THE ACCOUNTING REVIEW
Vol. 98, No. 5
September 2023
pp. 323–351

American Accounting Association
DOI: 10.2308/TAR-2020-0710

Auditors' Technological Proximity Knowledge

Yue He
Shanghai University of Finance and Economics

Jeong-Bon Kim
Bing Li
City University of Hong Kong

Zhenbin Liu
Hong Kong Baptist University

ABSTRACT: We exploit the technological closeness among clients of the same auditor to examine whether auditors accumulate knowledge from their clients' technological proximity. We find that a client firm's technological proximity to other clients of its audit office improves audit quality and results in an audit fee discount, even after controlling for the product similarity effect, auditors' overall technological expertise, and industry specialization. Both an increase in audit quality and a decrease in audit fees occur if a client firm exhibits greater technological similarity to clients of other audit offices within the same audit firm. Our findings suggest that the auditors' technological proximity knowledge enhances the effectiveness and efficiency of audit work at both the audit firm and audit office levels.

Data Availability: Data are available from the public sources cited in the text.

JEL Classifications: M41; M49; O30.

Keywords: technological proximity; audit quality; audit fees; auditors' technological proximity knowledge.

I. INTRODUCTION

The 2018 Nobel Laureate Paul Romer proposes that technology is the key input to a firm's production function and the key source of economic growth (Romer 1986, 1990). His models explain how the innovative technologies of the early 1990s, such as computer codes for word processors and the internet, gave rise to increasing returns to scale in production and sustained exponential economic growth. Currently, firms inspire innovation through their interactions, and technological advances by one firm can rapidly diffuse to other firms in related technological fields, even if they are not in the same product market (Bloom, Schankerman, and Van Reenen 2013). Indeed, technological knowledge spillovers have become increasingly important in firms' daily operations, growth, and productivity (Jaffe, Trajtenberg, and Henderson 1993). In the innovation- and technology-based economy, it is crucial for auditors to understand their clients' technological position in order to make better auditing decisions and professional judgments.

We gratefully acknowledge the comments of Chan Li (editor), two anonymous reviewers, Jong-Hag Choi, Tracy Gu, Linda Myers, Dan Simunic, Stephen Sun, and Ray Zhang. We also thank workshop participants at the City University of Hong Kong and Hong Kong Baptist University. The work described in this paper was fully supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. CityU 11502919). Zhenbin Liu acknowledges partial financial support for this project from the Research Grants Council of the Hong Kong Special Administrative Region, China (Grant No. 12501618). Yue He acknowledges financial support for this project from Ministry of Education of the People's Republic of China (the MOE Project of Key Research Institute of Humanities and Social Science in University) and Ministry of Science and Technology of the People's Republic of China (the 111 Project (Grant No. B18033)).

Yue He, Shanghai University of Finance and Economics, School of Accountancy, Institute of Accounting and Finance, Shanghai, China; Jeong-Bon Kim and Bing Li, City University of Hong Kong, College of Business, Department of Accountancy, Hong Kong, China; Zhenbin Liu, Hong Kong Baptist University, School of Business, Department of Accountancy, Economics and Finance, Hong Kong, China.

Editor's note: Accepted by Chan Li, under the Senior Editorship of W. Robert Knechel.

Submitted: November 2020
Accepted: December 2022
Early Access: April 2023

Prior literature shows that audit client similarity affects audit quality and audit fees because comparable client information provides cost advantages, efficiencies, and knowledge spillovers in the audit engagement (Brown and Knechel 2016; Zhang 2018; Bills, Cobabe, Pittman, and Stein 2020). To the best of our knowledge, however, existing literature pays scant attention to the ways in which auditor knowledge derived from client technological proximity—which we call auditors' technological proximity knowledge—might influence the effectiveness and efficiency of audit work. As a result, little is known about whether—and, if so, how—auditors' technological proximity knowledge affects audit quality and whether it entails a fee discount. To fill this void in the literature, we examine whether auditors benefit from client technological proximity, in addition to the impact of client product closeness, auditors' overall technological expertise, and industry specialization.[1]

It is important to investigate client firms' product and technology spaces separately because firms that are technologically related often come from different product markets (Bloom et al. 2013). For example, Lee, Sun, Wang, and Zhang (2019) find that an average (median) patent technology class includes firms from ten (ten) different two-digit SIC industries and 31 (26) different four-digit SIC industries. The literature further suggests that technology overlap is conceptually different from product closeness and that they are distinct economic forces (Bena and Li 2014; Cao, Ma, Tucker, and Wan 2018; Tan, Wang, and Yao 2019; Glaeser and Landsman 2021). We maintain that technological knowledge transfer could occur across traditional product market boundaries. Therefore, auditors' technological proximity knowledge should constitute a critical aspect of auditor knowledge, in addition to auditor product market knowledge. Empirically, we follow Bills et al. (2020) by adopting a research design that controls for product market linkage, auditors' overall technological expertise, and conventional auditor industry specialization measures when isolating the impact of technological proximity on audit quality and audit fees.

Auditors' technological proximity knowledge could benefit audit work, beyond the product market links, in two ways. First, auditors may be better able to assess and manage audit risks when they have more knowledge about how a client uses technology to execute and record business transactions. For example, auditors could better understand client inherent risks (e.g., sources of potential misstatements in the individual account balance or class of transactions) and identify control risks (e.g., deficiencies in clients' internal controls) within the information technology system, thus helping them to design/implement appropriate audit procedures. Key technological developments, such as the internet of things, artificial intelligence, and smart contracts used in financial reporting and internal controls, may lead to insufficient and inappropriate audit evidence generated by traditional audit substantive tests. Thus, auditors should be aware of the benefits and risks that result from the implementation of new technologies and how those benefits and risks may affect their assessment of client inherent risks, control risks, and planned audit procedures (Center for Audit Quality (CAQ) 2019). Second, auditor knowledge about technologies related to innovation and client-specific production could enable auditors to better assess client business risks, such as overall risks to client productivity and profitability. Suppose that a client's daily operations involve frequently changing technology, and, if not kept abreast of such changes, the client risks significant losses that will result in financial statement consequences, such as going concern problems and losses for obsolete inventory (Johnson and Wiley 2019). Technology applied in the client's daily operations could also directly affect accounting numbers; as such, the lack of auditor knowledge about client technology would likely impose high audit risks.

The accumulation of auditors' technological proximity knowledge can occur at the audit office level (within the audit office), the audit firm level (across different audit offices), or both. The technological evolution of certain clients may lead to a systemic change in an audit firm's training and information-sharing system. In such a case, audit quality and audit fees might be influenced across the entire audit firm (among all the offices of the audit firm), not just at the office that conducted the audit work for the clients. However, the technological proximity knowledge developed from audit engagements may be shared and communicated only between partners/personnel within the immediate audit office. Certain technological knowledge may not easily spill over to other offices of the same audit firm, especially when the technological knowledge is client specific and related only to the local (not the national) economic environment. Accordingly, we examine client technological proximity at both the audit office and audit firm levels when examining the association between audit quality/fees and client technological links.

As technological affinity could be distinct from product similarity, we investigate whether auditors develop *incremental* knowledge from clients' technological affinity over and above product market similarity.[2]Following

[1] Auditors' technological proximity knowledge is gained through auditing clients in a close technology space. It is distinct from auditors' overall technological expertise, e.g., when an auditor's clients have a large portion of the market share of patents. Similar to Bills et al. (2020), who examine the distinct impact of client product similarity on audit outcomes over and above auditor industry expertise, in this study, we investigate whether auditors' technological proximity knowledge affects audit quality and audit fees after controlling for auditors' overall technological expertise.

[2] As shown in Table 3, the Pearson (Spearman) correlation coefficient between the technology proximity score and product market similarity score at the audit office level is 0.112 (0.269); however, at the audit firm level, it is 0.156 (0.175), confirming that, despite some overlap in the product market and technology spaces, technological links might be a different and incrementally important information source for the development of auditors' technological proximity knowledge.

Bloom et al. (2013), we construct a technology proximity measure to capture firms' technology affinity with other firms audited by the same audit office/other offices of the same audit firm. We control for product similarity, auditors' overall technological expertise, and market share-based auditor industry specialization when assessing the incremental effect of client technological proximity on audit quality and audit fees.

We test our main hypotheses using a panel dataset that we construct for the period of 2000–2017 by merging two databases, Audit Analytics and Compustat. We find that audit quality increases and audit fees decrease when a client firm has a greater technological affinity with other clients of its audit office. We also find evidence of such technological knowledge spillovers at other audit offices of the same audit firm. Our findings indicate that auditors develop technological proximity knowledge at both the audit firm and audit office levels. Consistent with Zhang (2018), Bills et al. (2020), and Chang, Hsu, and Ma (2022), we also find some weak evidence that a company exhibits higher audit quality and lower audit fees when its product market is more similar to that of other clients of its audit office/audit firm. Overall, this evidence lends support to the intuition that auditors develop technology-specific knowledge on top of product market knowledge from their clients.

We undertake two cross-sectional tests to further validate our main results. First, we show that the impact of an auditor's accumulated technological proximity knowledge is more salient when the auditor's clients are technology intensive. Second, we find that the effects of client technological links on audit quality and audit fees are stronger for Big N auditors, which have more resources and a larger client base to accumulate technological proximity knowledge than non-Big N auditors.

Finally, we perform two additional tests to further distinguish between the technological proximity effect and the product similarity effect. We first show that our main findings hold in both high and low product similarity subsamples, suggesting that technological proximity has an independent impact on audit quality and audit fees, even when the product closeness is weak. In another test, we find that both the within- and across-industry technological proximities are significantly related to audit quality and audit fees measures, indicating that technological proximity has an incremental impact on audit outcomes beyond the traditional industry boundary where product linkage is mainly concentrated.

Our study contributes to the existing literature in three ways. First, given that the literature seldom examines the implications of auditors' technological proximity knowledge, our study provides novel evidence on this issue. Technology is the most pervasive of today's core business drivers. To develop a big picture of the strategic, operational, reporting, and compliance objectives of their client firms, auditors must gain a deep understanding of their clients' technological fields. Given the scarcity of empirical evidence on the effect of client technological affinity on auditor work, our study helps to narrow this knowledge gap by examining whether there is an increase in audit quality and a reduction in audit fees if an auditor's client portfolio exhibits strong technological similarity. By so doing, we also add to the emerging literature that investigates client similarity and auditor-client compatibility (Francis, Pinnuck, and Watanabe 2014; Brown and Knechel 2016; Zhang 2018; Bills et al. 2020). More specifically, our study extends this stream of research by examining client technological affinity above and beyond the traditional product market boundary and by showing that technological similarity is another important type of client comparability that affects audit quality and audit fees.

Second, our analysis broadens the auditor knowledge scope from industry and product market to technological proximity knowledge, which helps us better understand the potential benefits arising from auditing multiple clients with strong technological proximity. Our findings complement and extend the literature on industry specialist auditors (e.g., Solomon, Shields, and Whittington 1999; Owhoso, Messier, and Lynch 2002; Dunn and Mayhew 2004; Payne 2008; Behn, Choi, and Kang 2008; Bills et al. 2020) by showing that auditors derive technological proximity knowledge beyond traditional product market boundaries.

Third, our study provides a new perspective on office- versus firm-level auditor knowledge spillovers. DeFond and Zhang (2014) conclude that client-specific knowledge and local business conditions are the keys to audit office-level expertise, whereas opportunities for knowledge sharing drive audit firm-level specialization. Our findings that auditors develop technological proximity knowledge at both the office and firm levels extend prior studies on audit office-level versus audit firm-level knowledge transfer and industry specialization studies (Ferguson, Francis, and Stokes 2003; Francis, Reichelt, and Wang 2005; Li, Xie, and Zhou 2010; Reichelt and Wang 2010; Johnstone, Li, and Luo 2014).

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Prior Evidence on Client Similarity and Auditor-Client Compatibility

Recent studies investigating audit client similarity and auditor-client compatibility focus mainly on the industry or product market peers (Francis et al. 2014; Brown and Knechel 2016; Li, Sun, and Ettredge 2017; Zhang 2018; Bills et al. 2020; Ege, Kim, and Wang 2020; Chang et al. 2022). For example, Francis et al. (2014) document that clients in the same industry and year have more comparable earnings and accruals if they share the same auditor. Brown and Knechel (2016) create several auditor industry-year-level measures of client similarity using 10-K disclosures and find

American Accounting Association

that clients switch to auditors with client portfolios that are more similar to themselves. They also examine the audit quality implications and find that discretionary accruals are lower when client similarity is higher, although they do not find conclusive evidence when examining restatements and auditor going concern opinions. Li et al. (2017) show that clients are more likely to switch to an audit office that has a portfolio of more similar peers, as measured across a few dimensions, including geographic location, industry, size, and prior auditor type. Zhang (2018) finds that comparability in earnings among industry peer firms is related to less audit effort and better audit quality. Bills et al. (2020) use a client Text-Based Network Industry Classification (TNIC)-based product similarity measure derived from the business descriptions in the 10-K and find that more similar product market peers are more likely to select the same auditor and, as a result, benefit from higher quality audits at lower costs.

Prior Evidence on Auditor Industry Specialization

Existing literature contends that industry specialist auditors are better able to develop industry-specific skills and expertise (Dopuch and Simunic 1982; Balsam, Krishnan, and Yang 2003; Chi and Chin 2011). For example, O'Keefe, King, and Gaver (1994) suggest that national industry specialist auditors exhibit greater compliance with auditing standards than nonspecialist auditors. In addition, the literature generally documents a positive relation between auditor industry specialization and audit quality. Reichelt and Wang (2010) find that companies' absolute discretionary accruals are smaller, the likelihood of meeting or beating analysts' earnings forecasts is lower, and the likelihood of the auditor issuing a going concern opinion is higher if their auditors are industry specialists at the city or national level or at both levels.

The literature on the association between auditor industry specialization and audit fees seems to be mixed. One series of studies proposes that auditors with industry specialization can charge an audit fee premium, given that they provide higher quality audits (Craswell, Francis, and Taylor 1995; DeFond, Francis, and Wong 2000; Ferguson et al. 2003; Francis et al. 2005; Carson 2009; Zerni 2012; Goodwin and Wu 2014). Another series of studies documents a negative relation between auditor industry specialization and audit fees, suggesting that improved audit efficiency arising from (the economies of scale of) auditor industry specialization helps to significantly reduce audit costs (Mayhew and Wilkins 2003; Fields, Fraser, and Wilkins 2004; Cairney and Stewart 2015; Dekeyser, Gaeremynck, and Willekens 2019).

Hypotheses on the Relation between Technological Proximity and Audit Quality/Audit Fees

As discussed, prior studies provide ample evidence to suggest that auditor knowledge gained through auditing similar clients in the same industry or product market benefits audit work. In this study, we argue that technological proximity knowledge transfer could occur across traditional product market boundaries and that it constitutes an independent and important part of auditor knowledge accumulation. As such, technology acquaintance could also help auditors better understand their client firms' financial reporting processes and business operations. We further posit that auditors' technological proximity knowledge could play an important role in facilitating auditors to better assess and manage audit risk and client business risk, beyond the role that industry-/product market-specific knowledge and specialization play. We argue that this occurs in the following two ways.

First, incorporating new technology into business processes or information systems may change a client firm's inherent risks and internal control risks associated with financial reporting; it is thus important for auditors to evaluate their client's inherent and control risks that may arise and to minimize the risk of failure to identify material misstatements due to errors or intentional manipulation (American Institute of Certified Public Accountants (AICPA) 2006). For example, American Airlines Group Inc. (AA) and AT&T Inc. (AT&T) are both audited by the Ernst & Young Dallas office. AA is a U.S. airline holding company and belongs to the air transportation industry, whereas AT&T is the world's largest telecommunications company and is in the telephone communications industry. Although these two firms do not belong to the same industry or share any supply chain links, their main patents are in the same technological field of automated reservations system (four-digit Cooperative Patent Classifications (CPC): G06Q), and these patents constitute the online booking systems for their services/products. Different from the traditional financial reporting process, most of the audit evidence for AA and AT&T is available electronically, meaning that many tests of controls and substantive tests should be performed on these electronic data. These clients may face many nontraditional inherent risks related to their online reservation systems; examples of such risks include pervasive security risks (e.g., virus attacks or infrastructure failures) and transaction integrity risks (e.g., distinguishing among customer browsing, orders placed, and orders canceled). The auditors also need to conduct internal control effectiveness tests not only to determine whether the clients have implemented sufficient internal controls to address increased risks, such as security and integrity risks, but also to prevent unauthorized changes to the accounting system or records, which could raise both the inherent risks and control risks. It is plausible that Ernst & Young has developed audit knowledge in the technological field of automated reservations systems by auditing both AA and AT&T, which in turn facilitates its audit work for other clients that also use an automated reservations system. In a related vein, technological knowledge spillovers from other clients in the same CPC technology class G06Q would also benefit Ernst & Young's audits of AA and AT&T.

Second, technology/innovation is an important input for a firm's production function and its sustainable growth (Romer 1986, 1990). If a client is not well positioned to adjust to technological changes, it risks falling behind competitors and losing market share, which can affect the client's overall business risks in operations, profitability, and going concern status. This would further affect the auditor's assessment of the amount, timing, and uncertainty of future cash flows when evaluating the clients' inherent risks. For example, the Deloitte & Touche Chicago office provides audit services for both Deere & Co. (Deere) and Abbott Laboratories (Abbott). Deere is a U.S. corporation in the farm machinery and equipment industry that manufactures agricultural, construction, and forestry machinery. Abbott is a U.S. medical device and healthcare company that mainly focuses on the pharmaceutical preparations business. These two firms do not overlap in their supply chains or product markets. However, both of their patents cover the technological field of measuring liquid level (CPC: G01F), which is crucial for the firms' operations, as it provides a way to reliably and accurately measure and monitor liquid inventories across the production process. More experience with clients in the technological field of measuring liquid level helps the auditor better evaluate their clients' inventory, which could influence the whole production process. Any knowledge that Deloitte & Touche gains in liquid measuring from auditing Deere and Abbott would benefit its audit work in terms of better understanding client inherent risks and business risks for any other clients whose operations involve the same technology.

As illustrated by the above two examples, we conjecture that auditor knowledge could be developed from technological affinity among client firms, which extends beyond the traditional industry or product market boundaries. However, although prior studies document substantial independent variations in these two dimensions (Qiu and Wan 2015; Glaeser and Landsman 2021), they also find a significant correlation between these two measures, highlighting the importance of controlling for product market similarity when isolating the effect of technological proximity.

The related literature shows that greater technological affinity increases the probability that two firms merge (Bena and Li 2014), increases corporate cash holdings (Qiu and Wan 2015), decreases technologically related firms' value around the bankruptcy announcement (Qiu, J. Wang, and W. Wang 2017), reduces firm's stock price crash risk (Kim, Sun, and Zhang 2021), maintains strong predictive power for firm returns (Lee et al. 2019), and generates larger analyst coverage and increases analyst forecast accuracy (Tan et al. 2019). Given that technologically linked firms could affect each other and have similarities in their innovation/patent knowledge, auditors should gain a better and deeper understanding of the technologies applied in their clients' accounting practices and business operations from auditing clients that implement the same/similar technologies. Auditors' technological proximity knowledge enables auditors to better assess and manage audit risk. This is because such knowledge helps the auditors design more appropriate audit procedures to collect more relevant and reliable audit evidence in response to the potential inherent and control risks arising from their clients' adoption of new technologies. Moreover, such knowledge facilitates audit work in terms of understanding client business risks (e.g., clients' profitability and going concern status) and preventing, detecting, and correcting material misstatements in client firms' financial reports.

Based on the above discussions, we expect that audit quality is likely to be higher if an audit client shares greater technological proximity with the other clients of its auditor. To provide large-sample, systematic evidence on this unexplored issue, we propose and test the following hypothesis, stated in the alternative form:

H1: Audit quality increases with the extent to which a client firm is technologically proximate to the other clients in its auditor's client portfolio.

We examine H1 at both the audit office level and across the entire audit firm (e.g., at offices other than the focal firm's audit office). Given that local audit offices operate with a degree of autonomy and possess independent organizational and governance structures (Ferguson et al. 2003; Francis and Yu 2009; Choi, C. Kim, J. Kim, and Zang 2010; Reichelt and Wang 2010; Francis, Michas, and Yu 2013), each audit office has a distinctive client base and its own internal knowledge accumulation and sharing system (Danos, Eichenseher, and Holt 1989; Francis and Yu 2009; Choi et al. 2010). The decentralized organizational structure of audit firms also impedes interaction between audit offices and reduces interoffice audit quality spillover (Beck, Gunn, and Hallman 2019). Accordingly, H1 may hold at the audit office level, but not at the audit firm level if the individual audit office derives unique technological proximity knowledge that cannot be generalized and applied to the clients of other audit offices within the same audit firm. In contrast, if auditors accumulate generalized technology information that can be systematically applied to all clients of the entire audit firm, H1 is expected to hold at both the audit firm and audit office levels.

Next, we analyze whether and how technological affinity affects audit fees. Auditors must exert extra effort to gain and maintain their knowledge and refine their audit work, which requires a normal rate of return on such additional effort, as manifested in higher audit fees (Ferguson and Stokes 2002). In a similar vein, if auditors develop a reputation for better audit quality based on their accumulated technology experience, they can charge audit fee premiums for that technological proximity knowledge. Client firms are also willing to pay a fee premium for their auditors' technological proximity knowledge. However, auditors will charge lower fees if client technological knowledge spillover provides them with economies of scale (Scherer and Ross 1990; Mayhew and Wilkins 2003; Bills et al. 2020), saving the efforts required to understand, evaluate, and detect the accounting problems of client firms with strong technology similarities. Accordingly, it is ultimately an empirical question whether audit fees increase or decrease when a client firm's technological proximity to the other client firms in its auditor's client portfolio is significant. We therefore frame our second hypothesis, stated in the null form, as follows. Similarly to H1, we investigate H2 at both the audit office and audit firm levels.

H2: Audit fees are insensitive to the extent to which a client firm is technologically proximate to the other clients in its auditor's client portfolio.

With H1 and H2, we explore whether technological proximity has any incremental effect on audit quality and audit fees over and above product market links. It is probable that auditors develop technological proximity knowledge only from clients within the same product market, given that firms from different product markets may not share many similarities in accounting practices and business operations. Therefore, it is possible that the effect of technological affinity on audit quality and audit fees, if any, could be pre-empted by product market closeness. If this is the case, we will not observe that client technological proximity within its auditor's client portfolio has a significant effect on audit quality/fees over and beyond product similarity.

III. SAMPLE AND RESEARCH DESIGN

Sample and Data

Our sample begins with all the available firm-years in the Audit Analytics and Compustat merged database for the period from 2000 to 2017. Our sample starts in 2000 because that is the first year that Audit Analytics reported audit data. We obtain firms' patenting activities from the Bureau van Dijk's Orbis Intellectual Property (OrbisIP) patent database. Compared with the National Bureau of Economic Research (NBER) U.S. Patent Citations Data File and the patent data shared by Kogan, Papanikolaou, Seru, and Stoffman (2017), which are only available up to 2006 and 2009, respectively, OrbisIP provides the latest daily updated patent data.[3] As our proxy for technological proximity is constructed using firms' patent data for a three-year rolling window, we further restrict our sample to observations with at least one patent in the past three years (Tan et al. 2019).

Table 1, Panel A summarizes the sample-construction process, and Panel B reports the sample description by year. We begin with the 120,881 firm-years in the Audit Analytics and Compustat merged database from 2000 to 2017. We then remove 93,287 firm-years that have not received patent grants in the past three years. We also exclude 4,234 (1,740) firm-years that do not have any peer firms in their audit office (their audit firm's other offices) that have received patent grants over the past three years. We note here that our core results are even stronger if we retain them in the sample. We further drop 2,102 firm-years that do not have TNIC data to construct the product similarity control variable. After these sample-screening procedures, we get an initial sample of 19,518 firm-year observations for the 2000–2017 sample period. As 2,505 firm-years do not have the data necessary for the construction of the regression variables in the abnormal accruals (*accruals*) model, the final sample for this test is 17,013 firm-year observations. For the misstatement (*misstatement*) and fraud risk score (*fscore*) models, we similarly limit the sample to firm-year observations with data available for calculating all the regression variables in each model. After applying this sample-screening requirement, we obtain 17,806 observations for the misstatement model and 15,762 observations for the fraud risk score model. To test auditors' incidence to report internal control material weaknesses (*MW*), we limit the sample to firm-years with available SOX 404 audit opinion data and necessary regression variables. This yields a final sample of 10,166 observations from 2004 to 2017. Our sample for the audit fees model starts from 2001, as the regression model controls for one-year-lagged audit fees data and the audit fees data are only available since 2000 (Kim, H. Li, and S. Li 2015). The final sample for the audit fees model is 15,494 observations with nonmissing control variables.

Table 1, Panel B reports the sample observations and descriptive statistics for the audit quality and audit fees variables by year. Specifically, *#accruals*, *#misstatement*, *#fscore*, *#MW*, and *#lnaf* refer to the number of observations included in the abnormal accruals, misstatement, fraud risk score, internal control material weaknesses, and audit fees

[3] The numbers of U.S. patents provided by the OrbisIP database and those in Kogan et al. (2017) are comparable before 2009. The only difference is that the OrbisIP database provides patent data after 2009, whereas Kogan et al. (2017) do not. Untabulated tests show that our main regression results are robust, even when using the patent data from Kogan et al. (2017), although the results become less significant due to fewer sample observations.

TABLE 1

Sample Selection and Description

Panel A: Sample Selection

Firm-Years in Audit Analytics and Compustat merged database (2000–2017)	120,881
Less:	
Firm-years that do not receive patent grants over the past three years	(93,287)
Firm-years that do not have any peers in their audit office that receive patent grants over the past three years	(4,234)
Firm-years that do not have any peers in their audit firm's other offices that receive patent grants over the past three years	(1,740)
Firm-years that do not have TNIC data	(2,102)
Initial sample (2000–2017)	19,518
Initial sample (2000–2017)	19,518
Less: Missing data for abnormal accruals (*accruals*) model	(2,505)
Final sample for abnormal accruals model (2000–2017)	17,013
Initial sample (2000–2017)	19,518
Less: Missing data for misstatement (*misstatement*) model	(1,712)
Final sample for misstatement model (2000–2017)	17,806
Initial sample (2000–2017)	19,518
Less: Missing data for fraud risk score (*fscore*) model	(3,756)
Final sample for fraud risk score model (2000–2017)	15,762
Initial sample (2000–2017)	19,518
Less: Missing data for internal control material weaknesses (*MW*) model	(9,352)
Final sample for internal control material weaknesses model (2004–2017)[a]	10,166
Initial sample (2000–2017)	19,518
Less: Missing data for audit fees (*lnaf*) model	(4,024)
Final sample for audit fees model (2001–2017)[b]	15,494

(continued on next page)

models in each specific year. *Avg_accruals*, *Avg_fscore*, and *Avg_lnaf* indicate the mean values of abnormal accruals, fraud risk score, and logged audit fees in each year, respectively, whereas *N_misstatement* (*N_MW*) denotes the number of firms with financial statements that are misstated (receive adverse SOX 404 opinions from their auditors) in each year.

Research Design

Following the literature, we specify the baseline model below to test the effects of client technological links on audit quality and audit fees.

$$\begin{aligned}
&\textit{Audit quality/Audit fees}\\
&\quad = a_0 + a_1 \times \textit{audit office technology proximity} + a_2 \times \textit{other office technology proximity}\\
&\qquad + a_3 \times \textit{audit office product similarity} + a_4 \times \textit{other office product similarity}\\
&\qquad + a_5 \times \textit{audit office technology specialist} + a_6 \times \textit{other office technology specialist}\\
&\qquad + a_7 \times \textit{audit office industry specialist} + a_8 \times \textit{other office industry specialist}\\
&\qquad + a_9 \times \textit{audit office earnings comparability} + a_{10} \times \textit{other office earnings comparability}\\
&\qquad + \textstyle\sum_{k=11}^{n} a_k \times \text{Controls} + \text{Audit office \& Industry \& Year fixed effects} \qquad (1)
\end{aligned}$$

In the above, *Audit quality* is measured by either abnormal accruals (*accruals*), misstatement (*misstatement*), fraud risk score (*fscore*), or internal control material weaknesses (*MW*).[4] The first three measures are related to audit risks

[4] Prior literature uses auditor going concern opinions as an alternative to audit quality measure. Newton, Persellin, Wang, and Wilkins (2016) contend that going concern opinions have relatively lower incidence than adverse SOX 404 opinions. In addition, going concern opinions are exclusively issued to financially distressed clients, which reduces their generalizability to healthy firms (DeFond and Zhang 2014). Despite this fact, in untabulated analysis, we examine whether our results hold for going concern opinions. Consistent with the tabulated regression results in this study, we find that financially distressed firms are more likely to receive going concern opinions from their auditors if they have larger technological proximity with their auditor's other clients. The coefficients on *audit office technology proximity* and *other office technology proximity* are 0.035 (t-stat = 2.11) and 0.050 (t-stat = 2.03), respectively.

TABLE 1 (continued)

Panel B: Sample Description by Year (2000–2017)

Year	(1) #*accruals*	(2) *Avg_accruals*	(3) #*misstatement*	(4) *N_ misstatement*	(5) #*fscore*	(6) *Avg_fscore*	(7) #*MW*	(8) *N_MW*	(9) #*lnaf*	(10) *Avg_ Lnaf*
2000	1,156	0.004	1,241	130	993	1.322	NA	NA	NA	NA
2001	1,230	0.002	1,312	165	1,165	0.950	NA	NA	836	12.504
2002	1,205	0.007	1,247	186	1,115	0.858	NA	NA	1,155	12.812
2003	1,046	0.003	1,076	194	985	0.881	NA	NA	1,046	13.042
2004	1,029	−0.001	1,068	215	978	1.078	546	77	1,016	13.599
2005	967	0.001	1,001	159	907	0.956	810	92	976	13.867
2006	920	−0.005	959	131	857	1.029	802	82	931	14.024
2007	903	−0.004	947	92	845	1.027	796	59	906	14.064
2008	876	−0.002	910	84	808	0.948	775	27	892	14.078
2009	797	−0.004	825	80	734	0.833	716	17	811	14.070
2010	792	−0.003	817	86	732	0.953	694	11	799	14.024
2011	785	−0.010	808	116	718	1.017	694	22	789	14.053
2012	830	−0.001	859	129	770	0.982	722	37	827	14.078
2013	867	−0.012	912	117	815	0.986	730	23	853	14.100
2014	921	−0.005	979	96	857	1.009	763	34	922	14.140
2015	925	−0.006	982	105	864	0.979	763	40	939	14.182
2016	903	−0.008	951	71	832	0.918	697	49	915	14.192
2017	861	−0.010	912	48	787	1.013	658	28	881	14.247
Total	17,013	−0.002	17,806	2,204	15,762	0.987	10,166	598	15,494	13.803

Panel A of this table outlines the sample selection criteria. Panel B reports sample observations and descriptive statistics of the main variables by year for each of the audit quality and audit fees models.

[a] The sample period for the internal control material weaknesses model starts in year 2004, when the SEC began to implement Section 404 of SOX.

[b] The sample period for the audit fees model starts in year 2001 because one-year lagged audit fees is included as a control variable in the audit fees model (Audit Analytics provides full coverage of audit fees data since 2000).

Variable Definitions:

#*accruals* indicates the number of observations in each year included in the abnormal accruals model;

Avg_accruals is the mean value of signed abnormal accruals calculated following Kothari et al. (2005);

#*misstatement*, #*fscore*, #*MW*, and #*lnaf* refer to the number of observations included in the misstatement, fraud risk score, internal control material weaknesses, and audit fees models each year;

N_misstatement and *N_MW* refer to the number of firms whose financial statements are misstated and the number of firms that receive adverse opinions on internal controls from the external auditors in each year; and

Avg_fscore and *Avg_lnaf* indicate the mean value of *fscore* and *lnaf*, respectively.

(i.e., auditors' failure to detect earnings management and reporting errors/misstatement), and the last reflects the auditor's evaluation of client control risk (e.g., deficiencies in client's internal controls). *Accruals* is the residual from the performance-adjusted accruals model, following Kothari, Leone, and Wasley (2005). *Misstatement* captures whether the firm's financial statements are misstated or not. *fscore* is calculated based on the model in Dechow, Ge, Larson, and Sloan (2011), with larger values indicating higher probabilities of misstatement. *MW* measures whether the firm receives an adverse opinion on internal controls from its external auditor or not. In summary, higher values of *MW* and lower values of *accruals*, *misstatement*, and *fscore* are indicative of better audit quality. Audit fees are estimated by using the natural logarithm of the client's annual audit fees (*lnaf*).

We follow Bloom et al. (2013) to calculate a client firm's technology proximity with other clients of the same auditor. Specifically, *audit office technology proximity* is defined as the uncentered correlation between the technological activity of firm i and that of all of its audit office j's other clients in year t: $\frac{T_{it}\ T'_{-it}}{\sqrt{T_{it}\ T'_{it}}\sqrt{T_{-it}\ T'_{-it}}}$. The vector $T_{i,t} = (t_{i,1,t}, \ldots, t_{i,k,t}, \ldots, t_{i,K,t})$ captures client firm i's technological activity across four-digit CPC classes, and $T_{-i,t} = (t_{-i,1,t}, \ldots, t_{-i,k,t}, \ldots, t_{-i,K,t})$ reflects the technological activity of all other firms sharing the same audit office as firm i. $t_{i,k,t}$, the kth element of $T_{i,t}$, refers to the ratio of the number of patents in CPC technology class k for firm i to the total number of patents over the rolling past three years for firm i.[5] Comparatively, $t_{-i,k,t}$, the kth element of $T_{-i,t}$, stands for the ratio of the number of patents in CPC technology class k for other clients of audit office j to the total number of patents over the rolling past three years for other clients of audit office j. Similarly, we compute *other office technology proximity* as firm i's technological affinity to the clients of its audit firm's audit offices other than firm i's audit office (other audit offices). Depending on the degree of overlap in technological fields, *audit office technology proximity* (*other office technology proximity*) ranges between zero and one and varies from client to client within each audit office (audit firm).[6]

[5] Following prior studies (Leydesdorff, Kogler, and Yan 2017; Akcigit, Ates, Lerner, Townsend, and Zhestkova 2020; Mewes and Broekel 2022), we estimate client firms' patent distribution in each four-digit CPC class. If a client did not apply for any patents in a given patent class, the share of patents from that class is defined as zero (Bloom et al. 2013; Qiu and Wan 2015; Lee et al. 2019).

[6] Suppose, for example, that three firms, A, B, and C, share the same audit office. Each firm has ten patents over the past three years, and their patent distributions over the CPC technology classes are as follows: A = (5, 2, 3 … 0 … 0); B = (0, 0, 0 … 10 … 0); C = (1, 1, 3 … 0 … 5). Then, the audit office level technological proximity values for these three firms are calculated as follows:

$$\begin{aligned} \textit{audit office technology proximity}_A &= \frac{T_A T'_{\text{B\&C}}}{\sqrt{T_A T'_A}\sqrt{T_{B\&C} T'_{B\&C}}} \\ &= \frac{(0.5, 0.2, 0.3\ldots0\ldots0) \times (0.05, 0.05, 0.15\ldots0.5\ldots0.25)'}{\sqrt{(0.5, 0.2, 0.3\ldots0\ldots0) \times (0.5, 0.2, 0.3\ldots0\ldots0)'}\sqrt{(0.05, 0.05, 0.15\ldots0.5\ldots0.25) \times (0.05, 0.05, 0.15\ldots0.5\ldots0.25)'}} \\ &= 0.223 \end{aligned}$$

$$\begin{aligned} \textit{audit office technology proximity}_B &= \frac{T_B T'_{\text{A\&C}}}{\sqrt{T_B T'_B}\sqrt{T_{A\&C} T'_{A\&C}}} \\ &= \frac{(0, 0, 0\ldots1\ldots0) \times (0.3, 0.15, 0.3\ldots0\ldots0.25)'}{\sqrt{(0, 0, 0\ldots1\ldots0)(0, 0, 0\ldots1\ldots0)'}\sqrt{(0.3, 0.15, 0.3\ldots0\ldots0.25)(0.3, 0.15, 0.3\ldots0\ldots0.25)'}} \\ &= 0 \end{aligned}$$

$$\begin{aligned} \textit{audit office technology proximity}_C &= \frac{T_C T'_{\text{A\&B}}}{\sqrt{T_C T'_C}\sqrt{T_{A\&B} T'_{A\&B}}} \\ &= \frac{(0.1, 0.1, 0.3\ldots0\ldots0.5) \times (0.25, 0.1, 0.15\ldots0.5\ldots0)'}{\sqrt{(0.1, 0.1, 0.3\ldots0\ldots0.5)(0.1, 0.1, 0.3\ldots0\ldots0.5)'}\sqrt{(0.25, 0.1, 0.15\ldots0.5\ldots0)(0.25, 0.1, 0.15\ldots0.5\ldots0)'}} \\ &= 0.227 \end{aligned}$$

Although firms A, B, and C are audited by the same audit office, each firm has a different value for *audit office technology proximity*. For example, firm B has no overlap in the technological fields with clients A and C of its auditor; thus, *audit office technology proximity* for firm B has a value of 0. Client firm A (C) has a positive value for *audit office technology proximity* (but less than 1) because there are some overlaps in technological fields between A (C) and its peer firms B and C (A and B). If a firm and the other clients of its auditor perfectly overlap in their technological fields, then *audit office technology proximity* would have a value of 1. As the *audit office technology proximity* measure varies for each client firm of the same auditor, we can control for audit office fixed effects in our main models.

With H1, we predict that audit quality increases with the extent to which a client firm is technologically proximate to the other clients in its audit office's client portfolio. Accordingly, we should observe a significantly negative a_1 for the *accruals*, *misstatement*, and *fscore* models and a significantly positive a_1 for the *MW* model. If there is technological knowledge spillover across audit offices within an audit firm, we will observe a significantly negative a_2 for the *accruals*, *misstatement*, and *fscore* models and a significantly positive a_2 for the *MW* model. Regarding H2, we do not form a signed prediction of a_1 or a_2 in the audit fees model.

To isolate the incremental impact of technology proximity, if any, on audit quality and audit fees over and above the product similarity effect, we also include the product similarity measures in Equation (1). We adopt the TNIC-based product similarity as our product similarity proxy. Hoberg and Phillips (2010, 2016) estimate a product similarity measure using textual analysis based on unique words used in firms' business descriptions in their 10-K filings. They argue that actual market competition often occurs beyond the traditional fixed industry classification boundary. The TNIC-based approach provides a *continuous* measure of peer-to-peer product similarity that is better able to capture product similarity beyond traditional dichotomous industry classification, such as the SIC, Global Industry Classification Standard (GICS), or North American Industry Classification System (NAICS) codes. We follow Bills et al. (2020) to construct an *audit office product similarity* (*other office product similarity*) measure by averaging Hoberg and Phillips' (2010, 2016) product similarity scores between firm *i* and its audit office's other clients (the clients of its audit firm's other audit offices) in the same TNIC group.

Bills et al. (2020) argue that audit client-to-client product similarity and auditor overall product market specialization are two distinct constructs, and it is important to control for auditor industry specialization when investigating the impact of audit client product similarity on audit outcomes. In parallel, between-client technological similarity and auditors' overall technological expertise are two different concepts in the domain of technology space. Comparable to the regression model in Bills et al. (2020), we include auditors' overall technological expertise and auditor industry specialization as important additional control variables in Equation (1). Similar to the industry specialist measures that are defined based on the audit market shares, the auditors' overall technological expertise measures are identified based on the patent market shares.[7] In addition, Zhang (2018) finds that clients' earnings comparability affects audit quality and audit fees. Thus, we further control for financial statement comparability measures to alleviate the concern that clients with comparable earnings have a similar distribution of their technology usage. The comparability measures are estimated following De Franco, Kothari, and Verdi (2011).

We also follow prior research by including a full set of other important control variables in each specific model (J. Myers, L. Myers, and Omer 2003; Carey and Simnett 2006; R. Hoitash, U. Hoitash, and Bedard 2008; Francis and Yu 2009; Li, Sun, and Ettredge 2010; Lopez and Peters 2012; Carcello and Li 2013; Goh, Krishnan, and Li 2013; DeFond and Zhang 2014; Ettredge, Fuerherm, and Li 2014; Lennox and Li 2014; Goodwin and Wu 2016; Lamoreaux 2016; Lennox 2016; Newton et al. 2016). See Appendix A for a set of control variables included in Equation (1) and their operational definitions. We include audit office, industry, and year indicators to control for unobserved audit office, industry, and time trend characteristics. We do not control for firm fixed effects because the client portfolios of a firm's auditor are relatively stable across years and the within-firm variations in the technological proximity variable are small. The standard errors are adjusted for time-series dependence by clustering at both the firm and audit office levels (Petersen 2009).

IV. DESCRIPTIVE STATISTICS AND MAIN REGRESSION RESULTS

Descriptive Statistics

In Table 2, we report the descriptive statistics for the regression variables. For our independent variables in the abnormal accruals model, the mean values of *audit office technology proximity* and *other office technology proximity* are 0.153 and 0.183, respectively. The two product similarity measures, *audit office product proximity* and *other office product proximity*, have mean values of 0.023 and 0.026, respectively. The proportion of *audit office technology specialist*

[7] Auditors' technological proximity knowledge and auditors' overall technological expertise are two distinct measures. For example, the client firm Verint Systems Inc. (Align Technology Inc.) exhibits high (low) technological proximity with its audit peers, but the client's auditor possesses low (high) overall technological expertise. Specifically, Verint Systems Inc. was audited by the Deloitte & Touche New York office in 2016. It had *high* technological proximity with Deloitte & Touche New York audit office peers and other Deloitte & Touche audit peers in 2016 (*audit office technology proximity* = 0.750 and *other office technology proximity* = 0.508, respectively). In contrast, Deloitte & Touche shows *low* overall technological expertise at both New York city and national levels (*audit office technology specialist* = *other office technology specialist* = 0). Comparatively, the PwC San Jose office conducted an audit for Align Technology Inc. in 2005. Align Technology Inc. has *low* technological proximity with the PwC San Jose audit office peers, as well as other PwC audit peers in 2005 (*audit office technology proximity* = 0.000 and *other office technology proximity* = 0.003, respectively), whereas PwC is the overall technological expert at both San Jose city and the U.S. country levels (*audit office technology specialist* = *other office technology specialist* = 1).

TABLE 2

Summary Statistics

Panel A: Analyses of Accruals

Variables	Obs.	Mean	Median	Std. Dev.	25%	75%
accruals	17,013	−0.002	−0.002	0.105	−0.047	0.043
audit office technology proximity	17,013	0.153	0.028	0.234	0.000	0.213
other office technology proximity	17,013	0.183	0.156	0.154	0.043	0.287
audit office product similarity	17,013	0.023	0.000	0.040	0.000	0.034
other office product similarity	17,013	0.026	0.021	0.028	0.004	0.035
audit office technology specialist	17,013	0.101	0.000	0.302	0.000	0.000
other office technology specialist	17,013	0.020	0.000	0.140	0.000	0.000
audit office industry specialist	17,013	0.402	0.000	0.490	0.000	1.000
other office industry specialist	17,013	0.021	0.000	0.144	0.000	0.000
audit office earnings comparability	17,013	0.039	0.031	0.062	−0.002	0.071
other office earnings comparability	17,013	0.033	0.027	0.039	0.007	0.054
dec	17,013	0.691	1.000	0.462	0.000	1.000
lntenure	17,013	1.371	1.386	0.842	0.693	2.079
size	17,013	6.175	5.992	2.117	4.647	7.612
levt	17,013	0.467	0.425	0.364	0.234	0.616
mtb	17,013	3.568	2.478	7.426	1.434	4.309
roa	17,013	−0.116	0.020	0.484	−0.149	0.072
opcf	17,013	−0.025	0.068	0.341	−0.044	0.123
loss	17,013	0.429	0.000	0.495	0.000	1.000
exchange	17,013	0.900	1.000	0.300	1.000	1.000
nseg	17,013	1.990	1.000	1.392	1.000	3.000
audit market concentration	17,013	0.035	0.026	0.026	0.021	0.040
return	17,013	13.293	2.955	72.677	−27.450	34.542
return volatility	17,013	15.601	12.587	11.631	8.370	19.050
issue	17,013	0.174	0.040	0.318	0.010	0.203
S404	17,013	0.598	1.000	0.490	0.000	1.000
$S404 \times MW$	17,013	0.035	0.000	0.184	0.000	0.000
zscore	17,013	−1.120	−1.624	3.829	−2.808	−0.392
total accruals	17,013	−0.081	−0.063	0.130	−0.119	−0.024
NUM_TNIC_auditoffice	17,013	4.483	1.000	7.352	1.000	4.000
NUM_TNIC_otheroffice	17,013	18.180	5.000	29.820	1.000	21.000

Panel B: Analyses of Misstatement

Variables	Obs.	Mean	Median	Std. Dev.	25%	75%
misstatement	17,806	0.124	0.000	0.329	0.000	0.000
audit office technology proximity	17,806	0.152	0.028	0.234	0.000	0.212
other office technology proximity	17,806	0.181	0.154	0.153	0.042	0.286
audit office product similarity	17,806	0.023	0.000	0.041	0.000	0.034
other office product similarity	17,806	0.027	0.022	0.031	0.005	0.036
audit office technology specialist	17,806	0.101	0.000	0.302	0.000	0.000
other office technology specialist	17,806	0.020	0.000	0.139	0.000	0.000
audit office industry specialist	17,806	0.400	0.000	0.490	0.000	1.000
other office industry specialist	17,806	0.021	0.000	0.144	0.000	0.000
audit office earnings comparability	17,806	0.039	0.031	0.063	−0.002	0.071
other office earnings comparability	17,806	0.033	0.027	0.040	0.007	0.054
dec	17,806	0.696	1.000	0.460	0.000	1.000

(continued on next page)

TABLE 2 (continued)

Variables	Obs.	Mean	Median	Std. Dev.	25%	75%
lntenure	17,806	1.358	1.386	0.849	0.693	2.079
size	17,806	6.137	5.953	2.129	4.605	7.582
levt	17,806	0.472	0.424	0.408	0.233	0.619
mtb	17,806	3.582	2.495	7.666	1.434	4.349
roa	17,806	−0.134	0.018	0.552	−0.167	0.071
opcf	17,806	−0.035	0.066	0.358	−0.056	0.122
loss	17,806	0.438	0.000	0.496	0.000	1.000
exchange	17,806	0.897	1.000	0.304	1.000	1.000
nseg	17,806	1.976	1.000	1.386	1.000	3.000
audit market concentration	17,806	0.037	0.026	0.032	0.021	0.040
return	17,806	13.446	2.764	74.123	−28.000	34.728
return volatility	17,806	15.960	12.738	12.431	8.434	19.444
issue	17,806	0.186	0.041	0.337	0.010	0.217
S404	17,806	0.591	1.000	0.492	0.000	1.000
$S404 \times MW$	17,806	0.035	0.000	0.184	0.000	0.000
zscore	17,806	−1.001	−1.598	4.507	−2.786	−0.347
lag_mis	17,806	0.232	0.000	0.422	0.000	0.000
litigation	17,806	0.502	1.000	0.500	0.000	1.000
NUM_TNIC_auditoffice	17,806	4.531	1.000	7.429	1.000	4.000
NUM_TNIC_otheroffice	17,806	18.593	5.000	30.360	1.000	22.000

Panel C: Analyses of Fraud Risk Score

Variables	Obs.	Mean	Median	Std. Dev.	25%	75%
fscore	15,762	0.987	0.849	0.766	0.536	1.237
audit office technology proximity	15,762	0.152	0.028	0.235	0.000	0.213
other office technology proximity	15,762	0.182	0.155	0.154	0.043	0.286
audit office product similarity	15,762	0.023	0.000	0.041	0.000	0.034
other office product similarity	15,762	0.027	0.021	0.031	0.004	0.035
audit office technology specialist	15,762	0.100	0.000	0.300	0.000	0.000
other office technology specialist	15,762	0.020	0.000	0.139	0.000	0.000
audit office industry specialist	15,762	0.395	0.000	0.489	0.000	1.000
other office industry specialist	15,762	0.021	0.000	0.143	0.000	0.000
audit office earnings comparability	15,762	0.039	0.031	0.062	−0.002	0.071
other office earnings comparability	15,762	0.033	0.027	0.039	0.007	0.054
dec	15,762	0.700	1.000	0.458	0.000	1.000
lntenure	15,762	1.368	1.386	0.841	0.693	2.079
size	15,762	6.092	5.901	2.100	4.592	7.493
levt	15,762	0.469	0.419	0.385	0.231	0.614
mtb	15,762	3.591	2.496	7.676	1.430	4.356
roa	15,762	−0.129	0.017	0.543	−0.163	0.071
opcf	15,762	−0.030	0.066	0.344	−0.053	0.122
loss	15,762	0.440	0.000	0.496	0.000	1.000
exchange	15,762	0.897	1.000	0.304	1.000	1.000
nseg	15,762	1.936	1.000	1.356	1.000	3.000
audit market concentration	15,762	0.036	0.026	0.030	0.021	0.040
return	15,762	13.252	2.904	72.788	−27.950	35.004
return volatility	15,762	15.947	12.780	12.359	8.521	19.335
issue	15,762	0.181	0.040	0.332	0.010	0.211
S404	15,762	0.596	1.000	0.491	0.000	1.000

(continued on next page)

TABLE 2 (continued)

Variables	Obs.	Mean	Median	Std. Dev.	25%	75%
S404 × MW	15,762	0.036	0.000	0.186	0.000	0.000
zscore	15,762	−1.043	−1.625	4.389	−2.820	−0.368
litigation	15,762	0.503	1.000	0.500	0.000	1.000
cash	15,762	−1.692	−1.381	1.331	−2.397	−0.661
NUM_TNIC_auditoffice	15,762	4.551	1.000	7.400	1.000	4.000
NUM_TNIC_otheroffice	15,762	18.415	5.000	29.941	1.000	21.000

Panel D: Analyses of Internal Control Material Weaknesses

Variables	Obs.	Mean	Median	Std. Dev.	25%	75%
MW	10,166	0.059	0.000	0.235	0.000	0.000
audit office technology proximity	10,166	0.162	0.034	0.242	0.000	0.235
other office technology proximity	10,166	0.196	0.170	0.162	0.050	0.305
audit office product similarity	10,166	0.022	0.000	0.038	0.000	0.033
other office product similarity	10,166	0.027	0.022	0.033	0.005	0.036
audit office technology specialist	10,166	0.094	0.000	0.292	0.000	0.000
other office technology specialist	10,166	0.014	0.000	0.118	0.000	0.000
audit office industry specialist	10,166	0.413	0.000	0.492	0.000	1.000
other office industry specialist	10,166	0.028	0.000	0.165	0.000	0.000
audit office earnings comparability	10,166	0.038	0.031	0.060	−0.002	0.070
other office earnings comparability	10,166	0.034	0.027	0.039	0.007	0.054
dec	10,166	0.722	1.000	0.448	0.000	1.000
lntenure	10,166	1.743	1.946	0.765	1.386	2.303
size	10,166	6.825	6.622	1.941	5.381	8.066
levt	10,166	0.486	0.453	0.329	0.261	0.635
mtb	10,166	3.641	2.589	7.624	1.586	4.313
roa	10,166	−0.052	0.034	0.351	−0.061	0.079
opcf	10,166	0.020	0.081	0.261	0.015	0.129
loss	10,166	0.351	0.000	0.477	0.000	1.000
exchange	10,166	0.956	1.000	0.206	1.000	1.000
nseg	10,166	2.144	1.000	1.490	1.000	3.000
audit market concentration	10,166	0.036	0.025	0.034	0.020	0.040
return	10,166	13.346	6.633	57.356	−19.406	33.903
return volatility	10,166	12.258	10.572	7.917	7.378	15.043
issue	10,166	0.149	0.038	0.286	0.010	0.165
cash	10,166	−1.716	−1.482	1.236	−2.415	−0.752
foreign sales	10,166	0.728	1.000	0.445	0.000	1.000
lnreport_lag	10,166	4.112	4.094	0.226	4.007	4.263
lnaf	10,166	14.280	14.221	0.968	13.589	15.004
client importance	10,166	0.077	0.033	0.114	0.014	0.088
acquisition	10,166	0.027	0.000	0.061	0.000	0.020
NUM_TNIC_auditoffice	10,166	4.118	1.000	6.602	1.000	3.000
NUM_TNIC_otheroffice	10,166	16.646	5.000	29.001	1.000	18.000

Panel E: Analyses of Audit Fees

Variables	Obs.	Mean	Median	Std. Dev.	25%	75%
lnaf	15,494	13.803	13.819	1.208	12.934	14.685
audit office technology proximity	15,494	0.154	0.029	0.236	0.000	0.216
other office technology proximity	15,494	0.184	0.158	0.155	0.044	0.288

(continued on next page)

TABLE 2 (continued)

Variables	Obs.	Mean	Median	Std. Dev.	25%	75%
audit office product similarity	15,494	0.023	0.000	0.041	0.000	0.034
other office product similarity	15,494	0.027	0.022	0.032	0.004	0.036
audit office technology specialist	15,494	0.099	0.000	0.299	0.000	0.000
other office technology specialist	15,494	0.019	0.000	0.135	0.000	0.000
audit office industry specialist	15,494	0.402	0.000	0.490	0.000	1.000
other office industry specialist	15,494	0.023	0.000	0.149	0.000	0.000
audit office earnings comparability	15,494	0.038	0.030	0.060	−0.002	0.070
other office earnings comparability	15,494	0.033	0.027	0.038	0.007	0.053
dec	15,494	0.713	1.000	0.452	0.000	1.000
lntenure	15,494	1.510	1.609	0.783	1.099	2.079
size	15,494	6.247	6.083	2.135	4.693	7.705
levt	15,494	0.477	0.432	0.404	0.240	0.621
mtb	15,494	3.490	2.493	7.625	1.460	4.278
roa	15,494	−0.126	0.020	0.521	−0.154	0.072
opcf	15,494	−0.031	0.070	0.359	−0.044	0.124
loss	15,494	0.428	0.000	0.495	0.000	1.000
exchange	15,494	0.910	1.000	0.287	1.000	1.000
nseg	15,494	2.003	1.000	1.408	1.000	3.000
audit market concentration	15,494	0.036	0.026	0.030	0.021	0.039
return	15,494	14.081	3.989	71.055	−25.211	34.898
return volatility	15,494	14.710	12.042	10.787	8.098	17.950
issue	15,494	0.169	0.038	0.321	0.009	0.189
S404	15,494	0.671	1.000	0.470	0.000	1.000
$S404 \times MW$	15,494	0.039	0.000	0.193	0.000	0.000
zscore	15,494	−1.006	−1.582	4.457	−2.764	−0.335
foreign sales	15,494	0.679	1.000	0.467	0.000	1.000
restatement	15,494	0.072	0.000	0.258	0.000	0.000
nas	15,494	0.350	0.175	0.533	0.054	0.409
lag_lnaf	15,494	13.733	13.721	1.324	12.794	14.609
NUM_TNIC_auditoffice	15,494	4.412	1.000	7.221	1.000	4.000
NUM_TNIC_otheroffice	15,494	18.235	5.000	30.448	1.000	21.000

This table shows the descriptive statistics for the regression variables.
See Appendix A for detailed variable definitions.

(*other office technology specialist*) is 0.101 (0.020) in the sample, whereas the percentage of *audit office industry specialist* (*other office industry specialist*) is 0.402 (0.021). For the dependent variables, the mean value of *accruals* is −0.002, which is comparable to those reported in Cahan and Zhang (2006) and Krishnan, Sun, Wang, and Yang (2013). Similar to Newton, Wang, and Wilkins (2013), Brown and Knechel (2016), and Newton et al. (2016), 12.40 percent of observations in our sample misstate their financial statements and 5.90 percent receive an adverse opinion on internal controls from their external auditor. Consistent with the literature (e.g., Carcello, Hermanson, Neal, and Riley 2002; Minutti-Meza 2013; Fung, Raman, Sun, and Xu 2015), the mean values of *fscore* and *audit fees* are 0.987 and US$1.90 million, respectively.

Table 3 presents the correlations for the main variables, with the Pearson (Spearman) correlation coefficients shown in the lower (upper) triangle. Firms with a higher value of *audit office technology proximity* (*other office technology proximity*) tend to have lower abnormal accruals and a lower likelihood of fraudulent financial reporting in both the Pearson and Spearman correlations. However, the sign of the relation between internal control material weaknesses and *other office technology proximity* is the direct opposite of our expectations.[8] Regarding audit fees, both the Pearson and Spearman correlations show that auditors charge a fee premium for their client's technological similarity. In addition,

[8] The main reason for this finding is that we do not control for other factors that affect the relation between adverse SOX 404 opinions and technology proximity. For example, firm size—an important firm characteristic—may simultaneously affect both technological proximity and adverse SOX 404 opinions.

TABLE 3
Correlation Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) *accruals*		−0.004	**0.061**	0.011	**−0.084**	**−0.068**	**−0.112**	**−0.026**	−0.009	−0.001	**−0.022**	**−0.029**	−0.017	**−0.055**	**−0.046**	**−0.097**
(2) *misstatement*	−0.007		**0.041**	**0.223**	**0.055**	−0.017	−0.006	**−0.039**	−0.020	−0.019	**0.024**	**−0.023**	0.015	**0.035**	0.001	0.019
(3) *fscore*	**0.070**	**0.037**		**0.022**	**0.292**	**−0.101**	**−0.070**	**−0.236**	**−0.232**	−0.015	−0.016	0.012	−0.016	0.021	**0.040**	**0.266**
(4) *MW*	0.016	**0.223**	**0.039**		**0.034**	−0.011	−0.020	**−0.028**	−0.013	0.000	0.011	**−0.051**	−0.019	**−0.072**	**−0.076**	**−0.092**
(5) *lnaf*	**−0.067**	**0.054**	**0.201**	**0.034**		**0.092**	**0.098**	**−0.110**	**−0.111**	**0.030**	−0.002	**0.194**	**0.061**	**0.312**	**0.373**	**0.865**
(6) *audit office technology proximity*	**−0.055**	−0.019	**−0.081**	−0.003	**0.067**		**0.527**	**0.269**	**0.247**	**0.026**	0.007	**0.162**	**0.099**	**0.224**	**0.209**	**0.073**
(7) *other office technology proximity*	**−0.102**	−0.005	**−0.056**	**−0.024**	**0.125**	**0.434**		**0.254**	**0.175**	0.009	**0.041**	**0.096**	**0.034**	**0.166**	**0.104**	**0.073**
(8) *audit office product similarity*	0.003	**−0.034**	**−0.159**	**−0.038**	**−0.094**	**0.112**	**0.109**		**0.523**	**0.051**	−0.004	**0.125**	**0.080**	**0.175**	**0.137**	**−0.089**
(9) *other office product similarity*	0.011	**−0.034**	**−0.191**	**−0.026**	**−0.160**	**0.173**	**0.156**	**0.483**		**0.043**	−0.011	**0.111**	0.010	**0.191**	**0.043**	**−0.077**
(10) *audit office technology specialist*	0.003	−0.019	−0.015	0.000	**0.029**	**0.050**	0.004	**0.049**	**0.051**		−0.018	**0.268**	**−0.044**	**0.028**	**−0.128**	0.009
(11) *other office technology specialist*	−0.012	**0.024**	−0.011	0.011	−0.001	−0.006	**0.047**	−0.012	−0.016	−0.018		−0.016	**0.029**	**0.042**	0.001	0.001
(12) *audit office industry specialist*	**−0.026**	**−0.023**	0.008	**−0.051**	**0.198**	**0.116**	**0.090**	**0.079**	**0.107**	**0.268**	−0.016		**−0.130**	**0.241**	**0.135**	**0.220**
(13) *other office industry specialist*	−0.011	0.015	**−0.023**	−0.019	**0.059**	**0.088**	**0.042**	0.014	−0.016	**−0.044**	**0.029**	**−0.130**		**0.059**	**0.171**	**0.051**
(14) *Big N*	**−0.050**	**0.035**	0.000	**−0.072**	**0.317**	**0.131**	**0.150**	**0.106**	**0.145**	**0.028**	**0.042**	**0.241**	**0.059**		**0.391**	**0.257**
(15) *office size*	**−0.033**	−0.018	0.011	**−0.067**	**0.301**	**0.084**	**0.097**	**0.048**	−0.002	**−0.127**	**−0.021**	**0.113**	**0.172**	**0.213**		**0.371**
(16) *size*	**−0.074**	0.005	**0.168**	**−0.091**	**0.862**	**0.067**	**0.119**	**−0.048**	**−0.109**	0.018	0.000	**0.238**	**0.046**	**0.245**	**0.320**	

This table presents correlation estimates for the selected variables with Pearson's correlation coefficients shown below the diagonal and Spearman's rank correlations above the diagonal. The correlation coefficients between the audit quality/audit fees measures and the independent variables (except for the *Big N* and *office size* variables) are estimated based on the final sample of each model. The correlation coefficients between the *Big N/office size* variable and other variables are estimated based on our initial sample of 19,518 observations because the *Big N* and *office size* variables are not directly used as independent variables in the regression analyses. Bold text indicates statistical significance at the 5 percent level or better.

we find that the correlations between *audit office technology proximity* (*other office technology proximity*) and *audit office product similarity* (*other office product similarity*) are as low as 0.112 (0.156) in the Pearson correlation and 0.269 (0.175) in the Spearman correlation, which are all well below unity, implying substantial independent variation in the two measures. The correlation between *audit office technology proximity/other office technology proximity* and auditor size/client size are all positive and significant at the 5 percent level, indicating that the technology proximity measure is significantly larger for Big N auditors, large audit offices, and large clients than for non-Big N auditors, small offices, and small clients. We note, however, that all the correlations reported in Table 3 should be interpreted cautiously because they do not account for other factors that may be correlated with audit quality/fees (as we do in the multivariate tests in the following sections).

Main Regression Results

Technological Links and Audit Quality

In this section, we analyze the effect of client technological proximity on audit quality (H1). Table 4, columns (1)–(4) present the regression results for Equation (1) using, as the dependent variable, one of four audit quality measures: (1) abnormal accruals (*accruals*); (2) the likelihood of a misstatement (*misstatement*); (3) a Dechow et al. (2011) measure of fraud likelihood (*fscore*); and (4) the likelihood of client firms receiving adverse SOX 404 opinions from their external auditors (*MW*), respectively.

We find that audit quality improves when a client firm has a greater technological affinity with the other clients of its audit office. The estimated coefficients on *audit office technology proximity* in the *accruals*, *misstatement*, *fscore*, and *MW* models are −0.004 (t-stat = −2.10), −0.025 (t-stat = −2.43), −0.075 (t-stat = −2.01), and 0.022 (t-stat = 2.03), respectively. This finding suggests that, at the audit office level, auditors can derive technological proximity knowledge and thus provide higher quality audits. We also find that the estimated coefficients on *other office technology proximity* are all significant, indicating that audit quality increases when a client firm has greater technology proximity to the clients of the audit firm's offices other than its own audit office. These findings indicate that the benefits from auditor technological proximity knowledge can be spilled over or transferred to other audit offices within an audit firm. Reflecting the first-order economic impact, the coefficient estimates imply that, when *audit office technology proximity* (or *other office technology proximity*) increases from the bottom to the top quartile, on average, abnormal accruals decrease by 0.001 (or 0.003), which represents 1.22 (or 4.15) percent of the absolute value of abnormal accruals. For the other audit quality measures (misstatement, fraud risk score, and internal control material weaknesses), if *audit office technology proximity* or *other office technology proximity* increases from the bottom to the top quartile, on average, the likelihood of reporting a misstatement (fraud risk score) decreases by 0.53 percent or 0.88 percent (0.016 or 0.037), which is 4.28 percent or 7.08 percent (1.62 percent or 3.74 percent) of the mean; on the other hand, the likelihood of receiving an adverse opinion on internal controls from its external auditor increases by 0.52 percent or 1.20 percent, which represents 8.77 percent or 20.31 percent of the mean.[9] The coefficients on *audit office technology proximity* are not significantly different from those on *other office technology proximity*; t-statistics for testing the difference in the two coefficients are 1.63, 0.42, 1.14, and −0.90 for *accruals*, *misstatement*, *fscore*, and *MW* models, respectively.

Although the regression results are weaker, we do find some evidence that a company exhibits higher audit quality and lower audit fees when its product market is more similar to other clients of its audit office/audit firm. These findings are consistent with the prior literature investigating the impact of product similarity on audit outcomes (Zhang 2018; Bills et al. 2020; Chang et al. 2022). The results for other control variables are generally consistent with the expectations grounded in prior research. For example, firm size (*size*) is positively associated with abnormal accruals, whereas cash flows from operations (*opcf*) are negatively related to abnormal accruals.

Collectively, the results in Table 4, columns (1)–(4) support the hypothesis that auditors gain knowledge about a client firm's technological position from other clients in closely related technological fields, enabling them to provide higher quality audit services. Technological proximity knowledge accumulation occurs at both the audit office and audit firm levels. This result is consistent with the notion that technology-related auditing knowledge is not only accumulated and shared within the same audit office but also transferred and spilled over to other audit offices within the same audit firm.

[9] The economic significances documented in our paper are comparable to those in Reichelt and Wang (2010), Lennox and Li (2014), Fung et al. (2015), Lamoreaux (2016), and DeFond and Lennox (2017).

TABLE 4

Effect of Auditor Technological Proximity Knowledge Spillover on Audit Quality and Audit Fees

Dependent Variable	(1) *accruals*	(2) *misstatement*	(3) *fscore*	(4) *MW*	(5) *lnaf*
audit office technology proximity	−0.004**	−0.025**	−0.075**	0.022**	−0.040**
	(−2.10)	(−2.43)	(−2.01)	(2.03)	(−2.26)
other office technology proximity	−0.012***	−0.036**	−0.152***	0.047**	−0.101***
	(−2.92)	(−2.00)	(−2.77)	(2.01)	(−3.40)
audit office product similarity	0.010	−0.033**	−0.277*	0.014	−0.169*
	(0.96)	(−2.51)	(−1.70)	(0.21)	(−1.78)
other office product similarity	−0.034*	−0.179	−0.861***	0.126	−0.407***
	(−1.69)	(−1.57)	(−3.40)	(1.20)	(−2.59)
audit office technology specialist	−0.003**	−0.006	−0.077**	−0.002	−0.019
	(−2.06)	(−0.58)	(−2.36)	(−0.22)	(−1.35)
other office technology specialist	−0.004*	0.004	−0.007	0.002	−0.018
	(−1.65)	(0.33)	(−0.18)	(0.08)	(−1.11)
audit office industry specialist	0.001	−0.010	−0.035*	0.001	−0.020*
	(0.73)	(−1.62)	(−1.84)	(0.15)	(−1.72)
other office industry specialist	−0.004**	0.013	−0.029	−0.007	−0.011
	(−2.04)	(0.75)	(−1.16)	(−0.49)	(−0.58)
audit office earnings comparability	0.009	−0.005	0.050	0.039	−0.009
	(0.90)	(−0.12)	(0.33)	(0.73)	(−0.19)
other office earnings comparability	−0.018	0.086	−0.076	0.017	−0.096
	(−1.32)	(1.40)	(−0.34)	(0.24)	(−1.31)
dec	0.003***	−0.013**	0.037*	−0.014*	0.012
	(2.80)	(−2.49)	(1.72)	(−1.72)	(1.34)
lntenure	−0.001	0.009**	−0.081***	−0.017***	0.008
	(−0.74)	(2.40)	(−7.21)	(−3.83)	(1.49)
size	0.001*	0.007***	0.047***	−0.015***	0.152***
	(1.79)	(3.98)	(5.89)	(−3.63)	(21.11)
levt	0.007	−0.014	−0.301***	−0.005	0.100***
	(0.66)	(−1.65)	(−3.57)	(−0.37)	(5.26)
mtb	−0.000*	0.000	0.003***	0.000	0.000
	(−1.89)	(0.44)	(3.52)	(1.08)	(1.37)
roa	−0.016	0.018*	0.117	0.012	−0.038
	(−1.09)	(1.72)	(1.21)	(0.63)	(−1.57)
opcf	−0.069***	−0.008	−0.150**	0.010	0.025
	(−5.58)	(−0.68)	(−2.19)	(0.35)	(1.27)
loss	0.034***	−0.007	−0.085***	0.013	0.021**
	(22.65)	(−1.06)	(−4.44)	(1.58)	(2.46)
exchange	−0.010***	−0.011	0.051	−0.049**	0.012
	(−4.85)	(−1.41)	(1.46)	(−2.23)	(0.89)
nseg	0.000	−0.000	0.000	−0.005*	0.005
	(0.82)	(−0.10)	(0.01)	(−1.78)	(1.01)
audit market concentration	−0.148***	0.265	−1.049	−0.156	0.069
	(−3.79)	(1.23)	(−1.47)	(−0.90)	(0.24)
return	−0.000***	−0.000	0.000	−0.000**	−0.000**
	(−7.35)	(−0.15)	(0.05)	(−2.14)	(−2.26)
return volatility	0.000***	0.000**	0.003***	0.000	0.001**
	(4.94)	(2.36)	(3.30)	(0.86)	(2.04)
issue	0.030***	0.010	0.263***	−0.010	0.082***
	(6.37)	(1.46)	(6.21)	(−1.09)	(7.11)

(continued on next page)

TABLE 4 (continued)

Dependent Variable	(1) *accruals*	(2) *misstatement*	(3) *fscore*	(4) *MW*	(5) *lnaf*
S404	−0.006***	−0.033***	−0.103***		0.220***
	(−3.26)	(−4.15)	(−3.78)		(16.75)
S404 × MW	−0.001	0.133***	0.046		0.227***
	(−0.37)	(8.09)	(1.38)		(14.52)
zscore	−0.004**	0.002**	0.021		−0.004
	(−2.26)	(1.98)	(1.44)		(−1.65)
total accruals	0.744***				
	(61.54)				
lag_mis		0.492***			
		(53.45)			
litigation		0.009	0.078**		
		(1.01)	(2.38)		
cash			−0.251***	−0.006	
			(−16.92)	(−1.60)	
foreign sales				−0.014*	0.120***
				(−1.85)	(12.06)
lnreport_lag				0.400***	
				(13.82)	
lnaf				0.065***	
				(6.41)	
client importance				0.126***	
				(3.23)	
acquisition				−0.001	
				(−0.03)	
restatement					0.087***
					(6.25)
nas					−0.077***
					(−9.16)
lag_lnaf					0.573***
					(46.12)
NUM_TNIC_auditoffice	−0.000	0.001	0.001	−0.000	0.000
	(−0.16)	(1.48)	(0.42)	(−0.36)	(0.33)
NUM_TNIC_otheroffice	0.000	0.000	0.001**	−0.000**	−0.001**
	(0.49)	(1.63)	(2.41)	(−2.55)	(−2.24)
Constant	0.037***	−0.016	0.543***	−2.332***	4.692***
	(4.37)	(−0.85)	(5.51)	(−13.00)	(33.20)
Audit office	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Observations	17,013	17,806	15,762	10,166	15,494
Adjusted R^2	0.839	0.436	0.213	0.212	0.941

, * Indicate statistical significance at the 5 percent and 1 percent levels, respectively.
t-statistics are reported in parentheses.
This table investigates whether and how client firm technological affinity affects audit quality and audit fees. Columns (1)–(4) present the effect of auditors' technological proximity knowledge spillover on audit quality (H1), and column (5) shows how auditors' technological proximity knowledge spillover affects audit fees (H2). Specifically, audit quality is measured using abnormal accruals (*accruals*), misstatement (*misstatement*), fraud risk score (*fscore*), or internal control material weaknesses (*MW*), whereas audit fees are estimated using the natural logarithm of the client's annual audit fees (*lnaf*). We use linear regression in columns (1), (3), and (5) when the dependent variables *accruals*, *fscore*, and *lnaf* are continuous variables. Following Hanlon and Hoopes (2014), we apply the linear probability model in columns (2) and (4), where the dependent variables *misstatement* and *MW* are dummy indicators to avoid a huge drop in sample size when controlling for various fixed effects. The standard errors are adjusted for time-series dependence by clustering at each firm and audit office.
See Appendix A for detailed variable definitions.

Technological Links and Audit Fees

Next, we examine the effect of client technology proximity on audit fees (H2). We estimate Equation (1) with audit fees (*lnaf*) as the dependent variable.

As shown in Table 4, column (5), the estimated coefficients on *audit office technology proximity* and *other office technology proximity* are −0.040 (t-stat = −2.26) and −0.101 (t-stat = −3.40), respectively. These results suggest that client technological knowledge spillover provides an auditor with economies of scale, resulting in an audit fee discount. This effect exists at both the audit office and audit firm levels. Regarding economic significance, the coefficient estimate implies that audit fees decrease by US$0.016 million or US$0.047 million, which represents 0.87 percent or 2.46 percent of the mean, when *audit office technology proximity* or *other office technology proximity* increases from the bottom to the top quartile.[10] This is consistent with the argument that auditors will charge lower fees if client technological knowledge spillover provides them with economies of scale (Scherer and Ross 1990; Mayhew and Wilkins 2003; Bills et al. 2020). There is no significant difference in the coefficients on *audit office technology proximity* and *other office technology proximity* (t-stat = 1.60). Table 4, column (5) also shows a significantly negative relation between clients' product similarity and audit fees. The signs of the other control variables are generally consistent with those reported in the literature.

Altogether, Table 4, column (5) provides evidence that auditors obtain audit efficiencies in audits of technologically proximate clients at both the audit office and audit firm levels. The cost savings are passed on to clients in the form of lower audit fees.

V. CROSS-SECTIONAL TESTS

In this section, we test how the cross-sectional variations in client and auditor characteristics affect the roles that clients' technological closeness play in determining audit quality and audit fees. We examine whether the previously documented spillover effect of auditor technological proximity knowledge is stronger for either technology-intensive firms or Big N auditors.

First, we predict that the effect of auditor technological proximity knowledge on audit quality and audit fees is more salient when their clients are relatively more technology intensive. The underlying rationale is that, for technology-intensive firms, their business and financial operations may rely more on their technology-related activities; thus, a deep understanding of the client's technological fields helps the auditor make better auditing decisions and professional judgments. To test this conjecture, we follow Demers and Joos (2007), Organisation for Economic Co-operation and Development (OECD) (2011), and Lee et al. (2019) to measure a firm's *technology intensity* as the size of the firm's research and development (R&D) spending scaled by total sales. We partition the whole sample into two subgroups based on the *technology intensity* score. We define an indicator variable, *high technology intensity*, which equals 1 for firms whose technology intensity values are above the median value of the sample and 0 otherwise. As shown in Table 5, we find that the coefficients on the two interaction terms, *audit office technology proximity* × *high technology intensity* and *other office technology proximity* × *high technology intensity*, are significant with expected signs at the 1 percent level in two out of ten cases, at the 5 percent level in seven cases, and at the 10 percent level in one case. These findings indicate that the effects of client technological proximity on audit quality and audit fees are stronger in technology-intensive client firms.

Second, we investigate whether the effects of client technological knowledge spillover on audit quality and audit fees differ between Big N and non-Big N auditors. Prior literature suggests that the U.S. audit market is dominated by the Big N audit firms, which are known to more actively provide their staff with in-house training and audit support (Knechel, Naiker, and Pacheco 2007; Behn et al. 2008; Francis and Wang 2008; Francis and Yu 2009; Reichelt and Wang 2010; Chan and Wu 2011; Ege et al. 2020). Following this strand of studies, we predict that Big N auditors develop more technological knowledge from their clients' technological proximity than non-Big N auditors because larger auditors have more resources and a larger client base, which facilitate the accumulation of technological proximity knowledge. Consistent with our expectations, the results in Table 6 show that the effects of client technological affinity on audit quality and audit fees are generally stronger for Big N audit engagements, as compared with non-Big N audit engagements. Specifically, we find that the coefficients on the two interaction terms, *audit office technology proximity* × *Big N* and *other office technology proximity* × *Big N*, are significant at the 1 percent level in one out of ten cases, at the 5 percent level in seven cases, and insignificant only in two cases.

[10] The economic significance is comparable to that in Chaney, Jeter, and Shivakumar (2004), Donohoe and Knechel (2014), and Chang et al. (2022).

TABLE 5

Cross-Sectional Test: Technology Intensity

Dependent Variable	(1) *accruals*	(2) *misstatement*	(3) *fscore*	(4) *MW*	(5) *lnaf*
audit office technology proximity	−0.009**	−0.020**	−0.097**	0.034**	−0.063**
× *high technology intensity*	(−2.49)	(−1.97)	(−2.25)	(2.41)	(−2.14)
other office technology proximity	−0.009**	−0.053***	−0.226***	0.033*	−0.068**
× *high technology intensity*	(−2.43)	(−2.61)	(−3.28)	(1.80)	(−2.03)
audit office technology proximity	0.001	−0.025*	0.009	−0.002	−0.003
	(0.39)	(−1.65)	(0.26)	(−0.17)	(−0.22)
other office technology proximity	−0.003	−0.003	0.059	0.013	0.010
	(−0.87)	(−0.23)	(1.09)	(0.54)	(0.30)
high technology intensity	0.006***	0.020***	0.027	0.003	−0.035**
	(4.20)	(3.16)	(1.52)	(0.51)	(−2.57)
Controls	Yes	Yes	Yes	Yes	Yes
Audit office	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Observations	17,013	17,806	15,762	10,166	15,494
Adjusted R^2	0.839	0.349	0.295	0.208	0.946

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
t-statistics are reported in parentheses.
This table tests whether the effects of between-client technological proximity on audit quality and audit fees are stronger in technology-intensive firms. We predict that clients are more likely to benefit from auditors' technological proximity knowledge when they are more technology intensive. We partition the whole sample observations into two subgroups based on the *technology intensity* score, which is measured as the size of the firm's R&D spending scaled by total sales following Demers and Joos (2007), OECD (2011), and Lee et al. (2019). *High technology intensity* refers to the firms whose technology intensity values are above the median value of the sample.

VI. ADDITIONAL TESTS AND ROBUSTNESS CHECKS

Firms in the same industry are likely to use similar technologies; therefore, our measures of technological links may overlap product market similarity. Consequently, our results may possibly be driven by product market links, rather than by technological links. To further address this concern, we undertake two additional tests in this section to examine (1) whether the effect of technology proximity on audit quality and audit fees differs between high versus low product market similarity firms and (2) whether auditors accumulate technological proximity knowledge from clients, not only in the same industry but also in different industries. We then conduct several robustness tests of the main findings in Table 4.

High versus Low Product Market Similarity

We first split our sample into high versus low product similarity subsamples. If the technology proximity has an independent impact on audit quality and audit fees over and above product similarity, then our main findings should hold, even when the product similarity is low. To test our conjecture, we define an indicator variable, *high audit office product similarity* (*high other office product similarity*), which equals 1 if the product similarity between the focal firm and its audit office's other clients (the clients from its audit firm's other offices) is above the sample median and 0 otherwise. We incorporate the interaction term of technology proximity and high product similarity measures into each audit quality/audit fees model.

Table 7 reports the regression results. By design, the coefficient estimates on *audit office technology proximity* and *other office technology proximity* capture the effects of technology proximity on audit quality and audit fees for the low product similarity subsample. Consistent with our expectation, we find that the coefficients on *audit office technology proximity* and *other office technology proximity* are significant at the 1 percent level in four out of ten cases and significant at the 5 percent level in all of the other six cases, suggesting that technology proximity has significant impacts on

TABLE 6

Cross-Sectional Test: Big N versus Non-Big N

Dependent Variable	(1) *accruals*	(2) *misstatement*	(3) *fscore*	(4) *MW*	(5) *lnaf*
audit office technology proximity × Big N	−0.012**	−0.055	−0.175**	0.018	−0.086**
	(−2.11)	(−1.30)	(−2.10)	(0.32)	(−2.12)
other office technology proximity × Big N	−0.019***	−0.153**	−0.310**	0.069**	−0.095**
	(−2.81)	(−2.00)	(−2.42)	(2.20)	(−2.00)
audit office technology proximity	0.010	−0.046	0.142	0.011	0.019
	(1.46)	(−1.14)	(1.47)	(0.11)	(0.39)
other office technology proximity	0.002	0.098	0.176	−0.059	0.098*
	(0.31)	(1.06)	(1.37)	(−1.57)	(1.74)
Controls	Yes	Yes	Yes	Yes	Yes
Audit office	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Observations	17,013	17,806	15,762	10,166	15,494
Adjusted R^2	0.635	0.392	0.381	0.181	0.950

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
t-statistics are reported in parentheses.
This table investigates whether the effects of client technological affinity on audit quality and audit fees differ in Big N versus non-Big N auditors. The *Big N* is not separately included in the regression model, as it is perfectly correlated with audit office fixed effects.

TABLE 7

Additional Test: High versus Low Product Market Similarity

Dependent Variable	(1) *accruals*	(2) *misstatement*	(3) *fscore*	(4) *MW*	(5) *lnaf*
audit office technology proximity	0.008	0.020	−0.067	−0.016	0.006
× high audit office product similarity	(1.26)	(0.59)	(−1.18)	(−1.12)	(0.29)
other office technology proximity	−0.002	0.033	−0.041	−0.032	0.006
× high other office product similarity	(−0.25)	(1.24)	(−0.47)	(−1.15)	(0.13)
audit office technology proximity	−0.010**	−0.037**	−0.069***	0.033**	−0.038**
	(−2.17)	(−2.17)	(−2.70)	(2.08)	(−2.18)
other office technology proximity	−0.020***	−0.055**	−0.115***	0.062**	−0.107***
	(−3.28)	(−2.19)	(−2.72)	(2.26)	(−3.53)
high audit office product similarity	−0.001	0.002	0.016	0.007	−0.025***
	(−0.60)	(0.25)	(0.62)	(1.11)	(−2.99)
high other office product similarity	−0.000	−0.017**	−0.017	0.015	−0.011
	(−0.03)	(−2.28)	(−0.62)	(1.50)	(−1.01)
Controls	Yes	Yes	Yes	Yes	Yes
Audit office	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Observations	17,013	17,806	15,762	10,166	15,494
Adjusted R^2	0.777	0.436	0.214	0.214	0.942

, * Indicate statistical significance at the 5 percent and 1 percent levels, respectively.
t-statistics are reported in parentheses.
This table investigates whether the effect of client technological proximity on audit quality and audit fees differs in high versus low product market similarity subsamples. *High audit office product similarity* (*high other office product similarity*) is an indicator variable that equals 1 if the product similarity between the focal firm and its audit office's other clients (the clients from its audit firm's other offices) is above the sample median and 0 otherwise.

audit quality and audit fees when product similarity is low. What is more, the coefficients on the interaction terms are all insignificant, implying that the impact of technology proximity on audit quality and audit fees does not differ systematically between high and low product similarity subsamples. This additional test helps to alleviate the concern that our findings on technological proximity are driven mainly by product similarity.

Within-Industry versus Across-Industry Technological Proximity Knowledge Spillover

In the second test, we separately construct within- and across-industry technological proximity measures at both the audit office and other office levels: *audit office technology proximity in the same industry* (*different industries*) and *other office technology proximity in the same industry* (*different industries*). We then replace *audit office technology proximity* and *other office technology proximity* in our main regression model with these four within- and across-industry technology proximity measures. The regression results are reported in Table 8. We find that, in 19 out of 20 cases, the coefficients on *audit office technology proximity in the same industry* (*different industries*) and *other office technology proximity in the same industry* (*different industries*) are significant with expected signs. In Table 8, last two rows, we report the results of tests for differences in coefficients on within-industry versus across-industry measures. As shown, we find that the coefficients on the within-industry technology proximity measures are not significantly different from those on the across-industry technology proximity measures in nine out of ten cases and that the former coefficients are larger than the latter coefficients in the remaining one case (where the coefficient difference is significant).

Overall, the findings in Table 8 suggest that auditors develop technological proximity knowledge from *both* within- and across-industry clients. The findings are also consistent with the notion that technological proximity has an incremental impact beyond the traditional industry boundary, where product linkage is mainly concentrated.

TABLE 8

Additional Tests: Within-Industry versus Across-Industry Technological Proximity Knowledge Spillover

Dependent Variable	(1) *accruals*	(2) *misstatement*	(3) *fscore*	(4) *MW*	(5) *lnaf*
audit office technology proximity in the same industry (a)	−0.027***	−0.045**	−0.044***	0.039**	−0.064**
	(−3.87)	(−2.05)	(−2.61)	(2.29)	(−2.07)
other office technology proximity in the same industry (b)	−0.015***	−0.041*	−0.102***	0.009	−0.038*
	(−4.43)	(−1.66)	(−2.68)	(0.50)	(−1.92)
audit office technology proximity in different industries (c)	−0.012***	−0.080***	−0.077**	0.033**	−0.032**
	(−3.08)	(−4.60)	(−2.43)	(2.12)	(−2.07)
other office technology proximity in different industries (d)	−0.014***	−0.083**	−0.169***	0.029**	−0.054**
	(−2.75)	(−2.12)	(−2.74)	(2.20)	(−2.31)
Controls	Yes	Yes	Yes	Yes	Yes
Audit office	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Observations	17,013	17,806	15,762	10,166	15,494
Adjusted R^2	0.745	0.345	0.225	0.193	0.936
F-test of (a) − (c)	−0.015***	0.035	0.033	0.006	−0.032
	(p = 0.00)	(p = 0.28)	(p = 0.42)	(p = 0.72)	(p = 0.36)
F-test of (b) − (d)	−0.001	0.042	0.067	−0.020	0.016
	(p = 0.65)	(p = 0.41)	(p = 0.45)	(p = 0.37)	(p = 0.66)

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels.
t-statistics are reported in parentheses.
In this table, we calculate two other versions of technological proximity measures: (1) one based upon within-industry clients only and (2) the other based upon across-industry clients only. To be more specific, we construct *audit office technology proximity in the same industry* and *other office technology proximity in the same industry* measures only using clients in the same industry as the focal firm. In contrast, *audit office technology proximity in different industries* and *other office technology proximity in different industries* are estimated using clients who are not in the same industry as the focal firm. p-values for comparisons of the coefficient difference between within- and across-industry technological proximity measures are based on two-tailed F-tests.

Robustness Check

In this section, we conduct a range of sensitivity tests. First, we conduct a robustness test to ensure that our results are not driven by supply chain links (Johnstone et al. 2014). Specifically, we measure a client firm's technological proximity to the other clients of its auditor that are not suppliers or customers of the focal firm. The new *audit office technology proximity* (*other office technology proximity*) measure is calculated between the focal firm and the other clients of the focal firm's auditor that do not have supply chain links with the focal firm. Untabulated results reveal that the effect of the auditor's client technological closeness on audit quality and audit fees persists, even when we use this draconian method to tease out firms' supply chain links. Second, we replace TNIC-based product similarity with the product proximity measure constructed following Bloom et al. (2013). We find that *audit office technology proximity* and *other office technology proximity* continue to load in all audit quality and audit fees models. Third, we perform a robustness test by excluding the other office technology and product variables from the regression models and thus avoid losing observations due to unavailable other office measures. Untabulated results show that the coefficients on *audit office technology proximity* are even stronger than those reported in Table 4. Collectively, our main findings are not driven by clients' supply chain links, clients' product proximity, and loss of sample observations for other office variables.

VII. CONCLUSION

We exploit the technological proximity between a focal firm and the other clients of the focal firm's auditor to examine whether auditors develop technological proximity knowledge over and above clients' product market similarity. We find that audit quality improves when auditors provide audit services to clients with a high degree of technological proximity after controlling for product market similarity, auditors' overall technological expertise, and industry specialization effects. We also find that auditors offer audit fee discounts for their efficiency gains from auditing multiple clients with technological affinity. We further show that the benefit of the technological knowledge spillover holds at both the audit office and audit firm levels.

In cross-sectional tests, we find that the effects of client technological proximity on audit quality and audit fees are more pronounced when the clients are technology-intensive firms and appoint Big N auditors. We also perform two additional tests to further distinguish between the technological proximity and product similarity effects. We find that technological proximity has an independent impact on audit quality and audit fees, even when the product closeness is low, and that auditors develop technological proximity knowledge from clients in both the same industry and different industries. Collectively, our findings can be viewed as an indication that technological proximity has an incremental impact on audit quality and audit fees on top of the product market similarity and auditors' overall technology- and industry-specific expertise.

Our analysis broadens the scope of auditor knowledge from the traditional product market space to the technology space. We provide novel evidence that auditors deliver better audit quality and offer an audit fee discount when auditing clients with relatively high technological proximity. We find that the benefit of the technological proximity knowledge spillover not only resides within specific offices but also spreads to other offices of the same audit firm. Our study also extends the literature on technological information spillover to auditing research. We show that auditors benefit from technological information spillover when their clients are linked in technological fields, which is distinct from other economic links, including the industry and supply chain links.

REFERENCES

Akcigit, U., S. T. Ates, J. Lerner, R. R. Townsend, and Y. Zhestkova. 2020. Fencing off Silicon Valley: Cross-border venture capital and technology spillovers. University of Chicago, Federal Reserve Board, Harvard University, University of California, and University of Chicago (Working paper). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3691533

American Institute of Certified Public Accountants (AICPA). 2006. AU Section 314: Understanding the Entity and Its Environment and Assessing the Risks of Material Misstatement. New York, NY: AICPA.

Balsam, S., J. Krishnan, and J. S. Yang. 2003. Auditor industry specialization and earnings quality. *Auditing: A Journal of Practice & Theory* 22 (2): 71–97. https://doi.org/10.2308/aud.2003.22.2.71

Beck, M. J., J. L. Gunn, and N. Hallman. 2019. The geographic decentralization of audit firms and audit quality. *Journal of Accounting and Economics* 68 (1): 101234. https://doi.org/10.1016/j.jacceco.2019.101234

Behn, B. K., J. Choi, and T. Kang. 2008. Audit quality and properties of analyst earnings forecasts. *The Accounting Review* 83 (2): 327–349. https://doi.org/10.2308/accr.2008.83.2.327

Bena, J., and K. Li. 2014. Corporate innovations and mergers and acquisitions. *The Journal of Finance* 69 (5): 1923–1960. https://doi.org/10.1111/jofi.12059

Bills, K. L., M. Cobabe, J. Pittman, and S. E. Stein. 2020. To share or not to share: The importance of peer firm similarity to auditor choice. *Accounting, Organizations and Society* 83: 101115. https://doi.org/10.1016/j.aos.2020.101115

Bloom, N., M. Schankerman, and J. Van Reenen. 2013. Identifying technology spillovers and product market rivalry. *Econometrica* 81 (4): 1347–1393. https://doi.org/10.3982/ECTA9466

Brown, S. V., and W. R. Knechel. 2016. Auditor-client compatibility and audit firm selection. *Journal of Accounting Research* 54 (3): 725–775. https://doi.org/10.1111/1475-679X.12105

Cahan, S. F., and W. Zhang. 2006. After Enron: Auditor conservatism and ex-Andersen clients. *The Accounting Review* 81 (1): 49–82. https://doi.org/10.2308/accr.2006.81.1.49

Cairney, T. D., and E. G. Stewart. 2015. Audit fees and client industry homogeneity. *Auditing: A Journal of Practice & Theory* 34 (4): 33–57. https://doi.org/10.2308/ajpt-51040

Cao, S. S., G. Ma, J. W. Tucker, and C. Wan. 2018. Technological peer pressure and product disclosure. *The Accounting Review* 93 (6): 95–126. https://doi.org/10.2308/accr-52056

Carcello, J., D. R. Hermanson, T. J. Neal, and R. A. Riley. 2002. Board characteristics and audit fees. *Contemporary Accounting Research* 19 (3): 365–384. https://doi.org/10.1506/CHWK-GMQ0-MLKE-K03V

Carcello, J. V., and C. Li. 2013. Costs and benefits of requiring an engagement partner signature: Recent experience in the United Kingdom. *The Accounting Review* 88 (5): 1511–1546. https://doi.org/10.2308/accr-50450

Carey, P., and R. Simnett. 2006. Audit partner tenure and audit quality. *The Accounting Review* 81 (3): 653–676. https://doi.org/10.2308/accr.2006.81.3.653

Carson, E. 2009. Industry specialization by global audit firm networks. *The Accounting Review* 84 (2): 355–382. https://doi.org/10.2308/accr.2009.84.2.355

Center for Audit Quality (CAQ). 2019. *Emerging Technologies, Risk, and Auditor's Focus*. Washington, DC: CAQ.

Chan, K. H., and D. Wu. 2011. Aggregate quasi rents and auditor independence: Evidence from audit firm mergers in China. *Contemporary Accounting Research* 28 (1): 175–213. https://doi.org/10.1111/j.1911-3846.2010.01046.x

Chaney, P. K., D. C. Jeter, and L. Shivakumar. 2004. Self-selection of auditors and audit pricing in private firms. *The Accounting Review* 79 (1): 51–72. https://doi.org/10.2308/accr.2004.79.1.51

Chang, H., C. Hsu, and Z. Ma. 2022. Does product similarity of audit clients influence audit efficiency and pricing decisions? *Journal of Business Finance & Accounting* 49 (5–6): 807–840. https://doi.org/10.1111/jbfa.12578

Chi, H. Y., and C. L. Chin. 2011. Firm versus partner measures of auditor industry expertise and effects on auditor quality. *Auditing: A Journal of Practice & Theory* 30 (2): 201–229. https://doi.org/10.2308/ajpt-50004

Choi, J. H., C. Kim, J. B. Kim, and Y. Zang. 2010. Audit office size, audit quality, and audit pricing. *Auditing: A Journal of Practice & Theory* 29 (1): 73–97. https://doi.org/10.2308/aud.2010.29.1.73

Craswell, A. T., J. R. Francis, and S. L. Taylor. 1995. Auditor brand name reputations and industry specializations. *Journal of Accounting and Economics* 20 (3): 297–322. https://doi.org/10.1016/0165-4101(95)00403-3

Danos, P., J. W. Eichenseher, and D. L. Holt. 1989. Specialized knowledge and its communication in auditing. *Contemporary Accounting Research* 6 (1): 91–109. https://doi.org/10.1111/j.1911-3846.1989.tb00746.x

Dechow, P., W. Ge, C. Larson, and R. Sloan. 2011. Predicting material accounting misstatements. *Contemporary Accounting Research* 28 (1): 17–82. https://doi.org/10.1111/j.1911-3846.2010.01041.x

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

DeFond, M., J. R. Francis, and T. J. Wong. 2000. Auditor industry specialization and market segmentation: Evidence from Hong Kong. *Auditing: A Journal of Practice & Theory* 19 (1): 49–66. https://doi.org/10.2308/aud.2000.19.1.49

DeFond, M. L., and C. S. Lennox. 2017. Do PCAOB inspections improve the quality of internal control audits? *Journal of Accounting Research* 55 (3): 591–627. https://doi.org/10.1111/1475-679X.12151

De Franco, G., S. P. Kothari, and R. S. Verdi. 2011. The benefits of financial statement comparability. *Journal of Accounting Research* 49 (4): 895–931. https://doi.org/10.1111/j.1475-679X.2011.00415.x

Dekeyser, S., A. Gaeremynck, and M. Willekens. 2019. Evidence of industry scale effects on audit hours, billing rates, and pricing. *Contemporary Accounting Research* 36 (2): 666–693. https://doi.org/10.1111/1911-3846.12460

Demers, E., and P. Joos. 2007. IPO failure risk. *Journal of Accounting Research* 45 (2): 333–371. https://doi.org/10.1111/j.1475-679X.2007.00236.x

Donohoe, M. P., and W. R. Knechel. 2014. Does corporate tax aggressiveness influence audit pricing? *Contemporary Accounting Research* 31 (1): 284–308. https://doi.org/10.1111/1911-3846.12027

Dopuch, N., and D. Simunic. 1982. Competition in auditing: An assessment. In *Fourth Symposium on Auditing Research*, 401–405. Urbana, IL: University of Illinois.

Dunn, K. A., and B. W. Mayhew. 2004. Audit firm industry specialization and client disclosure quality. *Review of Accounting Studies* 9 (1): 35–58. https://doi.org/10.1023/B:RAST.0000013628.49401.69

Ege, M. S., Y. H. Kim, and D. Wang. 2020. Do global audit firm networks apply consistent audit methodologies across jurisdictions? Evidence from financial reporting comparability. *The Accounting Review* 95 (6): 151–179. https://doi.org/10.2308/tar-2018-0294

Ettredge, M., E. E. Fuerherm, and C. Li. 2014. Fee pressure and audit quality. *Accounting, Organizations and Society* 39 (4): 247–263. https://doi.org/10.1016/j.aos.2014.04.002

Ferguson, A., and D. Stokes. 2002. Brand name audit pricing, industry specialization, and leadership premiums post-Big 8 and Big 6 mergers. *Contemporary Accounting Research* 19 (1): 77–110. https://doi.org/10.1506/VF1T-VRT0-5LB3-766M

Ferguson, A., J. R. Francis, and D. J. Stokes. 2003. The effects of firm-wide and office-level industry expertise on audit pricing. *The Accounting Review* 78 (2): 429–448. https://doi.org/10.2308/accr.2003.78.2.429

Fields, L. P., D. Fraser, and M. S. Wilkins. 2004. An investigation of the pricing of audit services for financial institutions. *Journal of Accounting and Public Policy* 23 (1): 53–77. https://doi.org/10.1016/j.jaccpubpol.2003.11.003

Francis, J. R., and D. Wang. 2008. The joint effect of investor protection and Big 4 audits on earnings quality around the world. *Contemporary Accounting Research* 25 (1): 157–191. https://doi.org/10.1506/car.25.1.6

Francis, J. R., and M. Yu. 2009. Big 4 office size and audit quality. *The Accounting Review* 84 (5): 1521–1552. https://doi.org/10.2308/accr.2009.84.5.1521

Francis, J. R., P. N. Michas, and M. D. Yu. 2013. Office size of Big 4 auditors and client restatements. *Contemporary Accounting Research* 30 (4): 1626–1661. https://doi.org/10.1111/1911-3846.12011

Francis, J. R., M. L. Pinnuck, and O. Watanabe. 2014. Auditor style and financial statement comparability. *The Accounting Review* 89 (2): 605–633. https://doi.org/10.2308/accr-50642

Francis, J. R., K. Reichelt, and D. Wang. 2005. The pricing of national and city-specific reputations for industry expertise in the U.S. audit market. *The Accounting Review* 80 (1): 113–136. https://doi.org/10.2308/accr.2005.80.1.113

Fung, S. Y. K., K. K. Raman, L. Sun, and L. Xu. 2015. Insider sales and the effectiveness of clawback adoptions in mitigating fraud risk. *Journal of Accounting and Public Policy* 34 (4): 417–436. https://doi.org/10.1016/j.jaccpubpol.2015.04.002

Glaeser, S. A., and W. R. Landsman. 2021. Deterrent disclosure. *The Accounting Review* 96 (5): 291–315. https://doi.org/10.2308/TAR-2019-1050

Goh, B. W., J. Krishnan, and D. Li. 2013. Auditor reporting under Section 404: The association between the internal control and going concern audit opinions. *Contemporary Accounting Research* 30 (3): 970–995. https://doi.org/10.1111/j.1911-3846.2012.01180.x

Goodwin, J., and D. Wu. 2014. Is the effect of industry expertise on audit pricing an office-level or a partner-level phenomenon? *Review of Accounting Studies* 19 (4): 1532–1578. https://doi.org/10.1007/s11142-014-9285-8

Goodwin, J., and D. Wu. 2016. What is the relationship between audit partner busyness and audit quality? *Contemporary Accounting Research* 33 (1): 341–377. https://doi.org/10.1111/1911-3846.12129

Hanlon, M., and J. Hoopes. 2014. What do firms do when dividend tax rates change? An examination of alternative payout responses. *Journal of Financial Economics* 114 (1): 105–124. https://doi.org/10.1016/j.jfineco.2014.06.004

Hoberg, G., and G. Phillips. 2010. Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Review of Financial Studies* 23 (10): 3773–3811. https://doi.org/10.1093/rfs/hhq053

Hoberg, G., and G. Phillips. 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy* 124 (5): 1423–1465. https://doi.org/10.1086/688176

Hoitash, R., U. Hoitash, and J. C. Bedard. 2008. Internal control quality and audit pricing under the Sarbanes-Oxley act. *Auditing: A Journal of Practice & Theory* 27 (1): 105–126. https://doi.org/10.2308/aud.2008.27.1.105

Jaffe, A. B., M. Trajtenberg, and R. Henderson. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics* 108 (3): 577–598. https://doi.org/10.2307/2118401

Johnson, R., and L. Wiley. 2019. *Auditing: A Practical Approach with Data Analytics*. Hoboken, NJ: John Wiley & Sons, Inc.

Johnstone, K. M., C. Li, and S. Luo. 2014. Client-auditor supply chain relationships, audit quality, and audit pricing. *Auditing: A Journal of Practice & Theory* 33 (4): 119–166. https://doi.org/10.2308/ajpt-50783

Kim, J.-B., S. T. Sun, and Z. Zhang. 2021. Technology spillovers, information externality, and stock price crash risk. City University of Hong Kong (Working paper). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3063120

Kim, Y., H. Li, and S. Li. 2015. CEO equity incentives and audit fees. *Contemporary Accounting Research* 32 (2): 608–638. https://doi.org/10.1111/1911-3846.12096

Knechel, W. R., V. Naiker, and G. Pacheco. 2007. Does auditor industry specialization matter? Evidence from market reaction to auditor switches. *Auditing: A Journal of Practice & Theory* 26 (1): 19–45. https://doi.org/10.2308/aud.2007.26.1.19

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman. 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics* 132 (2): 665–712. https://doi.org/10.1093/qje/qjw040

Kothari, S. P., A. J. Leone, and C. E. Wasley. 2005. Performance matched discretionary accrual measures. *Journal of Accounting and Economics* 39 (1): 163–197. https://doi.org/10.1016/j.jacceco.2004.11.002

Krishnan, G. V., L. Sun, Q. Wang, and R. Yang. 2013. Client risk management: A pecking order analysis of auditor response to upward earnings management risk. *Auditing: A Journal of Practice & Theory* 32 (2): 147–169. https://doi.org/10.2308/ajpt-50372

American Accounting Association

Lamoreaux, P. T. 2016. Does PCAOB inspection access improve audit quality? An examination of foreign firms listed in the United States. *Journal of Accounting and Economics* 61 (2–3): 313–337. https://doi.org/10.1016/j.jacceco.2016.02.001
Lee, C. M., S. T. Sun, R. Wang, and R. Zhang. 2019. Technological links and predictable returns. *Journal of Financial Economics* 132 (3): 76–96. https://doi.org/10.1016/j.jfineco.2018.11.008
Lennox, C. S. 2016. Did the PCAOB's restrictions on auditors' tax services improve audit quality? *The Accounting Review* 91 (5): 1493–1512. https://doi.org/10.2308/accr-51356
Lennox, C. S., and B. Li. 2014. Accounting misstatements following lawsuits against auditors. *Journal of Accounting and Economics* 57 (1): 58–75. https://doi.org/10.1016/j.jacceco.2013.10.002
Leydesdorff, L., D. F. Kogler, and B. Yan. 2017. Mapping patent classifications: Portfolio and statistical analysis, and the comparison of strengths and weaknesses. *Scientometrics* 112 (3): 1573–1591. https://doi.org/10.1007/s11192-017-2449-0
Li, C., L. Sun, and M. Ettredge. 2010. Financial executive qualifications, financial executive turnover, and adverse SOX 404 opinions. *Journal of Accounting and Economics* 50 (1): 93–110. https://doi.org/10.1016/j.jacceco.2010.01.003
Li, C., Y. Xie, and J. Zhou. 2010. National level, city level auditor industry specialization and cost of debt. *Accounting Horizons* 24 (3): 395–417. https://doi.org/10.2308/acch.2010.24.3.395
Li, X. D., L. Sun, and M. Ettredge. 2017. Auditor selection following auditor turnover: Do peers' choices matter? *Accounting, Organizations and Society* 57: 73–87. https://doi.org/10.1016/j.aos.2017.03.001
Lopez, D. M., and G. F. Peters. 2012. The effect of workload compression on audit quality. *Auditing: A Journal of Practice & Theory* 31 (4): 139–165. https://doi.org/10.2308/ajpt-10305
Mayhew, B. W., and M. S. Wilkins. 2003. Audit firm industry specialization as a differentiation strategy: Evidence from fees charged to firms going public. *Auditing: A Journal of Practice & Theory* 22 (2): 33–52. https://doi.org/10.2308/aud.2003.22.2.33
Mewes, L., and T. Broekel. 2022. Technological complexity and economic growth of regions. *Research Policy* 51 (8): 104156. https://doi.org/10.1016/j.respol.2020.104156
Minutti-Meza, M. 2013. Does auditor industry specialization improve audit quality? *Journal of Accounting Research* 51 (4): 779–817. https://doi.org/10.1111/1475-679X.12017
Myers, J. N., L. A. Myers, and T. C. Omer. 2003. Exploring the term of the auditor-client relationship and the quality of earnings: A case for mandatory auditor rotation? *The Accounting Review* 78 (3): 779–799. https://doi.org/10.2308/accr.2003.78.3.779
Newton, N. J., D. Wang, and M. S. Wilkins. 2013. Does a lack of choice lead to lower quality? Evidence from auditor competition and client restatements. *Auditing: A Journal of Practice & Theory* 32 (3): 31–67. https://doi.org/10.2308/ajpt-50461
Newton, N. J., J. S. Persellin, D. Wang, and M. S. Wilkins. 2016. Internal control opinion shopping and audit market competition. *The Accounting Review* 91 (2): 603–623. https://doi.org/10.2308/accr-51149
O'Keefe, T. B., R. King, and K. M. Gaver. 1994. Audit fees, industry specialization, and compliance with GAAS reporting standards. *Auditing: A Journal of Practice & Theory* 13 (2): 41–55.
Organisation for Economic Co-operation and Development (OECD). 2011. ISIC Rev. 3 Technology Intensity Definition. Paris, France: OECD.
Owhoso, V. E., W. F. Messier, Jr., and J. G. Lynch, Jr. 2002. Error detection by industry-specialized teams during sequential audit review. *Journal of Accounting Research* 40 (3): 883–900. https://doi.org/10.1111/1475-679X.00075
Payne, J. L. 2008. The influence of audit firm specialization on analysts' forecast errors. *Auditing: A Journal of Practice & Theory* 27 (2): 109–136. https://doi.org/10.2308/aud.2008.27.2.109
Petersen, M. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22 (1): 435–480. https://doi.org/10.1093/rfs/hhn053
Qiu, J., and C. Wan. 2015. Technology spillovers and corporate cash holdings. *Journal of Financial Economics* 115 (3): 558–573. https://doi.org/10.1016/j.jfineco.2014.10.005
Qiu, J., J. Wang, and W. Wang. 2017. Valuation effects along the technology channel: Evidence from corporate bankruptcies. McMaster University, Wilfrid Laurier University, and Queen's University (Working paper). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2654853
Reichelt, K. J., and D. Wang. 2010. National and office-specific measures of auditor industry expertise and effects on audit quality. *Journal of Accounting Research* 48 (3): 647–686. https://doi.org/10.1111/j.1475-679X.2009.00363.x
Romer, P. 1986. Increasing returns and long-run growth. *Journal of Political Economy* 94 (5): 1002–1037. https://doi.org/10.1086/261420
Romer, P. 1990. Endogenous technological change. *Journal of Political Economy* 98 (5, Part 2): S71–S102. https://doi.org/10.1086/261725
Scherer, F. M., and D. Ross. 1990. *Industrial Market Structure and Economic Performance*. Boston, MA: Houghton Mifflin Company.
Solomon, I., M. D. Shields, and O. R. Whittington. 1999. What do industry-specialist auditors know? *Journal of Accounting Research* 37 (1): 191–208. https://doi.org/10.2307/2491403
Tan, H., J. Wang, and L. Yao. 2019. Analysts' technological expertise. McGill University, Wilfrid Laurier University, and Concordia University (Working paper). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2772363

Zerni, M. 2012. Audit partner specialization and audit fees: Some evidence from Sweden. *Contemporary Accounting Research* 29 (1): 312–340. https://doi.org/10.1111/j.1911-3846.2011.01098.x

Zhang, J. H. 2018. Accounting comparability, audit effort, and audit outcomes. *Contemporary Accounting Research* 35 (1): 245–276. https://doi.org/10.1111/1911-3846.12381

Zmijewski, M. E. 1984. Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research* 22: 59–82. https://doi.org/10.2307/2490859

APPENDIX A

Variable Definitions

Variables	Definition
Dependent Variable	
accruals	= The residual of the following accruals estimation model (Kothari et al. 2005): *Total Accruals* = $\alpha_1 + \alpha_2$ (*1/ lagged total assets*) + α_3 (Δ *REV* − Δ*AR*) + α_4*PPE* + α_5*ROA*. *Total Accruals* equals net income less cash flows from operations. Δ*REV*, Δ*AR*, *PPE*, and *ROA* refer to change in sales from year $t-1$ to year *t*; change in accounts receivable from year $t-1$ to year *t*; property, plant, and equipment; and return on assets, respectively. *Total Accruals*, Δ*REV*, Δ*AR*, and *PPE* are scaled by total assets. The model is estimated cross-sectionally on each two-digit SIC industry and year.
misstatement	= 1 if firm *i*'s financial statements issued in year *t* are misstated and 0 otherwise. For *misstatement*, we only include *misstatement* related to GAAP accounting failures that have a negative effect on the financial statements following Bills et al. (2020).
fscore	= The fraud risk score calculated based on the Dechow et al. (2011) model, with higher values indicating higher probabilities of misstatement. See Panel A (model 1) of Table 7 in Dechow et al. (2011).
MW	= 1 if the firm receives an adverse opinion on internal controls from the external auditor and 0 otherwise.
lnaf	= The natural logarithm of annual audit fees paid to the firm's auditor.
Variables of Interest	
audit office technology proximity	= Similar to the bilateral technological proximity measure in Bloom et al. (2013), we compute firm *i*'s technological proximity within its audit office *j*'s client portfolio as $\frac{T_{it}\ T'_{-it}}{\sqrt{T_{it}\ T'_{it}}\sqrt{T_{-it}\ T'_{-it}}}$, where the vector $T_{i,t} = (t_{i,1,t}, \ldots, t_{i,k,t}, \ldots, t_{i,K,t})$ captures the scope of technologies of firm *i* across four-digit CPC classes and $T_{-i,t} = (t_{-i,1,t}, \ldots, t_{-i,k,t}, \ldots, t_{-i,K,t})$ refers to the share of patents of audit office *j*'s all other clients across four-digit CPC classes. The *k*th element of $T_{i,t}$ ($T_{-i,t}$) is the ratio of the number of patents in technology class *k* for firm *i* (for audit office *j*'s clients other than firm *i*) to the total number of patents over the rolling past three years for firm *i* (for audit office *j*'s clients other than firm *i*). The higher the value of this variable, the higher the degree of technological similarity between firm *i* and other clients of its audit office *j*.
other office technology proximity	= Similar to *audit office technology proximity*, we compute firm *i*'s technological proximity with the clients of its audit firm's audit offices other than firm *i*'s audit office (other audit offices). The higher the value of this variable, the higher the degree of technological similarity between firm *i* and the clients of its audit firm's other audit offices.
Control Variables	
audit office product similarity	= The average of Hoberg and Phillips's (2010, 2016) product similarity score between firm *i* and its audit office's other clients in the same TNIC (Bills et al. 2020).
other office product similarity	= The average of Hoberg and Phillips's (2010, 2016) product similarity score between firm *i* and the clients of its audit firm's other audit offices in the same TNIC (Bills et al. 2020).
audit office technology specialist	= 1 if the patent market share covered by the clients of the audit office has the largest value in the local market and 0 otherwise.
other office technology specialist	= 1 if the patent market share covered by the clients of the audit firm's all other audit offices has the largest value in the national market and 0 otherwise.

(continued on next page)

APPENDIX A (continued)

Variables	Definition
audit office industry specialist	= 1 if the audit office has the largest market share in one industry in the local market and 0 otherwise. Auditor market share is based on client sales.
other office industry specialist	= 1 if the audit firm's all other audit offices have the largest aggregated market share in one industry in the national market and 0 otherwise. Auditor market share is based on client sales.
audit office earnings comparability	= The median value of firm *i*'s financial statement comparability with the other clients of its audit office. Financial statement comparability between firms *i* and its auditor's other client *j* is defined as the adjusted R^2 from the following model using 16 quarters of earnings data: $Earnings_{it} = \gamma_{0ij} + \gamma_{1ij}Earnings_{jt} + \varepsilon_{ijt}$. *Earnings* is the ratio of quarterly net income before extraordinary items to the lagged total assets.
other office earnings comparability	= The median value of firm *i*'s financial statement comparability with the clients of the audit firm's offices other than firm *i*'s audit office. Financial statement comparability between firms *i* and its auditor's other client *j* is defined as the adjusted R^2 from the following model using 16 quarters of earnings data: $Earnings_{it} = \gamma_{0ij} + \gamma_{1ij}Earnings_{jt} + \varepsilon_{ijt}$. *Earnings* is the ratio of quarterly net income before extraordinary items to the lagged total assets.
dec	= 1 if firm *i* has a fiscal year-end date of December and 0 otherwise.
lntenure	= The natural logarithm of auditor tenure with the client in years.
size	= The natural logarithm of a firm's total assets.
levt	= The ratio of debt to total assets.
mtb	= The ratio of a firm's market value to its book value.
roa	= Net income scaled by total assets.
opcf	= Firms' cash flows from operations scaled by total assets.
loss	= 1 if net income is negative and 0 otherwise.
exchange	= 1 if firm *i* is listed on a stock exchange in year *t* and 0 otherwise.
nseg	= The number of business and operating segments reported in the Compustat segment file.
audit market concentration	= The Herfindahl index based on the sales of the clients audited by each audit office in an industry-year, where industries are defined by two-digit SIC codes.
return	= The raw yearly stock return (%).
return volatility	= The standard deviation of the monthly return in year *t*.
issue	= The sum of new long-term debt plus new equity scaled by total assets.
S404	= 1 if firm *i* reports under SOX Section 404 and 0 otherwise.
S404 × *MW*	= 1 if at least one material weakness is disclosed in the auditor's internal control report in year *t* and 0 otherwise.
zscore	= The probability of bankruptcy score following Zmijewski (1984), with a higher value indicating a lower probability of bankruptcy.
total accruals	= Firms' total accruals in year *t*.
lag_mis	= 1 if firm *i*'s financial statements issued in years $t-3$ to $t-1$ are misstated and 0 otherwise.
litigation	= 1 if the firm operates in a high-litigation industry and 0 otherwise (SIC codes 2832–2837, 3569–3578, 3599–3675, 5199–5962, and 7370–7380)
cash	= The log of the ratio of cash and short-term investment scaled by total assets.
foreign sales	= 1 if a firm reports foreign sales in year *t* and 0 otherwise.
lnreport_lag	= The natural logarithm of 1 plus the number of days from a firm's fiscal year-end to the financial statement audit report date.
client importance	= Firm *i*'s audit fees divided by the sum of the audit fees that the local audit office earns from all its audit clients.
acquisition	= Cash flows for acquisitions scaled by total assets.
restatement	= 1 if firm *i* disclosed a restatement of previously reported earnings in year *t* and 0 otherwise.

(continued on next page)

APPENDIX A (continued)

Variables	Definition
nas	= The ratio of nonaudit service fees to audit fees.
lag_lnaf	= The natural logarithm of annual audit fees paid to the firm's auditor in year $t-1$.
NUM_TNIC_auditoffice	= The number of audit office's clients that are in the same TNIC group as the focal firm in year t.
NUM_TNIC_otheroffice	= The number of clients in the audit firm's other offices that are in the same TNIC group as the focal firm in year t.