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How Does Artificial Intelligence Shape Audit Firms?

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Abstract. Does artificial intelligence (AI) displace auditors? We exploit the staggered hiring of AI employees at audit office locations across the United States as a proxy for the use of AI at local audit offices. The main findings are as follows. First, relative to audit offices that do not yet hire AI employees, those that do hire AI employees have a 4.3% increase in the number of auditor jobs, particularly among junior and midlevel auditors. Second, using AI is associated with an increased demand for soft skills (e.g., cognitive skills) in auditor jobs. Third, audit offices that use AI have more accurate going concern and internal control opinions. Semistructured interviews of 11 seasoned audit partners confirm that investment in AI is centralized at the national level, but the decision to deploy it often resides at the local audit office level. Notably, none of the partners believe that AI has replaced or will replace human auditors. Overall, our study—comprising both empirical and qualitative data—suggests that using AI does not replace auditors, but rather changes the skills required for these jobs and improves audit quality.

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1. Introduction

Does artificial intelligence (AI) displace auditors? Although the media has not reached a clear consensus on this question, a growing stream of research suggests a nontrivial probability that AI could displace auditors in the future. For example, a recent study estimates a 94% probability that AI will automate auditor and accountant jobs in the near future (Frey and Osborne 2017).[1] Media reports of Big 4 audit firms' actions are consistent with these anecdotes: three of the Big 4 audit firms have reportedly invested more than $9 billion in AI technology and automation (Kapoor 2020). In a recent study, Fedyk et al. (2022) show that the use of AI reduces the growth rate of auditor jobs and claim that the use of AI "ultimately displaces human auditors." A reduced *growth rate*, however, does not necessarily mean a decrease in the number of such jobs; it could still be increasing at a slower pace. Their study does not directly address the overall change in the number of auditor jobs after audit firms begin using AI. Our study revisits this important yet unsettled claim.

Understanding whether AI displaces auditors is important for a few reasons. First, the possibility of being displaced by AI means a potential disruption in auditors' future careers. If such a disruption leads to worse career prospects, it could drive away the best talent in the audit profession and cause a brain drain. Second, for audit clients, displacing auditors with AI could have implications for how audit work will be conducted. For instance, although AI may enhance some aspects of auditing, replacing auditors' professional judgment entirely with AI could risk overlooking the complex decision making that human judgment could provide and affect audit quality. Last, for regulators, substituting auditors' judgment with AI outputs could have implications for audit quality and the design of corresponding regulations.[2]

In this paper, we exploit the staggered hiring of AI employees at audit office locations across the United States as a proxy for the use of AI at local audit offices.[3] Specifically, we follow the exact method in Fedyk et al. (2022), who identify AI employees by examining job titles or job descriptions to see if they contain AI keywords. We use a sample of more than 407,000 resumes from Revelio Labs—a workforce intelligence firm—that covers 648 audit offices of 163 audit firms from 2011 to 2019 to precisely identify which audit offices hire AI employees, and when they do so.[4]

We estimate a series of difference-in-differences (DiD) regressions to investigate the effect of AI use on the number of auditor jobs. We classify an audit office as "treated" if it has hired an AI employee and as a "control" if it does not have AI employees. We compare the headcounts of auditors in treated audit offices before and after they hire an AI employee to those of auditors in control offices. This allows us to estimate the effect of AI on the number of auditor jobs in audit offices. Our main regression specifications include *Audit Office Fixed Effects* so that the results are not driven by time-invariant heterogeneity in hiring practices, workplace culture or norms, or varying incentives across local audit offices in different cities that belong to the same audit firm. We also control for *Year Fixed Effects* to account for time trends in AI adoption in the audit industry.

Our DiD research design has three unique features that differ substantially from those of Fedyk et al. (2022). First, we include *Audit Office Fixed Effects* and audit-firm-specific variables in all our regressions to control for heterogeneity between local audit offices. Second, we include city-level control variables to mitigate the confounding effect of local factors such as local market conditions. Third, we use the natural logarithm of auditor headcounts as the dependent variable, instead of using percentage change in auditor headcount, to avoid the undue influence of outliers in our estimation.

It is not entirely clear whether and to what extent AI displaces auditors. On the one hand, a large body of research suggests that AI could replace humans in performing routine and repetitive tasks (e.g., Acemoglu and Restrepo 2019, 2020). Similarly, anecdotal evidence indicates that AI can take on many audit tasks and replace auditor jobs.[5] If AI can take on many routine audit tasks, audit offices using AI could have fewer auditor jobs in the future. A Big 4 respondent indicates, "You'll need less [sic] people to do the same amount of work, and the way that will happen isn't because people lose their jobs. You probably just would not hire as fast as you would otherwise when you're growing" (Cooper et al. 2019, p. 18).

On the other hand, it is theoretically and empirically possible that the use of AI in auditing will not lead to the displacement of auditors. Theoretically, AI use might not be a perfect substitute for auditors, and auditors still need to use their professional judgment before diverting resources to audit high-risk areas. A recent study suggests a similar finding: Brynjolfsson et al. (2018) find auditors in the bottom 20% of 964 occupations suitable for machine learning. The low suitability may indicate that the general public overestimates the potential for automation and AI in the audit profession. The most obvious limitation of using AI in the audit setting is that AI cannot easily replace social interaction among auditors. Prior literature shows that audit knowledge is transferred through social interaction and local knowledge sharing among auditors or between clients and auditors (e.g., Guan et al. 2016; He et al. 2017, 2022; Beck et al. 2019). Notably, a study by Babina et al. (2024), which includes two authors from Fedyk et al. (2022), presents a different perspective. It shows that firms with a one-standard-deviation increase in AI investment have experienced a 21.7% increase in job growth from 2010 to 2018. This emerging trend in the labor market aligns with our direct observations from the industry. In fact, none of the 11 audit partners we interviewed explicitly state that the use of AI has replaced or will replace human auditors. Several even indicate that AI has increased auditor headcount because of business growth.

Even if AI cannot completely displace auditors, it has the potential to significantly disrupt the way auditors conduct their work. For example, using AI could help auditors flag unusual patterns and identify anomalies in accounting records, but it could also require auditors to exercise more professional judgment. As a result, auditors could reduce audit errors and increase audit quality by detecting more financial misreporting. Such a change in tasks could lead to higher audit quality but require different skills for auditor jobs (e.g., cognitive abilities, efficiency). Hence, using AI could have a long-term impact on audit firms.

Our main results are as follows. First, relative to audit offices that do not yet hire AI employees, those that hire AI employees have a 4.3% increase in the number of auditor jobs. The increase is driven mainly by junior and midlevel auditors. Contrary to popular belief, our evidence suggests that the use of AI in auditing can actually create more job opportunities for auditors rather than displace them.

Second, we use 34,839 job postings from Burning Glass to see how skill requirements in job postings change after audit offices begin using AI. We find that using AI is associated with an increased demand for soft skills—such as cognitive abilities, efficiency, and customer service—in auditor jobs. The evidence suggests that audit offices with AI employees are not more likely to require more specific technical skills in computers and software (e.g., machine learning, deep learning, natural language processing). The evidence, however, does highlight an enhanced focus on general software proficiency.

Third, our results show that client firms audited by audit offices with AI employees have higher audit quality than client firms audited by audit offices without AI employees. Relative to client firms audited by audit offices without AI employees, those audited by audit offices with AI employees have more accurate going concern and internal control opinions. We also find that relative to client firms audited by audit offices without any AI employees, those audited by audit offices with AI employees experience a lower likelihood of Big R restatements (i.e., material nonreliance restatements) or restatements involving SEC investigations. On the other hand, no evidence suggests that using AI lowers the total costs in the audit engagement process. Even if using AI does save costs, audit firms do not necessarily pass the cost savings on to their clients. Insights from our semistructured interviews with seasoned audit partners support this observation, indicating that audit fees have not decreased despite potential cost savings from AI implementation.

One concern is that use of AI is potentially endogenous.[6] We use an instrumental variable (IV) approach to mitigate this concern. We follow Cao et al. (2023) to use the supply of AI talent at the local level as an IV for using AI. Cao et al. (2023) find that local AI talent supply is positively associated with AI ownership, but plausibly exogenous to firms and investors. Following the same idea, hiring AI employees is more feasible with a larger AI talent supply. However, AI talent supply is unlikely to be directly associated with local labor demand for professional services jobs (e.g., the number of auditor jobs). We show that our results are robust to the IV estimation.[7]

To provide additional insights into our empirical findings and corroborate evidence in the field, we follow Donelson et al. (2020) to conduct semistructured interviews with 11 seasoned audit partners in the United States who integrate AI in their audit engagements. These qualitative interviews yield the following insights. First, audit firms generally centralize AI investments at the national level because of budgetary and expertise considerations. Second, although the AI tools and technologies are primarily developed centrally, their implementation is decided primarily locally by the local audit offices. This local implementation of AI tools in the field further validates our key measure of the use of AI at the local office level. Third, client portfolios exert limited influence on AI and human capital investments. Moreover, AI does not significantly influence the criteria used for client acceptance. This is because audit offices generally adhere to consistent standards when selecting clients, regardless of the clients' involvement with AI technologies. Fourth, using AI has not led to a significant reduction in the headcount of auditors. None of the audit partners explicitly state that the use of AI has replaced or will replace human auditors. Moreover, several audit partners indicate that using AI led to an increase in headcount because of growth in business. Fifth, there is consensus that using AI has improved audit quality by reducing the likelihood of errors and identifying better areas for audit. Last, using AI has not led to a reduction in audit fees. Audit partners cite three main reasons: the high cost of initial AI investment, the continuous need to comply with audit standards, and the increased compensation. Overall, the qualitative evidence from semistructured interviews corroborates the empirical evidence from our empirical analyses.

In addition to our primary analysis, we examine the robustness of the findings reported by Fedyk et al. (2022). In Online Appendix Section 1, we detail a replication analysis of their study. Although Fedyk et al. highlight the reduction in the growth rate of auditor jobs due to AI, our analysis suggests a potential lack of robustness in their results when Big 4 indicator and firm size are not concurrently controlled. This is likely due to a high correlation (0.7) between the Big 4 indicator and firm size, which may inflate the statistical significance of the main estimate of AI. This raises questions about the strength of the claim that AI "ultimately displaces human auditors." Our findings and analyses in the Online Appendix contribute to preserving collective memory about the impact of AI in the auditing industry.

Our paper makes two main contributions. First, it provides large-scale evidence showing that AI use in audit firms increases the number of auditor jobs and does not replace auditors. Specifically, using AI is associated with an increased demand for soft skills—such as cognitive, efficiency, and customer service—in auditor jobs. Given that the demand for soft skills is increasing, our finding has immediate implications for audit offices planning to use AI. They may consider reviewing and updating their training programs to ensure that auditors are adequately equipped with the necessary soft skills. Our first-hand interviews with audit partners further validate our localized measure of AI usage. The audit partners we interviewed confirm that AI adoption neither impacts client selection criteria nor significantly reduces the auditor headcount. The qualitative evidence echoes our large-scale empirical evidence.

Second, we demonstrate that using AI is associated with higher audit quality. Our study is the first to show the direct benefits of AI in audit work, specifically in reducing going concern errors and improving material weakness accuracy. In audit work, auditors can use AI to conduct full-population analyses of transactions, pinpoint high-risk areas, and automate repetitive tasks. These improvements are directly captured by the outcomes of going concern errors and material weakness accuracy. The improvements are related to but distinct from the misstatements examined in Fedyk et al. because misstatements may arise from technical errors or fraud. Examining going concern errors and material weakness accuracy allows us to understand better the direct impact of using AI on audit work and, ultimately, audit quality. The consensus from our interviews confirms our findings on the direct effects of AI in improving audit quality.[8]

2. Related Literature and Hypotheses

2.1. Artificial Intelligence and Labor Market

Recent advances in AI have raised the possibility that AI will take over or significantly change the nature of high-skilled workers' jobs (e.g., lawyers, equity analysts, healthcare professionals). Whereas industrial robotic technology mainly affects blue-collar workers (e.g., Acemoglu and Restrepo 2019, 2020), AI is likely to impact high-skilled workers by replacing labor-intensive tasks with the use of AI (Webb 2019).[9] Unlike other white-collar professions, the audit profession is unique because it plays a vital role in verifying and validating the financial information firms provide. The findings of a recent paper by Brynjolfsson et al. (2018) can gauge the audit profession's uniqueness compared with other white-collar professions. Brynjolfsson et al. examine the suitability of machine learning based on different tasks of each occupation. They find that auditors are in the bottom 20% of 964 occupations suitable for machine learning, whereas financial analysts (lawyers) are in the top 20% (50%). These findings echo the recent ScaleFactor scandal in which even professional accountants cast doubt on the scalability of using AI to automate bookkeeping in the accounting industry.[10] Overall, although we understand that anecdotal evidence and surveys consistently suggest that AI appears to strongly affect white-collar professions (Dillender and Forsythe 2019) or audit industries (Cooper et al. 2019), it is not entirely clear whether those findings would generalize to audit firms in a large archival setting.

2.2. Hypotheses

The use of AI in audit offices has important implications for the demand for auditors and the skills auditors will need. On the one hand, prior studies have shown that AI could replace humans in performing routine and repetitive tasks (e.g., Remus and Levy 2017). Acemoglu and Restrepo (2018) term the displacement of human-performed tasks by AI or robotics as the *displacement effect*, showing that it leads to decreased labor demand and wages. Similarly, anecdotal and survey evidence indicates that AI can complete specific audit tasks significantly more efficiently than human auditors (Cooper et al. 2019).[11] For example, Christ et al. (2021) find that auditors increase efficiency in inventory counts by using drones and automated count software (e.g., they can reduce count time from 681 hours to 19 hours). In addition to saving auditor hours, AI achieves greater accuracy when dealing with such repetitive tasks. If AI can take on many routine audit tasks, audit offices using AI could save labor input and have fewer auditor jobs in the future. In other words, audit firms could substitute the labor input in audit firms with AI and reduce the demand for human auditors.

However, AI may not be a perfect substitute for auditors for several reasons. First, auditors' key tasks rely on their professional judgments. Prior literature suggests that it is difficult for AI to replace nonroutine tasks that require higher cognitive skills (e.g., Autor et al. 2003, Brynjolfsson et al. 2018). In fact, Acemoglu and Restrepo (2018) show that the substitution effect of AI for repetitive tasks could create a *productivity effect*. As the use of AI lowers production costs, it eventually increases the demand for labor in nonautomated tasks, which likely involve more professional judgment by human auditors. Second, AI cannot replace social interaction among humans. Prior literature shows that social interaction among auditors, or between clients and auditors, is an important channel for local knowledge sharing (e.g., Guan et al. 2016; He et al. 2017, 2022; Beck et al. 2019). Third, audit firms could divert their resources (i.e., labor saved from mundane tasks) to audit high-risk areas. Therefore, using AI might not lower the overall demand for labor input in audit firms because of the complementary role of AI for human auditors. As mentioned earlier in the Introduction, Babina et al. (2024) show that AI-investing firms have a 21.7% increase in job growth from 2010 to 2018. In view of the above, we state our first testable hypothesis *in the null form* as follows:

Hypothesis 1. *Use of AI in local audit offices is not associated with the number of auditor jobs.*

Viewing an occupation as a cluster of tasks (Autor et al. 2003), we form our second set of research questions on how AI reshapes the tasks of the auditing occupation. Specifically, we examine the effects of AI on employees' skill requirements. Autor et al. (2003) find that computerization reduces the labor input of routine tasks but increases the labor input of nonroutine cognitive tasks. If some auditing tasks are more prone to be replaced by AI, the skills required in the same jobs could substantially change after an audit office begins using AI. For example, using AI could help auditors flag unusual patterns and identify anomalies in accounting records. Using AI in this way might require auditors to acquire more soft skills (e.g., cognitive skills) to analyze patterns and outliers. At the same time, using AI might also require auditors to communicate better with colleagues and clients, as Deming

(2017) documents the increasing importance of social skills in reducing coordination costs. Such social skills could be associated with better audit quality (Ham et al. 2022). For example, one survey respondent in Cooper et al. (2019) suggests that using robotic process automation (RPA) software often requires extensive collaboration between accountants and software programmers.

Hypothesis 2. *Use of AI in audit offices is associated with an increased demand for soft skills.*

Last, using AI could affect audit quality and audit fees. First, we examine whether using AI could improve audit quality, an important issue regulators are concerned about (Public Company Accounting Oversight Board 2020a, b). As AI helps auditors reduce the time they spend processing mundane and repetitive tasks, audit firms could better allocate their resources to high-risk areas. Allocating additional resources to examining high-risk areas could help auditors detect and correct clients' misreporting. Anecdotal evidence suggests that using AI could require less auditor input and improve audit efficiency (Ernst & Young 2019).

Furthermore, new AI technology could help audit firms detect unidentified risks (Public Company Accounting Oversight Board 2020b), such as internal control risks and client firms' going concern risks (e.g., Ernst & Young uses machine learning to detect anomalies in invoicing). Greater access to nonauditor personnel with different expertise could also help improve audit quality (Sherwood et al. 2020). Therefore, we state our third testable hypothesis about the effect of AI use on audit quality as follows:

Hypothesis 3. *Use of AI in audit offices is associated with improved audit quality.*

Last, we examine whether using AI could affect audit fees. Even though using AI could help improve audit efficiency and save costs, it may also increase audit fees because of the cost structure of audit fees, which are determined by both fixed costs (e.g., investment in AI technology) and variable costs (e.g., primarily labor cost). As a result, audit offices could bear additional overhead costs ranging from increasing investments in software and salary premiums paid to AI employees to costs of training employees to use AI tools. If the increase in the fixed costs outweighs the saved variable costs, audit firms could increase audit fees to cover their total costs (see the interviews with chief audit executives in Eulerich et al. 2023). Furthermore, audit firms might not reduce their total audit hours, as they could reallocate the audit hours saved by using AI to high-risk areas to improve their audit quality. Therefore, the opposing effects of AI investments on the fixed costs and variable costs of audit fees might not guarantee a reduction in audit fees. Overall, the impact of using AI on audit fees is unclear ex ante. Therefore, we state our fourth testable hypothesis about the effect of using AI on audit fees *in the null form* as follows:

Hypothesis 4. *Use of AI in audit offices is not associated with audit fees.*

3. Data

Our main samples come from two large data sets: resume data from Revelio Labs and job posting data from Burning Glass. Revelio Labs is a leading workforce intelligence company specializing in collecting public employment records to create a resume and profile database of individuals (Li et al. 2022). The resume data allow us to pinpoint precisely when auditors and AI employees were hired in each audit office, and what main tasks employees perform in each job position. Our job posting data come from Burning Glass from 2010 to 2019. Burning Glass is an employment data analytics firm that provides real-time data on job postings and skills in demand. Accounting researchers have used job posting data to investigate several topics, including how firms' hiring practices respond to internal control weaknesses (Ege et al. 2023b, Gao et al. 2023), the overall trend in skill demands in the audit profession (Ham et al. 2022), and the impact of labor market competition on audit quality (Ege et al. 2023a, Aobdia et al. 2024). For brevity, we discuss the details and potential limitations of these two data sources in Online Appendix Section 2.

We construct our main sample as follows. First, we collect 1.1 million resumes of employees working in U.S. audit firms from Revelio Labs. Next, we manually match the employers' names in Revelio Labs with the names of auditors in Audit Analytics. Then, we extract the city locations of local audit offices from the Audit Opinion files in Audit Analytics. To minimize false positives, we retain only those jobs by audit offices with the same name and the same city in both Revelio Labs and Audit Analytics. After the manual matching, we have over 407,000 resumes in 193 cities and 47 states from 2010 to 2019.[12] This resume sample is about 30% (= [407,000 − 310,000] ÷ 310,000) larger than that used by Fedyk et al. (2022). As our main unit of analysis is at the local audit office-year level, we aggregate all jobs at that level (i.e., audit office-year level). Because our regression analysis requires lagged variables, our final sample starts in 2011. Our final main sample for empirical analyses is a panel of 4,417 audit office-year observations based on 648 audit offices of 163 audit firms from 2011 to 2019.

To obtain audit offices' job posting data, we manually match the employers' names in Burning Glass with the names of auditors in our main sample. We also require each employer to have at least 10 job postings during the sample period. In addition, we follow the norm in the literature to exclude internships as they are short term, usually involve fewer jobs, and have less clear job requirements. After the manual matching, we have 34,839 job postings of audit offices in our main sample.

For our client-level analysis, we merge Compustat data with Audit Analytics using historical Central Index Key (CIK) codes. We keep firm-year observations, in which the firms are clients of the audit offices in our main sample. After we require the availability of control variables in our client-level analysis, our final sample of client firms is a panel of 18,097 client firm-year observations based on 2,965 unique firms from 2011 to 2019.

4. Main Results: Auditors

4.1. Sample Overview

We first present the descriptive statistics of our sample. Table 1, panel A, gives an overview of our final sample. The top 10 audit firms account for about 70% of all audit office-year observations. KMPG has the highest number of observations, followed by the other Big 4 audit firms (Ernst & Young, PricewaterhouseCoopers, and Deloitte & Touche). In total, Big 4 audit firms account for about 48% of our audit office-year observations. Panel B of Table 1 tabulates the number of observations by geographic location. Twelve percent of observations represent audit offices in California, followed by New York and Texas. New York City (where the Big 4's headquarters are located) has the highest number (about 4%) of audit office-year observations, followed by Houston and Dallas.

We now examine the growth and geographic distribution of AI jobs. As mentioned in the Introduction, we classify an employee as an AI employee if the job title or job description contains any of the AI keywords used in Babina et al. (2024) and Fedyk et al. (2022). About 0.41% of employees of audit offices in our final sample are classified as AI employees.[13] Figure 1 reports the growth of AI jobs in the audit industry. We make two notable observations. First, the number of AI jobs in this sector has risen consistently and doubled from 2010 to 2019. Second, Big 4 audit firms have been much quicker to recruit AI employees than non-Big 4 audit firms. In 2019, Big 4 audit firms hired around three times more AI employees than their non-Big 4 counterparts.

Figure 2 presents the distribution of AI employees by state. Figure 2(a) displays the average number of AI employees per state, whereas Figure 2(b) shows the percentage of AI employees by state. Despite the common assumption that California has the most AI employees, Table 1, panel C, indicates that Illinois, New York, and Georgia actually have the highest number of AI employees. Panel D shows that the cities with the highest number of AI employees are New York, Chicago, and Atlanta. When we account for the total number of employees in our analysis, the top locations for AI employees shift. If Washington, DC, were a state, it would have the highest percentage of AI employees (0.217%), followed by Wisconsin (0.189%), Arizona (0.186%), and Illinois (0.184%). In contrast, the cities with the highest percentage of AI employees are Knoxville, TN; Scottsdale, AZ; and Madison, WI. The summary statistics of the main variables in our analyses are in Table 2.

4.2. Which Audit Offices Hire AI Employees?

In this section, we first ask what drives audit offices to hire AI employees. We estimate the following Cox proportional hazards model:

$$H(t|X_{jt-1}) = H_0(t) \times \exp(\beta X_{jt-1}) \tag{1}$$

The model estimates a hazard function (H) that predicts the probability that a failure event has occurred at an audit office j in a given year t. In our context, the failure event occurs when an audit office first hires an AI employee. Hence, we construct *Use of AI* to capture the event, where *Use of AI* is an indicator variable that equals one after an audit office has hired an AI employee.

X includes variables that could be associated with the likelihood that a local audit office will hire AI employees.[14] We also control for a spectrum of time-varying local county characteristics such as education, population, age, and income that could be associated with the likelihood of hiring AI employees in a local audit office.[15] As the residuals are likely correlated within a local audit office, we cluster all standard errors by local audit office.

Online Appendix Table 1 summarizes the results. Column 1 reports the coefficients under a Cox proportional hazards model. A positive coefficient of the Cox proportional hazards model suggests a shorter time span for an audit office to hire its first AI employee. We find that audit offices that belong to Big 4 audit firms and those that receive more audit fees hire AI employees earlier than other audit offices. The results suggest that larger audit offices have more resources to use AI than smaller audit offices. An audit office also hires AI employees later if it has a higher staff turnover. This evidence suggests that audit offices have fewer incentives to use AI if they need to hire new staff to replace outgoing staff more frequently. For the time-varying local county characteristics, we find that an audit office hires AI employees earlier when it is located in a county with a better-educated, larger, and younger population.

Because it is difficult to interpret the estimates of the Cox proportional hazards model, in column 2 we reestimate the same specification using a linear probability model (LPM) for ease of interpretation. The signs of all estimates are identical to those in column 1. As the specification is estimated using LPM, we can directly interpret the economic magnitude. The strongest determinant is whether an audit office is a Big 4 auditor: audit offices of

Table 1. Sample Overview

Panel A. By audit firm

Name of auditors	# Audit Office-Year (1)	% Audit Office-Year (2)
KPMG	569	12.88
Ernst & Young	551	12.47
PricewaterhouseCoopers	492	11.14
Deloitte & Touche	491	11.12
Grant Thornton	306	6.93
BDO	299	6.77
RSM	147	3.33
Moss Adams	101	2.29
BKD	73	1.65
Baker Tilly Virchow Krause	64	1.45
Others	1,324	29.97
Total	4,417	100.00

Panel B. By geography

Rank	Top 10 states	% Obs	Top 10 cities	% Obs
1	California	12.02	New York	4.10
2	New York	8.58	Houston	2.83
3	Texas	7.52	Dallas	2.24
4	Florida	6.84	Minneapolis	2.04
5	Ohio	4.57	Tampa	2.04
6	Pennsylvania	4.19	Los Angeles	1.99
7	North Carolina	4.10	Atlanta	1.90
8	New Jersey	3.19	Boston	1.77
9	Virginia	2.97	Charlotte	1.74
10	Missouri	2.81	Denver	1.74

Panel C. AI employees by state, including Washington, DC

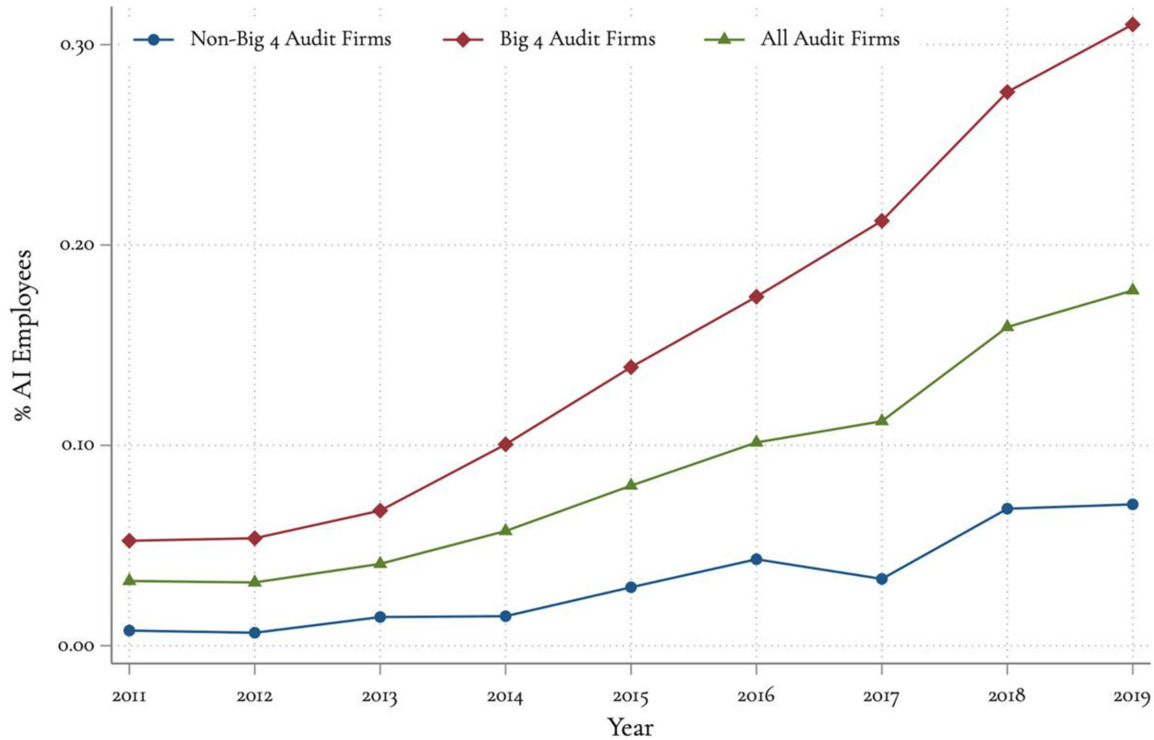
Rank	Top 10	# AI employees	Top 10	% AI employees
1	Illinois	5.831	Washington, DC	0.217
2	New York	4.075	Wisconsin	0.189
3	Georgia	3.610	Arizona	0.186
4	Massachusetts	2.006	Illinois	0.184
5	Washington, DC	1.600	Washington	0.177
6	Colorado	1.094	North Carolina	0.172
7	Washington	1.019	Georgia	0.161
8	Texas	0.937	Colorado	0.151
9	California	0.766	Minnesota	0.141
10	North Carolina	0.727	California	0.130

Panel D. AI employees by city, including Washington, DC

Rank	Top 10	# AI employees	Top 10	% AI employees
1	New York, NY	8.237	Knoxville, TN	1.220
2	Chicago, IL	6.915	Scottsdale, AZ	0.996
3	Atlanta, GA	3.722	Madison, WI	0.442
4	Boston, MA	2.403	San Ramon, CA	0.338
5	Dallas, TX	1.969	Short Hills, NJ	0.338
6	Los Angeles, CA	1.960	Irvine, CA	0.332
7	Washington, DC	1.600	Arlington, VA	0.310
8	Seattle, WA	1.593	Seattle, WA	0.261
9	Denver, CO	1.376	Austin, TX	0.248
10	McLean, VA	1.372	Raleigh, NC	0.234

Notes. Panel A tabulates the sample by audit firm. Panel B lists the top 10 states and cities of audit offices. We rank all states (cities) based on the number of audit offices in each state (city) across all years in the sample period. Panels C and D list the top 10 states and cities (including Washington, DC) with the highest number and percentage of AI employees. We calculate the average number (percentage) of AI employees in each state (city) in the following two steps: we first compute the cross-sectional average number (percentage) of AI employees across all audit offices in a state (city) in a given year. Then, we compute the time-series average of the cross-sectional average number (percentage) of AI employees for each state (city). Obs, observations.

Figure 1. (Color online) Growth of AI Employees



Notes. The figure summarizes the percentage of AI employees by year. Employees are identified as AI employees if their job titles or job descriptions contain the AI keywords in Babina et al. (2024) and Fedyk et al. (2022). Three lines with different markers represent three distinct groups: (1) non-Big 4 audit firms from our main sample (the line marked with circles), (2) Big 4 audit firms (the line marked with diamonds), and (3) all audit firms (the line marked with triangles).

the Big 4 audit firms are 12.2% more likely to hire AI employees than the audit offices of non-Big 4 audit firms.

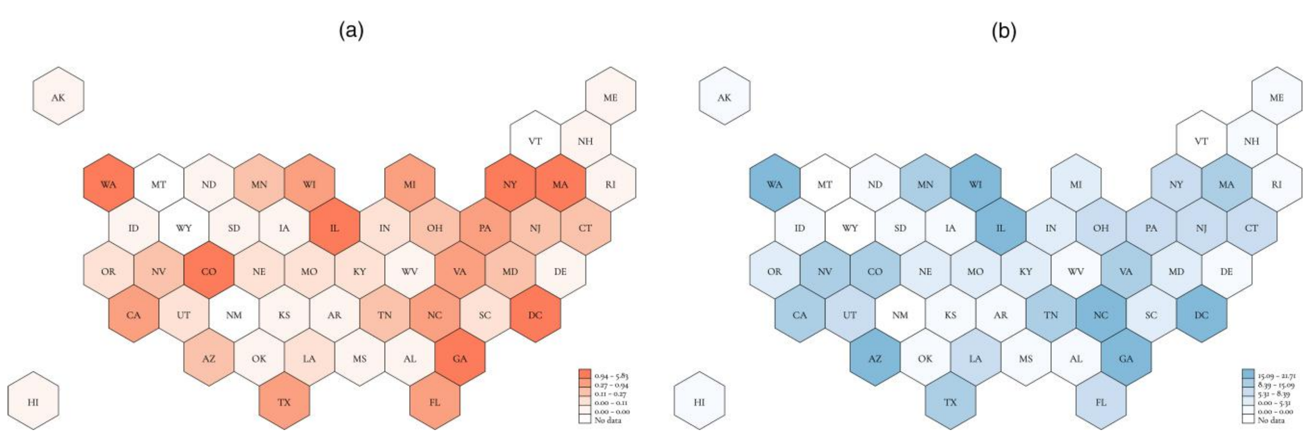
4.3. More Auditors

This section examines whether, relative to audit offices that do not yet have AI employees, audit offices with AI employees have an increased number of auditors. We estimate the following DiD specification:

$$\#\ Auditors_{jt} = \beta(Use\ of\ AI)_{jt} + X_{jt} + \delta_j + \gamma_t + \varepsilon_{jt} \qquad (2)$$

The dependent variable (# *Auditors*) is the number of auditors at an audit office j in a given year t.[16] As

Figure 2. (Color online) Geographical Distribution of AI Employees



Notes. The maps summarize the distribution of AI employees by state. (a) Summary of average number of AI employees by state. (b) Summary of average percentage of AI employees by state. First, we calculate the cross-sectional average number (percentage) of AI employees in all audit offices in a state in a given year. Second, we calculate the time-series average for each state across all years. The key on the bottom right of (a) refers to the average number of AI employees, and the key on the bottom right of (b) refers to the average percentage of AI employees (in basis points for readability).

Table 2. Summary Statistics

Variables	Mean (1)	Stdev (2)	25th (3)	50th (4)	75th (5)	# Obs. (6)
Table 3 (audit office level)						
Use of AI	0.204	0.403	0	0	0	4,417
# Auditors and Tax Advisors	126.991	256.036	22	53	126	4,417
# Auditors	77.459	144.985	13	34	82	4,417
# Tax Advisors	47.939	109.977	6	18	45	4,417
# Consultants	59.738	223.362	1	7	32	4,417
Complexity	4.983	4.608	2	3	7	4,417
Market Share	0.280	0.330	0.016	0.155	0.400	4,417
# Clients	9.209	12.202	2	5	11	4,417
Market Competition	5.800	2.639	4	6	8	4,417
Staff Turnover	0.230	0.103	0.188	0.231	0.275	4,417
$ Audit Fees (Ln)	14.972	2.162	13.257	15.049	16.643	4,417
Table 4 (audit office level)						
# Junior Auditors	51.102	100.228	7	21	54	4,417
# Midlevel Auditors	23.901	45.518	4	10	25	4,417
# Senior Auditors	2.456	4.099	0	1	3	4,417
Junior to Senior Ratio	13.243	20.192	0	6.75	19.714	4,417
Table 5, panel A (job posting level)						
Cognitive Skills	0.521	0.500	0	1	1	34,839
Efficiency Skills	0.387	0.487	0	0	1	34,839
Creativity Skills	0.077	0.266	0	0	0	34,839
Writing Skills	0.108	0.311	0	0	0	34,839
Social Skills	0.532	0.499	0	1	1	34,839
Customer Service Skills	0.468	0.499	0	0	1	34,839
Management Skills	0.489	0.500	0	0	1	34,839
People Management Skills	0.016	0.124	0	0	0	34,839
Project Management Skills	0.421	0.494	0	0	1	34,839
Table 5, panel B (job posting level)						
General Software Skills	0.023	0.151	0	0	0	34,839
Business Systems Skills	0.375	0.484	0	0	1	34,839
Database Skills	0.065	0.246	0	0	0	34,839
Data Skills	0.114	0.318	0	0	0	34,839
Machine Learning Skills	0.033	0.178	0	0	0	34,839
Artificial Intelligence Skills	0.019	0.135	0	0	0	34,839
Automation Skills	0.013	0.115	0	0	0	34,839
Robotic Process Automation Skills	0.013	0.113	0	0	0	34,839
Table 5, panel C (job posting level)						
# Soft Skills	3.018	1.931	1	3	5	34,839
# Hard Skills	0.655	1.048	0	0	1	34,839
Soft-to-Hard Skill Ratio	0.281	0.253	0.089	0.250	0.500	34,839
Table 6 (audit office level)						
AI Talent Supply	0.013	0.004	0.010	0.012	0.015	4,417
Table 7 (audit office level)						
Use of AI (Alternative)	0.266	0.442	0	0	1	4,417
# RPA	1.135	5.435	0	0	0	4,417
Table 8 (client level)						
Going Concern Error	0.018	0.134	0	0	0	18,097
Going Concern Error (Type 1)	0.015	0.123	0	0	0	18,097
Going Concern Error (Type 2)	0.003	0.054	0	0	0	18,097
Material Weakness Error	0.008	0.088	0	0	0	14,934
Table 9 (client level)						
Restatements	0.142	0.349	0	0	0	14,479
Big R Restatements	0.034	0.182	0	0	0	14,479
Little R Restatements	0.108	0.310	0	0	0	14,479
SEC Investigation	0.008	0.088	0	0	0	14,479

Notes. This table reports the summary statistics for the variables in this study. Detailed definitions of all variables are in Appendix A.

previously mentioned, *Use of AI* is an indicator variable that equals one after an audit office has hired an AI employee. Our main variable of interest is β. A positive β indicates that relative to audit offices that do not yet have AI employees, those that have AI employees have an increased number of auditors.

The DiD research design is similar to that of Bertrand and Mullainathan (2003). The first difference compares the number of auditors before and after audit offices hire AI employees. The second difference compares the number of auditors in the control group. The DiD estimator measures the difference between the first and the second differences. The staggered hiring of AI employees means that the control group is not restricted to audit offices that never have any AI employees; rather, it implicitly includes all audit offices that do not have AI employees at the same time as a particular treated audit office, even if the audit offices already have hired AI employees or will have AI employees later on.[17]

We include two sets of high-dimensional fixed effects in the specification. *Audit Office FEs* (δ) absorbs any time-invariant heterogeneity between audit offices.[18] *Year FEs* (γ) absorbs any changes in macroeconomic conditions in a given year. With these two sets of fixed effects, the two-way fixed effects specification is a DiD specification. X is a vector of control variables, including *Complexity*, *Market Share*, *# Clients*, *Market Competition*, *Staff Turnover*, and *$ Audit Fees*. Because local job market conditions are likely to be correlated by local area and year, we cluster all standard errors by Metropolitan Statistical Area (MSA)-year. Regressions are weighted by the number of employees at an audit office in a given year to account for the heterogeneity in audit office size.[19]

Table 3 summarizes the results. In column 1, we first use the number of auditors and tax advisors at an audit office in a given year as the dependent variable. We find that relative to audit offices that do not yet have AI employees, those that do have AI employees have an increased number of auditors and tax advisors. In columns 2–3, we decompose the dependent variable, *# Auditors and Tax Advisors*, into the number of auditors (*# Auditors*) and the number of tax advisors (*# Tax Advisors*). We find that the main effects are observed among auditors (column 2) but not tax advisors (column 3). Because all dependent variables are in natural logarithm, the estimate of *Use of AI* translates into a 4.3% increase in the number of auditors. In column 4, we focus on the number of consultants and repeat the same exercise. We find that relative to audit offices that do not yet have AI employees, those that have AI employees do not have an increased number of consultants.

We further classify auditors by their level of seniority and reestimate Equation (2) using the following measures. *# Junior Auditors* is the number of junior auditors

Table 3. More Auditors

	Dependent variables			
Independent variables	*# Auditors and Tax Advisors (Ln)* (1)	*# Auditors (Ln)* (2)	*# Tax Advisors (Ln)* (3)	*# Consultants (Ln)* (4)
Use of AI	0.023**	0.043***	−0.004	0.013
	(2.06)	(3.36)	(−0.28)	(0.67)
Complexity	0.002	0.004	−0.000	−0.000
	(0.88)	(1.22)	(−0.00)	(−0.09)
Market Share	0.099*	0.060	0.106*	0.035
	(1.96)	(1.04)	(1.79)	(0.48)
# Clients (Ln)	0.014	0.006	0.022	0.109***
	(0.81)	(0.24)	(1.23)	(3.44)
Market Competition	−0.004	0.002	−0.012**	−0.010
	(−0.81)	(0.37)	(−2.04)	(−1.04)
Staff Turnover	0.662***	0.844***	0.386***	0.191*
	(6.08)	(6.37)	(3.67)	(1.72)
$ Audit Fees (Ln)	0.034***	0.046***	0.021*	0.006
	(2.94)	(3.35)	(1.75)	(0.43)
Audit Office FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
# Observations	4,417	4,417	4,417	4,417
Adjusted R^2	0.995	0.992	0.992	0.990

Notes. This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the audit office-year level. *# Auditors and Tax Advisors* is the number of auditors and tax advisors at an audit office in a given year. *# Auditors* is the number of auditors at an audit office in a given year. *# Tax Advisors* is the number of tax advisors at an audit office in a given year. *# Consultants* is the number of consultants at an audit office in a given year. *Use of AI* is an indicator variable that equals one after an audit office has hired an AI employee. Our sample period is from 2011 to 2019. Regressions are weighted by the number of employees at an audit office in a given year. Standard errors clustered by MSA-year. Intercepts are included for estimation but not tabulated. FEs, fixed effects.

***, **, and * indicate two-tailed t-statistics in parentheses with statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. More Junior Auditors

	Dependent variables			
Independent variables	*# Junior Auditors (Ln)* (1)	*# Midlevel Auditors (Ln)* (2)	*# Senior Auditors (Ln)* (3)	*Junior to Senior Ratio (Ln)* (4)
Use of AI	0.047***	0.033**	−0.036	0.159**
	(3.32)	(2.08)	(−1.41)	(2.21)
Control variables	Identical to those in Table 3			
Audit Office FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
# Observations	4,417	4,417	4,417	4,417
Adjusted R^2	0.987	0.987	0.960	0.761

Notes. This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the audit office-year level. # *Junior Auditors* is the number of junior auditors at an audit office in a given year. # *Midlevel Auditors* is the number of midlevel auditors at an audit office in a given year. # *Senior Auditors* is the number of senior auditors at an audit office in a given year. *Junior to Senior Ratio* is the ratio of junior auditors to senior auditors at an audit office in a given year. *Use of AI* is an indicator variable that equals one after an audit office has hired an AI employee. Our sample period is from 2011 to 2019. Regressions are weighted by the number of employees at an audit office in a given year. Standard errors are clustered by MSA-year. Intercepts are included for estimation but not tabulated.

***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% levels, respectively.

at an audit office in a given year. # *Midlevel Auditors* is the number of midlevel auditors at an audit office in a given year. # *Senior Auditors* is the number of senior auditors at an audit office in a given year. *Junior to Senior Ratio* is the ratio of junior auditors to senior auditors at an audit office in a given year.

Table 4 summarizes the results. We find that the increase is observed mainly among junior and midlevel auditors (columns 1–2) but not among senior auditors (column 3). The estimate of *Use of AI* in column 1 (2) translates into a 4.7% (3.3%) increase in the number of junior (midlevel) auditors. In column 4, we focus on the ratio of junior auditors to senior auditors and repeat the same exercise. We find that relative to audit offices that do not yet have AI employees, those that have AI employees have a higher ratio of junior auditors to senior auditors.

Overall, these results suggest that relative to audit offices that do not yet hire AI employees, those that hire AI employees have an increased number of auditors. The increase in the number of auditors is driven mainly by junior and midlevel auditors. Our evidence suggests that rather than displacing auditors, the use of AI in auditing can actually create more job opportunities for auditors.

4.4. Soft and Hard Skills

This section examines whether audit offices change skill requirements in auditor jobs after hiring AI employees. Our earlier results do not reveal whether the skills required in auditor jobs change after auditor offices hire AI employees. Using AI could alter skill requirements in auditor jobs, as it changes key audit tasks. It could also reduce the need to hire auditors with hard and technical computer/software skills, and increase the need to hire auditors with soft and nontechnical skills.

We follow Deming and Noray (2020) to code the skills in Burning Glass's auditor job postings into various categories. *Cognitive Skills* is an indicator variable that equals one if an auditor job requires cognitive skills (e.g., problem solving, decision making, analysis). *Efficiency Skills* is an indicator variable that equals one if an auditor job requires efficiency skills (e.g., time management, prioritizing tasks, goal setting).[20] The other seven skills include creativity skills, writing skills, social skills, customer service skills, management skills, people-management skills, and project-management skills. To conserve space, we tabulate their definitions in Appendix A. Collectively, these nine nontechnical skills account for the soft skills mentioned in auditor job postings.

We continue to use the same specification as in Table 3 and replace *Year FEs* with the more granular *Job Title* × *Year FEs*. To ensure that our results capture the change in skill requirements for the same auditor job, *Job Title* × *Year FEs* absorbs the time-series variation in skill requirements within the same job title over time (e.g., a general increase in demand for specific skills for the same job title). With *Job Title* × *Year FEs*, our DiD estimation essentially compares the change in skill requirements for the same auditor job in the same audit office before and after it hires AI employees. Each unit of observation is an auditor job posting from 2011 to 2019. As the residuals are likely correlated within a job title, we cluster all standard errors by job title.

Table 5, panel A, summarizes these results. In columns 1 and 2, we find that relative to audit offices that do not yet have AI employees, those that have AI employees are 0.019 (0.017) more likely to require cognitive (efficiency) skills for the same auditor job in the same audit office. Relative to the sample mean of *Cognitive Skills* (*Efficiency Skills*), the estimate translates into about a 3.6% (4.4%) increase in the likelihood of

Table 5. Soft and Hard Skills

Panel A. Soft skills

Independent variables	*Cognitive Skills* (1)	*Efficiency Skills* (2)	*Creativity Skills* (3)	*Writing Skills* (4)	*Social Skills* (5)	*Customer Service Skills* (6)	*Management Skills* (7)	*People Management Skills* (8)	*Project Management Skills* (9)
Use of AI	0.019**	0.017**	0.002	−0.007	0.001	0.014*	−0.007	0.004	0.011
	(2.09)	(2.27)	(0.74)	(−1.44)	(0.11)	(1.84)	(−0.79)	(1.57)	(1.61)
Control variables	Identical to those in Table 3								
Audit Office FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job Title × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,839	34,839	34,839	34,839	34,839	34,839	34,839	34,839	34,839
Adjusted R^2	0.756	0.801	0.883	0.837	0.819	0.793	0.774	0.859	0.813

Panel B. Hard skills

Independent variables	*General Software Skills* (1)	*Business Systems Skills* (2)	*Database Skills* (3)	*Data Skills* (4)	*Machine Learning Skills* (5)	*Artificial Intelligence Skills* (6)	*Automation Skills* (7)	*Robotic Process Automation Skill* (8)
Use of AI	0.002*	0.006	−0.001	−0.000	−0.001	0.000	−0.002	−0.001
	(1.83)	(0.74)	(−0.40)	(−0.07)	(−0.52)	(0.04)	(−1.21)	(−1.09)
Control variables	Identical to those in Table 3							
Audit Office FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job Title × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,839	34,839	34,839	34,839	34,839	34,839	34,839	34,839
Adjusted R^2	0.844	0.822	0.877	0.864	0.833	0.846	0.840	0.838

Panel C. Soft to hard skills

Independent variables	*# Soft Skills (Ln)* (1)	*# Hard Skills (Ln)* (2)	*Soft-to-Hard Skill Ratio* (3)
Use of AI	0.029**	0.004	0.007*
	(2.38)	(0.56)	(1.86)
Control variables/FEs	Identical to those in Table 3		
Observations	34,839	34,839	34,839
Adjusted R^2	0.751	0.853	0.816

Notes. This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the job posting level. In panels A and B, the dependent variables are a set of indicator variables on skill requirements in each auditor job posting. For example, *Cognitive Skills* is an indicator variable that equals one if an auditor job requires cognitive skills (e.g., problem solving, decision making, analysis). In panel C, *# Soft Skills* is the sum of soft skills in panel A, and *# Hard Skills* is the sum of hard skills in panel B. *Soft-to-Hard Skill Ratio* is *Scaled # Soft Skills* minus *Scaled # Hard Skills*. *Scaled # Soft Skills* divides *# Soft Skills* by the maximum possible number of soft skills each year. *Scaled # Hard Skills* divides *# Hard Skills* by the maximum possible number of hard skills each year. A higher *Soft-to-Hard Skill Ratio* means that an auditor job requires more soft skills than hard skills. *Use of AI* is an indicator variable that equals one after an audit office has hired an AI employee. Our sample period is from 2011 to 2019. Standard errors are clustered by job title. Intercepts are included for estimation but not tabulated.

***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% levels, respectively.

requiring cognitive skills (efficiency skills) for the same auditor job in the same office.[21] The results on *Cognitive Skills* and *Efficiency Skills* suggest that auditors are required to be more efficient when their jobs require more cognitive skills. In column 6 on *Customer Service Skills*, we observe the same pattern. Relative to audit offices that do not yet have AI employees, audit offices that have AI employees are 3.0% (= 0.014 ÷ 0.468) more likely to require customer service skills for the same auditor job in the same audit office. The results are consistent with the findings in prior studies that the use of AI does not reduce the demand for skills involved in nonroutine tasks, such as cognitive skills (e.g., Autor et al. 2003, Brynjolfsson et al. 2018, Aobdia et al. 2024).[22]

A natural question is whether hiring AI employees could reduce the need to hire auditors with hard skills, such as specific technical skills in computers and software. Therefore, we construct the following skill variables to capture the demand for hard computer skills. *General Software Skills* is an indicator variable that equals one if an auditor job requires software skills (e.g., Excel, Microsoft Office). The other seven variables on hard, technical computer skills are business systems skills, database skills, data skills, machine learning skills, artificial intelligence skills, automation skills, and robotic process automation skills.

We summarize the results in Table 5, panel B. In column 1, the dependent variable is *General Software Skills*.

The estimated coefficient of *Use of AI* is positive but marginally significant. We find that relative to audit offices that do not yet have AI employees, audit offices that have AI employees are 8.7% (= 0.002 ÷ 0.023) more likely to require general software skills for the same auditor job in the same audit office. Because general software programs such as Microsoft Office and Excel are essential tools for auditors, we interpret the increase as indicating that audit firms place greater emphasis on skill proficiency. On the other hand, the estimated coefficients are all insignificant in the other columns. The evidence suggests that audit offices with AI employees are not more likely to require more specific technical skills in computers and software (e.g., machine learning, deep learning, natural language processing). The evidence, however, does highlight an enhanced focus on general software proficiency.

In the last part of our analyses, we examine the aggregate number of soft and hard skills. We construct *# Soft Skills* as the sum of all nine soft skills in panel A, and *# Hard Skills* as the sum of all eight hard skills in panel B. We summarize the results in panel C. The results in column 1 suggest that relative to audit offices that do not yet have AI employees, audit offices that have AI employees require 2.9% more soft skills for the same auditor job in the same audit office. On the other hand, we do not observe a symmetric pattern for hard skills in column 2. In column 3, we construct a ratio that combines *# Soft Skills* and *# Hard Skills*. Specifically, we construct *Soft-to-Hard Skill Ratio* as *Scaled # Soft Skills* minus *Scaled # Hard Skills*. *Scaled # Soft Skills* divides *# Soft Skills* by the maximum possible number of soft skills each year. *Scaled # Hard Skills* divides *# Hard Skills* by the maximum possible number of hard skills each year. A higher *Soft-to-Hard Skill Ratio* means that an auditor job requires more soft skills than hard skills. In column 3, we find that relative to audit offices that do not yet have AI employees, audit offices that have AI employees require more soft skills than hard skills for the same auditor job in the same audit office.

Overall, audit offices change the skill requirements for auditor jobs after hiring AI employees. Our evidence suggests that hiring AI employees is associated with an increased demand for soft skills—such as cognitive abilities, efficiency, and customer service—in auditor jobs. The evidence also indicates that audit offices hiring AI employees reduce the need to hire auditors with hard and technical computer and software skills. Instead, after hiring AI employees, audit offices substitute the demand for hard skills in auditor job postings with the demand for soft skills. Given that the demand for soft skills is increasing, audit offices that hire AI employees may want to consider reviewing and updating their training programs to ensure that auditors are adequately equipped with the necessary soft skills.

4.5. IV Estimations

Our main specification relies on the identification that comes from the staggered hiring of AI employees at the audit office level.[23] To further mitigate the endogeneity concern, we use two sets of instrumental variables for *Use of AI*. First, we use the AI talent supply as an instrumental variable for *Use of AI*. Cao et al. (2023) find that local AI talent supply (i.e., the percentage of population with college or graduate degrees in information technology) is positively associated with AI ownership, but plausibly exogenous to firms and investors. As hiring AI employees is more feasible with a larger AI talent supply, such AI talent supply is unlikely to be directly associated with local labor demand for professional services jobs (e.g., the number of auditors).

Table 6 summarizes the results. We construct *AI Talent Supply* as the percentage of the labor force with college or graduate-school degrees in information technology at the state-year level. In column 1, *AI Talent Supply* is positively associated with *Use of AI* at the local audit office level, which satisfies the relevance condition of a valid instrument variable. The first-stage *F*-statistic is above the threshold of 10, indicating that *AI Talent Supply* is a strong instrument (Stock and Yogo 2002). In column 2, the estimate of *Instrumented Use of AI* remains positive and statistically significant at the 5% level.

Second, we follow Forman et al. (2012) to use the number of historical Advanced Research Projects Agency Network (ARPANET) nodes as an instrument for the use of AI.[24] As the ARPANET nodes are historical communication choices for the exclusive needs of the military and universities, such historical choices are

Table 6. IV Estimation

	Dependent variables	
Independent variables	First stage *Use of AI* (1)	Second stage *# Auditors (Ln)* (2)
Instrumented *Use of AI*		0.779** (2.01)
AI Talent Supply	10.367*** (3.17)	
Control variables	Identical to those in Table 3	
Audit Office FEs	Yes	Yes
Year FEs	Yes	Yes
Observations	4,417	4,417
First-stage *F*-statistic	10.06	

Notes. This table reports the two-stage least squares model regressions. Each observation is at the audit office-year level. In column 2, *Use of AI* is instrumented with *AI Talent Supply*, which is the percentage of labor force with college or graduate-school degrees in information technology at the state-year level. Our sample period is from 2011 to 2019. Standard errors are clustered by local audit office and year. Intercepts are included for estimation but not tabulated.

***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% levels, respectively.

not likely correlated with audit offices' labor demand for auditors today, satisfying the exclusion restrictions for identification purposes. We follow Forman et al. (2012) to construct # *ARPANET Nodes*, which is the number of historical ARPANET nodes at the county level in 2005. Online Appendix Table 2 summarizes the results. In column 1, # *ARPANET Nodes* is positively associated with *Use of AI* at the local audit office level, which satisfies the relevance condition of a valid instrument variable. The first-stage *F*-statistic is well above the threshold of 10, indicating that # *ARPANET Nodes* is a strong instrument (Stock and Yogo 2002). In column 2, the estimate of *Instrumented Use of AI* is positive and statistically significant at least at the 1% level. Overall, the results in this section show that our main results are robust to using IV estimation.

4.6. Robustness Tests

We conduct several robustness tests in Table 7. First, in column 1, we construct an alternative definition of AI employees following the keyword list in Acemoglu et al. (2022). Second, to ensure that our results are not driven by any potential difference between treated audit offices (i.e., those hiring at least one AI employee) and never-treated audit offices, in column 2, we reestimate our main results in Table 3 using only audit offices that hire at least one AI employee in our sample period. Third, in column 3, to rule out the possibility that Big 4 audit offices mainly drive our results, we exclude Big 4 audit offices and reestimate our main specification in Table 3. Additionally, in column 4, we double-cluster the standard errors by audit firm and year to account for potential correlations between hiring AI employees and local labor demand within the same year. Our results remain robust in these tests.

A potential concern is that increased investment in general technology (e.g., automation software) may drive our results.[25] We construct # *RPA* as the number of employees with robotic process automation skills at an audit office in a given year. Then, we reestimate our main specification in Table 3. If an increase in general technology drove our earlier results, we should observe similar results for audit offices that hire employees with RPA skills. Table 7, column 5, summarizes the results. We do not find a similar pattern in the number of employees with RPA skills.

In Figure 3, we perform falsification tests to examine the relationship between the reported timing of AI adoption in local audit offices and the actual hiring of AI-specialized employees. The idea is as follows. If the timing of hiring AI employees systematically records the actual timing of hiring AI employees with a lapse, we should observe similar patterns even when we randomly assign the use of AI at the local audit offices. Our actual estimate in Table 3, column 2, is positioned far to the right of the entire distribution of estimates from these falsification tests.[26]

5. Main Results: Audit Quality and Audit Fees

5.1. Audit Quality

In our next set of analyses, we examine whether the clients of audit offices that hire AI employees have higher audit quality and pay higher audit fees than the clients of those that do not hire AI employees. To better control for client firm characteristics related to audit quality and audit fees, we conduct this set of analyses at the client firm-year level. Specifically, we estimate the following regression specification with a set of proxies for

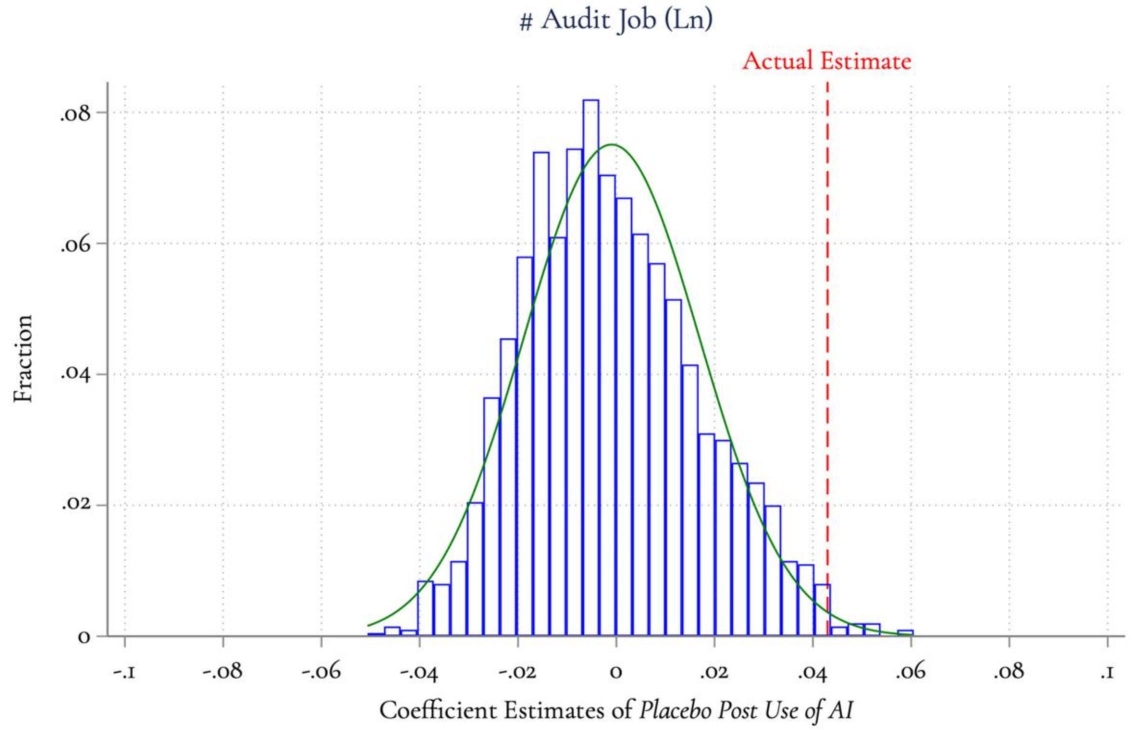
Table 7. Robustness Tests

	Dependent variables: # *Auditors (Ln)*				
Independent variables	Alternative *Use of AI* (1)	At least one AI employee (2)	Excluding Big 4 (3)	SE clustered by *Audit Firm* and *Year* (4)	# *RPA* *(Ln)* (5)
Use of AI		0.067*** (2.74)	0.036* (1.94)	0.043*** (3.38)	−0.045 (−0.94)
Use of AI (Alternative)	0.032*** (2.75)				
Control variables	Identical to those in Table 3				
Audit Office FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
# Observations	4,417	1,022	2,314	4,417	4,417
Adjusted R^2	0.992	0.991	0.977	0.992	0.944

Notes. This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the audit office-year level. Column 1 reconstructs *Use of AI* using an alternative definition using AI skill clusters in Acemoglu et al. (2022). In column 2, we limit our sample to audit offices that have at least one AI employee during our sample period. In column 3, we exclude audit offices of Big 4 audit firms. In column 4, we double-cluster the standard errors by audit firm and year. In column 5, # *RPA* is the number of employees with robotic process automation skills at an audit office in a given year. Our sample period is from 2011 to 2019. Regressions are weighted by the number of employees at an audit office in a given year. Standard errors are clustered by MSA-year. Intercepts are included for estimation but not tabulated.

***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 3. (Color online) Falsification Tests



Notes. The figure reports the distributions of coefficient estimates from falsification tests. The procedures for conducting the falsification tests are as follows. First, within each audit office, we randomly reassign the year when an audit office first hires an AI employee. We label this reassigned event as *Placebo AI Year*. Second, we construct *Placebo Use of AI* as an indicator variable that equals one on or after *Placebo AI Year*. Third, we replace *Use of AI* with *Placebo Use of AI* and reestimate our baseline specifications in Table 3, column 2. After repeating the procedures 2,000 times, we summarize the estimates of *Placebo Use of AI* in this figure. The dashed line represents the value of our actual estimated value of *Use of AI* from Table 3, column 2.

audit quality:

$$Audit\ Quality_{jt} = \beta\ Use\ of\ AI_{jt} + X_{jt} + \delta_j + \gamma_t + \theta_i + \varepsilon_{jt} \quad (3)$$

Audit Quality includes the following two sets of dependent variables. The first set is as follows. *Going Concern Error* is an indicator variable that equals one if a client firm *j* receives a going concern opinion but does not enter bankruptcy in the next 12 months, or a client firm *j* does not receive a going concern opinion but enters bankruptcy in the next 12 months. *Going Concern Error (Type 1)* is an indicator variable that equals one if a client firm receives a going concern opinion but does not enter bankruptcy in the next 12 months. *Going Concern Error (Type 2)* is an indicator variable that equals one if a client firm does not receive a going concern opinion but enters bankruptcy in the next 12 months.

We also examine how AI implementation affects auditors' assessment of internal control. Similar to our approach to *Going Concern Error*, we measure the accuracy of audit offices' assessment of internal control. We predict the probability of an internal control weakness following Doyle et al. (2007), Ashbaugh-Skaife et al. (2007), and Newton et al. (2016). We construct *Material Weakness Error* as an indicator variable that equals one if a client is in the top one percentile of the predicted probability of having an internal control weakness, but the client receives an effective internal control opinion.[27]

The second set of audit quality variables is as follows. We use client firms' restatements as a proxy to measure poor audit quality (DeFond and Zhang 2014, Aobdia 2019). Rajgopal et al. (2021) find that financial restatement is the best proxy to predict all the top six most cited audit violations. *Restatement* is an indicator variable that equals one if a client firm has a nonreliance restatement. In other words, the variable is based on the restated periods but not the years when restatements are announced. If audit quality increases after audit offices begin using AI, *Restatement* should be lower.

There are a few reasons why audit quality related to going concern errors and material weakness accuracy is more likely associated with the adoption of AI. First, instead of only sampling, AI allows auditors to analyze the full population of transactions and data for audit purposes. Auditors can use AI for a full-population analysis that is more comprehensive than a traditional audit sample method. Using AI makes identifying high-audit-risk areas, outliers, and anomalies at scale easier and is more efficient than traditional auditing methods.

Second, audit firms train their in-house AI models based on historical data to pinpoint audit areas traditionally associated with a higher risk of material errors or going concerns. The outputs from AI models flag the potential areas objectively because they are data driven, and subjectivity is less likely to play a major role in their output. Auditors can use these unbiased AI outputs to selectively focus their audit testing.

Last, using AI automates repeated compliance and audit tasks and frees up audit staffing. Auditors less drained by routine tasks can then allocate more time to client interactions and ask more insightful questions on areas with high audit risks and requiring higher judgment. These staffing reallocations would not be feasible were these routine tasks not automated by AI.

Following Audit Analytics classifications, we further categorize restatements into three types. *Big R Restatement* is an indicator variable that equals one if a client firm has a nonreliance restatement with references to an 8-K item 4.02 (i.e., nonreliance on previously issued financial statements or a related audit report or completed interim review). *Little R Restatement* is an indicator variable that equals one if a client firm has a nonreliance restatement without references to an 8-K item 4.02. *SEC Investigation* is an indicator variable that equals one if the SEC is involved in the restatement.

We follow prior studies to construct a vector of control variables (X), including *Size*, *BTM*, *CFO*, *ROA*, *Loss*, *Z Score*, *Sales Growth*, *Leverage*, *Age*, *# Business Segments*, *Foreign Sales*, *M&A*, *Restructure*, *% Institutional*, and *Litigation* (Ashbaugh-Skaife et al. 2007, Doyle et al. 2007, Newton et al. 2016). To conserve space, we present the definitions of these control variables in Online Appendix Table 6. All regressions continue to include *Audit Office FEs* (θ) and *Year FEs* (γ). For tests on going concern opinion accuracy and material weakness accuracy, we incrementally control for *Client Firm FEs* (δ).[28] We cluster all standard errors by client firm because residuals are likely correlated within a client firm.

We summarize the results of *Going Concern Error* and *Material Weakness Error* in Table 8. To conserve space, we tabulate the full set of coefficient estimates in Online Appendix Table 3. In column 1, relative to client firms audited by audit offices without AI employees, client firms audited by audit offices with AI employees have a lower going concern error (i.e., greater accuracy). Relative to the sample mean of *Going Concern Error*, this estimate translates into an improvement of about 33.3% (= $-0.006 \div 0.018$). The decrease in *Going Concern Error* comes primarily from the reduction in Type 1 error (column 2) rather than Type 2 error (column 3). In column 4, we also find that audit offices with AI employees have more accurate internal control opinions. Relative to the sample mean of *Material Weakness Error*, this estimate translates into an improvement of about 62.5% (= $-0.005 \div 0.008$).

Next, we tabulate the restatement results in Table 9. Again, we tabulate the full set of coefficient estimates in Online Appendix Table 4 to conserve space. In column 1, we do not observe any significant decrease in *Restatement*. We further break down the types of restatements in columns 2–4. We find that relative to client firms audited by audit offices without any AI employees, client firms audited by those with AI employees

Table 8. Reducing Going Concern Error

	Dependent variables			
Independent variables	*Going Concern Error* (1)	*Going Concern Error (Type 1)* (2)	*Going Concern Error (Type 2)* (3)	*Material Weakness Error* (4)
Use of AI	−0.006*	−0.006**	0.000	−0.005*
	(−1.80)	(−2.18)	(0.03)	(−1.95)
Control variables included	Yes	Yes	Yes	Yes
Audit Office FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Client Firm FEs	Yes	Yes	Yes	Yes
# Observations	18,097	18,097	18,097	14,934
Adjusted R^2	0.433	0.491	0.103	0.401

Notes. This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the client firm-year level. *Going Concern Error* is an indicator variable that equals one if a client firm receives a going concern opinion but does not enter bankruptcy in the next 12 months, or a client firm does not receive a going concern opinion but enters bankruptcy in the next 12 months. *Going Concern Error (Type 1)* is an indicator variable that equals one if a client firm receives a going concern opinion but does not enter bankruptcy in the next 12 months. *Going Concern Error (Type 2)* is an indicator variable that equals one if a client firm does not receive a going concern opinion but enters bankruptcy in the next 12 months. *Material Weakness Error* is an indicator variable that equals one if a client is in the top one percentile of the predicted probability of having an internal control weakness but the client receives an effective internal control opinion. *Use of AI* is an indicator variable that equals one after an audit office has hired an AI employee. Our sample period is from 2011 to 2019. Standard errors are clustered by client firm. Intercepts are included for estimation but not tabulated. To preserve space, we tabulate the full set of coefficient estimates in Online Appendix Table 3.

***, **, and * indicate two-tailed t-statistics with statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Reducing Restatements

	Dependent variables			
Independent variables	*Restatement* (1)	*Big R Restatement* (2)	*Little R Restatement* (3)	*SEC Investigation* (4)
Use of AI	0.007	−0.012*	0.019	−0.010*
	(0.60)	(−2.11)	(1.84)	(−2.21)
Control variables included	Yes	Yes	Yes	Yes
Audit Office FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
# Observations	14,479	14,479	14,479	14,479
Adjusted R^2	0.094	0.064	0.089	0.076

Notes. This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the client firm-year level. *Restatement* is an indicator variable that equals one if a client firm has a nonreliance restatement. *Big R Restatement* is an indicator variable that equals one if a client firm has a nonreliance restatement with references to an 8-K item 4.02. *Little R Restatement* is an indicator variable that equals one if a client firm has a nonreliance restatement without references to an 8-K item 4.02. *SEC Investigation* is an indicator variable that equals one if the SEC is involved in the restatement. *Use of AI* is an indicator variable that equals one after an audit office has hired an AI employee. Our sample period is from 2011 to 2017. Standard errors are clustered by client firm and year. Intercepts are included for estimation but not tabulated. To preserve space, we tabulate the full set of coefficient estimates in Online Appendix Table 4.

***, **, and * indicate two-tailed t-statistics with statistical significance at the 1%, 5%, and 10% levels, respectively.

experience a lower likelihood of *Big R Restatement* and *SEC Investigation*. Relative to the sample mean of *Big R Restatement* (*SEC Investigation*), this estimate translates into about a 35% (125%) improvement.[29] As *Big R Restatement* and *SEC Investigation* capture more severe cases of restatements, this evidence suggests that AI implementation might help audit offices reduce client risks by identifying severe anomalies in clients' financial reporting.

Overall, our results show that client firms audited by audit offices with AI employees have higher audit quality than those audited by audit offices without AI employees. Relative to client firms audited by audit offices without AI employees, those audited by audit offices with AI employees have a lower going concern error (i.e., greater accuracy) and more accurate internal control opinions. Furthermore, relative to client firms audited by audit offices without any AI employees, those audited by audit offices with AI employees experience a lower likelihood of Big R restatements and restatements that involve SEC investigations.

5.2. No Change in Audit Fees

Last, we examine whether, relative to audit offices that do not yet hire AI employees, those that hire AI employees experience any significant change in audit fees. We examine the same regression specification with a set of fee variables from Audit Analytics. *$ Audit Fees (Client)* is the audit fees of a client firm in a given year. *$ Nonaudit Fees (Client)* is the sum of audit-related fees, benefit plan-related fees, financial information systems design and implementation-related fees, tax-related fees, and other miscellaneous fees of a client firm in a given year. *$ Total Fees (Client)* is the sum of audit and nonaudit fees of a client firm in a given year.

We tabulate the full set of coefficient estimates in Online Appendix Table 5 to conserve space. We do not find any significant change in audit fees (column 1), nonaudit fees (column 2), or total fees (column 3) for client firms of audit offices that hire AI employees. There are two potential explanations for these results. First, using AI does not necessarily lower the initial or ongoing costs in the audit engagement process. Second, even if using AI does save costs, audit firms do not necessarily pass the cost savings on to their clients. Unfortunately, our data do not permit us to disentangle these explanations.

6. Additional Insights from Semistructured Interviews

To enrich our empirical findings, we conduct semistructured interviews with 11 seasoned audit partners from U.S. audit firms, most of whom are affiliated with the Big 4. These interviews, which follow well-established field research methods in audit quality (e.g., Malsch and Salterio 2016, Donelson et al. 2020, Ege et al. 2020), offer direct insights into the practical impacts of AI on auditing. Each interview was carried out via Zoom and lasted an average of 31 minutes. We used a targeted questionnaire (detailed in Appendix B) to explore specific aspects of AI's influence on auditor headcount, audit quality, and audit fees. To maintain confidentiality, we anonymize interviewees and refer to them by assigned numbers throughout our analysis. To conserve space here, we present a detailed discussion and additional direct quotations in Online Appendix Section 4.

6.1. AI Investment

The interviews with audit partners reveal a consistent trend of centralizing AI investment within audit firms, primarily driven by budgetary and technological considerations. "The tools are developed at a national level generally … it is a centralized national practice" (interviewee 9). As the partners emphasized, this centralized approach offers several benefits, including consistency in AI tool development, efficiency in deployment, alignment with safety standards, and the flexibility to adapt to emerging trends.

A key aspect of this centralization is the national-level decision making on AI investment, which emphasizes the strategic importance of AI in audit firms. Partners describe this focus with statements like "[AI investment is] driven on the national level … we have a national innovation team that does all the development and implementation of technology" (interviewee 6) and "We're investing significantly in technology, specifically in AI and automation tools … at the national level" (interviewee 3). These insights confirm that the strategic planning and execution of AI tools occur primarily in the higher echelons of the firms.

However, alongside this centralization, there is an emphasis on local customization to meet specific audit office needs. Partners note the availability of national resources for creating tailored AI solutions for unique engagement requirements, balancing firm-wide standardization with local applicability. For instance, one partner shares an experience of reaching out for a customized solution: "I reached out to that centralized group, and they created a customized solution for my specific engagement" (interviewee 9).

The centralized approach also fosters resource pooling and cross-firm knowledge sharing, making it possible to address a diverse range of audit scenarios effectively. As one partner puts it, "AI investment [is] generally [made] at the national level … because [the] firm prefers to negotiate" (interviewee 8). This observation suggests the broader resource capabilities at this level. Another partner highlights the expansive reach of these strategic decisions: " … the investments that we make in technology, including AI—all that happens at a very global level" (interviewee 2).

Flexibility and responsiveness are other key benefits of this approach, especially in adapting to and scaling AI technologies. The national-level strategy allows firms to respond to technological trends and regulatory changes rapidly, highlighting firms' proactive stance in integrating AI into their operations.

In summary, the centralized approach to AI investment in audit firms combines the strategic oversight of national-level decision making with the flexibility to adapt and customize solutions for local needs, ensuring AI's effective and efficient integration in audit practices.

6.2. AI Implementation

The interviews reveal a clear pattern of AI implementation within audit firms. Although AI tools and technologies are developed at a national level, their deployment and use are determined at the local level. One partner explains, "The tools are developed at a national level … However, as a local engagement team, we also play a role" (interviewee 9). This statement emphasizes local offices' role in effectively applying these technologies.

Another partner echoes this sentiment, noting the balance between global development and local application: " … we certainly do it [development] at [the] global or … the national level. Then, that gets pushed down as far as the actual implementation at the local level" (interviewee 2). This highlights the decentralized approach to implementing AI, which is tailored to local offices' specific needs and contexts.

Local autonomy in AI use is a recurring theme. As one partner mentions, " … it's really driven to the local level in terms of the technology use … but those decisions are made by us [at the] local level based on our needs and based on what we think is useful" (interviewee 10). This approach allows for flexibility and responsiveness to the unique requirements of each office and engagement.

Partners also shared insights into the variability in AI adoption across different offices. Factors like partners' comfort levels with AI, technical preparedness, and client readiness play a significant role in this variability. For instance, one partner notes, "AI is really driven by the local level. And I'd say it's also going to vary, based on maturity and the size of the firm at the local level" (interviewee 10). This highlights the importance of local conditions and capabilities in the effective use of AI.

In summary, although AI tools are centrally developed, their successful implementation hinges on local decision making and adaptation. This approach ensures that the benefits of AI are leveraged effectively while respecting the unique characteristics and needs of each local audit office.

6.3. Client Portfolio Influence and AI Strategy Impact on Client Acceptance

The interviews with audit partners reveal that client portfolios have minimal impact on audit firms' AI and human capital investment decisions. Our discussions confirm that AI investment strategies are predominantly formulated and executed nationally, largely independently of the local or regional client mix. This approach ensures that AI adoption and human capital strategies are consistent across various audit offices.

However, an equally important aspect to consider is whether the use of AI within audit firms influences their client acceptance policies. The interviews indicate that the use of AI in audit practices has not led to a noticeable change in the criteria for client selection. "I haven't seen much of that [the influence of AI use on client acceptance] … the areas that we focus on from a client-acceptance perspective and the factors that we consider are generally the same now as they have been previously" (interviewee 11). Another partner says, "But I just don't see it [AI] having a direct impact right now on our client acceptance. I don't see it like that in the future, either" (interviewee 5). This perspective is crucial as it shows that although AI is an essential tool, the decision to accept clients remains primarily influenced by broader risk management considerations, independent of a firm's AI capabilities.

However, our interviewees observed a notable shift in the growing emphasis on cognitive and soft skills within the audit profession. Partners identify an increasing need for inquisitiveness, effective time management, communication skills, and a broader, more holistic qualification base beyond just technical expertise. One partner says, "I'd rather have someone with a 3.3 GPA who is active in the community, does charity work, is a student-athlete, or volunteers in the community. These soft skills, combined with a desire to be tech-savvy, are crucial" (interviewee 3). This shift indicates a recognition that the evolving audit environment, influenced by AI, requires a diverse skill set.

Interviewees also reported that their firms are increasingly developing AI champions within local audit offices. These champions are key to effectively leveraging AI in audit engagements, highlighting a need for focused training and skill enhancement in AI and related technologies. Partners emphasize the importance of adaptability and continuous learning, with one stating, "I would not characterize it as a quote requirement, but on their resume, they are able to articulate a great deal of experience in the technologies that we're using" (interviewee 1).

In summary, although AI investments are centrally managed, efforts to enhance auditors' cognitive and soft skills and develop AI expertise locally align with the firms' objectives of maintaining high-quality audits in a technologically advancing landscape.

6.4. Auditor Headcount, Audit Quality, and Audit Fees

In exploring topics beyond the structured interview questions, we gain valuable insights into the impact of AI on auditor headcount, audit quality, and audit fees.

6.4.1. Auditor Headcount Unaffected by AI. The collective view among audit partners is that AI usage has not decreased auditor headcount. Notably, none of the partners believe that AI has replaced or will replace human auditors. In fact, some partners highlight an increase due to business growth. One states, " … we still hire roughly the same number of people or more as we grow. It [AI] just allows us to do more work right" (interviewee 6). Others echo this sentiment: "We haven't removed a person from a job because of AI … " (interviewee 7) and "AI can increase the volume of clients you serve … " (interviewee 10). These perspectives suggest that AI complements rather than replaces human auditors.

6.4.2. AI Enhances Audit Quality. The interviews consistently indicate that AI improves audit quality. This enhancement comes from reducing errors and identifying better audit areas. As one partner puts it, "The likelihood of an associate inputting data wrong … goes down when you're using [AI] technology" (interviewee 1). Another adds, "I think it significantly improves the audit quality because the teams are [able] to work at a higher level and look at the bigger picture of the transaction set that they're auditing … " (interviewee 5). These observations suggest that AI facilitates more focused and effective audits.

6.4.3. AI Does Not Reduce Audit Fees. Despite efficiency gains from AI, audit partners report no significant reduction in audit fees. The reasons cited include high initial AI investment costs, ongoing compliance with audit standards, and increased compensation demands. One partner notes, "Even with automation, you still keep someone to run it, analyze it, and document what those analyses or automation[s] are spilling out … " (interviewee 4). Another mentions, "This is a very complicated equation. These tools may save some labor costs, but they are very costly to invest in … " (interviewee 3). These comments reflect the complex financial dynamics of integrating AI into auditing.

In summary, the interviews reveal that although AI is reshaping the audit profession, it does so by enhancing audit quality and efficiency rather than reducing auditor numbers or audit fees. These insights again confirm AI's complementary role in the evolving auditing landscape.

6.5. Summary and Implications

Based on the semistructured interviews conducted with seasoned audit partners, the major takeaways regarding the initial impact of AI in the auditing industry are as follows:

- **Centralized AI strategy, localized implementation:** AI development is strategically centralized nationally, ensuring consistency and efficiency. However, the actual deployment of AI tools is tailored to the needs of local offices, allowing for flexibility and customization in their application.
- **AI complements but does not replace auditors:** Contrary to common perceptions, AI integration in auditing does not reduce auditor headcount. Instead, it enhances auditors' work, often leading to increased

headcount because of robust business growth and demand for more complex auditing skills.

- **Enhanced audit quality without reduced fees:** Although AI significantly improves audit quality by enabling more precise and error-free audits, it has not decreased audit fees. The high costs of AI implementation and ongoing operational expenses offset potential fee reductions.

These insights highlight AI's role as a catalyst for change in the audit sector, enhancing the quality of work and necessitating a shift in skills without displacing the human element essential to the profession.

7. Conclusion

This study examines whether AI displaces auditors. We exploit the staggered hiring of AI employees at audit office locations across the United States as a proxy for the use of AI at local audit offices. We use over 407,000 resumes from Revelio Labs, a workforce intelligence firm. We use the resume data, which cover 648 audit offices of 163 audit firms from 2011 to 2019, to precisely identify which audit offices hire AI employees, and when. We also use 34,839 job postings from Burning Glass to see how skill requirements in job postings change after audit offices begin using AI.

Our main results are as follows. First, relative to audit offices that do not yet hire AI employees, audit offices that hire AI employees have a 4.3% increase in the number of auditor jobs. The increase in the number of auditor jobs is driven mainly by junior and midlevel auditors. Second, AI use is associated with an increased demand for soft skills—such as cognitive abilities, efficiency, and customer service—in auditor jobs. The evidence suggests that audit offices with AI employees are not more likely to require more specific technical skills in computers and software (e.g., machine learning, deep learning, natural language processing). The evidence, however, does highlight an enhanced focus on general software proficiency. Third, client firms audited by audit offices with AI employees have higher audit quality (i.e., more accurate going concern and internal control opinions, and lower likelihood of Big R restatements) than client firms audited by audit offices without AI employees. Last, no evidence suggests that using AI lowers the total costs in the audit engagement process.

Our paper makes two main contributions. First, our study provides large-scale evidence showing that AI use in audit firms increases the number of auditor jobs and does not replace auditors. Second, we demonstrate that AI use is associated with higher audit quality. We are the first to show that audit offices that use AI can reduce going concern errors and improve material weakness accuracy. Our paper provides the first large-sample evidence—comprising both empirical and qualitative data—on the impact of AI on the audit profession. Although AI serves as a copilot in enhancing the audit process, it is not the autopilot; rather, it augments human expertise without replacing it. Overall, our evidence shows that using AI does not replace auditors, but rather changes the skills required for these jobs and improves audit quality.

As our study sheds light on the initial impact of AI on the audit profession, our evidence has important implications for audit regulatory bodies like the Public Company Accounting Oversight Board (PCAOB). First, our findings indicate a need for guidelines addressing AI's evolving role in enhancing audit quality and efficiency, including developing standards for AI-driven audit processes and outcomes. Second, professional training and certification programs should increasingly emphasize specific soft skills and general software skills to prepare auditors for the AI-integrated audit environment. Third, regulators should closely monitor the decentralization effects of AI on audit firm structures, ensuring consistency in AI applications across different offices while allowing for local adaptations. Fourth, regulatory bodies, including the PCAOB, currently foster a more open data policy to improve the quality and diversity of research, providing comprehensive insights for informed policymaking. There is a critical need for continuous engagement in endorsing and sponsoring longitudinal studies to track the evolving implications of AI in auditing. Ongoing research is essential for understanding AI's long-term impact and ensuring that regulations and practices evolve in line with technological advancements. We fully acknowledge that our current insights offer a preliminary view, not a definitive forecast, of AI's long-term influence.

Finally, the central findings of our study, which suggest that the use of AI increases the demand for auditors, might indeed seem at odds with the observed decline in accounting program enrollments and the trend of accountants leaving public accounting in the United States (Ellis 2022, Ellis and Overberg 2023). We can understand this apparent paradox by acknowledging the array of factors influencing the accounting profession, which extend beyond the realm of AI adoption. Although AI's integration into auditing drives demand for auditors, other significant factors, such as concerns about work-life balance, long working hours, comparatively low starting salaries, and limited career development opportunities, contribute to the profession's declining appeal. Thus, our study's observation of increased demand for auditors does not necessarily equate to a boost in enrollment or retention within the profession. Instead, it highlights a growing disconnect in the accounting labor market: the rapidly evolving nature of audit work, propelled by technological advancements, is not adequately reflected in the profession's overall attractiveness and satisfaction levels. This disconnect highlights the pressing need for employers, especially major audit firms such as the Big 4, to adopt a comprehensive approach to addressing the challenges the accounting profession faces in the era of AI adoption.

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Appendix A. Variable Definitions

Variables	Descriptions
Main variables	
Use of AI	Indicator variable that equals one after an audit office has hired an AI employee (source: Revelio Labs).
# Auditors and Tax Advisors	Number of auditors and tax advisors at an audit office in a given year (source: Revelio Labs).
# Auditors	Number of auditors at an audit office in a given year (source: Revelio Labs).
# Tax Advisors	Number of tax advisors at an audit office in a given year (source: Revelio Labs).
# Consultants	Number of consultants at an audit office in a given year (source: Revelio Labs).
# Junior Auditors	Number of junior auditors at an audit office in a given year (source: Revelio Labs).
# Midlevel Auditors	Number of midlevel auditors at an audit office in a given year (source: Revelio Labs).
# Senior Auditors	Number of senior auditors at an audit office in a given year (source: Revelio Labs).
Junior to Senior Ratio	Ratio of junior auditors to senior auditors at an audit office in a given year (source: Revelio Labs).
Cognitive Skills	Indicator variable that equals one if an auditor job requires cognitive skills (e.g., problem solving, decision making, analysis) (source: Burning Glass).
Efficiency Skills	Indicator variable that equals one if an auditor job requires efficiency skills (e.g., time management, prioritizing tasks, goal setting) (source: Burning Glass).
Creativity Skills	Indicator variable that equals one if an auditor job requires creativity skills (e.g., creativity, creative problem solving) (source: Burning Glass).
Writing Skills	Indicator variable that equals one if an auditor job requires writing skills (e.g., writing, editing, preparing reports) (source: Burning Glass).
Social Skills	Indicator variable that equals one if an auditor job requires social skills (e.g., communication, teamwork, collaboration) (source: Burning Glass).
Customer Service Skills	Indicator variable that equals one if an auditor job requires customer service skills (source: Burning Glass).
Management Skills	Indicator variable that equals one if an auditor job requires management skills (e.g., supervision, leadership, mentoring) (source: Burning Glass).
People Management Skills	Indicator variable that equals one if an auditor job requires people management skills (e.g., people development, people management) (source: Burning Glass).
Project Management Skills	Indicator variable that equals one if an auditor job requires project management skills (e.g., project management, project planning and development) (source: Burning Glass).
General Software Skills	Indicator variable that equals one if an auditor job requires software skills (e.g., Excel, Microsoft Office) (source: Burning Glass).
Business Systems Skills	Indicator variable that equals one if an auditor job requires business systems skills (e.g., systems integration, business intelligence, system integration) (source: Burning Glass).
Database Skills	Indicator variable that equals one if an auditor job requires database skills (e.g., data collection, data management, data structure) (source: Burning Glass).
Data Skills	Indicator variable that equals one if an auditor job requires data skills (e.g., data analysis, data modeling, big data) (source: Burning Glass).
Machine Learning Skills	Indicator variable that equals one if an auditor job requires machine learning skills (e.g., Python, Deep Learning, Support Vector Machines) (source: Burning Glass).
Artificial Intelligence Skills	Indicator variable that equals one if an auditor job requires artificial intelligence skills (i.e., artificial intelligence, natural language processing) in Acemoglu et al. (2022) (source: Burning Glass).

Appendix A. (Continued)

Variables	Descriptions
Automation Skills	Indicator variable that equals one if an auditor job requires automation skills (e.g., automation tools, automation systems) (source: Burning Glass).
Robotic Process Automation Skills	Indicator variable that equals one if an auditor job requires robotic process automation skills (e.g., RPA, robotic process automation) (source: Burning Glass).
# Soft Skills	Sum of *Cognitive Skills*, *Efficiency Skills*, *Creativity Skills*, *Writing Skills*, *Social Skills*, *Customer Service Skills*, *Management Skills*, *People Management Skills*, and *Project Management Skills* that an auditor job requires (source: Burning Glass).
# Hard Skills	Sum of *General Software Skills*, *Business Systems Skills*, *Database Skills*, *Data Skills*, *Machine Learning Skills*, *AI Skills*, *Automation Skills*, and *Robotic Process Automation Skills* that an auditor job requires (source: Burning Glass).
Soft-to-Hard Skill Ratio	*Scaled # Soft Skills* minus *Scaled # Hard Skills*. *Scaled # Soft Skills* divides *# Soft Skills* by the maximum possible number of soft skills each year. *Scaled # Hard Skills* divides *# Hard Skills* by the maximum possible number of hard skills each year. A higher *Soft-to-Hard Skill Ratio* means that an auditor job requires more soft skills than hard skills (source: Burning Glass).
AI Talent Supply	Percentage of labor force with college or graduate-school degrees in information technology at the state-year level (source: American Community Survey).
# RPA	Number of employees with robotic process automation skills at an audit office in a given year (source: Revelio Labs).
Going Concern Error	Indicator variable that equals one if a client firm receives a going concern opinion but does not enter bankruptcy in the next 12 months, or a client firm does not receive a going concern opinion but enters bankruptcy in the next 12 months (source: Audit Analytics).
Going Concern Error (Type 1)	Indicator variable that equals one if a client firm receives a going concern opinion but does not enter bankruptcy in the next 12 months (source: Audit Analytics).
Going Concern Error (Type 2)	Indicator variable that equals one if a client firm does not receive a going concern opinion but enters bankruptcy in the next 12 months (source: Audit Analytics).
Material Weakness Error	Indicator variable that equals one if a client is in the top one percentile of the predicted probability of having an internal control weakness but the client receives an effective internal control opinion (source: Audit Analytics).
Restatement	Indicator variable that equals one if a client firm has a nonreliance restatement (source: Audit Analytics).
Big R Restatement	Indicator variable that equals one if a client firm has a nonreliance restatement with references to an 8-K item 4.02 (source: Audit Analytics).
Little R Restatement	Indicator variable that equals one if a client firm has a nonreliance restatement without references to an 8-K item 4.02 (source: Audit Analytics).
SEC Investigation	Indicator variable that equals one if the SEC is involved in the restatement (source: Audit Analytics).
$ Audit Fees (Client)	Audit fees of a client firm in a given year (source: Audit Analytics).
$ Nonaudit Fees (Client)	Sum of audit-related fees, benefit plan-related fees, financial information systems design and implementation-related fees, tax-related fees, and other miscellaneous fees of a client firm in a given year (source: Audit Analytics).
$ Total Fees (Client)	Sum of audit and nonaudit fees of a client firm in a given year (source: Audit Analytics).
Other variables	
Complexity	Number of unique 2-digit Standard Industrial Classification (SIC) codes of the public clients of an audit office in a given year (source: Audit Analytics).
Market Share	Percentage of audit fees of an audit office relative to total audit fees of all audit offices in the same city in a given year (source: Audit Analytics).
# Clients	Number of public clients of an audit office in a given year (source: Audit Analytics).
Market Competition	Decile score of the Herfindahl index of audit fees across audit offices in a specific MSA (source: Audit Analytics).
Staff Turnover	Ratio of the number of employees who left during a given year divided by the number of employees at the beginning of the year (source: Revelio Labs).
$ Audit Fees	Sum of audit fees at an audit office in a given year (source: Audit Analytics).

Appendix B. Interview Questions

1. How is AI investment executed within audit firms, at a national or local level, and how does this affect human capital decisions?

Potential follow-up questions, if the interviewee hasn't addressed these topics sufficiently:

a. How is AI managed within the firm (e.g., centralized at the national level or decentralized at the local level)?
b. If AI is decentralized, why is there a delay in implementation with some offices using it and others not?
c. How do AI investments impact hiring decisions for audit personnel?

2. How do audit firms manage AI implementation and investments at the national and local levels, and how does this relate to the real-world application of AI in practice?

Potential follow-up questions, if the interviewee hasn't addressed these topics sufficiently:

a. Are there local champions in some offices who utilize AI more extensively?

b. Can you provide examples or insights into how AI is implemented in practice?

3. How do audit office client portfolio demands drive human capital investment decisions rather than AI investments?

Potential follow-up questions, if the interviewee hasn't addressed these topics sufficiently:

a. How do differences in audit client portfolios between offices with more AI investment and those without AI investment influence hiring decisions?

b. Were there new clients added to the portfolio? Did clients leave the portfolio? Did the client's risk profile change? Did the clients grow?

Endnotes

[1] This concern has also reduced the enrollment of accounting students by 4%–6% since 2016 (Association of International Certified Professional Accountants 2019).

[2] For example, a board member of the PCAOB (Public Company Accounting Oversight Board 2017) stated in a recent speech that auditors should not overrely on data analytics as the tools "are not substitutes for the auditor's knowledge, judgment, and exercise of professional skepticism." It is "important that auditors are transparent about the audit and their findings during the audit and that they use their enhanced technological tools to add value to their primary client." An oft-cited problem when implementing AI is machine bias. Auditors could unintentionally introduce machine bias into their auditing work because there are no regulations on the use and disclosure of AI in the audit industry. If auditors cannot understand the underlying algorithms and correct the machine bias promptly, replacing more auditors with AI could eventually lead to lower audit quality. As auditors increasingly use new technology in their auditing work, the PCAOB's Office of the Chief Auditor has initiated a project to assess the need for specific guidance on disclosing such use of technology or changes to audit standards (Public Company Accounting Oversight Board 2020a).

[3] Our semistructured interviews with audit partners suggest that many AI initiatives in audit firms were initiated by national offices. However, integrating or deploying these initiatives at regional audit offices would require the support of local AI employees in several areas. First, local AI employees could help troubleshoot any technical issues that may arise while implementing the AI tools developed nationally. Second, they could customize these tools for the specific needs of local audit engagements (e.g., to protect data privacy when analyzing customer-exclusive information, or to protect personally identifiable information when working with sensitive personal data). Third, they could work with local audit employees to develop tools tailored for local audit teams, as Cooper et al. (2019) suggest. Last, local AI employees could help train local employees to use AI tools or software in audit engagements. Empirically, we require hiring an AI employee at the local audit office level, as these employees work directly in their own audit offices and are more likely to provide direct support to audit engagements. Unfortunately, it was not possible for us to determine when and which specific AI technology was used in each local audit engagement.

[4] Identifying the use of AI in audit offices is challenging. A first-best approach to answering our research question would be to identify all AI personnel in all audit offices and survey the experience of each AI employee. Such a large-sample survey would be ideal, but it is implausible in our setting for two reasons. First, a large-scale accounting survey is likely to have a low response rate. For example, studies on financial analysts typically have a low response rate of about 5%–6% (Brown et al. 2015). As our regression specifications require multiple high-dimensional fixed effects, unbalanced panel data could render the estimation impossible. Second, surveys do not cover AI personnel who no longer work in an audit office. Hence, using a survey would introduce response bias into the data because the survey would exclude leavers. Drawing generalizable inferences from data with survivorship bias could bias the interpretations.

[5] For example, KPMG uses IBM Watson's deep learning to analyze banks' credit files for commercial loan portfolios (Sun and Vasarhelyi 2017). Ernst & Young uses machine learning to detect anomalies in invoicing and identify fraudulent invoices with a 97% accuracy rate (Zhou 2017). Deloitte uses natural language processing to reduce human time spent on extracting information from unstructured legal documents (Deloitte & Touche and Raphael 2015).

[6] First, audit firms' use of AI could simply reflect an expected increase in service demand or an expansion strategy, and such an expectation would be associated with variation in the number of auditor jobs. Hence, using AI is potentially endogenous. Second, use of AI could be driven by reverse causality. For example, audit firms may decide to expand their businesses in certain cities and hire more auditors. Again, such decisions could lead to more investments in AI. We fully acknowledge these limitations because our paper does not have a strong identification strategy. Hence, we caution readers not to take our descriptive evidence as causal because of the potential endogeneity of AI use. Instead, our primary contribution is to provide large-scale empirical evidence on unsettled research questions.

[7] We also use the number of historical connections to the ARPANET for the second IV. The ARPANET was the predecessor of the internet and the first wide-area network before the modern internet. The ARPANET was established by the Advanced Research Projects Agency (ARPA) of the United States Department of Defense in 1969 and formally decommissioned in 1990. Forman et al. (2012) find that firms in counties with more historical ARPANET nodes in the 1970s invest more in the internet because of better local data communications infrastructure in the 1990s. The identification of the ARPANET nodes comes from the premise that the number of historical ARPANET nodes in the 1970s is a historical choice on the connectivity to the Department of Defense or university networks. ARPANET facilitates data sharing via packet switching. Hence, the connection to ARPANET measures local data communications infrastructure and expertise. The identifying assumption is that audit offices in counties with more historical ARPANET nodes are more likely to use AI. Such historical choices, however, are unlikely to correlate with the number of local auditor jobs because the ARPANET was designed mainly for communication between U.S. military bases and university research centers. Please see Section 4.5 for further discussion of these IV results.

[8] Our paper also answers the call in DeFond and Zhang (2014) for more audit research to understand more about the use of audit technology in audit firms. Our results complement prior studies that have examined the impact of labor investments on audit quality (e.g., Knechel et al. 2013, Aobdia et al. 2018, Beck et al. 2018, Hoopes et al. 2018, Ham et al. 2022). Our qualitative data from semistructured interviews also highlight the reasons for nonreduction in audit fees despite AI adoption. Our evidence may be of interest to audit firms considering accelerating the use of AI during economic recessions, as well as to regulators looking to understand the impact of AI on audit quality.

[9] For example, Remus and Levy (2017) find that the use of technology in the legal profession reduces the demand for lawyers' labor

hours. Grennan and Michaely (2020) also show that analysts with more exposure to AI are more likely to reallocate their skill sets to soft skills or leave the profession. Dillender and Forsythe (2019) suggest that computerization reduces the employment of office and administrative support (OAS) jobs but increases wages for college graduates in OAS jobs. Goldfarb et al. (2020), however, document that the use of AI in healthcare remains relatively low compared with other sectors.

[10] ScaleFactor claimed to use AI to automate small businesses' bookkeeping, but *Forbes* reported that ScaleFactor actually hired accountants to manually complete customers' books on the back end (Jeans 2020). The tendency to overestimate the potential of AI to automate human work is often termed "fauxtomation" (Taylor 2018).

[11] One respondent in Cooper et al. (2019) suggests that new audit technology helps them complete a 16-hour task within 17 seconds.

[12] We start the sample period in 2010 because audit firms rarely used AI before 2010, although the earliest employment records in the resume data date back to 1950. The starting period also matches the starting year of job posting data from Burning Glass used in our later analyses. It is also consistent with the sample period in Fedyk et al. (2022).

[13] On the other hand, about 0.26% of employees of audit firms in our final sample are classified as AI employees, comparable to the 0.21% in Fedyk et al. (2022).

[14] First, we construct *Big 4 Auditor* to differentiate between Big 4 and non-Big 4 audit firms (Jiang et al. 2019). Second, we construct *Complexity*, which is the number of unique two-digit SIC codes of the public clients of an audit office in a given year. Hoopes et al. (2018) show that audit offices pay higher salaries for auditors to compensate for the complexity of audit tasks. Third, we construct *Market Share* to quantify the extent of competition among audit offices in the same city. Prior research finds that local competition and auditors' market share are salient auditor characteristics that affect the operations of audit firms (e.g., DeFond et al. 2000, Reichelt and Wang 2010, Numan and Willekens 2012). Next, to measure office size, we construct *# Clients* as the number of public clients of an audit office in a given year and *$ Audit Fees* as the total audit fees of public clients of an audit office in a given year. Prior research shows that office size is associated with office resources (e.g., Francis and Yu 2009, Bills et al. 2016, Donelson et al. 2020). Larger audit offices should have more resources to use new technologies to improve productivity than smaller audit offices. To measure market competition, we construct the Herfindahl index of audit fees across audit offices in a specific MSA. Following Newton et al. (2016), we use the decile score of the Herfindahl index as *Market Competition*. Lower values of *Market Competition* reflect greater audit market competition. To control for the labor demand due to employee turnover, we construct *Staff Turnover* as the ratio of the number of employees who left during a given year divided by the number of employees at the beginning of the year, following Khavis and Szerwo (2022). Controlling for *Staff Turnover* helps mitigate the concern that replacing outgoing auditors in the same office drives our results.

[15] *Education* is the percentage of population 25 years and over with at least a bachelor's degree in a county in year $t-1$. *Population* is the total population of a county in year $t-1$. *Income* is the median household income of a county in year $t-1$. *Age* is the median age of a county's population in year $t-1$. These data are obtained from the American Community Survey. Each unit of observation is an audit office-year from 2011 to 2019. As the residuals are likely correlated within a local audit office, we cluster all standard errors by local audit office.

[16] We cannot use the change rate as the dependent variable. If we did, the regression would become a change-in-change regression when we include *Audit Office Fixed Effects*, which differs from what we wanted to calculate.

[17] Our main findings remain qualitatively similar in a stacked DiD design using never-treated observations as the control group. These results are tabulated in Online Appendix Tables 9, 11, 12, and 13.

[18] The inclusion of *Audit Office FEs* as unit fixed effects in a DiD design results in a high adjusted R^2 in our main results. Armstrong et al. (2022) discuss the potential bias caused by high-powered fixed effects in a DiD design. However, our main findings remain robust when these fixed effects are excluded, indicating that the results are not driven solely by their inclusion. Furthermore, our main findings are also robust when we include fixed effects but exclude any additional control variables.

[19] Our main results remain robust when regressions are estimated without weighting.

[20] Deming and Noray (2020) label these as noncognitive skills.

[21] The value 3.6% = 0.019 ÷ 0.521. The value 4.4% = 0.017 ÷ 0.387.

[22] Our results are robust if we replace *Job Title* × *Year Fixed Effects* with *Year Fixed Effects*.

[23] Our IV estimation cannot help us differentiate whether AI is implemented at the national or regional level, but it does mitigate the concern that the hiring of AI employees is endogenous.

[24] We use the total number of ARPANET nodes in the year 2005 generously provided by Forman et al. (2012). They calculate the number of ARPANET nodes as the cumulative number of ARPANET nodes from 1970 to 2005. Forman et al. (2012) suggest that the number of historical ARPANET nodes at the county level reflects local internet communication infrastructure and expertise. The historical map of ARPANET nodes is in Online Appendix Figure 1. We build on this insight and use the number of historical ARPANET nodes at the county level as an instrument for audit offices that hire AI employees.

[25] For example, a recent survey study suggests that audit firms have increased their investment in software to automate audit tasks over the years (Austin et al. 2021). To mitigate this concern, we conduct a falsification test using the number of employees with RPA skills. RPA is related to AI, but the concepts are significantly different. RPA uses rule-based software to automate repetitive and routine tasks (i.e., taking the robot out of the human). In contrast, AI emphasizes using human intelligence to create rule-based environments to automate tasks (i.e., putting the human into the robot).

[26] In the last test, we measure the AI adoption at the audit firm level. Specifically, we identify the treatment status using the first AI job at the firm level. Our main results remain robust.

[27] We do not observe any case where a client is in the bottom one percentile of the predicted probability of having an internal control weakness but the client does not receive an effective internal control opinion.

[28] We include *Industry FEs* but not *Client Firm FEs* for restatement tests because prior studies show that restatement is generally tied to the culture of a specific firm. Controlling for *Client Firm FEs* would remove the substantial variation in restatements between firms. We end the sample period in 2017 to allow enough time to observe firm restatements.

[29] The value 35% = −0.012 ÷ 0.034, and 125% = −0.010 ÷ 0.008.

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