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Keywords: Artificial intelligence, auditors, machine learning, audit quality.
JEL Classifications: O33; M42; J6; J23; J24.

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1. Introduction

How does artificial intelligence (AI) technology shape the audit industry? While the media has not reached a clear consensus on this question, a growing stream of research suggests a very high probability that AI could lower the demand for auditors in the audit industry. 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). The respondents in a recent survey by Cooper, Holderness, Sorensen, and Wood (2019) state that it is increasingly common for Big Four audit firms to use software to automate repetitive processes and save human hours.[1] Media reports of Big Four audit firms' actions are consistent with these anecdotes: three of the Big Four audit firms have reportedly invested more than $9 billion in AI technology and automation (Bloomberg 2020). Yet there is no large-scale study that systematically examines how AI shapes the audit industry. Our study is the first empirical paper to fill this gap.

Understanding whether and how AI shapes the audit industry is important for a few reasons. First, for auditors, the possibility of being displaced by AI means a potential disruption in their future careers. If such a disruption leads to worse career prospects for auditors, it could drive away the best talent in the audit profession and cause a brain drain. Even if AI does not replace auditor jobs,[2] AI implementation could push auditors to upskill to maintain their competitiveness. Second, for audit clients, AI implementation could have implications for how audit work will be conducted. For example, instead of randomly sampling clients' vouchers, auditors could use AI technology to sweep the full population of accounting data for abnormality at a lower cost and a faster speed.

[1] In the accounting industry, such software is often called Robotic Process Automation (RPA) software. Popular RPA software from third-party vendors includes Automation Anywhere, UiPath, Pega Platform, and Blue Prism. RPA is related to AI, but the concepts differ. RPA focuses on using 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).
[2] Examples of auditor jobs are audit managers, audit associates, tax managers, and tax associates.

Last, for regulators, AI implementation could have implications for audit quality and the design of corresponding regulations. For example, a board member of the Public Company Accounting Oversight Board (PCAOB 2017) stated in a recent speech that auditors should "not over relying 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."[3]

To investigate how AI technology shapes the audit industry, we exploit the staggered hiring of personnel with AI skills ("AI personnel") at audit office locations across the United States as a proxy for the implementation of AI technology at local audit offices.[4] We identify the hiring of personnel with AI skills (i.e., skills in artificial intelligence, machine learning, natural language processing, or data science) at audit offices using data from more than a million job postings from Burning Glass Technology between 2010 and 2019. Burning Glass is an employment data analytics firm that provides real-time data on online job postings. To classify whether an audit office hires AI personnel, we use the job-level data in each job posting. If an audit office has a job that requires AI skills, we classify the audit office as treated. Such audit offices make up our treatment group. We classify audit offices that do not yet have any jobs that require AI skills as nontreated. Such audit offices make up our control group. We conduct two main sets of analyses. First, from all the job postings data in Burning Glass, we gather the number of auditor jobs for both groups. As we

[3] An oft-cited problem when implementing AI is machine bias. Because there are so far no regulations on the use and disclosure of AI technology in the audit industry, auditors could unintentionally introduce machine bias into their auditing work. If auditors cannot understand the underlying algorithms and correct the machine bias promptly, replacing more auditors with AI technology could eventually lead to lower audit quality.

[4] There is no anecdotal evidence indicating audit firm-wide mandates to implement AI technology. Even if the AI technology is developed by audit firms' headquarters, the implementation of the national AI technology still requires personnel with the corresponding AI skills at local offices. Using job postings for AI personnel helps identify when audit offices first hire such personnel to implement the audit-firm's AI technology.

cannot directly observe whether AI technology replaces audit tasks, we use the variation in the number of job ads as a proxy for the changing demand for auditor jobs. If an audit office reduces the number of auditor jobs after hiring AI personnel, the pattern would suggest that AI replaces auditor jobs. Second, from Audit Analytics, we gather the number of restatements for both groups. If the audit quality at an audit office improves, the percentage of clients with restatements should decrease after the office hires AI personnel.

Identifying the use of AI technology 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 personnel. Such a large-sample survey is ideal but implausible in our setting for two reasons. First, accounting surveys with such a scale could have a low response rate. For example, two recent studies on financial analysts have a low response rate of about 5-6%.[5] As our regression specifications require multiple high-dimensional fixed effects, an unbalanced panel data could render the estimation impossible. Second, surveys do not cover AI personnel who no longer work in an audit office. Hence, such surveying would introduce response bias in the data because the surveys exclude leavers as non-respondents. Drawing generalizable inferences on the data with survivorship bias could bias the interpretations.

It is not entirely clear whether the implementation of AI technology will have a long-term impact on the audit industry. 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

[5] For example, only 6% of analysts who had experience with Hurricane Katrina agreed to be interviewed in Bourveau and Law (2020). This number is in a similar ballpark to the response rate in analyst survey studies such as Dichev, Graham, Harvey, and Rajgopal (2013), where 5.4% of participants responded. Even with substantial monetary incentives (i.e., a $10,000 donation to charities), Brown, Call, Clement, and Sharp (2015) obtain an approximately 10% response rate.

jobs.[6] If AI can take on many routine audit tasks, audit offices that use AI technology could have fewer auditor jobs in the future, but the audit quality may or may not improve. A Big 4 respondent indicates that "You'll need less 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. 2020, p. 18).

On the other hand, the implementation of AI technology may not have a long-term impact on the audit industry. Prior literature suggests that it is difficult for AI technology to automate rule-based processes and replace nonroutine tasks that require higher cognitive skills (e.g., Autor, Levy, and Murnane 2003; Brynjolfsson, Mitchell, and Rock 2018). Recent scandals such as ScaleFactor also cast doubt on the scalability of using AI to automate bookkeeping.[7] AI technology is not a perfect substitute for auditors, and auditors still need to use their professional judgment before diverting resources to audit high-risk areas.[8] A recent study suggests a similar finding: Brynjolfsson et al. (2018) find that auditors are 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 in the audit profession. Perhaps the most obvious limitation is that AI technology cannot replace social interaction among humans. Prior literature shows that audit knowledge is transferred through social interaction and local knowledge sharing among auditors or between

[6] For example, KPMG uses IBM Watson's deep learning to analyze banks' credit files for commercial loan portfolios (CPA Journal 2017). Ernst and Young uses machine learning to detect anomalies in invoicing and identify fraudulent invoices with a 97% accuracy rate (Forbes 2017). Deloitte uses natural language processing to reduce human time spent on extracting information from unstructured legal documents (CFO.com 2015).
[7] 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 (*Forbes* July 20, 2020). The tendency to overestimate the potential of AI to automate human work is often termed "fauxtomation" (Taylor 2018).
[8] One potential explanation for audit offices to hire AI personnel is to understand better the AI technology implemented by their audit clients. Our untabulated results, however, show that audit office offices with more audit clients that implement AI technology do not necessarily hire more AI personnel.

clients and auditors (e.g., Guan, Su, Wu, and Yang 2016; He, Pittman, Rui, and Wu 2017; Beck, Gunn, and Hallman 2019; He, Kothari, Xiao, and Zuo 2020).

Even if AI technology cannot displace an occupation, it could reshape the tasks of the occupation. For example, AI technology could help auditors to flag unusual patterns and identify anomalies in accounting records. Auditors could reduce audit errors and increase audit quality by detecting more financial misreporting. Such a change in tasks could lead to a different set of skills required for audit jobs. Hence, the use of AI technology could have a long-term impact on the audit industry.

Our main results, which are based on 628 audit offices from 43 audit firms in 189 cities between 2011 and 2019, are as follows. First, we find that relative to audit offices that do not yet have any jobs requiring AI skills, audit offices that have jobs requiring AI skills experience a 16.2% increase in the number of auditor jobs. The effects are stronger when audit offices are in less urbanized areas, and when audit offices have more jobs that could be replaced by AI.

Second, relative to audit offices that do not yet have any jobs requiring AI skills, audit offices that have AI jobs require 7% more specialized skills per auditor job (such as budgeting, internal auditing, and business processes). Such audit offices also require 2-3% more cognitive skills, social skills, writing skills, and people management skills per auditor job. We do not, however, observe any systematic difference in the requirements for baseline skills (leadership, project planning and development, and building effective relationships) or for software skills (e.g., Excel, SAP, and Oracle) for the auditor jobs in audit offices that have AI jobs.

In terms of education requirements, we observe the same pattern of upskilling. Relative to audit offices that do not have any jobs requiring AI skills, audit offices that have jobs requiring AI skills are more likely to require that applicants have at least a bachelor's degree and to specify minimum education requirements for auditor jobs. For each auditor job, such offices also require job applicants to have more certifications. These offices are also more likely to open their auditor jobs to science, technology, engineering, and mathematics (STEM) graduates. The evidence is consistent with anecdotal evidence that employers in non-STEM occupations are actively seeking to hire more STEM graduates (Association of International Certified Professional Accountants 2019; Grinis 2019).

Our results suggest that the upskilling necessary to meet more stringent skill and education requirements increases audit offices' costs. First, we find that auditor jobs requiring AI skills command an 8% higher salary than jobs that do not require AI skills. Second, relative to audit offices that do not have any jobs requiring AI skills, audit offices that have jobs requiring AI skills have more fluctuation in salaries because of the increased fluctuation in the maximum salary offered for auditor jobs.

In the last set of analyses, we examine how AI technology impacts audit quality and audit fees. First, we follow prior literature to use financial restatements as a proxy for audit quality (DeFond and Zhang 2014; Hoopes, Merkley, Pacelli, and Schroeder 2018; Aobdia 2019; Rajgopal, Srinivasan, and Zheng 2020). We find that the percentage of clients that experience financial restatements in audit offices that have jobs requiring AI skills is 4.6% lower than that in audit offices that do not yet have such jobs. Relative to the sample mean of restatements, this estimate translates into about 49% of clients that experience financial restatements in an audit office in a given year. The decrease in the client portfolio's restatement rate comes primarily from fewer restatements with adverse effects rather than from fewer restatements with improving effects. We also show that the percentage of clients that experience material non-reliance restatements (i.e., big R restatements) is lower in audit offices that have jobs requiring AI skills than in audit offices that do not yet have such jobs. We also observe that the average number of audit lag (defined as the number of days between an audit client's fiscal year-end and the date of audit opinion) significantly reduces among those audit offices that hire auditors with AI skills. We do not, however, observe any substantial change in other audit quality proxies such as going concern opinions, frauds, or accrual measures.

Second, we do not find any significant change in audit or tax fees for firms that have auditor jobs requiring AI skills. There are two potential explanations for these results. First, AI implementation does not necessarily lower the costs of audit engagements. Second, even if AI implementation did save costs, audit firms do not necessarily pass the cost-savings on to audit clients. Because we do not have access to audit offices' accounting records, our data do not permit us to disentangle these alternative explanations.

All our regression specifications include city-quarter fixed effects (i.e., *City* × *Year-Quarter Fixed Effects*) so that the comparison is between audit offices in the same city and the same quarter. We also control for auditor-city fixed effects (i.e., *Auditor-City Fixed Effects*) so that the results are not driven by heterogeneity in hiring practices, culture, or norms or caused by varying incentives within the same audit firm across different cities.

A potential concern is that the hiring of personnel with AI skills is endogenous. Audit firms hiring AI personnel could simply reflect an expected increase in service demand, and such an expectation would be associated with the variation in the number of job ads. To mitigate this concern, we follow Bénabou, Ticchi, and Vindigni (2013; 2015) to use local religious belief as an instrumental variable (IV) for the hiring of personnel with AI skills. Bénabou et al. (2013; 2015) find that areas with stronger religious belief are significantly associated with a less favorable view of innovation. The identification of the IV is based on the premise that local religious belief (i.e., belief or disbelief in God) is exogenous to the number of auditor jobs. We show that our main results are robust to using IV estimation for AI implementation at local audit offices.

Our paper makes two main contributions. First, we provide the first large-scale evidence showing that AI technology in audit firms has a long-term impact on the audit industry.

Implementing AI technology in audit firms increases the number of auditor jobs. We show that such audit offices upskill their auditor jobs and require more specialized skills and higher education requirements, which comes at a cost. Our evidence also suggests that even though AI technology can perform repetitive audit tasks, audit offices cannot use AI to perform audit tasks that require higher cognitive and social skills. Our results on the increase in skill and education requirements have implications for auditors in audit offices that implement (or are about to implement) AI technology.

Second, we show that AI technology is associated with higher audit quality. Our paper is the first study to document that audit offices can enhance audit quality by hiring more auditors with AI skills. Our findings complement those of prior studies showing the impact of investments in labor on audit quality (e.g., Knechel, Niemi, and Mikko 2013; Aobdia, Srivastava, and Wang 2018; Beck, Francis, and Gunn 2018; Hoopes et al. 2018). Our new findings show that hiring auditors with AI skills can reduce clients' future restatements and enhance audit quality. Recent studies show that economic recessions accelerate the pace at which employers implement technological changes (Hershbein and Kahn 2018; Modestino, Shoag, and Ballance 2019). Our evidence may be of interest to auditors who are interested in accelerating AI implementation during economic recessions, and to regulators who want to understand the impact of AI implementation on audit quality.

Our paper is related to a small yet growing literature on how AI impacts white-collar professions: lawyers (Remus and Levy 2017), office and administrative support (Dillender and Forsythe 2019), and health care professionals (Goldfarb, Taska, and Teodoridis 2020). Our paper is the first paper to analyze the impact of AI technology on the audit profession. Chen and Srinivasan (2019) find that non-technology firms that adopt artificial intelligence have a higher market valuation. Cao (2018) shows that job specificity positively predicts employee satisfaction, productivity, and corporate accounting performance and negatively predicts employee turnover rate.

Bao, Ke, Li, Yu, and Zhang (2020) demonstrate that machine learning outperforms accounting ratio–based methods to detect accounting frauds. Gao, Merkley, and Pacelli (2020) show that firms hire more employees with financial skills after disclosing an internal control weakness. Bloomfield, Brüggemann, Christensen, and Leuz (2017) show that regulatory harmonization facilitates labor mobility in the accounting profession. Our research question, which focuses on AI implementation in the audit profession, is entirely different.

2. Data and Descriptive Statistics

Our main sample comes from Burning Glass data from 2010 to 2019. Burning Glass is an employment data analytics firm that provides real-time data on job postings and skills in demand. According to Burning Glass, it crawls nearly 40,000 online job boards and company websites to scrape and code information on job postings. After removing duplicated job postings, for each job posting, Burning Glass extracts and standardizes the job-level characteristics such as employer name, job title, location of the position, salary, education requirements, skill requirements, certification requirements, etc. Labor economists have been using Burning Glass in recent years to examine the changing landscape of the U.S. labor market (e.g., Deming and Kahn 2018; Hershbein and Kahn 2018).

Although the original job advertisements are not made available to researchers, Burning Glass data have three unique features that help researchers examine the dynamics in the labor market. First, Burning Glass's extensive coverage of online job boards covers about 60-70% of online job postings with a particular tilt toward high-skill professions (Carnevale, Jayasundera, and Repnikov 2014). Carnevale et al. (2014) find that more than 80% of jobs that require at least Bachelor's degrees are posted online. Hershbein and Kahn (2018) find that Burning Glass has better coverage of local job postings in the U.S. than other national survey-based data such as the Job Openings and Labor Turnover Survey (JOLTS).

Second, Burning Glass standardizes information at the job-posting level through its proprietary machine-learning algorithm. Standardized job-level characteristics allow researchers to examine various dimensions of labor demand across local establishments (e.g., different audit offices by the same audit firm) and occupations (e.g., different occupations in the same audit office, such as audit managers and tax managers). Hence, researchers can observe the change in the composition of jobs within the same establishment and the shift in skill requirements within the same occupation (e.g., auditors) or geographical locations (e.g., the city of Chicago). Last, Burning Glass scrapes online job postings data in real time. While traditional labor data sources such as O*NET update data annually, Burning Glass's high-frequency data allow researchers to observe job postings and skill data in a more timely manner.

Burning Glass data do, however, have limitations. First, as mentioned earlier, Burning Glass scrapes and parses only online job postings. As professions requiring skilled labor are more likely to post their jobs in online job boards, the sample tilts toward higher-skilled occupations and away from lower-skilled occupations (e.g., jobs in retail businesses or restaurants). This bias, however, is unlikely to substantially affect our sample because we focus on the audit profession. Second, employers may post identical job postings in multiple online job boards, which could present a counting issue. The potential measurement issue, however, is unlikely to affect our sample because Burning Glass has already removed duplicate online job postings. Third, large audit firms tend to use a blanket advertisement to recruit new auditors through campus recruiting events. Large audit firms might also offshore various tasks to foreign countries. These would under-count the number of actual job positions and bias against any growth in job positions.[9] Last, while Burning Glass data provide employers' trade names (e.g., KPMG), they do not provide employers' exact legal names.

We construct our main sample as follows. First, we collect 1.2 million job postings by all employers in accounting, tax preparation, bookkeeping, and payroll services (NAICS 5412) from 2010 to 2019. We then remove government entities, noncommercial firms, and nonprofit organizations (e.g., State of Wisconsin, Defense Agency, Tax Court, etc.). We manually match the employers' names in Burning Glass with the names of auditors in Audit Analytics. We extract the city locations of local audit offices in the "City" column using 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 Burning Glass and Audit Analytics. Burning Glass data cover approximately 90% of the audit offices in Audit Analytics.[10] We also require each employer to have at least ten job postings during the sample period. We exclude internships as they are short-term and usually involve fewer jobs and have less clear job requirements.[11] After the manual matching, we have 633,223 jobs in 200 cities and 49 states from 2010 to 2019. As our main unit of analysis is at the local audit office level, we aggregate all jobs at that level (i.e., audit firm-city level). Because our regression analysis requires lag variables, our final sample starts in 2011. Our final main sample for empirical analyses is a panel of 13,971 audit office–quarter observations based on 628 audit offices from 43 audit firms in 189 cities from 2011 to 2019.[12]

[9] An audit office, for instance, could hire multiple auditors through one job posting. Because our measure is based on the number of job postings rather than the number of job applicants eventually hired, our measure would be under-estimated and this will bias against finding any growth in auditor demand.

[10] The only exception is CliftonLarsonAllen LLP (CLA). The names of the local audit offices of CLA do not necessarily include CLA. Hence, we only retain those office locations with CLA in the auditor's names. Our results remain robust if we exclude CLA from our final sample.

[11] Internship only accounts for 2.04% of the total number of job postings.

[12] If an auditor maintains two offices in the same city in a given quarter, we aggregate the jobs at these two offices into one observation.

Before reporting the summary statistics, we validate the quality of the information in Burning Glass data. The validation is challenging because there are no publicly available data on the actual number of personnel hired in each local audit office-year. We validate the data by examining the number of worker visa applications (H-1B visas) in each audit office. The H-1B visa permits employers to temporarily hire foreign workers in specific occupations (e.g., audit industry). Prior research also uses the number of worker visa applications to proxy for the demand for audit personnel (e.g., Aobdia et al. 2018; Hoopes et al. 2018). We download the number of worker visa applications sponsored by Big Four audit firms from the Department of Labor. We aggregate the number of H-1B visas per audit office-year from 2011 to 2019, and merge the data with Burning Glass data. Even though the H-1B visas data only capture the number of foreign workers, we find that the correlation is 53%.

Table 1, panel A presents an overview of our final sample. The top 20 audit firms account for 96.1% of all audit office–quarter observations. KPMG has the highest number of observations, followed by the other Big Four audit firms (Ernst and Young, PricewaterhouseCoopers, and Deloitte and Touche). In total, Big Four audit firms account for about 56% (84%) of our audit office–quarter (job postings) observations. In columns 3 and 4, we show that the number of audit offices in Burning Glass is comparable to the number of audit offices in Audit Analytics.

Panel B tabulates the number of observations by years. The number of observations slightly increases from 1,202 in the year 2011 to 1,568 in the year 2019. The increase reflects an increased coverage in Burning Glass over the years. The number of audit offices is stable over the years with an average of 438 audit offices. About half of the audit offices belong to the Big Four audit firms.

Panel C tabulates the number of observations by geographic locations. 11% of observations represent audit offices in California, followed by Florida and Texas. New York City (where the Big Four's headquarters are located) has the highest number of observations, followed by Minneapolis and Chicago. Of the states with at least 1,000 jobs in our sample, the states with the highest percentage of AI jobs are Colorado, the District of Columbia, and Washington. We plot the distributions for all states in figure 1.

About 1.43% of the jobs in our final sample are AI jobs, and the growth of AI jobs significantly increased to about 2.5-3% in 2018-2019. To put this number into perspective, in figure 2 we compare the percentage of AI jobs by three industries: (a) audit services, (b) finance and insurance, and (c) professional services (e.g., legal, computer design, and engineering) excluding audit services. Audit firms have a higher percentage of AI jobs than finance and insurance, but a slightly lower percentage than other professional services such as legal services, architectural or engineering services, and design services.

Panel D reports the top five job titles and O*Net job classifications. The job titles are based on the job titles standardized by Burning Glass to enhance comparability and categorization. The top five AI job titles are software development engineer, business analyst, risk manager, data architect, and natural language processing scientist. The top five jobs based on O*NET classifications are auditors, managers (all other), computer and information research scientists, software developers, and computer occupations.

3. Main Results

Our empirical analyses proceed as follows. In the first part of our analyses, we ask what drives audit offices to hire AI personnel. Then, we conduct difference-in-differences tests to assess whether, relative to audit offices that do not yet have jobs requiring AI skills, audit offices that have such jobs experience an increase in the number of auditor jobs. We further examine whether the hiring of personnel with AI skills shifts and increases skill and education requirements. We ask whether audit firms that hire AI personnel are more likely to open their auditor jobs to STEM graduates. Next, we conduct tests to determine whether hiring AI personnel costs audit offices more. We estimate instrumental variables to provide evidence mitigating the concern of endogeneity in the hiring of personnel with AI skills. Last, we examine whether the hiring of auditors with AI skills is associated with higher audit fees and audit quality.

3.1 Using Artificial Intelligence

In this section, we ask what drives audit offices to hire AI personnel. As mentioned earlier, we classify a job as an AI job if it requires skills in artificial intelligence, machine learning, natural language processing, or data science; or if it requires a specific AI skill listed in Appendix B, following Acemoglu, Autor, Hazell, and Restrepo (2020). We construct *Use of AI* as an indicator variable that equals one if an audit office in city *c* posts an AI job in a given quarter *t*. To understand why audit offices hire AI personnel, we estimate the following linear probability model:

$$\text{Use of AI}_{jct} = \alpha + \beta X_{jct\text{-}1} + \delta + \varepsilon_{jct} \tag{1}$$

Each unit of observation is an audit office–quarter over the sample period from 2011 to 2019. The dependent variable, *Use of AI*, is an indicator variable that equals one if an audit office *j* in city *c* posts a job requiring artificial intelligence skills in a given quarter *t*.

X includes four sets of variables that could be associated with the likelihood of using AI technology in a local audit office. The first set of variables measures the spillover of local knowledge (e.g., Guan et al. 2016; He et al. 2017; Beck et al. 2019; He et al. 2020). We construct *Peer Use of AI*, the percentage of audit offices with AI jobs in a city *c* in year *t*-1. The second set of variables measures local competition among auditors that could be associated with AI technology implementation. Prior research finds that local competition is a salient auditor characteristic that affects audit pricing and audit quality (e.g., Numan and Willekens 2012). We construct *Market Concentration* to quantify the extent of competition among audit offices in the same local geographic segment (i.e., the same city). *Market Concentration* is the Herfindahl-Hirschman index (HHI) of the number of jobs by all audit offices in a city in year *t*-1. Prior research shows that knowledge sharing is associated with auditors' market share and industry expertise (e.g., Reichelt and Wang 2010; Minutti-Meza 2017; Beck et al. 2019). The third set of variables includes a spectrum of time-variant local county characteristics such as unemployment rate, population, education, income, and age that could be associated with AI implementation. The last set of variables includes a vector of time-variant or invariant audit office characteristics. *Firm Size* is the quintile score based on the number of states where auditors have their offices in a given year. Prior research shows that audit size and growth are associated with office resources (e.g., Francis and Yu 2009; Bills, Swanquist, and Whited 2016; Donelson, Ege, Imdieke, and Maksymov 2020). *#Occupations* is the number of occupations in the job ads by an audit office in a city in a given year. *#Occupations* captures business diversity because an audit office is more likely to use AI technology if it has operations in more business lines. *PCAOB Registrant* is an indicator variable that equals one if an auditor is registered with the Public Company Accounting Oversight Board (PCAOB). Larger audit firms should have more resources to implement new technologies to improve productivity than smaller audit firms. DeFond and Lennox (2011; 2017) also show that PCAOB status is associated with high-quality auditors. Hence, these three variables capture audit office characteristics associated with AI implementation at the local audit office.

We also include a set of high-dimensional fixed effects (i.e., δ) in our regression specifications. These fixed effects include *City Fixed Effects*, *Year-Quarter Fixed Effects*, *Auditor Fixed Effects*, or *City* × *Year-Quarter FEs* (depending on the regression specification). *City Fixed Effects* absorbs a host of city-invariant factors that can affect AI implementation in a city (e.g., variation in city culture of using AI, or differences in demographics and labor market conditions in a given city). Prior research finds that city-specific labor characteristics are associated with auditing practices (e.g., Beck et al. 2018). *Year-Quarter Fixed Effects* absorbs any aggregate shock to AI implementation during the sample period. As the residuals are likely correlated within a local audit office, we cluster all standard errors at the local audit office. *Auditor Fixed Effects* absorbs any auditor-invariant characteristics in AI implementation (e.g., heterogeneity in firm culture, business models, business strategies, or incentive structure).

Table 3 summarizes the results. In column 1, we regress *Use of AI* on *Peer Use of AI* and *Market Concentration* with *City Fixed Effects*, *Year-Quarter Fixed Effects*, and *Auditor Fixed Effects*. The results show that an audit office is more likely to use AI technology when more local peers recently used it. The results suggest a knowledge spillover effect from other auditors who are geographically proximate in the same city; this evidence is consistent with prior findings on local knowledge sharing (e.g., Guan et al. 2016; He et al. 2017; Beck et al. 2019; He et al. 2020). Local competition, however, does not seem to explain AI implementation in an audit office because the coefficient of *Market Concentration* is not significant. In column 2, we also include county-level variables with the same set of fixed effects. With the set of county-level variables, *Peer Use of AI* continues to predict AI implementation strongly. We find that an audit office is more likely to adopt AI when it is located in counties with higher income and fewer males. Local unemployment rate appears to be negatively associated with AI implementation. The pattern indicates that firms are more likely to invest in AI technology when local macroeconomic conditions are good. In column 3, we include more time-variant audit office characteristics such as firm size, business resources, and business diversity. The estimate of *Peer Use of AI* continues to be strongly positive. The results in column 3 also show that audit offices with more resources are more likely to use AI technology.

In column 4, we include two finer sets of fixed effects: *City* × *Year-Quarter FEs* and *Auditor* × *City FEs*. *City* × *Year-Quarter FEs* absorbs any changes in local business or macroeconomic conditions in a given city-quarter. *City* × *Year-Quarter FEs* subsumes *Peer Use of AI*, *Market Concentration*, and all time-variant county-level characteristics. *Auditor* × *City FEs* absorbs any heterogeneity in AI implementation between auditors. Prior research shows that larger audit offices provide higher audit quality than smaller audit offices (e.g., Jiang, Wang, and Wang 2019). These fixed effects ensure that heterogeneity in auditing practices does not drive the results. With these two sets of fixed effects, the residual variation comes from the within-auditor AI implementation in different audit offices. The number of observations slightly declines because the use of high-dimensional fixed effects in estimations drops audit offices with singleton observations. Despite the tightened sets of fixed effects, *Firm Size* continues to be statistically significant and positively associated with AI implementation. The pattern again suggests that larger audit firms have more resources to use AI technology than smaller audit firms. The adjusted R-squared is the highest. The pattern suggests that time-invariant, unobservable county-specific factors are strong determinants of AI technology implementation in a local audit office.

3.2 More Jobs

In this section, we examine whether AI technology replaces auditor jobs. We estimate the following difference-in-differences model specification:

$$\#\,\text{Jobs}_{jct} = \beta(\text{ Post Use of AI})_{jct} + X_{jct\text{-}1} + \delta + \varepsilon_{jct} \quad (2)$$

The dependent variable *# Jobs* is the number of jobs at an audit office in a given quarter. We follow Deming and Kahn (2018) to use the number of jobs as a proxy for the number of employees hired at an establishment (i.e., an audit office in our setting). *Post Use of AI* is an indicator variable that equals one after an audit office in city *c* has posted a job requiring AI skills in a given quarter. Following our earlier specification, we include *City* × *Year-Quarter FEs* and *Auditor* × *City FEs* so that an audit office that uses AI is compared with other audit offices in the same city in the same quarter. Our main variable of interest is *β*. A positive (negative) *β* indicates that AI implementation is associated with more (fewer) jobs. The difference-in-differences research design is similar to that in

Bertrand and Mullainathan (2003). The first difference compares the number of jobs before and after the AI implementation in audit offices. The second difference compares the number of jobs of the control group. The difference-in-differences estimator measures the difference between the first and the second differences. The staggered hiring of personnel with AI skills means that the control group is not restricted to audit offices that never have any jobs requiring AI skills, but implicitly includes all audit offices that do not yet have any jobs requiring AI skills at the same time as a particular treated audit office, even if the audit offices already have jobs requiring AI skills or will have jobs requiring AI skills later on. *X* is a vector of control variables including *Firm Size* and # *Occupations*. As in table 3, standard errors are clustered at the local audit office level.

Table 4, panel A summarizes the results. In column 1, we find that, relative to audit offices that do not have jobs requiring AI skills, audit offices that do have such jobs experience an increase in the number of jobs. In terms of economic magnitude, the estimate of *Post Use of AI* translates into a 43.9% increase in jobs. Columns 2-4 further decompose the types of new job postings. The dependent variable in column 2 is # *AI Jobs*, which counts AI-related jobs only. The five most common AI-related jobs are software development engineers, business analysts, risk managers, data architects, and natural language processing scientists. The results suggest that audit offices that had AI jobs continue to have strong demand for skilled AI professionals after their initial AI implementation. The increase, however, is not restricted to AI-related jobs. We construct # *Non-AI Jobs*, the number of non-AI-related jobs at an audit office in a given quarter. # *Auditor Jobs* is the number of auditor jobs at an audit office in a given quarter. The top five most common auditor jobs are audit managers, audit senior associates, audit associates, tax managers, and tax associates. We observe that the increase extends to non-AI jobs (column 3) and auditor jobs (column 4). In column 4, relative to audit offices that do not have jobs requiring AI skills, audit offices that have such jobs experience a 16.2% increase in the number of auditor jobs. Overall, these results suggest that AI implementation in audit offices is associated with more jobs, which counters the common concern that AI implementation will eliminate auditor jobs.[13]

Figure 3 plots the changes in auditor jobs around the implementation of AI. The figure shows a parallel trend that, before AI implementation, the number of auditor jobs in both audit offices with and without AI implementation remains largely similar. In table 4, panel B, we construct *Pre Use of AI*, An indicator variable that equals one for the four quarters before an audit office posts a job requiring AI skills. We augment *Pre Use of AI* with our baselines, and we re-estimate the regression specifications. In columns 1, 2, and 4, we do not find any systematic difference in the number of jobs before an audit office posts a job requiring AI skills. As expected, the estimate of *Pre Use of AI* is negative and statistically significant because local audit offices do not have any jobs requiring AI skills before they post jobs requiring AI skills.

Table 4, panel C summarizes the results of the cross-sectional tests. In column 1, we further decompose *Use of AI* into two non-mutually exclusive categories of *Use of Broad AI* and *Use of Narrow AI*. *Use of Broad AI* is about general AI technology (e.g., artificial intelligence, machine learning), whereas *Use of Narrow AI* is about specific AI technology (e.g., Word2Vec). We find that the effect comes mainly from jobs requiring skills in general AI technology because *Post Use of Broad AI* is statistically positive, but *Post Use of Narrow AI* is not. The pattern is not surprising because only a handful of specific AI technology is not included in the category of general AI technology.

In column 2, we examine how the effects vary between audit offices in urban and rural areas. We use the rural-urban continuum score from 1 (urban) to 7 (rural) from the U.S. Department of Agriculture to measure the degree of urbanization.[14] Column 2 suggests that audit offices in less

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[13] In untabulated tests, we also augment a tighter set of fixed effects *Auditor* × *Year* × *Quarter Fixed Effects* into our baseline regressions and we re-estimate the baseline regressions. Our results continue to remain robust with this additional set of fixed effects.

[14] The original rural-urban continuum score runs from 1 (urban) to 9 (rural). Because we do not have any job postings from local audit offices in extremely rural areas, our sample's maximum continuum score is 7.

urbanized areas benefit more from AI implementation than audit offices in more urbanized areas. As jobs are associated with office productivity, the results indicate that AI implementation has a strong, beneficial impact in areas where skilled labor is scarce.

Last, we examine how the effect of AI implementation on auditor jobs varies with how replaceable the audit office's labor pool is. Following Felten, Raj, and Seamans (2018), we measure the replaceability of an office's labor pool using the occupation-level AI exposure score in the first quarter when an audit office initially posts a job. A higher *Initial AI Exposure* suggests that an audit office has greater opportunities to replace its current workers with AI technology. In column 3, we find that the effect of implementing AI technology is more pronounced when audit offices have more jobs that could be replaced by AI technology.

In figure 4, we conduct falsification tests. The procedures are as follows. First, we randomly re-assign *Use of AI* to indicate whether an audit office posts a job requiring AI skills. We label this new variable as *Placebo Use of AI*. Second, for each audit office with *Placebo Use of AI* equal to one, we randomly assign the quarter when an audit office first posts a job requiring AI skills. We label this new variable as *Placebo Post*. We then replace *Post Use of AI* with *Placebo Post* × *Placebo Use of AI* and we re-estimate our baseline specifications in table 4, panel A. After repeating the procedures 1,000 times, we summarize the estimates of *Placebo Post* × *Placebo Use of AI* in figure 4. The dotted line represents the values of our estimate of *Post Use of AI*. Our main effects in table 4 are positioned far to the right of the entire distribution of estimates from these falsification tests. Overall, we do not find systematic patterns showing a change in the number of jobs across all four dependent variables.

Overall, these findings suggest that the effects of AI implementation on the number of auditor jobs are more pronounced when audit offices are in less urbanized areas and when audit offices have more jobs that are replaceable by AI.

3.3 Upskilling in Job Requirements

In this section, we examine whether AI technology shifts and upskills job requirements. Our earlier results show that the number of auditor jobs increases after audit offices implement AI technology. The results, however, do not reveal whether the skills required in auditor jobs change after AI implementation. 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 technology, within the same local audit office, the skills required in jobs could be substantially different after an audit office implements AI technology.

We examine the three broad skills categorized by Burning Glass: (1) baseline skills, (2) special skills, and (3) software skills in auditor jobs. Baseline skills are generic skills common to all occupations such as leadership, project planning and development, and building effective relationships. Specialized skills are specific to auditor jobs. Examples include budgeting, internal auditing, and business processes. Software skills are computer software skills required in day-to-day auditor jobs such as Excel, SAP, or Oracle. We estimate the same difference-in-differences regression specification with these new dependent variables.[15]

Table 5, panel A summarizes the results. We do not find any changes in the baseline and software skills for auditor jobs in audit offices that implement AI technology. We do find, however, that relative to audit offices that do not have jobs requiring AI skills, audit offices that have AI jobs require more specialized skills. Relative to the mean of *# Specialized Skills*, the estimate translates into a 7% increase in the number of specialized skills per auditor job.

We delve more deeply into the nature of specific skills, following Deming and Khan (2018) to categorize the skills required in each job into ten classifications. *# Cognitive Skills* is the average

[15] A job could require multiple skills. In our sample, a job requires an average of 13 skills.

number of cognitive skills (e.g., problem solving, critical thinking) required per auditor job at an audit office in a given quarter. # *Social Skills* is the average number of social skills (e.g., communication, teamwork) required per auditor job at an audit office in a given quarter. Deming (2017) finds that employees with better social skills are valuable in lowering coordination costs. #*Writing Skills* is the average number of writing skills (e.g., written communication, proposal writing) required per auditor job at an audit office in a given quarter. # *People Management Skills* is the average number of people management skills (e.g., leadership, staff management) required per auditor job at an audit office in a given quarter. # *Character Skills*, # *Customer Service Skills*, # *Project Management Skills*, # *Financial Skills*, # *General Computer Skills*, and # *Specific Computer Skills* are similarly defined. Appendix A lists the descriptions for the other classifications. We then re-estimate our baseline regressions.

Table 5, panel B summarizes the results. We find that, relative to audit offices that do not yet have any jobs requiring AI skills, audit offices that have AI jobs require 2-3% more cognitive skills, social skills, writing skills, and people management skills per auditor job. The results confirm those of prior studies suggesting that nonroutine skills are less likely to be displaced by AI technology (e.g., Autor et al. 2003; Brynjolfsson et al. 2018). Perhaps more surprising is the finding that the demand for general or specific software skills does not significantly change after audit offices start using AI technology.

Overall, the evidence suggests that, relative to audit offices that do not yet have any jobs requiring AI skills, audit offices that have AI jobs shift and upskill their job requirements.

3.4 Upskilling in Education Requirements

In this section, we examine whether AI technology shifts and upskills education requirements. Recent anecdotal evidence on the declining enrollment in accounting programs shows that graduates of accounting programs face increasing competition for jobs from graduates in other disciplines such as STEM. For example, a recent survey by AICPA (2019) shows that the percentage of non-accounting graduates in audit firms continues to increase, reaching about 30% of all new graduate hires.

We use the following dependent variables to estimate the same baseline specification in table 4. To examine whether AI technology shifts and upskills education requirements for auditor jobs, we focus on two sets of education requirements: years of education and degree requirements. For years of education, the dependent variables include *# Years of Education*, *% At Least a Bachelor*, *% At Least a Master*, and *% No Minimum Education*. *# Years of Education* is the average years of education required per auditor job at an audit office in a given quarter. *% At Least a Bachelor* is the percentage of auditor jobs requiring at least a bachelor's degree at an audit office in a given quarter. *% At Least a Master* is the percentage of auditor jobs requiring at least a master's degree at an audit office in a given quarter. A higher value in each of these variables indicates a more stringent education requirement for auditor jobs (i.e., education upskilling). *% No Minimum Education* is the percentage of auditor jobs that do not specify minimum education requirements at an audit office in a given quarter. A higher value of *% No Minimum Education* means a lower education requirement. We also construct *# Certification* as the average number of certifications required per auditor job at an audit office in a given quarter. More certifications required for an auditor job indicate a more stringent requirement.

Table 6, panel A presents the results. In column 1, relative to audit offices that do not yet have jobs requiring AI skills, audit offices that have such jobs do not increase the years of education required for their auditor jobs. In column 3, we also find that audit offices that have jobs requiring AI skills do not have more auditor jobs requiring at least a master's degree. In column 2, however, we find that the auditor jobs of audit offices that have AI jobs are 3% more likely to require applicants to have at least a bachelor's degree than audit offices that do not yet have any jobs requiring AI skills. The tightening requirement is surprising because 90% of auditor jobs in audit firms already require at least a bachelor's degree. In column 4, we also find that relative to audit offices that do not yet have any jobs requiring AI skills, audit offices that have such jobs are 32% (=0.029÷0.091) more likely to specify minimum education requirements for their jobs. In column 5, relative to audit offices that do not yet have jobs requiring AI skills, audit offices that have AI jobs require more certifications for their auditor jobs. Overall, these results suggest that relative to audit offices that do not yet have any jobs requiring AI skills, audit offices that have AI jobs increase their education requirements.

Next, we ask whether audit firms are more likely to open their auditor jobs to STEM graduates. We construct *% Accounting Major*, *% Business Major*, *% Tax or Law Major*, and *% STEM Major*. A higher % indicates that audit offices have more auditor jobs that specify job applicants with a particular major. Table 6, panel B summarizes the results. In columns 1 and 2, relative to audit offices that do not yet have jobs requiring AI skills, audit offices that have AI jobs are not less likely to specify an accounting or business major. In columns 3 and 4, however, we find that the audit offices that use AI technology have more (fewer) auditor jobs open to applicants with a STEM (tax or law) background. These results suggest that while applicants with accounting and business majors can continue to apply for auditor jobs, audit offices that use AI technology are opening up auditor jobs to STEM applicants.

Overall, the evidence suggests that, relative to audit offices that do not yet have any jobs requiring AI skills, audit offices that have AI jobs shift and upskill their education requirements. Such audit offices also are more likely to open their auditor jobs to applicants with a STEM background.

3.5 Does AI Increase Costs?

Next, we ask whether AI technology increases costs for audit offices. As we do not have access to audit offices' books, we use the salary information in job listings as a proxy for audit offices' costs.

We construct *\$ Job Salary*, which is defined as the salary for a job. We follow Deming and Kahn (2018) to regress *\$ Job Salary* on the ten skillsets we used earlier. Each observation is at the job level. Table 7 summarizes the results. We find that auditor jobs requiring AI skills command an 8% higher salary than jobs that do not require AI skills. This is consistent with the findings in Alekseeva, Azar, Gine, Samila, and Taska (2020) that AI jobs on average command a higher premium than other jobs.

Moving to a broader level, we now ask how AI technology impacts the salary structure of audit firms. To test this, we construct two sets of variables on salaries. The first set of salary variables captures the level of audit salaries. *\$ Salary* is the average salary per auditor job at an audit office in a given quarter. *\$ Salary Min* is the average of the minimum salary per auditor job at an audit office in a given quarter. *\$ Salary Max* is the average of the maximum salary per auditor job at an audit office in a given quarter.

The second set of salary variables captures the fluctuation of auditors' salaries. *\$ Salary Fluctuation* is the standard deviation of salary per auditor job at an audit office in a given quarter. *\$ Min Salary Fluctuation* is the standard deviation of the minimum salary per auditor job at an audit office in a given quarter. *\$ Max Salary Fluctuation* is the standard deviation of the maximum salary per auditor job at an audit office in a given quarter. Each observation is at the audit office–quarter level. We estimate the same baseline regression specification for each of the eight salary variables above.

Before proceeding with the analyses, we suggest that readers interpret the analyses below with caution because only 5% of all job postings in the Burning Glass data contain salary information. Hence, the number of observations for these tests is significantly smaller than in our main sample.

Table 8 summarizes the results. In column 1, there is no evidence that AI implementation lowers the average salaries of auditor jobs. In columns 2-3, the average minimum and maximum levels remain similar before and after AI implementation. In column 4, relative to audit offices that do not yet have any jobs requiring AI skills, audit offices that have AI jobs experience a higher fluctuation in their salary structure. The standard deviation of the average salary for auditor jobs increases by 71% after AI implementation. Column 6 shows that the increase is mainly because of the increased fluctuation in the maximum salary offered in auditor jobs. Overall, the evidence confirms that jobs requiring AI skills cost audit firms more, and relative to audit offices that do not yet have any jobs requiring AI skills, audit offices that have jobs requiring AI skills have more fluctuation in salaries because of the increased fluctuation in the maximum salary offered in auditor jobs.

3.6 IV Estimates

Our main specification relies on the identification that comes from the staggered hiring of personnel with AI skills at the audit office level. A potential concern is that the hiring of applicants with AI skills is endogenous, even though we have controlled for a wide array of control variables and sets of high-dimensional fixed effects that could be associated with AI implementation at the audit office level.

To further mitigate the endogeneity concern, we follow Bénabou et al. (2013; 2015) to use religious belief as an instrumental variable for the *Use of AI*. Bénabou et al. (2013; 2015) find a significant negative relationship between religious belief and patent innovation at the state and individual levels. The same pattern is also observed across countries, even after controlling for income per capita, population, education, patent-rights protection, and foreign investment. We build on this strand of literature and use religious belief as an instrument for AI implementation. As people with more religious faith find it more challenging to accept AI, areas with stronger religious belief (e.g., belief in God) are significantly associated with a less favorable view of innovation (i.e., religious belief satisfies the relevance condition, as we show in table 9). To serve as a valid instrument variable, local religious belief (i.e., belief or disbelief in God) must also satisfy the exclusion condition: local religious belief must not be associated with the number of auditor jobs demanded by local audit offices after we condition on other explanatory variables. Although it is challenging to test the exclusion condition, we argue that religious belief is unlikely to be directly associated with local labor demand for professional services jobs (e.g., auditing jobs).

We follow Bénabou et al. (2013; 2015) to construct two variables on religious belief. *Religion Is Important* is a decile score based on the percentage of respondents in a state in a given year who answer "very important" to "How important is religion in your life?" in the Religious Landscape Survey by the Pew Research Center. *Believe in God* is a decile score based on the percentage of respondents in a state in a given year who answer "yes" to "Do you believe in God or a universal spirit?" in the same survey. As the information on these two questions at the state level is available for 2008 and 2014, we follow previous literature (Alesina and La Ferrara 2000; Hilary and Hui 2009) and linearly interpolate the data to obtain the values in the missing years (from 2011-2013, from 2015-2019). Following our earlier specification in table 4, panel A, column 4, we replace *City* × *Year-Quarter FEs* with *Year-Quarter FEs* because *City* × *Year-Quarter FEs* will subsume the religious belief variables.

Table 9 summarizes the results. Panel A tabulates the IV estimation results using *Religion is Important*. In column 1, *Religion is Important* is negatively associated with AI implementation by a local audit office. The results confirm the findings of prior literature on the negative association between religious belief and innovation. The first-stage *F*-statistic is 9.74, indicating that *Religion is Important* is a strong instrument because its *F*-statistic is borderline around the threshold of 10 (Stock and Yogo 2002). Across columns 2-5, all estimates of *Instrumented Use of AI* are positive and statistically significant at least at the 5% level.

In panel B, we replace *Religion is Important* with *Believe in God*. We then re-estimate all regression specifications. In column 1, we continue to find that a strong religious belief in God is strongly associated with a lower AI implementation. The first-stage *F*-statistic, however, is well below the rule of thumb of 10, suggesting that *Believe in God* is a weak instrument for *Use of AI*. Except for *#AI Jobs*, no regressions are statistically significant.[16] Overall, these results provide evidence showing that our main results are robust to using IV estimation for AI implementation at local audit offices.[17]

3.7 Audit Fees and Audit Quality

In our last set of analyses, we examine whether AI technology is associated with higher audit fees and higher quality. Anecdotal evidence suggests that AI technology could increase audit efficiency and save human inputs (Ernst and Young 2019). As these tests directly relate to auditors, we construct *Post Use of Auditors with AI Skills* as an indicator variable that equals one after an audit office has posted an auditor job requiring artificial intelligence skills in a given quarter. We replace *Post Use of AI* with *Post Use of Auditors with AI Skills* and estimate the same regression specification:

$$\$\ \text{Fees}_{jct} = \beta(\text{Post Use of Auditors with AI Skills})_{jct} + X_{jct-1} + \delta + \varepsilon_{jct} \tag{4}$$

The dependent variable *$ Fees* is a set of fee-related variables from Audit Analytics. *$ Audit Fees* is the sum of audit fees at an audit office in a given year. *$ Tax Fees* is the sum of tax fees at an audit office in a given year. *$ Non-Audit Fees* is the sum of non-audit fees at an audit office in a given

[16] We cannot conduct an over-identification test because the two instruments are highly correlated.
[17] We do not use local religion belief to conduct instrumental variables estimation for audit quality because prior research shows that accounting restatements and irregulatiry are associated with local religiosity (McGuire, Omer, and Sharp 2012).

year. *$ Total Fees* is the sum of total fees at an audit office in a given year. *$ Benefits Plan Audit Fees* is the sum of benefits fees at an audit office in a given year. *$ IT Fees* is the is the sum of financial information systems design and implementation related fees at an audit office in a given year. *$ Tax Compliance Fees* is the sum of tax compliance fees at an audit office in a given year. *$ Tax Advisory Fees* is the sum of tax advisory fees at an audit office in a given year. As the Audit Analytics data are at the yearly level, the unit of observation for the analyses is at the audit office–year level.

We summarize the results on *Audit Fees* and *Tax Fees* in table 10, columns 1-2.[18] We find that audit and tax fees do not significantly change after audit offices have auditor jobs that require AI skills. There are two potential explanations for these results. First, AI implementation does not necessarily lower costs in the audit engagement process. Second, even if AI implementation did save costs, audit firms do not necessarily pass the cost savings on to their clients. Our data do not permit us to disentangle these explanations.

In this section, we examine whether AI technology is associated with higher audit quality. To examine this possibility, we examine the same regression specification with a set of proxies for audit quality. *% Going Concern Audit Opinions* is the percentage of audit clients with going concern audit opinions at an audit office in a given year. *% Restatements* is the percentage of audit clients with restatements at an audit office in a given year. We use restatements as a proxy to measure poor audit quality (DeFond and Zhang 2014; Aobdia 2019). Rajgopal et al. (2020) find that financial restatement is the best proxy to predict all of the top six most cited audit violations. If audit quality increases after audit offices begin using auditors with AI skills, *% Restatements* should be lower. *% Adverse Restatements* is the percentage of audit clients with restatements that have an adverse effect on financial statements at an audit office in a given year. *% Improving Restatements* is the percentage of

[18] The results for other fee proxies are tabulated in Online Appendix Table 1.

audit clients with restatements that have an improving effect on financial restatements at an audit office in a given year. *% Frauds* is the percentage of audit clients with frauds in their financial statements at an audit office in a given year. Prior research shows that clients of the same auditor have similar financial adviser misconduct profiles (Cook, Kowaleski, Minnis, Sutherland, and Zehms 2020). *% Clerical Errors* is the percentage of audit clients with clerical errors in their financial statements at an audit office in a given year. Hennes, Leone, and Miller (2008) find that some restatements are unintentional errors. *% Restatements due to SEC Investigations* is the percentage of audit clients with restatements due to SEC investigations at an audit office in a given year. *% Effective Internal Control* is the percentage of audit clients with effective internal control at an audit office in a given year. We also follow Ashraf, Michas, and Russomanno (2019) to construct two variables on restatements. *% Big R Restatements* is the percentage of audit clients with big R restatements at an audit office in a given year. *% Small R Restatements* is the percentage of audit clients with small R restatements at an audit office in a given year. *Audit Lag* is the number of days between an audit client's fiscal year-end and the date of audit opinion following Bronson, Hogan, Johnson, and Ramesh (2011). It is averaged by audit-office per year.

We summarize the results in table 10, columns 3-8.[19] In column 3, we find that the percentage of clients that experience financial restatements in audit offices that have jobs requiring AI skills is 4.6% lower than that in audit offices that do not yet have such jobs. Relative to the sample mean of *% Restatements*, this estimate translates into about 49% (=-0.046÷0.0939) of clients that experience financial restatements in an audit office in a given year.

The decrease in the client portfolio's restatement rate comes primarily from fewer restatements with adverse effects rather than from fewer restatements with favorable effects. In

[19] The complete set of results for the other audit quality proxies is tabulated in Online Appendix Table 2.

column 5, we show that the percentage of clients that have restatements with adverse effects in audit offices that have jobs requiring AI skills is 3.8% lower than that in audit offices that do not yet have such jobs. Relative to the sample of *% Adverse Restatements*, this estimate translates into about 50% (=-0.038÷0.0767) of clients that experience adverse financial restatements in an audit office in a given year.

We also show that the percentage of clients that experience material non-reliance restatements (i.e., big R restatements) is lower in audit offices that have jobs requiring AI skills than in audit offices that do not yet have such jobs. In column 6, we find that the percentage of clients that have big R restatements in audit offices that have jobs requiring AI skills is 2.2% lower than that in audit offices that do not yet have such jobs. Relative to the sample mean of *% Big R Restatements*, this estimate translates into about 63% (=-0.022÷ 0.035) of clients that experience big R restatemetns in an audit office in a given year. In column 8, we show that the average audit lag is significantly lower in audit offices that have jobs requiring AI skills than in audit offices that do not yet have such jobs.

We do not, however, observe any substantial change in other audit quality proxies such as going concern opinions, frauds, or accrual measures. Alternatively, we measure audit quality using clients' discretionary accruals based on the modified Jones model (Dechow, Sloan, and Sweeney 1995) and performance-matched discretionary accruals (Kothari et al. 2005; 2016). However, we fail to observe any significant change in accruals measures.[20] We interpret the accrual results as consistent with the notion that AI helps auditors to detect clients' misstatements but not to dampen clients' earnings management. Overall, the results suggest that AI implementation in audit offices does not significantly lower audit and tax fees, but it does significantly reduce their percentage of

[20] Results for the accruals proxies are tabulated in Online Appendix Table 3.

clients with restatements.

4. Conclusion

This study examines how AI technology shapes the audit industry. We exploit the staggered hiring of personnel with AI skills at audit office locations across the United States as a proxy for the implementation of AI technology at local audit offices. We show in a difference-in-differences setting that relative to audit offices that do not yet have jobs requiring AI skills, audit offices that do have such jobs experience an increase in the number of auditor jobs. The effects are stronger when audit offices are in less urbanized areas and when audit offices have more jobs that could be replaced by AI. We estimate instrumental variable regressions and find similar patterns. AI implementation also significantly increases the skill and education requirements for auditing jobs. Last, we find that hiring auditors with AI skills does not significantly lower audit and tax fees, but it does significantly reduce the percentage of clients with adverse restatements and audit lag. Overall, our evidence indicates that AI does not replace auditor jobs but leads to upskilling in auditor jobs and improves audit quality.

Our contributions are as follows. First, we provide the first large-scale evidence showing that the use of AI technology in audit firms has a long-term impact on the audit industry. Implementing AI technology in audit firms increases the number of auditor jobs. We also show that such audit offices upskill their auditor jobs, and that requiring more specialized skills and higher education requirements comes at a cost. Our evidence suggests that even though AI technology can perform repetitive auditing tasks, audit offices cannot use AI to perform audit tasks that require higher cognitive and social skills. Our results on the increased skill and education requirements have implications for auditors in audit offices that implement (or are about to implement) AI technology.

Second, we show that AI technology is associated with higher audit quality. Our paper is the first study to document that audit offices can enhance audit quality by hiring more auditors with AI skills. Our novel findings show that hiring auditors with AI skills can reduce clients' future restatements and enhance audit quality. Our evidence should be of interest to auditors who would like to accelerate AI implementation during economic recessions, and to regulators who would like to understand the impact of AI implementation on audit quality.

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Appendix A
Variable Definitions

Main Variables	**Descriptions**
Use of AI	Indicator variable that equals one if an audit office posts a job requiring artificial intelligence skills in a given quarter. [Source: Burning Glass]
Peer Use of AI	Percentage of audit offices with jobs requiring artificial intelligence skills in a city in year *t-1*. [Source: Burning Glass]
Post	Indicator variable that equals one after an audit office posts a job requiring artificial intelligence skills. [Source: Burning Glass]
Post Use of AI	Indicator variable that equals one after an audit office has posted a job requiring artificial intelligence skills in a given quarter. [Source: Burning Glass]
Post Use of Auditors with AI Skills	Indicator variable that equals one after an audit office has posted an auditor job requiring artificial intelligence skills in a given quarter. [Source: Burning Glass]
Pre Use of AI	An indicator variable that equals one for the four quarters before an audit office posts a job requiring artificial intelligence skills. [Source: Burning Glass]
Broad AI	Indicator variable that takes one if an audit office posts a job requiring skill clusters on artificial intelligence, machine learning, natural language processing, or data science. [Source: Burning Glass]
Narrow AI	Indicator variable that takes one if an audit office posts a job requiring any AI skills in the Appendix B. [Source: Burning Glass]
Rural	Rural-urban continuum score from 1 (urban) to 7 (rural) of the county where an audit office is located. [Source: United States Department of Agriculture]
Initial AI Exposure	Occupational-level AI exposure score following Felten et al. (2018) in the first quarter when an audit office initially posts a job. A higher *Initial AI Exposure* means that an audit office has greater opportunities to replace their current workers with AI technology. [Source: Burning Glass and Felten et al. 2018]
# Jobs	Number of jobs at an audit office in a given quarter. [Source: Burning Glass]
# AI Jobs	Number of AI-related jobs at an audit office in a given quarter. [Source: Burning Glass]
# Non-AI Jobs	Number of non-AI-related jobs at an audit office in a given quarter. [Source: Burning Glass]
# Auditor Jobs	Number of auditor jobs at an audit office in a given quarter. [Source: Burning Glass]
# Baseline Skills	Average number of baseline skills (e.g., analytical, multitasking) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
# Specialized Skills	Average number of specialized skills (e.g., budgeting, internal auditing) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
# Software Skills	Average number of software skills (e.g., Excel, SAP) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
# Cognitive Skills	Average number of cognitive skills (e.g., problem solving, critical thinking) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
# Social Skills	Average number of social skills (e.g., communication, teamwork) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]

Appendix A

Variable Definitions – *Continued*

Main Variables	Descriptions
# *Character Skills*	Average number of character skills (e.g., detailed-oriented, organizational skills) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
# *Writing Skills*	Average number of writing skills (e.g., written communication, proposal writing) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
# *Customer Service Skills*	Average number of customer service skills (e.g., customer services, customer contact) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
# *Project Management Skills*	Average number of project management skills (e.g., project management, technical project management) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
# *People Management Skills*	Average number of people management skills (e.g., leadership, staff management) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
# *Financial Skills*	Average number of financial skills (e.g., accounting, budgeting) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
# *General Computer Skills*	Average number of general computer skills (e.g., Excel, Microsoft Office) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
# *Specific Software Skills*	Average number of specific software skills (e.g., Oracle, SAP) required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
# *Years of Education*	Average years of education required per auditor job at an audit office in a given quarter. [Source: Burning Glass]
% *At Least a Bachelor*	Percentage of auditor jobs requiring at least a bachelor's degree at an audit office in a given quarter. [Source: Burning Glass]
% *At Least a Master*	Percentage of auditor jobs requiring at least a master's degree at an audit office in a given quarter. [Source: Burning Glass]
% *No Minimum Education*	Percentage of auditor jobs that do not specific minimum education requirements at an audit office in a given quarter. [Source: Burning Glass]
% *Accounting Major*	Percentage of auditor jobs requiring a major in accounting at an audit office in a given quarter. [Source: Burning Glass]
% *Business Major*	Percentage of auditor jobs requiring a major in business at an audit office in a given quarter. [Source: Burning Glass]
% *Tax or Law Major*	Percentage of auditor jobs requiring a major in tax or law at an audit office in a given quarter. [Source: Burning Glass]
% *STEM Major*	Percentage of auditor jobs requiring a major in STEM (e.g. computer science, engineering, information technology, statistics, mathematics) at an audit office in a given quarter. [Source: Burning Glass]
# *Certification*	Average number of certifications required per auditor job at an audit office in a given quarter. [Source: Burning Glass]

Appendix A
Variable Definitions – *Continued*

Main Variables	Descriptions
$ Job Salary	Salary for a job. [Source: Burning Glass]
$ Salary	Average salary per auditor job at an audit office in a given quarter. [Source: Burning Glass]
$ Salary Min	Average minimum salary per auditor job at an audit office in a given quarter. [Source: Burning Glass]
$ Salary Max	Average maximum salary per auditor job at an audit office in a given quarter. [Source: Burning Glass]
$ Salary Fluctuation	Standard deviation of salary per auditor job at an audit office in a given quarter. [Source: Burning Glass]
$ Min Salary Fluctuation	Standard deviation of the minimum salary per auditor job at an audit office in a given quarter. [Source: Burning Glass]
$ Max Salary Fluctuation	Standard deviation of the maximum salary per auditor job at an audit office in a given quarter. [Source: Burning Glass]
Religion is Important	A decile score based on the percentage of respondents in a state in a given year who answer "very important" to "how important is religion in your life?" in the Religious Landscape Survey by Pew Research Center. A score of ten means a very strong belief that religion is important. [Source: Pew Research Center]
Believe in God	A decile score based on the percentage of respondents in a state in a given year who answer "yes" to "do you believe in God or a universal spirit?" in the Religious Landscape Survey by Pew Research Center. A score of ten means a very strong belief in God. [Source: Pew Research Center]
$ Audit Fees	Sum of audit fees at an audit office in a given year. [Source: Audit Analytics]
$ Tax Fees	Sum of tax fees at an audit office in a given year. [Source: Audit Analytics]
$ Non-Audit Fees	Sum of audit related, benefit plan related fees, financial information systems design and implementation related fees, tax related fees, and other miscellaneous fees at an audit office in a given year. [Source: Audit Analytics]
$ Total Fees	Sum of total audit and nonaudit fees at an audit office in a given year. [Source: Audit Analytics]
$ Benefit Plan Audit Fees	Sum of audit fees for benefit plans at an audit office in a given year. [Source: Audit Analytics]
$ IT Fees	Sum of financial information systems design and implementation related fees at an audit office in a given year. [Source: Audit Analytics]
$ Tax Fees	Sum of tax fees at an audit office in a given year. [Source: Audit Analytics]
$ Tax Compliance Fees	Sum of tax compliance fees at an audit office in a given year. [Source: Audit Analytics]
$ Tax Advisory Fees	Sum of tax advisory fees at an audit office in a given year. [Source: Audit Analytics]

Appendix A

Variable Definitions – *Continued*

Main Variables	Descriptions
% Going Concern Audit Opinions	Percentage of audit clients with going concern audit opinions at an audit office in a given year. [Source: Audit Analytics]
% Restatements	Percentage of audit clients with restatements at an audit office in a given year. [Source: Audit Analytics]
% Adverse Restatements	Percentage of audit clients with restatements that have an adverse effect on financial statements at an audit office in a given year. [Source: Audit Analytics]
% Improving Restatements	Percentage of audit clients with restatements that have an improving effect on financial restatements at an audit office in a given year. [Source: Audit Analytics]
% Frauds	Percentage of audit clients with frauds in their financial statements at an audit office in a given year. [Source: Audit Analytics]
% Clerical Errors	Percentage of audit clients with clerical errors in their financial statements at an audit office in a given year. [Source: Audit Analytics]
% Restatements due to SEC Investigations	Percentage of audit clients with restatements due to SEC investigations at an audit office in a given year. [Source: Audit Analytics]
% Effective Internal Control	Percentage of audit clients with effective internal control at an audit office in a given year. [Source: Audit Analytics]
% Big R Restatements	Percentage of audit clients with big R restatements at an audit office in a given year. A big R restatement is a non-reliance restatement with references to an 8-K item 4.02 [Source: Audit Analytics]
% Small R Restatements	Percentage of audit clients with small R restatements at an audit office in a given year. A small R restatement is a non-reliance restatement without references to an 8-K item 4.02 [Source: Audit Analytics]
Audit Lag	Number of days between an audit client's fiscal year-end and the date of audit opinion. It is averaged by audit-office per year. [Source: Audit Analytics]
Signed Discretionary Accruals Modified Jones Model	Signed discretionary accruals estimated using modified Jones model. [Source: Compustat]
Signed Discretionary Accruals Kothari et al. (2005)	Signed performance-matched discretionary accruals following Kothari et al. (2005). [Source: Compustat]
Signed Discretionary Accruals Kothari et al. (2015)	Signed performance-matched discretionary accruals following Kothari et al. (2015) with firm and year fixed effects included in accrual estimation. [Source: Compustat]
Absolute Discretionary Accruals Modified Jones Model	Absolute value of discretionary accruals estimated using modified Jones model. [Source: Compustat]
Absolute Discretionary Accruals Kothari et al. (2005)	Absolute value of performance-matched discretionary accruals following Kothari et al. (2005). [Source: Compustat]
Absolute Discretionary Accruals Kothari et al. (2015)	Absolute value of performance-matched discretionary accruals following Kothari et al. (2015) with firm and year fixed effects included in the accrual estimation. [Source: Compustat]

Appendix A

Variable Definitions – *Continued*

Other Variables	**Descriptions**
Market Concentration	Herfindahl-Hirschman index (HHI) of the number of jobs by all audit offices in a city in year *t*-1. [Source: Burning Glass]
Firm Size	Quintile score based on the number of states where auditors have their offices in a given year. [Source: Burning Glass]
# Occupations	Number of occupations in the job ads by an audit office in a given year. [Source: Burning Glass]
PCAOB Registrant	An indicator variable that equals one if an auditor is registered with the Public Company Accounting Oversight Board.
Unemployment Rate	Percentage of a county's unemployed population 16 years and over in a given quarter. [Source: American Community Survey]
Population	Total population of a county in year *t*-1. [Source: American Community Survey]
Education	Percentage of population 25 years and over with at least a bachelor's degree in a county in year *t*-1. [Source: American Community Survey]
Income	Median household income of a county in year *t*-1. [Source: American Community Survey]
Age	Median age of a county's population in a year *t*-1. [Source: American Community Survey]
Household	Percentage of a county's family households in year *t*-1. [Source: American Community Survey]
Male	Percentage of a county's male population in year *t*-1. [Source: American Community Survey]
Minority	Percentage of non-White population of a county in a year *t*-1. [Source: American Community Survey]

Appendix B
List of Specific AI Skills

- AI ChatBot
- Chatbot
- Computer vision
- Deep learning
- Gradient boosting
- Image processing
- Image recognition
- Keras
- Kernel methods
- Latent dirichlet allocation
- Latent semantic analysis
- Libsvm
- Machine learning
- Machine translation
- Machine vision
- Mahout
- Neural networks
- Nnatural language processing
- Object recognition
- OpenCV
- Pattern recognition
- Predictive models
- Random forests
- Recommender systems
- Sentiment analysis
- Sentiment classification.
- Speech recognition
- Supervised learning
- Support vector machines
- Text mining
- Unsupervised learning
- Virtual agents
- Word2Vec
- Xgboost

Appendix C
Classifications of Specific Skills

The classifications are based on the 10-category skills in Deming and Khan (2018).

Skills	**Descriptions**
Cognitive	Problem solving, research, analytical, critical thinking, math, statistics
Social	Communication, teamwork, collaboration, negotiation, presentation
Character	Organized, planning, detail-oriented, multi-tasking, time management, meeting-deadlines, energetic
Writing	Writing
Customer service	Customer, sales, client, patient
Project management	Project management
People management	Supervisory, leadership, management (not project), mentoring, staff
Financial	Budgeting, accounting, finance, cost
Computer (general)	Computer, spreadsheets, common software (e.g., Microsoft Excel, PowerPoint)
Software (specific)	Programming language or specialized software (e.g., Java, SQL, Python)

Figure 1

Geographical Distribution of AI Jobs

This map below summarizes the percentage of jobs requiring AI skills by states. The steps to calculate are as follows. First, for each state across all years, we separately sum the number of all jobs, and the number of all jobs requiring AI skills for audit offices. Second, we divide the number of jobs requiring AI skills by the number of all jobs. The legend on the bottom right refers to the percentage of jobs requiring AI skills.

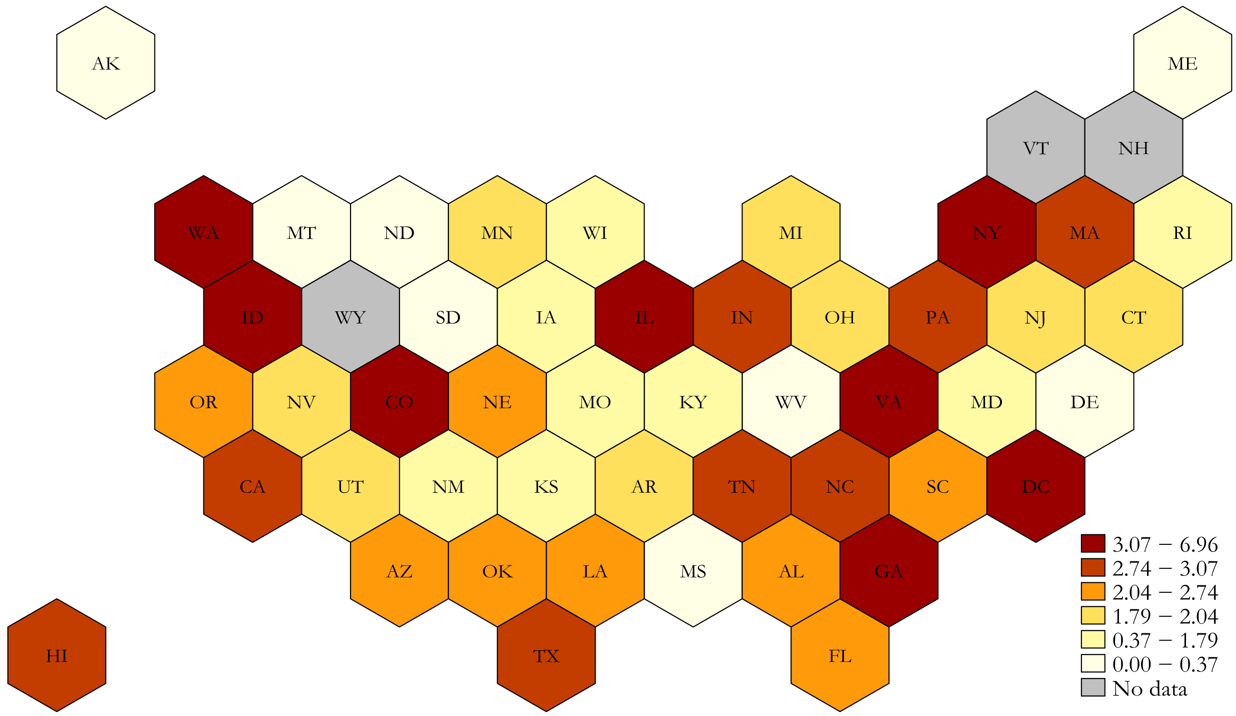

Figure 2
Growth of AI Jobs

This figure below summarizes the percentage of jobs requiring AI skills by years. Three lines represent three distinct groups: (1) audit services from our main sample, (2) finance and insurance (NAICS 52), and (3) professional services (NAICS 541) excluding audit services. Examples of professional services are legal services, architectural or engineering services, or design services.

Figure 3
Parallel Trends

This figure below plots the average number of auditor jobs (# *Auditor Jobs*) per audit office around the AI implementation. Red line with triangle marker is based on the average number of auditor jobs in audit offices with AI implementation, and blue line with circle marker is based on the average number of auditor jobs in audit offices in the same city-quarter without AI implementation. Quarter 0 is the quarter when an audit office has posted a job requiring artificial intelligence skills

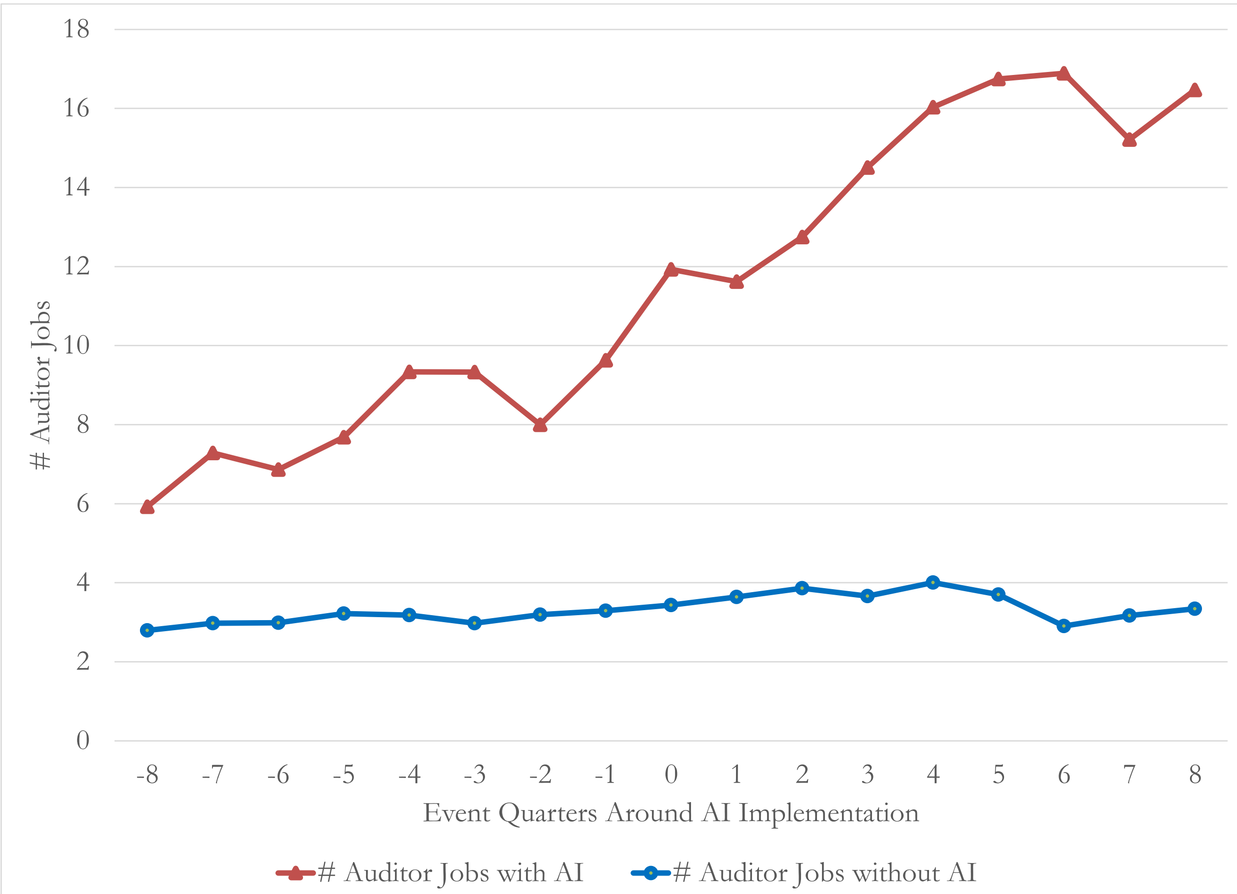

Figure 4
Placebo Tests

This figure below reports the distributions of coefficient estimates from falsification tests. The procedures of conducting the falsification tests are as follows. First, we randomly re-assign *Use of AI* to indicate whether an audit office posts a job requiring AI skills. We label this new variable as *Placebo Use of AI*. Second, for each audit office with *Placebo Use of AI* equal to one, we randomly assign the quarter when an audit office first posts a job requiring AI skills. We label this new variable as *Placebo Post*. We then replace *Post Use of AI* with *Placebo Post* × *Placebo Use of AI* and we re-estimate our baseline specifications in table 4, panel A. After repeating the procedures 1,000 times, we summarize the estimates of *Placebo Post* × *Placebo Use of AI* in this firgure. The dotted line represents the values of our estimate of *Post Use of AI*.

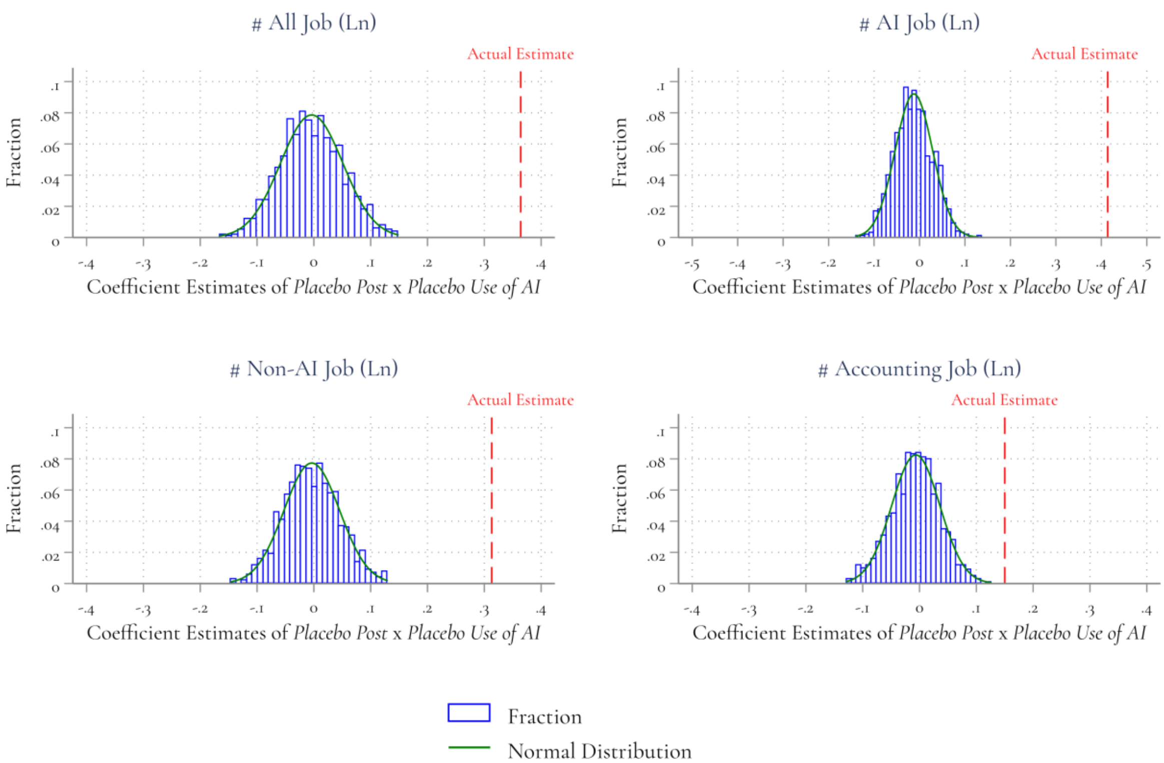

Table 1

Sample Overview

Panel A (Panel B) tabulates the main sample by auditors (by years). Panel C reports the top ten states and cities of jobs. Panel D reports the top 5 job titles (standardized by Burning Glass) and job classifications.

Panel A: By Auditors

Name of Auditors	# Obs (1)	% Obs (2)	# Offices in Burning Glass (3)	# Offices in Audit Analytics (4)
KPMG	2,254	16.1	76	80
Ernst and Young	2,059	14.7	71	76
PricewaterhouseCoopers	1,995	14.3	62	65
Deloitte	1,468	10.5	61	67
Grant Thornton	1,279	9.2	49	51
BDO	1,052	7.5	46	50
RSM	934	6.7	49	52
BKD	396	2.8	17	21
Baker Tilly Virchow Krause	310	2.2	16	19
Crowe	280	2.0	20	25
CohnReznick	258	1.9	15	18
Moss Adams	257	1.8	17	21
Dixon Hughes Goodman	203	1.5	12	13
Plante and Moran	178	1.3	9	9
Eide Bailly	129	0.9	9	10
Wipfli	95	0.7	9	10
EisnerAmper	93	0.7	7	8
CliftonLarsonAllen	81	0.6	6	6
Horne	57	0.4	3	3
Cherry Bekaert and Holland	54	0.4	9	11
Other audit firms	539	3.9		
Total	13,971	100.0		

Table 1
Sample Overview – *Continued*

Panel B: By Years

Year	# Obs	#Audit Firms	#Audit Offices	#Audit Offices of Big Four
	(1)	(2)	(3)	(4)
2011	1,202	31	342	198
2012	1,208	30	368	227
2013	1,499	36	424	254
2014	1,665	34	459	253
2015	1,707	36	465	252
2016	1,708	31	469	246
2017	1,681	31	480	242
2018	1,733	31	479	243
2019	1,568	23	455	238
Average	1,552	31	438	239

Panel C: By Geography

Rank	Top 10 States	% Obs	Top 10 Cities	% Obs
1	California	10.77	New York	2.95
2	Florida	7.27	Minneapolis	2.39
3	Texas	6.53	Chicago	2.25
4	Ohio	5.85	Los Angeles	2.20
5	New York	5.83	Atlanta	2.13
6	North Carolina	4.6	Cleveland	2.03
7	Pennsylvania	4.17	Dallas	2.00
8	Missouri	3.58	Denver	1.89
9	Virginia	3.34	Milwaukee	1.88
10	Michigan	3.26	San Francisco	1.88

Panel D: By Job Titles and Classifications

Rank	Top 5 AI Job Titles	% Obs	Top 5 O*Net Job Classifications	% Obs
1	Software Development Engineer	10.6%	Auditors	10.7%
2	Business Analyst	7.4%	Managers, All Other	10.5%
3	Risk Manager	6.4%	Computer and Info. Research Scientists	10.2%
4	Data Architect	6.3%	Software Developers	5.5%
5	Natural Language Processing Scientist	6.2%	Computer Occupations	5.2%

Table 2
Summary Statistics

This table reports the summary statistics for the variables in this study. Detailed definitions of all variables are in Appendix A. The % sign indicates that the numbers reported are expressed in percentage points.

	Mean	Stdev	25th	50th	75th	#Obs.
Table 3	(1)	(2)	(3)	(4)	(5)	(6)
Use of AI	0.198	0.398	0	0	0	13,971
Peer Use of AI	0.017	0.027	0	0.01	0.03	13,971
Market Concentration	0.448	0.247	0.28	0.37	0.53	13,971
Firm Size	2.875	1.361	2	3	4	13,971
# Occupations	97.6	44.2	65	96	136	13,971
PCAOB Registrant	0.996	0.062	1.00	1.00	1.00	13,971
Unemployment Rate %	5.372	2.074	3.80	4.87	6.63	13,971
Population	1.477	1.647	0.66	0.95	1.60	13,971
Education %	0.220	0.050	0.185	0.207	0.252	13,971
Income	57,666	15,224	47,499	53,822	64,309	13,971
Age	36.016	2.539	34.20	35.80	37.40	13,971
Household %	61.113	7.643	57.61	62.30	66.37	13,971
Male-to-Female	95.362	3.575	93.21	94.88	97.66	13,971
Minority	35.011	13.579	25.01	34.93	43.32	13,971
Table 4						
Post Use of AI	0.420	0.494	0	0	1	12,010
Post Use of Broad AI	0.420	0.494	0	0	1	12,010
Post Use of Narrow AI	0.276	0.447	0	0	1	12,010
Post Use of AI × Rural	0.452	0.558	0	0	1	12,010
Post Use of AI × Initial AI Exposure	0.140	0.167	0	0	0.33	12,010
# Jobs	50.38	113.11	5	12	38	12,010
# AI Jobs	1.495	5.498	0	0	0	12,010
# Non-AI Jobs	48.88	109.07	4	12	37	12,010
# Auditor Jobs	11.34	22.99	2	4	11	12,010
Table 5						
Post Use of AI	0.443	0.497	0	0	1	10,554
# Baseline Skills	3.892	2.086	2.37	3.50	5.00	10,554
# Specialized Skills	10.073	4.280	7.25	9.79	12.50	10,554
# Software Skills	1.589	1.629	0.28	1.11	2.38	10,554
# Cognitive Skills	0.752	0.637	0.33	0.63	1.00	10,554
# Social Skills	1.168	0.780	0.60	1.04	1.67	10,554
# Character Skills	0.752	0.581	0.33	0.67	1.00	10,554

Table 2

Summary Statistics – *Continued*

	Mean	Stdev	25th	50th	75th	#Obs.
Table 5 – *Continued*	(1)	(2)	(3)	(4)	(5)	(6)
# Writing Skills	0.437	0.411	0.00	0.36	0.67	10,554
# Customer Service Skills	0.618	0.589	0.19	0.50	1.00	10,554
# Project Management Skills	0.225	0.268	0.00	0.17	0.33	10,554
# People Management Skills	0.614	0.497	0.25	0.50	1.00	10,554
# Financial Skills	3.731	2.132	2.25	3.35	4.80	10,554
# General Computer Skills	0.723	0.931	0.00	0.40	1.00	10,554
# Specific Software Skills	0.274	0.513	0.00	0.00	0.40	10,554
Table 6						
# Years of Education Mean	15.845	1.421	16	16	16	11,563
% At Least a Bachelor	0.907	0.173	0.88	1.00	1.00	11,563
% At Least a Master	0.036	0.124	0.00	0.00	0.00	11,563
% No Minimum Education Requirements	0.091	0.172	0.00	0.00	0.12	11,563
# Certification	1.683	0.850	1.00	1.50	2.00	12,414
% Accounting Major	0.794	0.310	0.67	1.00	1.00	10,736
% Business Major	0.607	0.372	0.33	0.67	1.00	10,736
% Tax or Law Major	0.248	0.313	0.00	0.13	0.40	10,736
% STEM Major	0.091	0.187	0.00	0.00	0.11	10,736
Table 7						
$ Job Salary	97,319	38,786	71,770	93,000	118,500	15,753
Table 8						
$ Salary	95,831	25,465	81,000	94,500	109,500	953
$ Salary Min	80,002	20,391	67,000	78,000	91,700	953
$ Salary Max	111,661	32,516	94,000	110,000	128,250	953
$ Salary Fluctuation	24,646	13,074	15,513	24,705	32,914	574
$ Min Salary Fluctuation	20,409	11,063	12,503	20,748	27,592	574
$ Max Salary Fluctuation	29,371	15,711	19,336	28,787	38,711	574
Table 9						
Use of AI	0.218	0.413	0.00	0.00	0.00	12,010
Religion is Important	0.528	0.087	0.45	0.52	0.59	12,010
Believe in God	0.869	0.047	0.84	0.87	0.91	12,010

Table 2

Summary Statistics – *Continued*

	Mean	Stdev	25th	50th	75th	#Obs.
Table 10	(1)	(2)	(3)	(4)	(5)	(6)
Post Use of Auditors with AI Skills	0.212	0.409	0	0	0	3,240
Expressed in percentage points:						
% Going Concern Audit Opinions (in %)	5.59	15.47	0	0	0	3,240
% Restatements	9.39	15.48	0	0	14.9	3,240
% Adverse Restatements	7.67	13.99	0	0	11.8	3,240
% Improving Restatements	2.14	7.08	0	0	0	3,240
% Frauds	0.07	0.85	0	0	0	3,240
% Clerical Errors	0.03	1.76	0	0	0	3,240
% Restatements due to SEC Investigations	0.32	2.35	0	0	0	3,240
% Effective Internal Control	94.20	15.20	95.7	1	1	2,875
% Big R *Restatements*	3.48	10.32	0	0	0	2,709
% Small R *Restatements*	10.66	17.52	0	0	16.67	2,709
Audit Lag (in days)	71.28	20.92	59.17	67.00	77.20	2,957
Firm Size	2.838	1.246	2	3	4	3,240
# Occupations	98.31	45.01	67.0	100.0	136.0	3,240

Table 3

Using Artificial Intelligence

This table reports the coefficient estimates of linear probability model regressions. Each observation is at the audit office-quarter level. *Use of AI* is an indicator variable that equals one if an audit office posts a job requiring artificial intelligence skills in a given quarter. *Peer Use of AI* is the percentage of audit offices with jobs requiring artificial intelligence skills in a city in year *t*-1. *Market Concentration* is the Herfindahl-Hirschman index (HHI) of the number of jobs by all audit offices in a city in year *t*-1. *Firm Size* is the quintile score based on the number of states where auditors have their offices in a given year. *# Occupations* the number of occupations in the job ads by an audit office in a given year. Details of other variables are in Appendix A. Our sample of quarterly panel of audit offices is from 2011 to 2019. Standard errors clustered by local audit office are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variable: *Use of AI*			
Independent Variables	(1)	(2)	(3)	(4)
Peer Use of AI	0.521**	0.404*	0.523**	
	(0.221)	(0.210)	(0.224)	
Market Concentration	0.012	0.010	-0.004	
	(0.021)	(0.021)	(0.023)	
Firm Size			0.018**	0.080***
			(0.008)	(0.022)
# Occupations			0.164***	0.007
			(0.019)	(0.025)
PCAOB Registrant			-0.304***	
			(0.109)	
Unemployment		-0.021***	-0.018**	
		(0.008)	(0.009)	
Population		0.172	0.162	
		(0.147)	(0.167)	
Education		0.394	0.288	
		(1.658)	(1.819)	
Income Ln		0.499*	0.522*	
		(0.289)	(0.308)	
Age		-0.037	-0.039	
		(0.022)	(0.025)	
Household		-0.363	-0.663	
		(0.967)	(1.058)	

Table 3

Using Artificial Intelligence – *Continued*

	Dependent Variable: *Use of AI*			
Independent Variables	(1)	(2)	(3)	(4)
Male		-0.020**	-0.024**	
		(0.009)	(0.010)	
Minority		-0.006	-0.005	
		(0.005)	(0.006)	
City FEs	Yes	Yes	Yes	
Year-Quarter FEs	Yes	Yes	Yes	
Auditor FEs	Yes	Yes		
City × Year-Quarter FEs				Yes
Auditor × City FEs				Yes
# Observations	13,971	13,971	13,971	12,010
Adjusted R-squared	0.407	0.409	0.262	0.475
# Audit firms	43	43	43	41
# Audit offices	628	628	628	517
# Cities	189	189	189	89

Table 4

Use of AI Technology Creates More Jobs

This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the audit office-quarter level. In panels A and B, *# Jobs* is the number of jobs at an audit office in a given quarter. *# AI Jobs* is the number of AI-related jobs at an audit office in a given quarter. *# Non-AI Jobs* is the number of non-AI-related jobs at an audit office in a given quarter. *# Auditor Jobs* is the number of auditor jobs at an audit office in a given quarter. *Post* is an indicator variable that equals one after an audit office posts a job requiring artificial intelligence skills. *Post Use of AI* is an indicator variable that equals one after an audit office has posted a job requiring artificial intelligence skills in a given quarter. In panel B, *Pre Use of AI* is an indicator variable that equals one for the four quarters before an audit office posts a job requiring artificial intelligence skills. In Panel C, *Broad AI* is an indicator variable that takes one if an audit office posts a job requiring skill clusters on artificial intelligence, machine learning, natural language processing, or data science. *Narrow AI* is an indicator variable that takes one if an audit office posts a job requiring any AI skills in the Appendix B. *Rural* is the rural-urban continuum score from 1 (urban) to 7 (rural) of the county where an audit office is located. *Initial AI Exposure* is the occupational-level AI exposure score following Felten et al. (2018) in the first quarter when an audit office initially posts a job. A higher *Initial AI Exposure* means that an audit office has greater opportunities to replace their current workers with AI technology. Details of other variables are in Appendix A. Our sample of quarterly panel of audit offices is from 2011 to 2019. Standard errors clustered by local audit office are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Number of Jobs

	Dependent Variables:			
	# Jobs (Ln)	*# AI Jobs (Ln)*	*# Non-AI Jobs (Ln)*	*# Auditor Jobs (Ln)*
Independent Variables	(1)	(2)	(3)	(4)
Post Use of AI	0.364***	0.414***	0.313***	0.150***
	(0.059)	(0.038)	(0.052)	(0.044)
Firm Size	0.134*	0.121***	0.125*	0.166***
	(0.080)	(0.040)	(0.073)	(0.053)
# Occupations	0.991***	-0.049	0.850***	0.594***
	(0.067)	(0.043)	(0.062)	(0.056)
City × Year-Quarter FEs	Yes	Yes	Yes	Yes
Auditor × City FEs	Yes	Yes	Yes	Yes
# Observations	12,010	12,010	12,010	12,010
Adjusted R-squared	0.773	0.660	0.787	0.671
Economic Magnitude of *Post Use of AI*	43.9%	51.3%	36.8%	16.2%

Table 4

Use of AI Technology Creates More Jobs – *Continued*

Panel B: Pre-Trends

Independent Variables	*# Jobs (Ln)* (1)	*# AI Jobs (Ln)* (2)	*# Non-AI Jobs (Ln)* (3)	*# Auditor Jobs (Ln)* (4)
Pre Use of AI	0.015	-0.191**	0.018	0.021
	(0.192)	(0.088)	(0.175)	(0.103)
Post Use of AI	0.371***	0.321***	0.322***	0.161***
	(0.051)	(0.042)	(0.046)	(0.044)
Firm Size	0.134	0.116	0.125	0.167
	(0.297)	(0.119)	(0.273)	(0.176)
# Occupations	0.991***	-0.052	0.850***	0.594***
	(0.155)	(0.095)	(0.143)	(0.117)
City × Year-Quarter FEs	Yes	Yes	Yes	Yes
Auditor × City FEs	Yes	Yes	Yes	Yes
# Observations	12,010	12,010	12,010	12,010
Adjusted R-squared	0.773	0.663	0.787	0.671

Panel C: Cross-Sectional Tests

	Dependent Variable: # *Auditor Jobs (Ln)*		
Independent Variables	(1)	(2)	(3)
Post Use of Broad AI	0.128**		
	(0.051)		
Post Use of Narrow AI	0.045		
	(0.054)		
Post Use of AI × Rural		0.130***	
		(0.037)	
Post Use of AI × *Initial AI Exposure*			0.498***
			(0.134)
Control Variables	Identical to those in table 4, panel A, column 4		
City × Year-Quarter FEs	Yes	Yes	Yes
Auditor × City FEs	Yes	Yes	Yes
# Observations	12,010	12,010	12,010
Adjusted R-squared	0.671	0.671	0.671
Economic Magnitude of			
Post Use of Broad AI	13.7%		
Post Use of AI × Rural		13.9%	
1 S.D. Δ in *Post Use of AI × Initial AI Exposure*			8.7%

Table 5
Upskilling in Job Requirements

This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the audit office-quarter level. *Post Use of AI* is an indicator variable that equals one after an audit office has posted a job requiring artificial intelligence skills in a given quarter. In Panel A, # *Baseline Skills* is the average number of baseline skills (e.g., analytical, multitasking) required per auditor job at an audit office in a given quarter. # *Specialized Skills* is the average number of specialized skills (e.g., budgeting, internal auditing) required per auditor job at an audit office in a given quarter. # *Software Skills* is the average number of software skills (e.g., Excel, SAP) required per auditor job at an audit office in a given quarter. In Panel B, # *Cognitive Skills* is the average number of cognitive skills (e.g., problem solving, critical thinking) required per auditor job at an audit office in a given quarter. # *Social Skills* is the average number of social skills (e.g., communication, teamwork) required per auditor job at an audit office in a given quarter. # *Writing Skills* is the average number of writing skills (e.g., written communication, proposal writing) required per auditor job at an audit office in a given quarter. # *People Management Skills* is the average number of people management skills (e.g., leadership, staff management) required per auditor job at an audit office in a given quarter. Details of other variables are in Appendix A. Our sample of quarterly panel of audit offices is from 2011 to 2019. Standard errors clustered by local audit office are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Skill Classifications Based on Burning Glass			
	Dependent Variables:		
	# Baseline Skills (Ln)	*# Specialized Skills (Ln)*	*# Software Skills (Ln)*
Independent Variables	(1)	(2)	(3)
Post Use of AI	0.029	0.068***	0.026
	(0.020)	(0.023)	(0.027)
Control Variables	Identical to those in table 4, panel A, column 4		
City × Year-Quarter FEs	Yes	Yes	Yes
Auditor × City FEs	Yes	Yes	Yes
# Observations	10,554	10,554	10,554
Adjusted R-squared	0.485	0.354	0.465
Economic Magnitude of *Post Use of AI*		7.0%	

Table 5

Upskilling in Job Requirements – *Continued*

Panel B: Skill Classifications Based on Deming and Khan (2018)										
	Dependent Variables:									
	# Cognitive Skills (Ln)	*# Social Skills (Ln)*	*# Character Skills (Ln)*	*# Writing Skills (Ln)*	*# Customer Service Skills (Ln)*	*# Project Management Skills (Ln)*	*# People Management Skills (Ln)*	*# Financial Skills (Ln)*	*# General Computer Skills (Ln)*	*# Specific Software Skills (Ln)*
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post Use of AI	0.030*	0.033*	0.022	0.021*	0.011	0.008	0.026*	0.016	-0.016	0.025
	(0.017)	(0.019)	(0.018)	(0.012)	(0.016)	(0.010)	(0.015)	(0.028)	(0.018)	(0.015)
Control variables	Identical to those in table 4, panel A, column 4									
City × Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Auditor × City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	10,554	10,554	10,554	10,554	10,554	10,554	10,554	10,554	10,554	10,554
Adjusted R-squared	0.441	0.469	0.328	0.462	0.432	0.275	0.382	0.336	0.590	0.355
Economic Magnitude of *Post Use of AI*	3.0%	3.4%		2.1%			2.6%			

Table 6
Upskilling in Education Requirements

This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the audit office-quarter level. *Post Use of AI* is an indicator variable that equals one after an audit office has posted a job requiring artificial intelligence skills in a given quarter. *# Years of Education (Ln)* is the average years of education required per auditor job at an audit office in a given quarter. *% At Least a Bachelor* is the percentage of auditor jobs requiring at least a bachelor's degree at an audit office in a given quarter. *% At Least a Master* is the percentage of auditor jobs requiring at least a master's degree at an audit office in a given quarter. *% No Minimum Education Requirements* Percentage of auditor jobs that do not specific minimum education requirements at an audit office in a given quarter. *# Certification* is the average number of certifications required per auditor job at an audit office in a given quarter. In Panel B, *% Accounting Major* is the percentage of auditor jobs requiring a major in accounting at an audit office in a given quarter. *% Business Major* is the percentage of auditor jobs requiring a major in business at an audit office in a given quarter. *% Tax or Law Major* is the percentage of auditor jobs requiring a major in tax or law at an audit office in a given quarter. *% STEM Major* is the percentage of auditor jobs requiring a major in STEM (e.g. computer science, engineering, information technology, statistics, mathematics) at an audit office in a given quarter. Details of other variables are in Appendix A. Our sample of quarterly panel of audit offices is from 2011 to 2019. Standard errors clustered by local audit office are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Education

	Dependent Variables:				
	# Years of Education (Ln)	*% At Least a Bachelor*	*% At Least Master*	*% No Minimum Education*	*# Certification (Ln)*
Independent Variables	(1)	(2)	(3)	(4)	(5)
Post Use of AI	-0.007	0.030***	0.001	-0.029***	0.040*
	(0.011)	(0.010)	(0.007)	(0.010)	(0.020)
Control Variables/FEs	Identical to those in table 4, panel A, column 4				
# Observations	11,563	11,563	11,563	11,563	12,414
Adjusted R-squared	0.321	0.231	0.141	0.234	0.345

Table 6

Upskilling in Education Requirements – *Continued*

Panel B: Majors				
	% Accounting Major	*% Business Major*	*% Tax or Law Major*	*% STEM Major*
Independent Variables	(1)	(2)	(3)	(4)
Post Use of AI	-0.016	0.004	-0.076***	0.024**
	(0.014)	(0.017)	(0.016)	(0.011)
Control Variables/FEs	Identical to those in table 4, panel A, column 4			
# Observations	10,736	10,736	10,736	10,736
Adjusted R-squared	0.571	0.472	0.339	0.203

Table 7
AI Increases Costs

This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the job level. In this table, *Job Salary* is the salary in a job. *AI Skills* is an indicator variable that equals one if a job requires artificial intelligence skills. Other independent variables are similarly constructed. Each variable is an indicator variable that equals one if a job requires that particular type of skills. Standard errors clustered by local audit office are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variable: *$ Job Salary (Ln)*			
Independent Variables	(1)	(2)	(3)	(4)
AI Skills	0.151***	0.113***	0.092***	0.073***
	(0.012)	(0.014)	(0.013)	(0.016)
Specific Software Skills		0.100***	0.077***	0.060***
		(0.011)	(0.012)	(0.012)
General Computer Skills		-0.109***	-0.060***	-0.046***
		(0.013)	(0.011)	(0.008)
Cognitive Skills		0.028**	-0.003	-0.027***
		(0.011)	(0.008)	(0.007)
Social Skills		0.059***	0.041***	0.013*
		(0.009)	(0.008)	(0.008)
Character Skills		-0.025**	-0.019*	0.004
		(0.011)	(0.010)	(0.009)
Writing Skills		0.025***	0.010	0.016**
		(0.009)	(0.008)	(0.007)
Customer Service Skills		-0.001	0.007	0.019***
		(0.008)	(0.008)	(0.007)
Project Management Skills		0.096***	0.063***	0.029***
		(0.012)	(0.011)	(0.009)
People Management Skills		0.097***	0.050***	0.014
		(0.011)	(0.010)	(0.008)
Financial Skills		0.096***	0.026***	0.009
		(0.014)	(0.009)	(0.009)
City × Year-Quarter FEs	Yes	Yes	Yes	Yes
Auditor × City FEs	Yes	Yes	Yes	Yes
Job Title FEs			Yes	Yes
Occupation × City FEs				Yes
# Observations	15,753	15,753	15,529	14,434
Adjusted R-squared	0.257	0.315	0.525	0.609

Table 8

More Fluctuation in Salary Structure

This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the audit office-quarter level. *Post Use of AI* is an indicator variable that equals one after an audit office has posted a job requiring artificial intelligence skills in a given quarter. *$ Salary* is the average salary per auditor job at an audit office in a given quarter. *$ Salary Min* is the average minimum salary per auditor job at an audit office in a given quarter. *$ Salary Max* is the average of the maximum salary per auditor job at an audit office in a given quarter. *$ Min Salary Fluctuation* is the standard deviation of the minimum salary per auditor job at an audit office in a given quarter. *$ Max Salary Fluctuation* is the standard deviation of the maximum salary per auditor job at an audit office in a given quarter. Details of other variables are in Appendix A. Our sample of quarterly panel of audit offices is from 2011 to 2019. Standard errors clustered by local audit office are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variables:					
	$ Salary (Ln)	*$ Salary Min (Ln)*	*$ Salary Max (Ln)*	*$ Salary Fluctuation (Ln)*	*$ Min Salary Fluctuation (Ln)*	*$ Max Salary Fluctuation (Ln)*
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Post Use of AI	0.063	0.061	0.062	0.538*	0.359	0.745**
	(0.042)	(0.041)	(0.044)	(0.317)	(0.280)	(0.367)
Control variables	Identical to those in table 4, panel A, column 4					
City × Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Auditor × City FEs	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	953	953	953	574	574	574
Adjusted R-squared	0.322	0.301	0.332	0.554	0.545	0.572
Economic Magnitude of *Post Use of AI*				71%		111%

Table 9

IV Tests

This table reports the two-stage least squares model regressions. Each observation is at the audit office-quarter level. *Use of AI* is separately instrumented by two variables. In Panel A, *Religion is Important* is a decile score based on the percentage of respondents in a state in a given year who answer "very important" to "how important is religion in your life?" in the Religious Landscape Survey by Pew Research Center. A score of ten means a very strong belief that religion is important. In Panel B, *Believe in God* is a decile score based on the percentage of respondents in a state in a given year who answer "yes" to "do you believe in God or a universal spirit?" in the Religious Landscape Survey by Pew Research Center. A score of ten means a very strong belief in God. Details of other variables are in Appendix A. Our sample of quarterly panel of audit offices is from 2011 to 2019. Standard errors clustered by local audit office are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Religion is Important as IV					
	First-Stage	Second-Stage			
		Dependent Variables:			
	Use of AI	*# Jobs (Ln)*	*# AI Jobs (Ln)*	*# Non-AI Jobs (Ln)*	*# Auditor Jobs (Ln)*
Independent Variables	(1)	(2)	(3)	(4)	(5)
Religion is Important	-0.014** (0.006)				
Instrumented *Use of AI*		3.208** (1.520)	1.185*** (0.453)	2.439** (1.229)	2.655** (1.326)
Control variables	Identical to those in table 4, panel A, column 4				
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes
Auditor × City FEs	Yes	Yes	Yes	Yes	Yes
# Observations	12,010	12,010	12,010	12,010	12,010
First-stage *F*-statistic	9.74*** (p=0.008)				

Table 9

IV Tests – *Continued*

Panel B: Believe in God as IV					
	First-Stage	Second-Stage			
	Dependent Variables:				
	Use of AI	*# Jobs (Ln)*	*# AI Jobs (Ln)*	*# Non-AI Jobs (Ln)*	*# Auditor Jobs (Ln)*
Independent Variables	(1)	(2)	(3)	(4)	(5)
Believe in God	-0.013**				
	(0.006)				
Instrumented *Use of AI*		-0.324	2.216***	-0.149	0.498
		(1.169)	(0.657)	(0.991)	(0.940)
Control variables	Identical to those in table 4, panel A, column 4				
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes
Auditor × *City FEs*	Yes	Yes	Yes	Yes	Yes
# Observations	12,010	12,010	12,010	12,010	12,010
First-stage *F*-statistic	5.46**				
	(p=0.019)				

Table 10

Audit Fees and Audit Quality

This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the audit office-year level. *Post Use of Auditors with AI Skills* is an indicator variable that equals one after an audit office has posted an auditor job requiring artificial intelligence skills in a given year. *$ Audit Fees* is the sum of audit fees at an audit office in a given year. *$ Tax Fees* is the sum of tax fees at an audit office in a given year. *% Restatements* is the percentage of audit clients with future restatements at an audit office in a given year. *% Adverse Restatements* is the percentage of audit clients with restatements that have an adverse effect on financial statements at an audit office in a given year. *% Improving Restatements* is the percentage of audit clients with restatements that have an improving effect on financial restatements at an audit office in a given year. *% Big R Restatements* is the percentage of audit clients with big R restatements at an audit office in a given year. *% Small R Restatements* is the percentage of audit clients with small R restatements at an audit office in a given year. *Audit Lag* is the number of days between an audit client's fiscal year-end and the date of audit opinion. *Audit Lag* is averaged by audit-office per year. Details of other variables are in Appendix A. Online appendices tables 1 and 2 include the coefficient estimates of other fee-related and audit-quality variables. Our sample of yearly panel of audit offices is from 2011 to 2019. Standard errors clustered by local audit office are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variables:							
	$ Audit Fees (Ln)	*$ Tax Fees (Ln)*	*% Restatements*	*% Adverse Restatements*	*% Improving Restatements*	*% Big R Restatements*	*% Small R Restatements*	*Audit Lag (Ln)*
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Use of Auditors with AI Skills	-0.217	0.084	-0.046***	-0.038***	-0.012*	-0.022**	-0.021	-0.033**
	(0.479)	(0.224)	(0.012)	(0.011)	(0.007)	(0.010)	(0.016)	(0.016)
Control Variables/FEs	Identical to those in table 4, panel A, column 4							
City × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Auditor × City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	3,240	3,240	3,240	3,240	3,240	2,709	2,709	2,957
Adjusted R-squared	0.538	0.333	0.322	0.325	0.168	0.276	0.394	0.421

Online Appendices

How Does Artificial Intelligence Shape the Audit Industry?

Online Appendix Table 1
Audit Fees

This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the audit office-year level. *Post Use of Auditors with AI Skills* is an indicator variable that equals one after an audit office has posted an auditor job requiring artificial intelligence skills in a given year. *$ Audit Fees* is the sum of audit fees at an audit office in a given year. *$ Non-Audit Fees* is the sum of audit related, benefit plan related fees, financial information systems design and implementation related fees, tax related fees, and other miscellaneous fees at an audit office in a given year. *$ Total Fees* is the sum of audit and non-audit fees at an audit office in a given year. *$ Benefit Plan Audit Fees* is the sum of audit fees for benefit plans at an audit office in a given year. *$ IT Fees* is the sum of financial information systems design and implementation related fees at an audit office in a given year. *$ Tax Fees* is the sum of tax fees at an audit office in a given year. *$ Tax Compliance Fees* is the sum of tax compliance fees at an audit office in a given year. *$ Tax Advisory Fees* is the sum of tax advisory fees at an audit office in a given year. Details of other variables are in Appendix A. Our sample of yearly panel of audit offices is from 2011 to 2019. Standard errors clustered by local audit office are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variables:							
	$ Audit Fees (Ln)	*$ Non-Audit Fees (Ln)*	*$ Total Fees (Ln)*	*$ Benefit Plan Audit Fees (Ln)*	*$ IT Fees (Ln)*	*$ Tax Fees (Ln)*	*$ Tax Compliance Fees (Ln)*	*$ Tax Advisory Fees (Ln)*
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Use of Auditors with AI Skills	-0.217	-0.148	-0.276	-0.028	-0.413	0.084	0.097	-0.146
	(0.479)	(0.422)	(0.484)	(0.076)	(0.389)	(0.224)	(0.149)	(0.417)
Control variables	Identical to those in table 4, panel A, column 4							
City × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Auditor × City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	3,240	3,240	3,240	3,240	3,240	3,240	3,240	3,240
Adjusted R-squared	0.538	0.542	0.540	0.417	0.528	0.333	0.293	0.498

Online Appendix Table 2

Audit Quality

This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the audit office-year level. *Post Use of Auditors with AI Skills* is an indicator variable that equals one after an audit office has posted an auditor job requiring artificial intelligence skills in a given year. *% Going Concern Audit Opinions* is the percentage of audit clients with going concern audit opinions at an audit office in a given year. *% Restatements* is the percentage of audit clients with future restatements at an audit office in a given year. *% Adverse Restatements* is the percentage of audit clients with restatements that have an adverse effect on financial statements at an audit office in a given year. *% Improving Restatements* is the percentage of audit clients with restatements that have an improving effect on financial restatements at an audit office in a given year. *% Frauds* is the percentage of audit clients with frauds in their financial statements at an audit office in a given year. *% Clerical Errors* is the percentage of audit clients with clerical errors in their financial statements at an audit office in a given year. *% Restatements due to SEC Investigations* is the percentage of audit clients with restatements due to SEC investigations at an audit office in a given year. *% Effective Internal Control* is the percentage of audit clients with effective internal control at an audit office in a given year. *% Big R Restatements* is the percentage of audit clients with big R restatements at an audit office in a given year. *% Small R Restatements* is the percentage of audit clients with small R restatements at an audit office in a given year. Details of other variables are in Appendix A. Our sample of yearly panel of audit offices is from 2011 to 2019. Standard errors clustered by local audit office are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variables:									
	% Going Concern Audit Opinions	*% Restatements*	*% Adverse Restatements*	*% Improving Restatements*	*% Frauds*	*% Clerical Errors*	*% Restatements due to SEC Investigations*	*% Effective Internal Control*	*% Big R Restatements*	*% Small R Restatements*
Independent Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post Use of Auditors with AI Skills	0.006	-0.046***	-0.038***	-0.012*	-0.000	0.001	-0.001	0.006	-0.022**	-0.021
	(0.011)	(0.012)	(0.011)	(0.007)	(0.001)	(0.001)	(0.002)	(0.013)	(0.010)	(0.016)
Control variables	Identical to those in table 4, panel A, column 4									
City × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Auditor × City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	3,240	3,240	3,240	3,240	3,240	3,240	3,240	2,875	2,709	2,709
Adjusted R-squared	0.486	0.322	0.325	0.168	0.239	-0.100	0.288	0.253	0.276	0.394

Online Appendix Table 3
Earnings Management

This table reports the coefficient estimates of ordinary least squares model regressions. Each observation is at the audit office-year level. *Post Use of Auditors with AI Skills* is an indicator variable that equals one after an audit office has posted an auditor job requiring artificial intelligence skills in a given year. *Signed (Absolute) Discretionary Accruals – Modified Jones Model* is the signed (absolute value of) discretionary accruals estimated using modified Jones model. *Signed (Absolute) Discretionary Accruals - Kothari et al. (2005)* is the signed (absolute value of) performance-matched discretionary accruals following Kothari et al. (2005). *Signed (Absolute) Discretionary Accruals - Kothari et al. (2015)* is the signed (absolute value of) performance-matched discretionary accruals following Kothari et al. (2015) with firm and year fixed effects included in the accrual estimation. Details of other variables are in Appendix A. Our sample of yearly panel of audit offices is from 2011 to 2019. Standard errors clustered by local audit office are in parentheses. Intercepts are included for estimation but not tabulated. ***, **, and * indicate two-tailed *t*-statistics with statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variables:					
	Signed Discretionary Accruals: Modified Jones Model	*Signed Discretionary Accruals: Kothari et al. (2005)*	*Signed Discretionary Accruals: Kothari et al. (2015)*	*Absolute Discretionary Accruals: Modified Jones Model*	*Absolute Discretionary Accruals: Kothari et al. (2005)*	*Absolute Discretionary Accruals: Kothari et al. (2015)*
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Post Use of Auditors with AI Skills	-0.006 (0.006)	-0.014* (0.009)	-0.001 (0.004)	0.005 (0.005)	0.001 (0.007)	0.003 (0.004)
Control Variables/FEs	Identical to those in table 4, panel A, column 4					
City × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Auditor × City FEs	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	2,766	2,766	2,782	2,766	2,766	2,782
Adjusted R-squared	0.157	0.098	0.134	0.326	0.246	0.383