced when the audit client firms have greater workforce technology competency.

Furthermore, *TECH* might largely depend on the industry, firms in certain industries may naturally be easier to transition to remote auditing. For example, compared to manufacturing firms that have large amounts of physical assets, technology firms have fewer physical assets and are more likely to have previous experience in remote auditing. Different industries may also concentrate in certain states (like technology firms tend to locate in California and other coastal states) and our *COVID* dummy is a state-level measure based on when each state declares a COVID-19 emergency, endogeneity may also arise in our analysis. To account for this industry effect using two approaches and address the endogeneity concern, we adopt two approaches. . First, we remove technology firms (firms with SIC-3 of 357, 481, or 737) from our sample to eliminate the advantages of the technology firms in remote auditing Second, we use an industry-adjusted *TECH*, which is the difference between a firm's *TECH* rating and the industry mean of *TECH* by using the two-digit SIC code to identify industries. Table 8 reports the results of these two tests. As shown in Panels A and B of Table 8, we find that eliminating the high-tech companies and using the industry-adjusted *TECH* measure yields qualitatively similar results, suggesting that our empirical findings are robust to the definition of workforce technology competency.

In addition, , we acknowledge that auditors' offices might have different levels of technological capacity that might affect their interactions with their clients during COVID-19. Due to our data limitations, we are not able to precisely break down auditors job postings data to the office level. We, however, address auditors' *TECH* variance by including auditor fixed effects in our regression models. Table 9 tabulate the results, which are consistent with our main findings, suggesting that *TECH* variances of auditors do not drive our results.

Lastly, to further our analysis on broader accounting quality measures, although might not affected by auditors work, we examine our hypotheses on the three proxies for real earnings management, including abnormal cash flows from operations, abnormal production costs, and abnormal discretionary expenses. We have also tested restatement and internal control weakness (*ICW404*). Table 10 summarizes the major results for hypothesis testing. We observe similar significant interaction effects on abnormal cash flows and abnormal production costs, but abnormal discretionary expenses is not significant. As Chi, Lisic, and Pevzner (2011) suggest, real earnings management activities are less likely to attract auditors' scrutiny as they comply with GAAP as long as being properly disclosed. Thus, real earnings management measures may be less likely to be related to auditors' quality of work. Furthermore, we don't observe significant interaction effects when we use restatement and *ICW404* as the dependent variables. Since restatement is a more extreme measure of audit quality and there might be a delay for restatement to be identified[8]. *ICW404* is more of a system measure for firms' internal control effectiveness for which firms establish gradually rather than experience sudden changes during COVID-19, and thus are less likely to be changed due to auditors' quality of work.

Additional Analyses

Local versus non-local client analysis

We investigate how geographical proximity between audit firms and audit clients may play a role in affecting our results. Prior studies suggest that auditor-client geographical distance may negatively affect audit quality; auditors tend to produce higher-quality audits for local clients than for non-local clients (e.g., Jensen, Kim, and Yi 2015; Choi et al. 2012). Compared to firms that use local audit offices, audit client firms that use non-local audit offices may rely more on

[8] Since the data source for our TECH measure is obtained by a one-time purchase from BGT without data updates based on the purchasing contract, we have limited access to the data in the post-COVID years, which constraints our ability to test the interaction effect on restatement. We call for future studies to investigate the long-term effects of TECH under remote-auditing arrangement on restatement.

communication technologies and be more familiar with remote information exchanges before the outbreak of COVID-19. Hence, other things equal, the disruptions to auditing services following the outbreak of COVID-19 should be less likely to affect audit quality when audit client firms and their audit offices are not located in the same region.

In Table 11, we partition our sample into local clients and non-local clients two subsamples based on the geographical proximity between audit client firms and their audit offices. Specifically, we define local clients as those within 100 miles of audit offices, and non-local clients as those that are more than 100 miles from audit offices. In untabulated tests, we also define local/non-local using cutoffs of 50-mile and 150-mile and the results are virtually the same. In Panel A, accounting quality is measured using *Dechow1995*; in Panel B, accounting quality is measured using *Kothari2005*.

We observe notable differences in the coefficient estimates of the interaction term *COVID* × *TECH*. In both Panel A and Panel B of Table 11, the coefficient of *COVID* × *TECH* is significantly negative at the level of one percent for the local client subsample but is statistically insignificant for the non-local client subsample. In other words, the results in Table 5 are primarily driven by audit client firms that use local audit offices. These firms could be less technology-savvy and depend more on conventional, face-to-face communications and means of information exchange with their auditors, and hence are more vulnerable to the sudden change to remote audit services brought by COVID-19. The correlation matrix in Table 4 also suggests that these firms tend to be smaller, less profitable, and less likely to use bigger audit offices. Disruptions to conventional audit services can be costlier to such audit client firms.

Big4 versus Non-Big4 Analysis

Although Lowe et al. (2018) suggest that Big 4 auditors do not have technological advantages over non-Big 4 auditors, prior studies do suggest that Big 4 auditors have more resources to advance their technological capabilities compared to non-Big 4 auditors (e.g., Cooper et al. 2022; Dowling and Leech 2014). This resource advantage suggests that Big 4 auditors might benefit more from their client firms' use of technology to improve engagement audit quality. Consistently, Baatwah et al. (2023) and Gong et al. (2023) argue that non-Big 4 auditors may struggle more significantly with audit quality under remote conditions. To examine the differences between Big4 and non-Big4 audit firms, we partition our sample into two groups – Big 4 and non-Big 4 – in our analysis. The results, as reported in Table 12, show significant interaction effects for both groups. However, the significance level for Big 4 auditors is much stronger at the 1 percent level, compared to the 10 percent level for non-Big 4 auditors. This finding supports our conjecture that Big 4 auditors are likely to benefit more from their tech-ready client firms due to their richer technological resources for remote auditing arrangements.

V. CONCLUSION

With more and more companies providing a permanent remote working environment for their employees, remote working arrangements bring significant challenges for accounting firms to maintain high-quality auditing services without the traditional ways of communication and interactions with their client firms. This study aims to evaluate whether and how client firms' workforce technology competency may contribute to improving the audit quality with remote audits. Utilizing a unique labor-market database to measure firms' workforce technology competency, we document empirical evidence suggesting that, whilst audit quality deteriorates with remote audits caused by COVID-19, this negative impact can be largely mitigated by clients' workforce technology competency.

Our study focuses on a shorter time period and provides valuable insights into the effect of remote auditing induced by COVID-19. The results of this study highlight the importance of building up a modern technology infrastructure in the transition to the new remote working paradigm. Our findings also present important policy implications for standard setters to identify firms that are more vulnerable to the adverse impacts brought by COVID-19 and provide resources for practitioners to meet the future technology demand. Building on our findings, future studies may adopt an extended sample period to explore the long-term effect of remote auditing and identify the learning curves of remote working in various industries and for different types of workforces.

DECLARATION OF GENERATIVEAIAND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used ChatGPT in order to reduce grammatic errors and improve the clarity of some sentences in the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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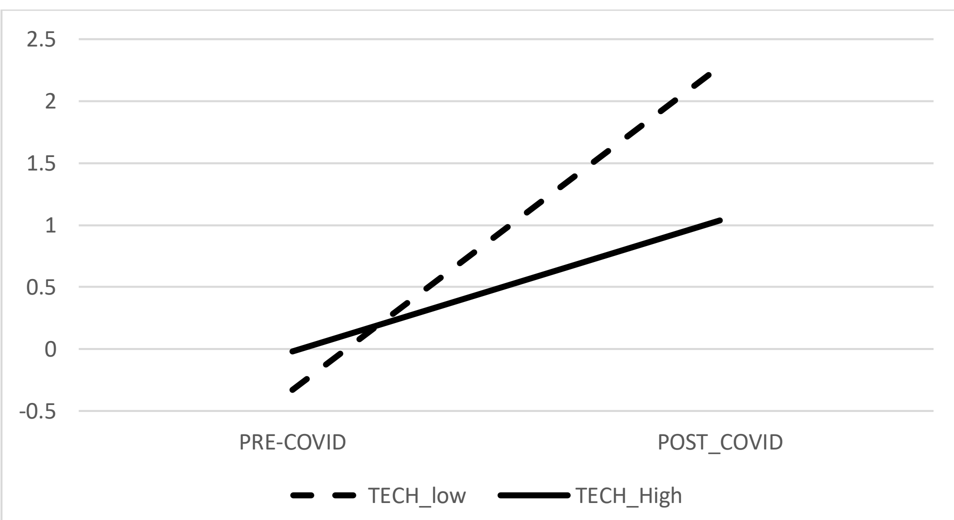
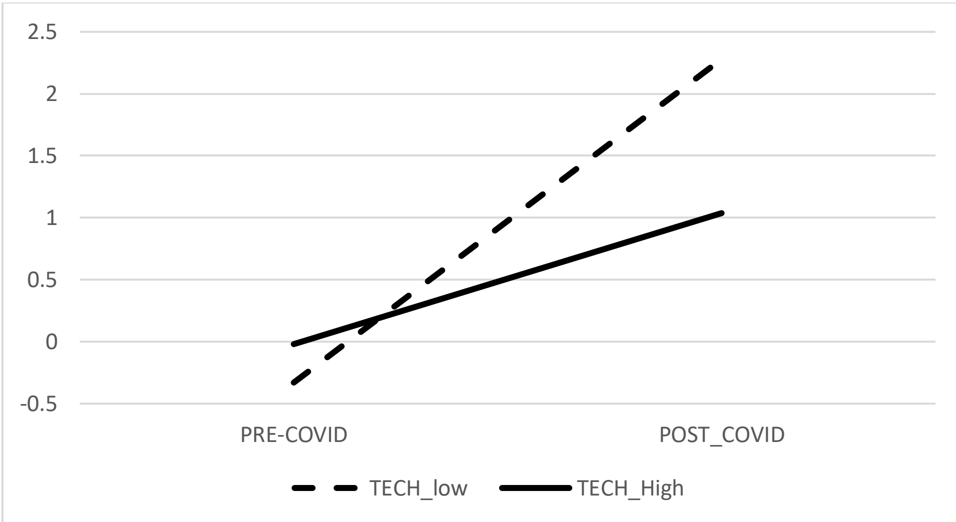
Figure 1: Visualizing the Effect of *COVID* and *TECH* on Audit Quality

Panel A: Audit Quality is measured by *Dechow1995*



Panel B: Audit Quality is measured by *Kothari2005*



Note: This figure illustrates the interaction effects of remote auditing and firms' technology competency on audit quality. The X-axis shows the time frame of pre- and post-COVID periods, while the Y-axis indicates the predicted discretionary accruals, measured by Dechow (1995) in Panel A and Kothari (2005) in Panel B, based on the regression results. The solid line represents firms with higher workforce technology competency, whereas the dashed line represents firms with lower workforce technology competency.

Table 1: Sample Reduction Process

Compustat 2017-2020	33,251
Remove regulated industry	27,585
PCAOB (partner gender info and US firms only)	14,371
Job postings	8,077
Remove missing values (Dechow1995)	5,853
Remove missing values (Kothari2005)	5,743

Table 2: Sample Frequencies and the Mean Values of *TECH*

Panel A: DV = Dechow1995				*Panel B: DV = Kothari2005*			
Frequency across years							
Year	Frequency	Percent	*TECH*	Year	Frequency	Percent	*TECH*
2017	1,396	23.851	0.132	2017	1,373	23.907	0.133
2018	1,494	25.525	0.128	2018	1,462	25.457	0.128
2019	1,521	25.987	0.127	2019	1,494	26.014	0.127
2020	1,442	24.637	0.124	2020	1,414	24.621	0.124
Frequency across Pre- to Post- COVID periods							
Remote	Frequency	Percent	*TECH*	Remote	Frequency	Percent	*TECH*
Pre	4,299	73.450	0.129	Pre	4,219	73.463	0.129
Post	1,554	26.550	0.125	Post	1,524	26.537	0.124

Table 3: Descriptive Statistics

	Overall			Pre_*COVID*			Post_*COVID*			Pre-Post Changes		
Variable	N	Mean	S.D.	N	Mean	S.D.	N	Mean	S.D.	ΔMean	ΔMean (%)	P-value
Panel A: AQ=Dechow1995												
Dechow1995	5,853	1.024	3.565	4,299	0.520	1.603	1,554	2.418	6.176	1.898	364.779	<.001
TECH	5,853	0.128	0.085	4,299	0.129	0.086	1,554	0.125	0.083	-0.004	-3.101	0.065
GENDER	5,853	0.762	0.426	4,299	0.764	0.425	1,554	0.756	0.430	-0.008	-1.019	0.537
TOT_ACC	5,853	-0.088	0.419	4,299	-0.085	0.437	1,554	-0.099	0.366	-0.014	16.333	0.265
ASSET	5,853	7.010	2.038	4,299	6.963	2.053	1,554	7.139	1.991	0.176	2.533	0.003
FOREIGN	5,853	0.674	0.469	4,299	0.671	0.470	1,554	0.683	0.465	0.013	1.905	0.357
INV_REC	5,853	0.243	0.172	4,299	0.248	0.174	1,554	0.230	0.164	-0.018	-7.211	0.000
LOSS	5,853	0.350	0.477	4,299	0.331	0.471	1,554	0.400	0.490	0.069	20.836	<0.001
MTB	5,853	4.554	12.995	4,299	4.294	12.834	1,554	5.274	13.407	0.980	22.830	0.011
LEV	5,853	0.644	1.202	4,299	0.653	1.349	1,554	0.621	0.634	-0.032	-4.839	0.375
FYR	5,853	0.709	0.454	4,299	0.728	0.445	1,554	0.656	0.475	-0.072	-9.908	<0.001
CFO	5,853	0.041	0.357	4,299	0.033	0.397	1,554	0.063	0.209	0.030	89.987	0.005
SALE	5,853	0.173	0.889	4,299	0.208	0.917	1,554	0.077	0.799	-0.131	-63.166	<0.001
BIG4	5,853	0.755	0.430	4,299	0.757	0.429	1,554	0.749	0.434	-0.008	-1.011	0.548
ACCEL	5,853	0.843	0.364	4,299	0.843	0.364	1,554	0.843	0.364	0.000	0.000	0.999
SCI	5,853	-0.297	0.863	4,299	-0.298	0.863	1,554	-0.293	0.863	0.005	-1.821	0.832

Table 3: Descriptive Statistics (Continued)

	Overall			Pre_*COVID*			Post_*COVID*			Pre-Post Changes		
Variable	N	Mean	S.D.	N	Mean	S.D.	N	Mean	S.D.	ΔMean	ΔMean (%)	P-value
Panel B: AQ=Kothari2005												
Kothari2005	5,743	0.613	1.567	4,219	0.509	0.988	1,524	0.900	2.537	0.391	76.851	<0.001
TECH	5,743	0.128	0.085	4,219	0.129	0.086	1,524	0.124	0.083	-0.005	-3.799	0.054
GENDER	5,743	0.764	0.425	4,219	0.766	0.423	1,524	0.757	0.429	-0.009	-1.240	0.455
TOT_ACC	5,743	-0.090	0.423	4,219	-0.087	0.440	1,524	-0.100	0.370	-0.013	15.526	0.283
ASSET	5,743	6.989	2.044	4,219	6.941	2.059	1,524	7.120	1.997	0.179	2.580	0.003
FOREIGN	5,743	0.681	0.466	4,219	0.678	0.467	1,524	0.691	0.462	0.013	1.962	0.340
INV_REC	5,743	0.241	0.167	4,219	0.246	0.170	1,524	0.227	0.158	-0.019	-7.839	0.000
LOSS	5,743	0.354	0.478	4,219	0.336	0.472	1,524	0.404	0.491	0.068	20.237	<0.001
MTB	5,743	4.606	13.112	4,219	4.340	12.949	1,524	5.343	13.529	1.004	23.130	0.010
LEV	5,743	0.645	1.213	4,219	0.653	1.362	1,524	0.621	0.640	-0.033	-4.993	0.368
FYR	5,743	0.709	0.454	4,219	0.728	0.445	1,524	0.654	0.476	-0.074	-10.154	<0.001
CFO	5,743	0.041	0.360	4,219	0.033	0.400	1,524	0.063	0.211	0.030	89.948	0.006
SALE	5,743	0.174	0.889	4,219	0.209	0.914	1,524	0.078	0.807	-0.131	-62.680	<0.001
BIG4	5,743	0.755	0.430	4,219	0.757	0.429	1,524	0.750	0.433	-0.007	-0.962	0.571
ACCEL	5,743	0.842	0.365	4,219	0.842	0.365	1,524	0.842	0.365	0.000	-0.033	0.980
SCI	5,743	-0.290	0.863	4,219	-0.292	0.864	1,524	-0.286	0.862	0.006	-1.955	0.825

Note: All variables are defined in Appendix A. P-values are based on two-tailed tests.

Table 4: Pearson Correlation Coefficient with *AQ* measured by *Dechow1995* (below 1) and *Kothari2005* (above 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) *AQ*	1	**0.11**	0.01	0.00	**-0.09**	**-0.11**	-0.01	**-0.05**	**0.06**	0.01	**0.18**	**0.06**	**-0.14**	**0.05**	**-0.07**	**-0.12**	-0.01
(2) *COVID*	**0.24**	1	-0.03	-0.01	-0.01	**0.04**	0.01	**-0.05**	**0.06**	0.03	-0.01	**-0.07**	**0.04**	**-0.07**	-0.01	-0.000	0.00
(3) *TECH*	-0.02	-0.02	1	0.01	0.00	0.03	**0.22**	**-0.05**	**0.04**	**0.10**	0.00	-0.01	**0.05**	-0.02	0.02	**0.05**	**-0.06**
(4) *GENDER*	0.00	-0.01	0.02	1	0.00	**-0.09**	-0.03	0.03	0.03	-0.02	0.00	0.01	**-0.04**	0.01	**-0.13**	**-0.07**	0.00
(5) *TOT_ACC*	**-0.14**	-0.01	0.00	0.00	1	**0.13**	**0.05**	**0.05**	**-0.15**	0.01	**-0.40**	-0.02	**0.49**	**-0.07**	**0.06**	**0.09**	0.03
(6) *ASSET*	**-0.06**	**0.04**	0.03	**-0.09**	**0.13**	1	**0.37**	**-0.20**	**-0.37**	**0.05**	**-0.13**	0.03	**0.32**	**-0.10**	**0.58**	**0.62**	**-0.05**
(7) *FOREIGN*	0.00	0.01	**0.22**	**-0.03**	**0.05**	**0.35**	1	0.01	**-0.09**	**0.05**	**-0.06**	0.00	**0.13**	**-0.05**	**0.28**	**0.32**	0.03
(8) *INV_REC*	**-0.05**	**-0.05**	**-0.05**	0.03	**0.05**	**-0.18**	0.00	1	**-0.10**	**-0.07**	0.02	**-0.16**	**0.05**	**-0.11**	**-0.20**	**-0.10**	**0.09**
(9) *LOSS*	**0.07**	**0.06**	**0.04**	0.03	**-0.15**	**-0.37**	**-0.08**	**-0.11**	1	-0.01	**0.09**	**0.10**	**-0.34**	**0.08**	**-0.13**	**-0.28**	**-0.05**
(10) *MTB*	0.02	0.03	**0.10**	-0.02	0.005	**0.04**	**0.05**	**-0.07**	-0.01	1	-0.03	0.01	0.00	**0.05**	**0.05**	**0.06**	-0.01
(11) *LEV*	**0.09**	-0.01	0.00	0.00	**-0.40**	**-0.13**	**-0.06**	0.02	**0.09**	-0.03	1	0.03	**-0.53**	**0.07**	**-0.05**	**-0.09**	**-0.04**
(12) *FYR*	**0.05**	**-0.07**	-0.01	0.00	-0.02	0.03	0.00	**-0.16**	**0.10**	0.01	0.03	1	**-0.09**	**0.06**	**0.06**	**0.04**	**-0.06**
(13) *CFO*	**-0.11**	**0.04**	**0.05**	**-0.04**	**0.49**	**0.32**	**0.13**	**0.05**	**-0.34**	0.00	**-0.53**	**-0.09**	1	**-0.15**	**0.14**	**0.24**	0.02
(14) *SALE*	0.01	**-0.07**	-0.02	0.01	**-0.07**	**-0.10**	**-0.05**	**-0.10**	**0.08**	**0.05**	**0.07**	**0.06**	**-0.15**	1	0.00	**-0.03**	-0.01
(15) *BIG4*	**-0.04**	-0.01	0.02	**-0.13**	**0.06**	**0.58**	**0.27**	**-0.19**	**-0.13**	**0.05**	**-0.04**	**0.06**	0.133	0.01	1	**0.50**	**0.03**
(16) *ACCEL*	**-0.07**	0.00	**0.05**	**-0.07**	**0.09**	**0.62**	**0.31**	**-0.08**	**-0.28**	**0.06**	**-0.09**	0.04	**0.24**	**-0.04**	**0.50**	1	0.01
(17) *SCI*	-0.01	0.00	**-0.06**	-0.01	0.03	**-0.05**	0.03	**0.09**	**-0.05**	-0.01	**-0.04**	**-0.05**	0.02	-0.01	**0.04**	0.01	1

Note: Coefficients highlighted in Bold are statistically significant at the 1% level. All variables are defined in Appendix A.

Table 5: Interaction effects of *COVID* and *TECH* on Audit quality

	Panel A: DV = *AQ* (*Dechow1995*)						Panel B: DV = *AQ* (*Kothari2005*)					
	(1)		(2)		(3)		(1)		(2)		(3)	
Variables	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	0.114	0.600	-0.204	0.612	-0.369	0.354	0.100	0.648	4.511	<.001	4.422	<.001
COVID	**1.904**	**<.001**	**1.930**	**<.001**	**2.804**	**<.001**	**1.946**	**<0.001**	**0.434**	**<.001**	**0.884**	**<.001**
TECH	-0.663	0.341	-0.330	0.632	**1.385**	**0.049**	-0.555	0.429	-0.117	0.703	**0.755**	**0.015**
COVID×TECH					**-6.931**	**<.001**					**-3.581**	**<.001**
GENDER			-0.062	0.525	-0.073	0.455			-0.070	0.119	-0.076	0.089
TOT_ACC			-1.000	0.005	-0.987	0.007			-0.067	0.341	-0.059	0.390
ASSET			-0.048	0.137	-0.045	0.152			-0.043	0.053	-0.042	0.060
FOREIGN			0.210	0.027	0.215	0.023			0.123	0.006	0.126	0.004
INV_REC			1.038	0.002	1.039	0.002			0.489	0.009	0.497	0.008
LOSS			-0.350	0.001	-0.378	0.001			-0.275	<.001	-0.289	<.001
MTB			0.001	0.775	0.001	0.704			-0.001	0.324	-0.001	0.381
LEV			0.138	0.064	0.137	0.071			0.221	<.001	0.220	<.001
FYR			0.139	0.086	0.129	0.110			0.037	0.459	0.031	0.525
CFO			0.039	0.858	0.023	0.917			0.047	0.840	0.038	0.872
SALE			-0.183	<.001	-0.179	<.001			-0.058	0.014	-0.056	0.015
BIG4			-0.166	0.139	-0.171	0.125			-0.060	0.269	-0.063	0.245
ACCEL			0.019	0.896	0.012	0.935			-0.164	0.024	-0.166	0.021
SCI			0.191	0.271	0.185	0.279			0.114	0.326	0.111	0.338
Industry FE	Yes		Yes		Yes		Yes		Yes		Yes	
State FE	Yes		Yes		Yes		Yes		Yes		Yes	
N	5,853		5,853		5,853		5,743		5,743		5,743	
Adj R2	0.168		0.191		0.196		0.171		0.225		0.232	

Note: All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. Statistically significant main effects and interaction effects are highlighted in bold.

Table 6: Lag Analysis

Variables	DV = *AQ* (*Dechow1995*)				DV = *AQ* (*Kothari2005*)			
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-0.910	0.136	-1.057	0.080	2.497	0.000	2.271	0.002
COVID	**1.207**	**<.001**	**1.422**	**<.001**	**0.433**	**<.001**	**0.754**	**<.001**
Lag_TECH	-0.033	0.963	**1.020**	**0.091**	-0.209	0.609	**1.371**	**0.002**
COVID×Lag_TECH			**-1.695**	**0.094**			**-2.533**	**<.001**
Controls	Yes		Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes		Yes	
State FE	Yes		Yes		Yes		Yes	
N	4,543		4,543		4,457		4,457	
Adj R2	0.195		0.195		0.334		0.337	

Note: All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. Statistically significant main effects and interaction effects are highlighted in bold.

Table 7: Alternative AQ measure for hypothesis testing

Variables	Panel A: DV=AQ (*DD2002)*				Panel B: DV=AQ (*MN2002)*			
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	0.116	0.091	0.111	0.108	0.127	0.090	0.117	0.120
COVID	**0.018**	**0.044**	**0.057**	**0.001**	**0.027**	**0.019**	**0.086**	**<.001**
TECH	-0.033	0.717	0.051	0.586	-0.129	0.288	-0.003	0.985
COVID×TECH			**-0.325**	**0.004**			**-0.486**	**0.000**
Controls	Yes		Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes		Yes	
State FE	Yes		Yes		Yes		Yes	
N	2282		2282		2192		2192	
Adj. R2	0.387		0.389		0.2439		0.248	

Note: All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. Statistically significant main effects and interaction effects are highlighted in bold.

Table 8: Controlling for Industry Effects

Panel A: Remove High-Tech Firms (SIC3=357, 481, or 737)

Variables	DV = *AQ* (*Dechow1995*) Estimate	P-value	DV=AQ (*Kothari2005)* Estimate	P-value
Intercept	-5.232	<.001	4.237	<.001
COVID	**5.335**	**<.001**	**0.851**	**<.001**
TECH	**46.596**	**<.001**	**0.641**	**0.036**
COVID×TECH	**-26.295**	**<.001**	**-2.767**	**0.002**
Controls	Yes		Yes	
Industry FE	Yes		Yes	
State FE	Yes		Yes	
N	5078		4969	
Adj R2	0.226		0.226	

Panel B: Using Industry Adjusted *TECH* (*TECH-IND*)

Variables	DV = *AQ* (*Dechow1995*) Estimate	P-value	DV=AQ (*Kothari2005)* Estimate	P-value
Intercept	-5.621	<.0001	3.546	<.0001
COVID	**4.557**	<.0001	1.675	**<.0001**
TECH-IND	**54.931**	<.0001	9.371	**<.0001**
COVID×TECH-IND	**-18.240**	<.0001	-9.542	**<.0001**
Controls	Yes		Yes	
Industry FE	Yes		Yes	
State FE	Yes		Yes	
N	5853		5743	
Adj. R2	0.222		0.248	

Note: All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. Statistically significant main effects and interaction effects are highlighted in bold.

Table 9: Including Auditor Fixed Effects

Variables	DV = *AQ* (*Dechow1995*)				DV = *AQ* (*Kothari2005*)			
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-2.327	0.100	-2.639	0.078	3.869	<.0001	3.706	<.0001
COVID	**1.944**	**<.001**	**2.846**	**<.001**	**0.438**	**<.0001**	**0.903**	**<.0001**
TECH	-0.474	0.511	**1.270**	**0.082**	-0.137	0.651	**0.747**	**0.013**
COVID×TECH			**-7.144**	**<.001**			**-3.696**	**<.0001**
Controls	Yes		Yes		Yes		Yes	
Industry	Yes		Yes		Yes		Yes	
States	Yes		Yes		Yes		Yes	
Auditors	Yes		Yes		Yes		Yes	
N	5,853		5,853		5,743		5,743	
Adj R2	0.1918		0.1972		0.2444		0.2518	

Note: All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. Statistically significant main effects and interaction effects are highlighted in bold.

Table 10: Summary of results with other dependent variables that we have attempted

Dependent Variables	Main Effect: *COVID*	Interaction Effect: *COVID* × *TECH*
Abnormal Operating Cash Flows	Estimate = 0.046; P-value = 0.007	Estimate = -1.151; P-value < 0.001
Abnormal Production Costs	Estimate = -0.048; P-value < 0.001	Estimate = -0.739; P-value < 0.001
Abnormal Discretionary Accruals	Estimate = -0.337; P-value < 0.001	Estimate = 0.245; P-value = 0.496
Restatement	Estimate = -0.024; P-value = 0.001	Estimate = -0.041; P-value = 0.632
Internal Control Weakness (ICW404)	Estimate = -0.003; P-value = 0.784	Estimate = -0.034; P-value = 0.795

Note: This table summarizes the estimates and p-values of the main effects of *COVID* and the interaction effects of *COVID×TECH* on the corresponding dependent variables. Other information is not exhibited for brevity.

Table 11: Interaction Effects of *COVID* and *TECH* on Audit Quality for Local versus Non-Local clients

	Panel A: DV = *AQ (Dechow1995)*				Panel B: DV = *AQ (Kothari2005)*			
	Local Client		Non-Local Client		Local Client		Non-Local Client	
Variables	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	-0.339	0.466	0.142	0.926	3.741	<.001	8.531	<.001
COVID	**2.926**	**<.001**	**1.991**	**0.005**	**0.934**	**<.001**	0.319	0.162
TECH	**1.685**	**0.022**	-1.623	0.442	**0.790**	**0.013**	-0.703	0.596
COVID×TECH	**-7.701**	**<.001**	-3.149	0.383	**-4.046**	**<.001**	-0.239	0.876
GENDER	-0.049	0.628	-0.137	0.784	-0.056	0.219	-0.233	0.153
TOT_ACC	-0.041	0.835	-1.292	<.001	-0.038	0.674	0.376	0.116
ASSET	-0.052	0.133	-0.325	0.008	-0.052	0.037	-0.073	0.328
FOREIGN	0.185	0.066	0.838	0.051	0.120	0.010	0.434	0.121
INV_REC	1.179	0.001	0.618	0.474	0.534	0.010	0.023	0.965
LOSS	-0.227	0.048	-0.312	0.362	-0.246	<.001	-0.266	0.107
MTB	0.002	0.653	0.005	0.668	-0.001	0.657	-0.005	0.172
LEV	0.284	0.000	-0.018	0.830	0.306	<.001	0.152	0.001
FYR	0.102	0.240	0.064	0.769	0.043	0.411	-0.049	0.687
CFO	0.636	0.015	-0.177	0.687	0.420	0.030	-0.906	0.125
SALE	-0.176	<.001	-0.074	0.739	-0.050	0.045	-0.067	0.499
BIG4	-0.216	0.060	0.230	0.586	-0.048	0.393	-0.282	0.274
ACCEL	0.043	0.777	0.417	0.533	-0.178	0.022	0.119	0.793
SCI	0.060	0.758	2.622	0.073	0.078	0.555	0.340	0.511
Industry FE	Yes		Yes		Yes		Yes	
State FE	Yes		Yes		Yes		Yes	
N	5,237		616		5,140		603	
Adj R2	0.187		0.374		0.233		0.390	

Note: All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. Statistically significant main effects and interaction effects are highlighted in bold.

Table 12: Big 4 versus Non-Big 4 auditors

Variables	DV = *AQ* (*Dechow1995*)				DV = *AQ* (*Kothari2005*)			
	Non-Big 4		Big 4		Non-Big 4		Big 4	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	0.819	0.370	-1.060	0.030	4.181	<.001	4.110	<.001
COVID	**2.945**	**<.001**	**2.810**	**<.001**	**0.776**	**0.025**	**0.932**	**<.001**
TECH	0.298	0.817	2.015	0.032	-0.127	0.860	1.153	0.000
COVID×TECH	**-6.542**	**0.074**	**-7.304**	**<.001**	**-3.036**	**0.083**	**-3.816**	**<.001**
Controls	Yes		Yes		Yes		Yes	
Years	Yes		Yes		Yes		Yes	
States	Yes		Yes		Yes		Yes	
N	1,436		4,417		1,405		4,338	
R2	0.194		0.188		0.238		0.224	

Note: All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. Statistically significant main effects and interaction effects are highlighted in bold.

Appendix A: Definition of Variables

Variables	**Definition**
AQ	Audit Quality measured by absolute value of discretionary accruals, following Dechow et al. (1995) and Kothari et al. (2005)
COVID	Binary variable = 1 for observations after state emergency declarations, and 0 otherwise
TECH	The number of software skills required in job postings scaled by the total number of skills required in job postings by a firm in a given fiscal year
GENDER	Audit partners' gender as identified using their profile pictures from their LinkedIn profiles or audit firm's website, Male =1 and Female =0
TOT_ACC	Income before extraordinary items minus cash flow from operations excluding extraordinary and discontinued operations scaled by total assets
ASSET	Natural logarithm of total assets
FOREIGN	Binary variable = 1 if a firm reports foreign income in a given year, and 0 otherwise
INV_REC	Inventories plus receivables scaled by total assets in a given year
LOSS	Binary variable = 1 if a firm report a loss in a given year, and 0 otherwise
MTB	Market value of the common stock divided by total common stockholders' equity
LEV	Total assets minus total common stockholders' equity scaled by total assets
FYR	Binary variable = 1 if a firm has a fiscal year ended in December, and 0 otherwise
CFO	Cash flow from operations scaled by total assets
SALE	Changes in sales in a given year divided by one year lagged sales
BIG4	Binary variable = 1 if an auditor is one of the Big 4 audit firms, and 0 otherwise
ACCEL	Binary variable = 1 if a firm is an SEC accelerated filer, and 0 otherwise
SCI	Social capital index developed by the Social Capital Project in 2017