Digitalization, Accounting Jobs, and Financial Reporting Quality*

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May 2022

ABSTRACT

This study examines the effect of firm digitalization on the demand for corporate accountants and their digital skills. Using 170,000 job posts for corporate accountants made by U.S. non-technology firms during the 2011–2019 period, we find that firms that adopt digital technologies demand more digital skills from financial specialists who are responsible for financial reporting, budgeting, and forecasting, but not for financial clerks who mainly focus on administrative financial tasks. Meanwhile, we find the overall demand for financial specialists does not change, but that for financial clerks reduces. Furthermore, we find that firm digitalization and financial specialists' digital skills jointly improve financial accounting quality. Our results suggest that firm digitalization does not substitute for financial specialists and that investment in employees' digital skills is necessary for a firm to benefit from its digitalization strategy.

Keywords: digitalization, accountants, digital skills, human capital, financial reporting quality

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* We wish to thank the workshop participants at Singapore Management University for their helpful comments. Cheng acknowledges funding from the Lee Kong Chian Chair Professorship and Wang acknowledges funding from the Lee Kong Chian Fellowship at Singapore Management University. Please contact the authors at aawyong.2018@phdacc.smu.edu.sg (Amanda Awyong), qcheng@smu.edu (Qiang Cheng), tian.deng.2018@phdacc.smu.edu.sg (Tian Deng), and rcwang@smu.edu.sg (Rencheng Wang) for comments.

1 Introduction

The last decade has witnessed increasing corporate investment in digital technologies, such as analytics, automation, artificial intelligence, big data, cloud computing, and machine learning. Investment in such technologies is now a key component of business strategy. According to the McKinsey Global Institute (2021), nearly 90% of surveyed executives agreed that their company could only remain economically viable by developing new digital businesses and embedding digital technologies in their current business model.[1] In the accounting profession, the increasing application of digital technologies has provided novel opportunities. For instance, such technologies can generate fresh insights that can inform corporate decision-making. At the same time, they bring many challenges, as they change the skillset required of accounting professionals and potentially substitute for accounting jobs. However, to date, there has been little large-scale empirical research on how digital technologies affect the corporate accounting labor market. This paper fills this gap by examining whether digital technologies substitute for or complement accounting human capital in the labor market for accounting professionals and by considering their effect on financial reporting quality.

It is important to examine the relation between firms' adoption of digital technologies and accounting human capital for three reasons. First, investments in digital technologies are projected to be over US$4.5 trillion in 2022 worldwide (Gartner 2021). Despite these substantial investments, previous studies have not reached a consensus on whether and how these investments yield economic gains. For example, while Brynjolfsson, Rock, and Syverson (2018) and Cockburn, Henderson, and Stern (2018) argue that digital technologies increase firms' growth opportunities and productivity, Chen and Srinivasan (2021) find that

[1] The online survey garnered responses from 700 participants representing a full range of regions, industries, company sizes, functional specialities, and tenures.

firm digitalization is associated with lower profit margins and sales growth. We contribute to this debate by examining the impact of firm digitalization on a specific corporate decision—the number of accountants to recruit and their required skillsets—and on a specific corporate outcome, financial reporting quality.

Second, there is limited evidence on whether digital technologies substitute for or complement accounting human capital, which is an issue with important implications for the six million accountants in the U.S.[2] Some commentators and researchers argue that digital technologies will result in job losses because they can replace routine and repetitive tasks (Autor, Levy, and Murnane 2003; Acemoglu and Restrepo 2019). Others argue that digital technologies can improve firm productivity and increase the demand for new goods and services. As firms increase in size and complexity, accounting professionals can use their digital skills, such as data analytics, to obtain valuable insights from financial data, identify areas for process improvements, increase efficiency, and better manage risk—tasks that cannot be easily performed by machines (McKinsey Global Institute 2017). Thus, how applications of digital technologies affect the demand for corporate accounting professionals and their skillsets is an important yet underexplored empirical question.

Third, understanding how digital technologies transform the demand for accounting professionals has implications for accounting educators. Accounting programs are increasingly integrating digital technologies such as data analytics into their curricula. While the Association to Advance Collegiate Schools of Business (AACSB) mandates such integration in its accredited schools, specific guidance is limited (Andiola, Masters, and

[2] The Bureau of Labor Statistics estimates that there were over six million accountants including financial specialists and financial clerks in the U.S. in 2020. Financial specialists are workers with a Standard Occupational Classification (SOC) code of 13-2000, which includes financial analysts, internal auditors, and accountants. Financial clerks are workers with an SOC code of 43-3000. See details at https://www.bls.gov/emp/tables/occupational-projections-and-characteristics.htm.

Norman 2020).[3] A large-scale empirical investigation of the demand for and usefulness of data analytics skills in the workplace can contribute to the design of accounting curricula.

We begin our study by investigating how firm digitalization affects the demand for corporate accountants and the skills required of them. If most accounting jobs involve repetitive and routine tasks, for which digital technologies can be substituted (Frey and Osborne 2017; West 2018; Susskind 2020; Fedyk et al. 2021), digitalized firms would experience a decrease in the demand for accountants. However, we would not observe such an effect if accounting jobs require cognitive skills because, as suggested by Autor et al. (2003) and Brynjolfsson, Mitchell, and Rock (2018), it is difficult for digital technologies to replace tasks that require sophisticated cognitive skills.[4] In addition, accountants are required to interact with people both within and outside of the accounting department (Ham et al. 2021), and such interactions, which are critical to information transfer within a firm, cannot be replaced by technologies (Deming 2017). However, even if firm digitalization does not reduce the demand for accountants, it might affect the skills required of accountants.

We next examine how financial reporting quality is affected by firm digitalization and its interaction with the skillsets of accounting human capital. Technology is integral to the financial reporting process and affects the quality of accounting information (Lim et al. 2011; Masli et al. 2011; Ashraf, Michas, and Russomanno 2020). Firms may leverage technology by deploying it to perform routine and time-consuming tasks, thereby improving the quality and efficiency of information processing (Trentmann 2022). If technology substitutes for accounting human capital, we expect financial reporting quality to be affected independently

[3] The 2018 AACSB standard (Standard A9) requires AACSB-accredited business schools to include "current emerging business statistical techniques, data management, data analytics and information technology in the curriculum (AACSB 2018, 37)."
[4] For example, the scandals surrounding ScaleFactor cast doubt on the ability of technology to automate bookkeeping. ScaleFactor claimed to use AI to automate bookkeeping for small businesses, but Forbes reported that ScaleFactor actually hired accountants to manually complete customers' books on the back end (Jeans 2020).

by both the adoption of digital technologies and the skillsets of accounting human capital. However, if technology complements accounting human capital, we expect firms' financial reporting quality to be affected jointly by the adoption of digital technologies and the skillsets of accounting human capital, particularly digital skills.

Empirically, we follow Chen and Srinivasan (2021) and measure the level of a non-technology firm's digitalization based on the number of digital-related terms in its 10-K filings.[5, 6] Our sample period is 2011–2019, during which firm digitalization became more prevalent. To examine how firm digitalization affects the hiring of accountants, we use a near-universe of online job postings in the U.S. from Burning Glass Technologies. Each job post in the dataset includes detailed information on the employer, occupation, and skills demanded of the prospective candidate. Our sample focuses on corporate accounting professionals, including around 170,000 job posts over our sample period for the sample firms. We follow Standard Occupational Classification (SOC) defined by the Bureau of Labor Statistics and focus on two groups of corporate accountants, financial specialists and financial clerks. Financial specialists are those who are responsible for financial reporting, budgeting, forecasting, and specific requirements such as those under the SOX Act, while financial clerks perform administrative financial tasks such as entering transactions into accounting software, sending invoices to customers, and administering employee payrolls. We find that firm digitalization is not associated with the overall number of accountants that a firm tries to recruit. However, when we separate financial specialists from financial clerks, we find that while firm digitalization is not associated with the number of financial specialists, it is negatively associated with the number of financial clerks that a firm tries to recruit. These results suggest that digital technologies reduce the demand for jobs that are

[5] While initial investments in new digital technologies were concentrated in technology industries, such investments were mostly related to development of digital products, which is outside the scope of our study.
[6] Please refer to Appendix A for the list of keywords used to identify digital-related terms in firms' 10-K filings.

relatively repetitive but do not affect the demand for jobs that require professional judgment.

We next examine how firm digitalization affects the skillsets required of accountants. Following prior studies (e.g., Acemoglu et al. 2020; Chen and Srinivasan 2021; Gao, Huang, and Wang 2021), we use a series of keywords from the job postings to capture the digital skills specified in each job post.[7] We find that firm digitalization increases the percentage of job postings for financial specialists that require them to have digital skills. Specifically, a one-standard-deviation increase in our firm digitalization measure is associated with a relative increase of 10% in the percentage of job postings requiring financial specialists to have digital skills relative to the sample mean. However, firm digitalization does not increase the demand for financial specialists' other skills (e.g., financial skills, social skills, and accounting majors) or for their general ability (e.g., a CPA designation, a Bachelor's degree, and work experience), suggesting that the results on financial specialists' digital skills are not driven by firms' demand for more qualified financial specialists. In contrast, we find that firm digitalization does not increase the demand for financial clerks' digital skills. These results hold when we control for the factors that may affect a firm's decision to digitalize and firm and year fixed effects. These results suggest that financial specialists' digital skills are more relevant to a firm's digitalization strategy than financial clerks' digital skills or financial specialists' non-digital skills.

We next examine whether firm digitalization and financial specialists' digital skills independently or jointly affect financial reporting quality. Using a set of accrual-based measures, namely discretionary accruals (Dechow, Sloan, and Sweeney 1995), discretionary working capital accruals (McNichols 2002; Francis et al. 2005), and discretionary revenues (McNichols and Stubben 2008; Stubben 2010), and a composite measure of the three individual measures, we first show that firm digitalization alone does not affect financial

[7] Please refer to Appendix B for the list of keywords used to identify digital skills in job postings.

reporting quality. Similarly, financial specialists' digital skills per se do not affect a firm's financial reporting quality. We next show that digitalized firms that hire more financial specialists with digital skills have higher financial reporting quality than other firms. Specifically, one-standard-deviation increases in firm digitalization and the percentage of financial specialists with digital skills lead to a relative decrease of 2.1% to 3.9% of the standard deviation of the financial reporting quality measures. A cross-sectional analysis indicates that this effect is stronger for firms with more Level 2 and Level 3 fair value-based assets and liabilities, consistent with the notion that digital technologies and accountants' digital skills together help firms to better measure balance sheet items that are inherently difficult to estimate. Further analyses indicate that the complementary effect is not driven by the digital skills of non-accountant employees, financial specialists' other skills, or financial specialists' general ability. Taken together, these results suggest that digital technologies and accounting human capital do not substitute for but complement each other in improving financial reporting quality.

We conduct a series of additional analyses to examine the sensitivity of our main results and to provide additional insights. First, we conduct a coarsened exact matching (CEM) analysis to address concerns that digitalized and non-digitalized firms are inherently different, and obtain the same inferences. Second, we examine the sensitivity of the baseline results to unobserved correlated variables using the method developed by Frank (2000), and the analysis indicates that it is unlikely that an unobserved confounding variable drives our results. Third, we find that our results continue to hold when we measure firm digitalization based on the intensity of different types of digitalization rather than the overall digitalization of a firm. Fourth, to address the concern that our measure of accountants' digital skills does not capture the skills of actual employees within a firm (i.e., the positions in the job postings remain unfilled), we use an alternative data source, the resumes of accountants working at

S&P 1500 firms, and confirm that job postings for accountants reasonably mirror the stock of accountants working in a firm in our sample. Lastly, we find that digital skills of accountants are not free: accountants with digital skills command higher annual salary than those without.

Our paper contributes to the literature in three ways. First, it extends the literature on the impact of technological changes on the demand for jobs (Deming 2017; Frey and Osborne 2017; Deming and Kahn 2018; Hershbein and Kahn 2018; Dillender and Forsythe 2019). Agrawal, Gans, and Goldfarb (2019) argue that the impact of technologies on the number of jobs varies by profession. It is thus important to examine this question for specific professions. In addition, given that the value created by technology investments is determined in part by the supply of professionals who can utilize the technologies to make better business decisions, it is surprising that there is little research on the labor market for skills complementary to digital transformation (Tambe 2014). Prior studies provide some evidence of the importance of technology-related human expertise, but mostly at the top management level (Ashraf et al. 2020; Chen and Srinivasan 2021). Aside from top management, rank-and-file employees, particularly those in accounting-related functions, are an important stakeholder group, yet their effect has remained relatively unexplored. We provide large-sample evidence that digital technology investments have a profound impact on accounting human capital, including the demand for and skills required of accountants.

Second, we add to the broad literature on the impact of human capital and technology investment on financial reporting quality. Prior studies have documented that human capital and technology investments influence financial reporting quality (Call et al. 2017; Pincus et al. 2017). However, there is little research examining how the interaction between human capital and technology investments affects financial reporting quality. Our study contributes to this line of research by showing that the complementarity between digital technologies and accounting human capital improves financial reporting quality.

Third, our study has important implications for the development of accounting professionals. At the operational level, the cost of adopting digital technologies is substantial for both firms and educational institutions (Heriot et al. 2009). While some call for an overhaul of accounting curricula to include more technology-oriented courses (PwC 2015), others caution that accounting professionals may only need to know how to interpret and convey the results and do not need programming and statistical analysis skills (Earley 2015). Our study shows that firm digitalization requires more accountants with digital skills and that technology and accounting human capital complement each other in improving financial reporting quality, suggesting the importance of digital skills for accountants.

Three recent studies examine the impact of digital technologies on the labor market for auditors. Law and Shen (2021) find that audit offices that have jobs requiring AI skills experience an increase in the number of auditor jobs and that AI implementation increases the skill and education requirements for auditor jobs. In contrast, Fedyk et al. (2021) find that audit firms' investments in AI reduce the number of employees over time. Ham et al. (2021) find that the demand for cognitive, social, and digital technology-related skills has increased for audit firms over time but that audit firms demand more social skills than the other two types of skills. Our study complements these studies by documenting that digital technologies have different impacts on corporate accounting professionals, who are less homogenous and have a wider range of tasks than auditors.

2 Literature Review and Hypothesis Development

2.1 Technologies and Jobs

Much of the public attention to technological advances focuses on their impact on employment. Early studies find that technological changes make middle-class jobs—those requiring a moderate skill level, like autoworkers' jobs—disappear relative to those at the top that require higher skill levels (Autor et al. 2003; Goos and Manning 2007; Autor, Katz, and Kearney 2008; Autor and Dorn 2013). For example, Autor et al. (2003) document that occupations in which there are larger capital investments in computers experience bigger decreases in the labor input of routine tasks. Dillender and Forsythe (2019) find that technology adoption is associated with a decrease in employment among many types of workers, including secretaries, administrative assistants, schedulers, and dispatchers. Recent studies further argue that while information technology (IT) has been historically confined to routine tasks involving explicit rule-based activities (Autor et al. 2003; Autor and Dorn 2013), algorithms for big data are now rapidly entering domains that rely on pattern recognition and can further substitute for a wider range of labor (Brynjolfsson and McAfee 2011; Acemoglu and Restrepo 2019). Acemoglu et al. (2020) find empirical evidence that the adoption of artificial intelligence (AI) has led to the automation of some tasks formerly performed by human labor and is associated with lower hiring in these occupational areas.

Other studies suggest that technologies could have a positive impact on jobs depending on the nature of the job and the related skillset. Autor et al. (2003) find that occupations in which there are larger capital investments in computers experience greater increases in the labor input of non-routine tasks. Technological changes require a large number of highly skilled and trained managers, highly trained technicians to design and maintain new tools, and front-line employees to use these tools (Frey and Osborne 2017). While Brynjolfsson and McAfee (2014) argue that advances in computing power can rapidly expand the set of tasks that machines can perform, skills and tasks that cannot be substituted for by technology are generally complemented by it (Autor, Dorn, and Hanson 2015). Consistent with this notion, recent studies suggest that it is difficult for technology to replace non-routine tasks that require strong social skills (Deming 2017) or cognitive skills (Brynjolfsson, Mitchell, and Rock 2018). In addition, technology may create new decision tasks by automating predictions and enabling new decisions that were previously impossible to tackle (Agrawal et al. 2019). Accordingly, whether technologies substitute for or complement human capital depends on the nature of the tasks, and evidence of the impact of technologies on labor demand in one profession does not necessarily generalize to another profession (Agrawal et al. 2019).

Although the literature has explored the impact of digital technologies on jobs in general, there is little large-scale empirical evidence on how digital technologies affect the demand for corporate accounting jobs and related skillsets. As such, our first research objective is to examine the impact of the adoption of digital technologies on the corporate accounting labor market.

Given the ambiguous impact of digital technologies on the job market, as discussed above, the impact of firm digitalization on the demand for corporate accountants can be either positive or negative because of the heterogeneous nature of corporate accountants' jobs and skillsets. Frey and Osborne (2017) regard "bookkeeping, accounting, and auditing clerks" as being at "high risk" of substitution through digitalization.[8] However, many commentators suggest that digitalization offers opportunities for accountants to create innovative new services, serve entirely new markets, and tap into fast-growing networks (e.g., Marr 2018). Thus, we state our first hypothesis in the null form:

> ***H1***: *The adoption of digital technologies has no impact on a firm's demand for corporate accountants.*

2.2 Technologies, Economics Gains, and Change in Labor Skillsets

A large stream of the literature examines whether technologies generate economic gains for firms. Some recent studies find that the adoption of digital technologies such as data

[8] For example, Microsoft uses a "host of technologies, including artificial intelligence, bots, the cloud, data lakes and machine learning" to reduce its head count in the accounting and finance function by automating manual and forecasting tasks (https://www.wsj.com/articles/microsoft-keeps-its-finance-head-count-flat-with-ai-bots-and-other-tech-11644489001). However, its CFO states that there are problems that "technology still can't help us solve very well, like negotiating with business partners or looking for greenfield opportunities or managing complex projects."

analytics and AI can improve firm productivity and growth (Tambe 2014; Babina et al. 2020).[9] However, other studies suggest that the frictions associated with the adoption of new technologies may delay or reduce their benefits (Bresnahan et al. 1996; Brynjolfsson, Rock, and Syverson 2018). One major issue is that it usually takes a long time to realize the benefits of adopting digital technologies, but investing in them is costly in the short run (Chen and Srinivasan 2021).

In addition, adopting technologies requires the development of complementary organizational capabilities (Bresnahan et al. 1996) and managerial expertise (Bloom et al. 2012). Recent studies provide evidence of the importance of digital technology–related human expertise, mostly at the top management level (Haislip and Richardson 2018; Ashraf et al. 2020; Chen and Srinivasan 2021). Although it is likely that rank-and-file employees must acquire expertise in these technologies for value generation to occur (Cockburn et al. 2018), there is limited empirical evidence on this issue, especially in a corporate accounting function setting.

Our second research objective is thus to examine whether firms' adoption of digital technologies affects the skillsets required of corporate accountants. To the extent that firm digitalization can fulfill its potential only when the employees (i.e., accountants) have the ability and skillset to harness its benefits, digitalized firms are expected to change the skillsets required of their accountants, particularly digital skills. While there is no well-accepted definition of digital skills, they usually include skills related to programming, data visualization, data analytics, and the ability to use business intelligence applications.[10] However, if firms use digital technologies to replace accountants, their demand for accountants' skillsets would not change. As such, our second hypothesis is stated in the null

[9] Early studies suggest that technologies can increase productivity (Brynjolfsson and Hitt 1996), expand the business more effectively (Hitt 1999), and improve inventory management (Brynjolfsson and Hitt 2000).
[10] https://digitalskillsglobal.com/blog/the-top-10-digital-skills-tech-companies-are-looking-for-today.

form:

> ***H2**: The adoption of digital technologies does not change a firm's demand for accountants' digital skills.*

2.3 Technologies, Human Capital, and Financial Reporting Quality

2.3.1 Technologies and Financial Reporting Quality

Technology is an integral part of the financial reporting process and affects the quality of accounting information (e.g., Ashraf et al. 2020). Digital technologies can enhance a firm's implementation of internal controls, leading to high-quality financial reporting (Nolan and McFarlan 2005; AICPA 2006; Masli et al. 2011; Geerts et al. 2013). Consistent with this view, previous studies find that stronger IT is associated with timelier corporate disclosures (Brazel and Dang 2008; Holder et al. 2016), better quality of management forecasts and internal controls over financial reporting (Dorantes et al. 2013), and better loan terms (Kim, Song, and Stratopoulos 2018). However, dependence on IT is not without risk and does not always have a positive impact on financial reporting quality. For example, Lawrence et al. (2018) find that data breaches (i.e., failures in IT and cybersecurity) are positively associated with future internal control material weaknesses, restatements, Securities and Exchange Commission (SEC) comment letters, and audit fees. Ashraf et al. (2020) find that general IT expenditures or management with IT expertise do not seem to have a positive impact on financial reporting quality.

Recent studies shift the focus from capital investments in IT to the relevant human capital of corporate leaders. For example, Ashraf et al. (2020) find that firms with an audit committee with information technology expertise have a lower likelihood of restatements and IT-related internal control material weaknesses and provide more timely earnings announcements. Overall, previous studies find some evidence that a firm's capital investment in digital technologies, or the information technology expertise of its management or directors, may positively affect a firm's information production quality. However, it is unclear whether accountants' digital skills and firm digitalization affect financial reporting quality independently or jointly.

2.3.2 Human Capital and Financial Reporting Quality

Most previous studies of the impact of human capital on financial reporting quality focus on the role of top executives' characteristics, such as their incentives, reputation, style, and ability (for a review of this literature, see Dechow, Ge, and Schrand 2010). Some recent studies focus on employees in general or non-executive accounting employees (e.g., Call et al. 2017; Chen et al. 2020; Gao et al. 2020) and argue that non-executive employees also shape a firm's financial reporting quality, because the financial reporting process requires the consolidation of information at various levels. For example, Call et al. (2017) find that the average workforce education level in the Metropolitan Statistical Area (MSA) in which the firm operates is associated with better reporting outcomes. Focusing on accounting employees, Chen et al. (2020) further show that a higher quality of accounting human capital is associated with a lower likelihood of restatements and lower discretionary accruals. Lastly, Gao et al. (2020) document a significant increase in firms' demand for employees with financial skills following the disclosure of internal control weaknesses and find that increased demand for financial skills is associated with a higher likelihood of internal control remediation. Overall, these papers provide evidence that the general ability of non-executive human capital plays an important role in shaping firms' financial reporting quality. Our paper extends this line of research by examining how a firm's hiring of accountants with digital skills as part of its digitalization strategy affects financial reporting quality.

2.3.3 Technologies and Human Capital: Complements or Substitutes?

While studies have examined the separate effects of technologies and human capital on financial reporting quality, there is little research on whether the two jointly affect financial reporting quality. Routine accounting tasks such as bookkeeping can be automated (Goos, Manning, and Salomons 2009). Advances in digital technologies can increase the supply of routine informational inputs, both in quantity and quality (Autor et al. 2003). As a result, digital technologies and human capital can be substitutes in affecting financial reporting quality. However, accounting tasks are often not black and white, and they often involve professional judgment, which currently cannot be automated. Rather, advances in digital technologies can increase the productivity of accounting professionals with digital skills and improve the quality of their judgment.[11] Thus, human capital investments and IT investments can complement each other in shaping financial reporting quality. Given this non-directional prediction, we state the third hypothesis in the null form:

> ***H3***: *Digital technologies and accountants' digital skills independently affect financial reporting quality.*

3 Data and Research Design

3.1 Sample Selection

Panel A of Table 1 presents the sample selection procedure. We begin with all U.S. firms in the Compustat database and obtain 85,902 firm-year observations from 13,411 unique firms in the 2010–2019 period. We then exclude 21,133 observations from the financial and utility industries (SIC 6000–6999, 4900–4949), because the typical financial reporting quality proxies do not apply to these industries. To mitigate measurement errors in identifying firm digitalization based on the textual analysis of 10-K filings, we follow Chen and Srinivasan (2021) and focus on non-technology firms classified based on the SIC, NAIC,

[11] For example, controllers in Google are "now using machine learning to close the books," and Google gives accountants "access to business intelligence and machine learning tools, so that [accountants] are not spending time on things that can be automated." More importantly, Google also acknowledge that "there's so much judgment that is required as a finance organization." (https://www.wsj.com/articles/google-finance-head-anything-that-can-be-automated-we-strive-to-automate-11649676600). These discussions suggest that automation and digitalization per se cannot fully replace accountants to realize the intended benefits.

and GICS industry definitions. Specifically, these firms are not in industries related to computers, electronics, communications, data processing, or Internet services. Please see Appendix B of Chen and Srinivasan (2021) for the list of industry codes for technology industries.

We obtain data on the demand for accountants and their skillsets from Burning Glass, an employment data analytics firm that provides real-time data on job postings and the skills demanded of prospective candidates. According to Burning Glass, its algorithm crawls nearly 40,000 online job boards and company websites to scrape and code information on job postings. Burning Glass's proprietary algorithms remove duplicate postings and convert them into a machine-readable format. Burning Glass also standardizes the job-level characteristics such as employer name, job title, location of the position, salary, education requirements, and skill requirements. Recent labor economics studies have used Burning Glass data to examine the changing landscape of the U.S. labor market (e.g., Deming and Kahn 2018; Hershbein and Kahn 2018).

We merge the Compustat sample with the data on job postings from Burning Glass. We first use an algorithm to conduct a fuzzy match between the Burning Glass and Compustat data based on employer names. We then manually go through the links identified in Burning Glass to ensure the accuracy of our matching.[12] Lastly, because we use one-year-lagged independent variables, our final sample period is 2011–2019. We drop observations that have missing data needed to calculate the variables used in the analyses. Because we control for firm fixed effects, we exclude singleton firm observations (deHaan 2021). Our final sample consists of 7,050 firm-years from 1,333 unique firms in the 2011–2019 period.

[12] Some employers in Burning Glass are subsidiaries of Compustat firms. Focusing on the parent firms, we exclude data from subsidiaries from Burning Glass in our sample selection procedure.

3.2 *Variable Measurement*

3.2.1 Firm Digitalization Measure

Following Chen and Srinivasan (2021), we construct a measure of the level of a firm's digitalization in a given year based on the number of digital-related terms in the firm's 10-K filings. We use the dictionary of digital-related terms created by Chen and Srinivasan (2021), which include analytics, automation, artificial intelligence (AI), big data, cloud computing, digitization, and machine learning (ML).[13] Appendix A lists the keywords used to identify these terms in Panel A and provides two examples of discussions in 10-K filings that include such terms in Panel B. To capture the potential nonlinear effect of the number of digital-related terms, we convert the raw number into a rank variable (*Digitalization*) as follows: *Digitalization* is set to zero if no digital-related term is mentioned in a firm's 10-K filing and as 1, 2, or 3 if the number of digital-related terms falls into the bottom, middle, or top tercile of the sample distribution in the year, respectively.

Table 1, Panel B reports the annual distribution of firm digitalization (*Digitalization* > 0), which suggests an increasing trend toward digitalization over the years, from 12% of firms in 2011 to 51% in 2019. Table 1, Panel C presents the distribution of firm digitalization by industry, using the 12-industry Fama–French classification. Business equipment and telephone and television transmission industries have the highest percentage of digitalized firms (around 50% of firms with *Digitalization* > 0), while oil, gas, coal extraction and products and chemical and allied products industries have the lowest percentage of digitalized firms (fewer than 15% of firms with *Digitalization* > 0).

[13] Chen and Srinivasan (2021, 13) identify those terms "from numerous articles on the digital phenomena as well as glossaries of digital terms provided by consulting firms that specialize in digital transformation." Chen and Srinivasan (2021) also validate this measure and find that the digitalization measure is positively associated with the digital-related activities of a firm.

3.2.2 Measures of the Demand for Accountants and Accountants' Digital Skills

We construct the measures of a firm's demand for accountants (*Accountants*) and accountants' digital skills (*Digital Skills^{Acct}*) based on the job posting data from Burning Glass. *Accountants* is defined as the number of job postings for accountants divided by the total postings of a firm in a year. We use the scaled measure to control for the effect of firm size and growth. As such, our measure essentially captures the demand for accountants relative to the demand for all types of employees. We set *Accountants* to zero if a firm does not have a job post for accountants but has a job post for other jobs in a year.

Accountant positions are those with a Standard Occupational Classification (SOC) code of 13-2000 ("Financial Specialists") and 43-3000 ("Financial Clerks"), as classified by Burning Glass.[14] Although both of them are broadly defined as accountants, they have fundamentally different job responsibilities. Financial specialists tend to focus on financial reporting, budgeting, forecasting, and specific requirements such as those under the SOX Act, Panel B of Appendix B provides some examples of job scopes of financial specialists. In contrast, financial clerks mainly focus on administrative financial tasks such as entering transactions into accounting software, sending invoices to customers, and administering employee payrolls.[15] As such, we create two variables, *Accountants^{FS}* and *Accountants^{FC}*, for jobs postings for financial specialists and financial clerks, respectively. Appendix D reports

[14] We exclude the sub-categories that are unlikely to be related to accounting tasks in the corporate setting, including 13-2021 Property Appraisers and Assessors, 13-2041 Credit Analysts, 13-2052 Personal Financial Advisors, 13-2053 Insurance Underwriters, 13-2071 Credit Counselors, 13-2072 Loan Officers, 13-2081 Tax Examiners and Collectors, and Revenue Agents, 43-3041 Gambling Cage Workers, and 43-3071 Tellers. We do not exclude 13-2051 Financial Analyst because it includes "corporate financial analysts," whose job responsibilities are related to financial reporting and analysis. Although code 13-2051 includes jobs related to investment advisory and analysis in financial industries, we exclude firms in financial industries, reducing the likelihood of including non-accountants.

[15] Untabulated results show that most financial clerks are either not specifically required to have a diploma (30%) or only required to have a high school diploma (45%). In contrast, 78% of financial specialists are required to have a Bachelor's degree. In addition, financial specialists on average are required to have 3.8 years of working experience, while it is 2.3 for financial clerks. To mitigate the concern that our results of financial specialists and financial clerks are driven by those dimensions, we create a general ability variable for financial specialists (*General Ability^{FS}*) and show that firm digitalization does not affect the demand for financial specialists' general ability, as reported later (Table 5).

the most common accountant job titles of each group.

Digital Skills ^{Acct} captures the demand for accountants' digital skills and is measured as the number of postings for accountants that require at least one digital skill divided by the number of postings for all types of accountants for a firm in a year. *Digital Skills* ^{Acct} is set to zero when a firm does have not a job post for accountants but has a job post for other jobs in a year.[16] *Digital Skills* ^{FS} and *Digital Skills* ^{FC} are constructed similarly for the digital skills of financial specialists and financial clerks, respectively. We identify digital skills by searching for the relevant keywords in each job posting. We use the digital-related terms developed by Chen and Srinivasan (2021), as discussed above. To mitigate the concern that these digital-related terms are too broad to capture the specific digital skills in the field, we complement the dictionary in Chen and Srinivasan (2021) with a list of skill-based terms (such as *Python* and *SQL*) developed by Acemoglu et al. (2020) and Gao, Huang, and Wang (2021). Appendix B lists the terms used to identify digital skills in Panel A and provides a few examples of job postings for accountants with digital skills in Panel B.

Table 1, Panel B reports the annual distribution of firms hiring accountants with digital skills (*Digital Skills* $^{Acct} > 0$). Similar to firm digitalization, there is an increasing trend towards hiring accountants with digital skills, from 21% of firms in 2011 to 39% in 2019. Table 1, Panel C presents the distribution of firms hiring accountants by industry. Business equipment, consumer nondurables, and telephone and television transmission industries have the highest percentage of firms hiring accountants with digital skills (about 40% of firms with *Digital Skills* $^{Acct} > 0$), while healthcare, medical equipment, and drugs industry has the lowest percentage of firms hiring accountants with digital skills (21% of firms with *Digital Skills* $^{Acct} > 0$).

[16] Untabulated analysis indicates that our inferences remain the same if we further control for an indicator variable for firms without job postings for accountants in a year in the tests for accountants' digital skills or if we add this indicator variable and its interaction with firm digitalization in the tests of financial reporting quality.

Table 1, Panel D further reports the annual distribution of accounting job postings requiring digital skills. While only 10% of accounting job postings in 2011 require digital skills, this figure increases to 15% in 2019. In addition, the average number of digital skills required per job postings rose from 1.5 to 2.1 over the same period.[17]

3.2.3 Financial Reporting Quality Measures

We use four accrual-based financial reporting quality measures: discretionary accruals (*DA*), discretionary working capital accruals (*DD*), discretionary revenue (*DR*), and a composite measure (*FRQ_PC*). *DA* is estimated from the modified Jones model (Jones 1991; Dechow et al. 1995). *DD* is estimated from a modified version of the cross-sectional Dechow and Dichev (2002) model (McNichols 2002; Francis et al. 2005). *DR* is estimated from the model developed by McNichols and Stubben (2008) and Stubben (2010). Appendix C provides a more detailed discussion of the estimation procedure for these three measures. Finally, we construct a composite measure of financial reporting quality (*FRQ_PC*) based on the first principal component of the three individual measures.[18] This composite measure extracts the commonality across the three individual measures and reduces the measurement error in the individual measures.

3.3 Research Design

We use the following model to examine the effect of firm digitalization on the demand for accountants and accountants' digital skills:

$$Accountants_{i,t}, Digital\ Skills_{i,t}^{Acct} = \beta_0 + \beta_1 Digitalization_{i,t-1} + \gamma\ Controls_{i,t-1} + \alpha_i + \theta_t + \varepsilon_{i,t} \quad (1)$$

where *i* and *t* denote firm *i* and year *t*, respectively. *Accountants*, *Digital Skills* ^{Acct}, and

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[17] Untabulated results show that the most common digital skills stipulated in accounting job postings are "analytics," "sql,", "business intelligence," "data miming,", and "tableau."

[18] The first principal component has an eigenvalue of 1.55, and the other components have eigenvalues below 1.

Digitalization are defined as above.[19] The coefficient β_1 captures the effect of firm digitalization on the demand for accountants and their skills.

Following prior studies (e.g., Gao et al. 2020; Chen and Srinivasan 2021), we control for a set of firm characteristics that might affect a firm's decision to adopt digital technology and the demand for accountants or their skills. Chen and Srinivasan (2021) find that younger firms (*Age*), bigger firms (*Size*), and firms with a higher leverage ratio (*Leverage*), higher return volatility (*RetVolt*), slower sales growth (*Sales Growth*), worse stock performance (*Return*), smaller capital expenditures (*CAPEX*), larger S&GA expenditures (*SG&A*), and lower research and development expenditures (*R&D*) are more likely to engage in digitalization. Gao et al. (2020) find that firms with fewer growth opportunities (*MTB*) or poorer performance (*ROA*) hire more skillful accountants.[20] Appendix C provides the variable definitions. We winsorize all of the continuous variables at the top and bottom 1% levels.

We further include firm fixed effects (α_i) and year fixed effects (θ_t) to control for the impact of time-invariant firm characteristics and time trends on the demand for accountants and their skills. We cluster standard errors at the firm level to address potential time series dependencies in the error term.

We next estimate the following model to examine the effect of firm digitalization and the demand for accountants' digital skills on financial reporting quality (FRQ):

$$\begin{aligned} FRQ_{i,t} = \ & \beta_0 + \beta_1 Digitalization_{i,t-1} + \beta_2 Digital\ Skills^{Acct}_{i,t-1} \\ & + \beta_3 Digitalization_{i,t-1} \times Digital\ Skills^{Acct}_{i,t-1} + \gamma\ Controls_{i,t-1} \\ & + \alpha_i + \theta_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

FRQ is one of four accrual-based proxies for financial reporting quality: *DA*, *DD*, *DR*, and *FRQ_PC*. We measure all of the independent variables in Equation (2) with a one-year lag

[19] Untabulated results suggest that our findings continue to hold if we further control for *Digitalization* measured in *t*-2, suggesting that our results are not affected by the stickiness of this measure.

[20] Our results do not change if we further control for whether a firm has adopted an enterprise resource planning (ERP) system in Equation (1) and further control for its interaction term with digital skills of accountants in Equation (2) (untabulated). It suggests that firm digitalization differs from conventional ERP adoption.

relative to *FRQ* to allow the effect of a firm's digitalization and its accountants' digital skills on financial reporting to materialize. A positive (negative) coefficient β_3 indicates a negative (positive) interaction effect of firm digitalization and accountants' digital skills on firms' financial reporting quality, implying a substitution (complementary) effect of the two on financial reporting quality.

3.4 Descriptive Statistics

Table 2 reports the summary statistics on the variables used in the analyses. The mean of *Digitalization* is 0.385. On average, job postings for accountants make up 4.3% of total job postings (*Accountants*), of which 3% are financial specialists ($Accountants^{FS}$) and 1.2% are for financial clerks ($Accountants^{FC}$). Meanwhile, the mean of $Digital\ Skills^{Acct}$ is 6.9%, and the mean of $Digital\ Skills^{FS}$ (8.5%) is higher that of $Digital\ Skills^{FC}$ (1.4%). The financial reporting quality measures have means around zero by construction (note that the measures are multiplied by 100 for ease of presentation). However, the standard deviations of these measures are reasonably large, 9.1%, 5.0%, 3.0%, and 1.0% of total assets for *DA*, *DD*, *DR*, and *FRQ_PC*, respectively. The descriptive statistics on the control variables are largely consistent with those reported in prior studies (e.g., Chen and Srinvasan 2021). Untabulated variance inflation factor (VIF) tests show that all of the VIFs are below 10, indicating that multicollinearity is not a serious concern in our tests.

4 Digitalization and Demand for Accountants and Accountants' Skills

4.1 Baseline Results for the Tests of H1 and H2

We first examine whether firm digitalization affects the demand for accountants and accountants' skills. Table 3 reports the results of testing H1. As reported in Column (1), the coefficient on *Digitalization* is insignificant at conventional levels when *Accountants* is the dependent variable. The coefficient on *Digitalization* is also insignificant when $Accountants^{FS}$

is the dependent variable, as reported in Column (2). These results suggest that a firm's digitalization strategy does not change its demand for accountants overall and financial specialists in particular. However, unlike the results for financial specialists, we find that the coefficient of *Digitalization* is negatively significant (t = -2.56) when we focus on financial clerks (*Accountants*^{FC}), as reported in Column (3). This finding indicates that firm digitalization reduces the demand for financial clerks, consistent with the notion that financial clerks' jobs are limited to bookkeeping and other basic administrative tasks, most of which can be automated once firms go digital.

We next examine the impact of firm digitalization on the demand for accountants' digital skills. Table 4 reports the results of testing H2. We find that the coefficient on *Digitalization* is significantly positive in the first two columns (t = 1.87 and 2.33, respectively) when we focus on all accountants (*Digital Skills*^{Acct}) or financial specialists only (*Digital Skills*^{FS}), suggesting that firm digitalization increases the demand for digital skills from accountants, primarily from financial specialists. These results are economically significant. The results in Column (1) suggest that a one-standard-deviation increase in *Digitalization* is associated with an increase of 0.0054 (= 0.771 × 0.007) in the demand for accountants with digital skills, or a relative increase of 7.8% from the sample mean of *Digital Skills*^{Acct}.[21] The economic effect is greater for financial specialists: a one-standard-deviation increase in *Digitalization* is associated with an increase of 0.0085 (= 0.771 × 0.011) in the demand for financial specialists with digital skills, or a relative increase of 10% from the sample mean of *Digital Skills*^{FS}. In contrast, we find that there is no significant change in

[21] Dey and White (2021) and deHaan (2021) recommend that researchers use the within-fixed-effect standard deviation of variables (i.e., the standard deviation of the residuals from the regression of the variable on the fixed effects) when interpreting economic significance for regression models with fixed effects. Our inference does not change based on this approach. Specifically, the increase in *Digital Skills*^{Acct} is 0.0032 (= 0.007 × 0.450) for a within-fixed-effect one-standard-deviation increase in *Digitalization* (the within-fixed-effect standard deviation of *Digitalization* is 0.450). This represents a relative increase of 4.6% from the sample mean of *Digital Skills*^{Acct}.

the demand for financial clerks' digital skills (*Digital Skills*^{FC}), as reported in Column (3), suggesting that firm digitalization does not require financial clerks to have more digital skills.

Altogether, we find that the impact of firm digitalization varies with the nature of the jobs. While firm digitalization does not affect the demand for financial specialists, it increases the demand for their digital skills. In contrast, while firm digitalization reduces the demand for financial clerks, it does not affect the demand for their digital skills.

4.2 Placebo Tests: Analysis of Other Skills

The results reported above suggest that firm digitalization does not affect the overall demand for accountants, and particularly financial specialists, but it increases firms' demand for financial specialists with digital skills. One concern with the results is that firm digitalization might simply capture firms' demand for high-quality financial specialists, not just their digital skills. To address this concern, we examine the impact of firm digitalization on financial specialists' other skills: social skills, financial skills, accounting major, and general ability (Deming and Kahn 2018; Chen et al. 2020; Gao et al. 2020; Ham et al. 2021). For this purpose, we construct four variables, *Social Skills*^{FS}, *Financial Skills*^{FS}, *Accounting Major*^{FS}, and *General Ability*^{FS}, which are measured as the number of job postings for financial specialists with social skills, financial skills, accounting major, and high general ability, respectively, divided by the total number of job postings for financial specialists for a firm in a year. Again, these measures are set to zero for firm-years without job postings for financial specialists.[22] We define a job posting as demanding financial specialists with high general ability if it requires a Certified Public Accountant (CPA) designation, a Bachelor's degree, and work experience. We then re-estimate Equation (1) with these variables as the dependent variables. If the results reported above are driven by the

[22] The mean of *Social Skills*^{FS}, *Financial Skills*^{FS}, *Accounting Major*^{FS}, and *General Ability*^{FS} are 0.403, 0.566, 0.397, and 0.158, respectively.

demand for high-quality financial specialists by firms with digitalization strategies, we would expect the effect of firm digitalization on those skills to be similar to that on digital skills.

Table 5 reports the regression results. Inconsistent with the alternative explanation, we find that the coefficient on *Digitalization* is insignificant in the analyses of all four variables, suggesting that firm digitalization does not affect the demand for financial specialists' other skills or their general ability. This finding suggests that our results concerning financial specialists' digital skills are unlikely to be driven by correlated omitted variables of other skills.

5 Digitalization, Digital Skills, and Financial Reporting Quality

5.1 Baseline Results for Tests of H3

In this section, we examine whether firm digitalization and accountants' digital skills affect financial reporting quality. Given that we find the firm digitalization only increase the demand for financial specialists' but for financial clerks' digital skills, we focus on financial specialists in the tests of H3.

Table 6 reports the regression results for the analyses of *DA*, *DD*, and *DR* in Panel A and the analysis of the composite measure *FRQ_PC* in Panel B. We first examine the effect of firm digitalization (accountants with digital skills) alone. We find that the coefficients on *Digitalization* and *Digital Skills*^{FS} are insignificant at conventional levels. This finding suggests that firm digitalization alone and accountants' digital skills alone do not affect financial reporting quality.

We next investigate the joint effect of firm digitalization and accountants' digital skills, i.e., their interaction effect as specified by Equation (2). Columns (3), (6), and (9) of Panel A and Column (3) of Panel B of Table 6 report the regression results. We find that while the coefficients on *Digitalization* and *Digital Skills*^{FS} are still insignificant, the coefficient on

Digitalization × *Digital Skills*^{FS} is significantly negative across all of the specifications (t = -1.79, -3.16, -2.34, and -3.32 for the analyses of *DA*, *DD*, *DR*, and *FRQ_PC*, respectively). This finding suggests that firm digitalization and accountants' digital skills complement each other: a greater level of firm digitalization, combined with having more accountants with digital skills, is associated with better financial reporting quality.

In terms of economic significance, a one-standard-deviation increase in both *Digitalization* and *Digital Skills*^{FS} leads to relative decreases of 2.1%, 3.1%, 3.5%, and 3.9% of the standard deviations of *DA*, *DD*, *DR*, and *FRQ_PC*, respectively.[23] We do not use the means of these measures to evaluate the economic significance because they are essentially zero.

5.2 Cross-Sectional Analysis

To shed light on the underlying mechanisms through which firm digitalization and accountants' digital skills complement each other, we conduct a cross-sectional test. Specifically, we focus on whether the effect on financial reporting quality varies with the difficulty or uncertainty associated with accounting estimates. Many accounting estimates are complex, involving high levels of uncertainty with multiple assumptions and forecasts of future events. These estimates can lead to measurement uncertainty (PCAOB 2014). The estimation uncertainty, along with financial market volatility, macroeconomic risks, and managerial biases, can make auditing of these estimates particularly challenging (e.g., Beatty and Webber 2006; Bratten et al. 2013; Griffith et al. 2015). We expect financial specialists

[23] We calculate the relative change for *DA* as follows: 2.1% = 0.771 (the standard deviation of *Digitalization*) × 0.188 (the standard deviation of *Digital Skills*^{FS}) × (-1.321) (the coefficient on *Digitalization* × *Digital Skills*^{FS}) / 9.093 (the standard deviation of *DA*). The relative changes for *DD*, *DR*, and *FRQ_PC* are calculated similarly. If we follow Dey and White (2021) and deHaan (2021) and use the within-fixed-effect standard deviation of all variables, the economic significance is smaller: a within-fixed-effect one-standard-deviation increase in both *Digitalization* and *Digital Skills*^{FS} leads to relative decreases of 1.6%, 2.0%, 2.3%, and 2.7% of the standard deviations of *DA*, *DD*, *DR*, and *FRQ_PC*, respectively. The within-fixed-effect standard deviations of *Digital Skills*^{FS}, *DA, DD, DR*, and *FRQ_PC* are 0.14, 7.14, 4.36, 2.69, and 0.84, respectively.

with digital skills can at least partially alleviate this concern by, for example, collecting information about hard-to-value accounting estimates using extensive and automated Internet search methods running over extended periods. The increasing sophistication of statistical software and power of computing hardware enable more intelligent and accurate estimates of the value and likelihood of future events, improving financial reporting quality. Therefore, we predict that the positive effect on financial reporting quality is stronger for firms with more uncertain accounting estimates.

Empirically, we use a firm's amount of Level 2 and Level 3 fair value to construct a conditional variable *FV*, which is the sum of the absolute value of Level-2 fair value assets, Level-2 fair value liabilities, Level-3 fair value assets, and Level-3 fair value liabilities, divided by the sum of total assets and liabilities. We then partition the sample based on the median of *FV* and re-run the Equation (2) for each subsample. We expect the results to be stronger for the subsample for high *FV*, for which digital skills of financial specialists likely play a positive role on financial reporting quality together with overall corporate digitalization. We report the regression results in Table 7. We find that the coefficient on *Digitalization* × $\textit{Digital Skills}^{FS}$ is only significantly negative in the high *FV* sample (t = -2.59, -2.01, and -2.25 for the analyses of *DD*, *DR*, and *FRQ_PC*, respectively), suggesting that the complementary effect of firm digitalization and accountants' digital skills is stronger for firms with hard-to-value accounting estimates.

5.3 Robustness Checks

To strengthen our inferences, we conduct three robustness tests. First, firm digitalization may increase the demand not only for accountants' digital skills but also for other employees' digital skills. Therefore, it is possible that our results are an outcome of having other employees with digital skills. To address this concern, we add $\textit{Digital Skills}^{NonAcct}$ and its interaction with *Digitalization* to Equation (2). $\textit{Digital Skills}^{NonAcct}$

is measured as the number of job postings for positions other than accountant positions that require at least one digital skill divided by the total number of job postings for positions other than accountant positions.

Table 8, Panel A reports the regression results. We find that the coefficients on *Digital Skills* ^{NonAcct} and its interaction with *Digitalization* are insignificant at conventional levels, except for that on *Digitalization* × *Digital Skills*^{NonAcct} in the analysis of *DR*, which is significantly positive. This finding suggests that having other employees with digital skills does not affect financial reporting quality. More importantly, the coefficient on *Digitalization* and *Digital Skills*^{FS} remains significantly negative for the analyses of *DD*, *DR*, and *FRQ_PC*.

Second, our results above indicate that firm digitalization increases a firm's demand for accountants with digital skills but not other skills. Prior research finds that accounting professionals' financial and social skills are important in explaining financial reporting quality and audit quality. For example, Gao et al. (2020) find that an increase in the demand for financial skills is associated with an improvement in the quality of internal control over financial reporting. Ham et al. (2021) find that the demand for social skills has a positive impact on audit quality among accounting firms, while the demand for technology skills does not.[24] To explore whether accountants' other skills, including financial skills, social skills, and accounting majors, drive our results, we add accountants' other skills (*Other Skills*^{FS}) and its interaction with *Digitalization* to Equation (2). Table 8, Panel B reports the regression results. We find that the coefficient on *Digitalization* × *Digital Skills*^{FS} is significantly negative in the analysis of *DA*, *DD*, *DR*, and *FRQ_PC* (t = -2.08, -2.31, -2.05, and -2.92, respectively), but the coefficient on *Digitalization* × *Other Skills*^{FS} is insignificant. These results suggest that it is accountants' digital skills, not their other skills, that improve the

[24] One of the reasons that our results appear to be different from Ham et al.'s is that their definition of technology skills is based on Burning Glass's definition and is very general and broad. For example, they include Microsoft PowerPoint and Microsoft Excel as part of technology skills.

financial reporting quality of digitalized firms.

Lastly, we explore whether the effect of accountants' digital skills is driven by their general ability. It is possible that accountants with high general ability are more likely to acquire new skills, such as digital skills. Chen et al. (2020) find that the quality of accounting human capital is associated with a lower likelihood of restatements because of accounting irregularities and lower discretionary accruals. To explore whether accountants' general ability drives our results, we add the measure of accountants' general ability (*General Ability* ^{FS}) and its interaction with *Digitalization* to Equation (2). Table 8, Panel C reports the regression results. *General Ability*^{FS} is as defined above. Again we find that the coefficient on *Digitalization* × *Digital Skills*^{FS} continues to be significantly negative in three out of the four specifications, but that on *Digitalization* × *General Ability*^{FS} is insignificant. These results suggest that the positive effect of accountants' digital skills on digitalized firms' financial reporting quality is unlikely to be explained by their general ability.

5.4 Validating the Measure of Accountants' Digital Skills

One concern with the measure of accountants' digital skills based on the Burning Glass data is that it merely captures a firm's demand for accountants with digital skills rather than the digital skills of existing accountants in the firm. We use the one-year-lagged value of *Digital Skills*^{FS} in the analyses to ensure that the jobs are filled and that existing accountants have the digital skills specified in job postings. Prior studies have validated the Burning Glass job posting data using employee resumes or H1B visa applications and concluded that job postings are a reasonable proxy for a firm's actual hiring (e.g., Acemoglu et al. 2020; Law and Shen 2021). For example, in an examination of the effect of AI applications on firm growth, Babina et al. (2021) document similar results when using the AI skills required of employees based on the Burning Glass job posting data and when using employees' AI skills based on employee resume data.

To further mitigate concerns about our measure of accountants' digital skills, particularly financial specialists', we conduct a validation test using employee resume data from People Data Labs. Specifically, we obtain the resumes of all financial specialists who disclose skills and are currently working in S&P 1500 firms. As the data were downloaded at a single time point, we use financial specialists' prior work experience to obtain information about the financial specialists who worked in our sample firms in 2019 (the last year of our sample).[25] This procedure leads to a sample of accountants from 271 firms in our main sample.

Based on the resume data, we construct an alternative measure of financial specialists' digital skills for each firm, $\textit{Digital Skills}^{FSPDL}$, which is calculated as the total number of financial specialists with at least one digital skill divided by the total number of financial specialists with information on their skills. Untabulated results indicate that $\textit{Digital Skills}^{FSPDL}$ is positively correlated with one-year-lagged $\textit{Digital Skills}^{FS}$ (with a correlation coefficient of 0.182, significant at the 0.01 level).[26] When we regress $\textit{Digital Skills}^{FSPDL}$ on $\textit{Digital Skills}_{t-1}^{FS}$ and the control variables, we find a significantly positive coefficient on $\textit{Digital Skills}_{t-1}^{FS}$ (untabulated). These results suggest that job postings for financial specialists capture the skills of actual financial specialists working in a firm.

6 Additional Analyses

6.1 Evaluation of the Effect of Unobserved Correlated Variables

A possible concern with the above reported results is that the results are affected by

[25] Data on accountants' skills are from the time point when we downloaded the data in 2021. As such, we assume that the accountants had the same skills in 2019. We acknowledge that this assumption may introduce measurement error because some accountants might not have had digital skills until 2021.
[26] The low level of correlation could be due to the weak test power of this analysis. Specifically, while focusing on accountants who disclose skills mitigates measurement error, doing so significantly reduces the sample size and the power of the tests.

unobservable firm characteristics. For example, the digitalization decision could be affected by business uncertainties, industry trends, or technological development (e.g., Chen and Srinivasan 2021). Although we control for a number of firm characteristics and firm-fixed effects in our analyses, in this section, we perform two additional tests to further mitigate this concern.

First, we follow DeFond, Erkens, and Zhang (2017) and conduct a coarsened exact matching (CEM) analysis to address concerns that digitalized (*Digitalization* > 0) and non-digitalized firms (*Digitalization* = 0) inherently differ in their firm characteristics. The CEM approach allows us to use more homogenous subsamples to test the effect of firm digitalization on accountants and their skills. CEM reduces the effect of potential misspecification (e.g., omitted variables) and is less likely to be subject to the random matching problem inherent in other matching techniques (e.g., King et al. 2011).[27] Untabulated analysis indicates that while digitalized and non-digitalized firms are significantly different in nine firm characteristics prior to the CEM, the matched samples based on the CEM different only in three firm characteristics. We re-estimate Equations (1) and (2) using the matched sample and report the results in Table 9. We find that the inferences remain the same: the coefficient on *Digitalization* remains insignificant in the analysis of *Accountants* and $Accountants^{FS}$, significantly negative in the analysis of $Accountants^{FC}$, and significantly positive in the analysis of $Digital\ Skills^{FS}$. In addition, the coefficient on $Digitalization \times Digital\ Skills^{FS}$ remains significantly negative for the analyses of *DA*, *DD*, and *FRQ_PC*.

Second, following the suggestion of Larcker and Rusticus (2010), we further assess the sensitivity of the baseline results to unobserved correlated variables using the method

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[27] Instead of exact matches, CEM requires control firms to be matched with treatment firms only within an acceptable range.

developed by Frank (2000), which assesses the likelihood that an unobserved confounding variable significantly affects the results. For this purpose, we derive the minimum correlation necessary to turn a statistically significant effect of the variable of interest (e.g., *Digitalization* in Equation (1)) into a borderline insignificant result. To identify such a borderline, we derive the impact threshold for a confounding variable (ITCV). ITCV is defined as the lowest product of (1) the partial correlation between the *x*-variable (e.g., *Digitalization* in Equation (1)) and the confounding variable that makes the coefficient on the *x*-variable insignificant and (2) the partial correlation between the *y*-variable (e.g., *Digital Skills*^{FS} in Equation (1)) and the same confounding variable. If the ITCV of the *x*-variable is high, then our baseline results are less likely to be affected by an omitted variable.

Table 10 reports the results. For brevity, we focus on *Digital Skills*^{FS} in Panel A and discuss how we examine the sensitivity of the baseline results in Table 4. Specifically, we find that the ITCV of *Digitalization* based on the specification in Column (2) of Table 4 is 0.034.[28] To determine whether this value is high or low, we compute the impact measures (*Impact*) of the control variables in Equation (1). Specifically, the *Impact* of a control variable is the product of the partial correlation between *Digitalization* and the control variable and the partial correlation between *Digital Skills*^{FS} and the control variable (controlling for the effect of the other control variables). We find that *Age* is most highly correlated with *Digitalization* and *Digital Skills*^{FS} and thus has the highest value of *Impact*. However, the *Impact* of *Age* is only 0.005, much smaller than the ITCV of *Digitalization* (0.034). This implies that we would need a confounding variable that has a much stronger correlation with both *Digital Skills*^{FS} and *Digitalization* than *Age* does to render the coefficient on

[28] This value (0.034) is calculated as the product of 0.183 and 0.183 based on the procedure developed by Xu et al. (2019). Specifically, an omitted variable would have to be correlated at 0.183 with the outcome variable, *Digital Skills*^{FS}, and at 0.183 with the independent variable of interest, *Digitalization* (conditional on the observed covariates used in Column 2 of Table 4), to invalidate the inference.

Digitalization in Table 4 insignificant.[29] Thus, our results from this analysis suggest that the possibility that an unobserved confounding variable is driving our results in Table 4 is very small.

Panel B reports the results when we examine the ITCV of *Digitalization* × *Digital Skills*^{FS} in the analysis of financial reporting quality. The results also suggest that the possibility that an unobserved confounding variable is driving the results in Table 6 is very small.

6.2 Alternative Definitions of Digitalization

Next, we conduct robustness checks using two alternative definitions of *Digitalization*. First, we recalculate *Digitalization* based on the number of *unique* digital-related terms instead of the total number of digital-related terms. This new measure, *Digitalization Unique*, highlights the intensity of *different* dimensions of a firm's digitalization, whereas our baseline measure may capture the overall level of firm digitalization. Second, we recalculate *Digitalization* based on the number of sentences that contain at least one digital-related term. This new measure, *Digitalization Sent*, could mitigate the concern that we might overestimate the level of firm digitalization if a firm only mentions digital-related terms in a small number of sentences in its 10-K filings.

Table 11 reports the regression results based on these alternative measures of digitalization, with Panel A based on *Digitalization Unique* and Panel B based on *Digitalization Sent*.[30] We find that the results are qualitatively similar to those reported above, suggesting that our results are robust to alternative measures of firm digitalization.

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[29] Untabulated results show that our inference does not change when we focus on a more conservative measure of *Impact* in which we do not tease out the effect of other control variables when we focus on one control variable (Larcker and Rusticus 2010).

[30] *Digitalization Unique* and *Digitalization Sent* are both significantly correlated with *Digitalization.* Their Pearson correlation coefficients with *Digitalization* are 0.90 and 0.85, respectively.

6.3 Pay for Accountants' Digital Skills

Given the documented benefits of requiring digital skills from accountants, a natural question is why firms do not require all accountants to have digital skills. In addition, one might be concerned that the digital skills listed in job postings are simply a tool to screen better job candidates in the labor market and that the requirement does not necessarily suggest that a firm indeed utilize these skills. To shed light on these issues, we examine the pay gap between accountants with and those without digital skills. We conduct job posting-level analyses using the sample of job postings that have salary information for accountants.[31]

Table 12 reports the regression results. We find that the annual pay of accountants with digital skills is significantly higher than that for those without digital skills. The coefficient on *Digital Skills* is significantly positive (t = 9.32). Firms are willing to pay 20.4% (= $e^{0.186}$ - 1) higher annual salary for accountants with digital skills than those without. When we separately investigate the annual salary of financial specialists (Column (2)) and financial clerks (Column (3)), we find the results hold for both groups: those with digital skills have higher annual salary than those without. These findings suggest that it is costly for a firm to hire accountants with digital skills.

7 Conclusions

Our study provides the first large-sample empirical evidence for the effect of firm digitalization on the demand for corporate accountants and their skillsets and how the number of corporate accountants and their skillsets in turn affect financial reporting quality. Based on 170,000 job posts for corporate accountants by U.S. non-technology firms from 2011 to 2019, we document a significant increase in the demand for financial specialists with digital skills among firms adopting digital technologies, with no change in the overall demand for

[31] About 3.0% of job postings for accountants (5,013 postings) in our sample have salary information and data for other variables used in the analysis.

financial specialists. In contrast, firm digitalization reduces the number of job posts for financial clerks without changing the demand for their digital skills. Our results suggest that firm digitalization reduces the demand for workers who perform jobs that are relatively repetitive and can be automated but does not reduce the demand for workers who perform jobs requiring professional judgment; instead, it increases the demand for the digital skills required to perform such jobs.

In terms of financial reporting quality, we find that firm digitalization alone and hiring financial specialists with digital skills alone do not improve financial reporting quality. Instead, firm digitalization and hiring financial specialists with digital skills work together to improve financial reporting quality. These results suggest that the digital skills of accountants and a firm's digitalization complement each other in improving financial reporting quality.

Overall, our results shed light on the impact of a firm's adoption of digital technologies on the skill development of corporate accounting professionals, which positively affects financial reporting quality. Such findings can inform industry leaders, policy makers, and educational institutions concerning how firm digitalization affects the development of the corporate accounting profession and the quality of the corporate information environment.

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Appendix A
Identifying Firms with Digitalization Strategies

Panel A: Keywords used to identify firm digitalization

This appendix lists the keywords used to identify firms' digitalization activities based on the dictionary of digital-related terms developed in Chen and Srinivasan (2021). The keywords are self-explanatory. Note that "DevOps" is a set of practices that combine software development and operations; it increases an organization's ability to deliver applications and services faster than traditional software development processes; "digita" is the short root word for words containing "digita," such as "digitalization" and "digital"; and "biometric" is used to capture automatic recognition of biometric characteristics.

AI related, AI tech, analytics, artificial intelligence, augmented reality, automation solutions, autonomous tech, big data, biometric, business intelligence, cloud based, cloud computing, cloud deployment, cloud enablement, cloud platform, cognitive computing, computer vision, conversational AI, customer intelligence, data lake, data mining, data science, deep learning, DevOps, digital marketing, digital revolution, digital strategy, digital transformation, digital twin, digiti, edge computing, evolutionary AI, evolutionary computing, facial recognition, hybrid cloud, image recognition, intelligent automation, intelligent system, machine learning, marketing automation, natural language processing, neural network, operating intelligence, process automation, proprietary algorithm, robotic process automation, smart data, speech recognition, virtual agent, virtual assistant, virtual machine, virtual reality

Panel B: Examples of disclosures in 10-K filings that contain digital-related terms

This panel includes two examples of 10-K filings where firms discuss their digitalization strategies, with the most relevant passages underlined.

Tyson Foods
10-K for the fiscal year ended September 30, 2017
https://www.sec.gov/Archives/edgar/data/0000100493/000010049317000133/tsn201710kq4.htm

Information technology is an important part of our business operations and we increasingly rely on information technology systems to manage business data and increase efficiencies in our production and distribution facilities and inventory management processes. We also use information technology to process financial information and results of operations for internal reporting purposes and to comply with regulatory, legal and tax requirements. <u>In addition, we depend on information technology for digital marketing and electronic communications between our facilities, personnel, customers and suppliers.</u> Like other companies, our information technology systems may be vulnerable to a variety of disruptions, including but not limited to the process of upgrading or replacing software, databases or components thereof, natural disasters, terrorist attacks, telecommunications failures, computer viruses, cyber-attacks, hackers, unauthorized access attempts and other security issues. Attempted cyber-attacks and other cyber incidents are occurring more frequently, are constantly evolving in nature, are becoming more sophisticated and are being made by groups and individuals with a wide range of motives and expertise.

We are engaged in a multi-year implementation of an enterprise resource planning ("ERP") system. Such an implementation is a major undertaking from a financial, management, and personnel perspective. The implementation of the ERP system may prove to be more difficult, costly, or time consuming than expected, and there can be no assurance that this system will continue to be beneficial to the extent anticipated… <u>Additionally, our implementation of the ERP system may involve greater utilization of third-party "cloud" computing services in connection with our business operations. Problems faced by us or our third-party "cloud" computing providers, including technological or business-related disruptions, as well as cybersecurity threats, could adversely impact our business, results of operations and financial condition for future periods</u>.

ABM Industries
10-K for the fiscal year ended October 31, 2020
https://www.sec.gov/ix?doc=/Archives/edgar/data/0000771497/000077149720000018/abm-20201031.htm

Human Resources and Labor Management
<u>During 2019 we launched our new cloud-based human capital management system.</u> This investment will create an HR structure that centralizes and standardizes hiring and training practices to help us make more informed decisions and ultimately manage certain costs. We have also introduced new tools to help our operators manage labor more efficiently, and we continue to invest in attracting, developing, and retaining talent.

Evaluation of Goodwill Impairment Charge
The following are the primary procedures we performed to address this critical audit matter. We evaluated the design and tested the operating effectiveness of an internal control over the Company's goodwill impairment process including the evaluation of the forecasted revenue growth rates, operating margins, and discount rate assumptions used to estimate the fair value of the reporting units. We performed sensitivity analyses over the forecasted revenue growth rates, operating margins, and discount rate assumptions to assess the impact of the changes in those assumptions on the impairment charge. <u>We evaluated the Company's forecasted revenue growth rates and operating margins for the Aviation and Education reporting units by comparing them to underlying business strategies and growth plans and to relevant industry information, including trends and analytics.</u>

Appendix B
Identifying Job Posts for Accountants with Digital Skills

Panel A: Keywords used to identify digital skills

This panel lists the keywords used to identify accountants' digital skills. It includes the digital-related terms developed by Chen and Srinivasan (2021) and the digital-related skill terms developed by Acemoglu et al. (2020) and Gao et al. (2021).

acl, ai chatbot, ai related, ai tech, amazon web services, analytics, apache, apache drill, apache flink, apache hbase, apache hdfs, apache hive, apache pig, apache presto, apache samza, apache spark, apache storm, apache zookeeper, artificial intelligence, audit command language, augmented reality, automation solutions, autonomous tech, big data, biometric, business intelligence, caffe, caseware analytics, chatbot, cloud based, cloud computing, cloud deployment, cloud enablement, cloud platform, cntk, cognitive computing, computer vision, conversational ai, customer intelligence, data lake, data mining, data scien, data visualization, deep learning, devops, digital marketing, digital revolution, digital strateg, digital transformation, digital twin, digiti, eclipse deeplearning4j, edge computing, evolutionary ai, evolutionary computing, facial recognition, gradient boost, hadoop, hybrid cloud, idea data analysis, image processing, image recognition, intelligent automation, intelligent system, keras, kernel method, kylin, latent dirichlet allocation, latent semantic analysis, libsvm, machine learning, machine translation, machine vision, mahout, mapreduce, marketing automation, microsoft powerbi, microsoft visio, mongodb, mxnet, mysql, natural language processing, neural network, nosql, object recognition, opencv, operating intelligence, opinion mining, pattern recognition, predictive model, process automation, proprietary algorithm, python, pytorch, qlikview, random forest, recommender system, robotic process automation, sas, scala, scikit-learn, scipy, sentiment analysis, sentiment classifi, smart data, spark mllib, speech recognition, spss, sql, structured query language, supervised learning, support vector machine, tableau, tensorflow, text mining, theano, unsupervised learning, vba, virtual agent, virtual assistant, virtual machine, virtual realit, visual basic for application, visualization, word2vec, xgboost

Panel B: Examples of job posts with descriptions of digital skills

This panel includes a few examples of job postings for accountants with digital skills, with the most relevant passages underlined.

JOB TITLE: Senior Accountant

ORGANIZATION: Tyson Foods

JOB LOCATION: Springdale, AR

POSITION TYPE: Full-Time

JOB DESCRIPTION:
As part of Corporate Accounting, this position is responsible for managing all aspects of the Enablement Finance & Report Automation Team. Primary responsibilities include facilitating the Shared Services accounting process in its entirety, which includes ensuring the accuracy of the Shared Services financial statements in accordance with Generally Accepted Accounting Principles and ensuring that our Shared Services group leaders and their team members are informed of and understand their financial statements so they can better manage the finances of their areas alerting them to issues and trends seen in the financial results. Additionally, this position will be responsible for driving projects that result in standardizing, simplifying and modernizing current processes. This will also include the successful execution of sustainable, value-added reporting capabilities across Corporate Accounting and the Enterprise. Other essential duties and responsibilities include, but are not limited to; evaluating all Cloud Computing Arrangements and other internally developed software projects to ensure proper accounting treatment, participating in the evaluation of new accounting standards, ensuring the successful execution of the annual AOP process for each of the supported Shared Services groups, including providing accurate, timely and ongoing insights to the plan (AOP, SP, etc.). Additionally, this position will be responsible for accurately forecasting financials of the supported Enablement Functions and optimizing management's decision-making capabilities. Assist in the preparation and review of capital requests. Assist in managing the Company's Financial Fitness activities, including evaluating and reporting out monthly results. Assisting with other quarter-close activities and ad-hoc projects. Building and maintaining effective working relationships with various levels in the organization and being a champion of Tyson's mission, core values, and team behaviors (the 5 Cs) are critical.

QUALIFICATIONS:

- Bachelor's degree in an academic field directly related and essential to this job (Accounting or Finance degree preferred)
- 10+ years of progressive experience
- Working knowledge of SAP and basic knowledge of Microsoft Office applications including Excel, Word, Outlook, PowerPoint, Preferred. <u>Additionally, basic knowledge of Power BI and Tableau is also preferred</u>
- Excellent verbal and written communication skills; strong presentation skills
- Certified Public Accountant, eligible to sit for CPA exam, preferred, but not required. Strong analytical skills and people skills; must be comfortable working with Enabling Functions leaders; possess good knowledge of Generally Accepted Accounting Principles and SOX 404

JOB TITLE: Corporate Financial Analyst

ORGANIZATION: ABM Industries

JOB LOCATION: Sugar Land, TX

POSITION TYPE: Full-Time

JOB DESCRIPTION:
The Financial Analyst is a key member of the Corporate team. This position will be responsible for developing and supporting process automation, utilizing TRECS and our current ERP JDE, and improving the current account reconciliation process. The Financial Analyst will have 3 primary functions: Developing and implementing new processes and tools utilizing various business technologies like Excel, Power BI, TRECS, and Cloud Fusion; Supporting the implementation of process improvements; GL Account Reconciliations. Build tools and processes to enable business process improvement initiatives by automating repetitive processes, improving controls through standardization of workflows, providing enhanced analytical capabilities, and performing complex calculations on large data sets. Create monthly reporting to calculate time savings from robotics and other automation tools. Develop and maintain documentation needed to understand and maintain solutions. Collaborate with IT to integrate new data elements and facilitate data transformations.

QUALIFICATIONS:

- Bachelor of Science in Accounting, Finance, or Information Systems/Technology or related field
- 2 years of relevant professional experience
- GL Account Reconciliation experience
- Proficient in software such as Excel, Power BI, TRECS, and Cloud Fusion Strong organizational skills including attention to detail and multi-tasking
- Ad-hoc reporting experience
- Able to define a problem, generate potential solutions, and evaluate those solutions
- Willingness to learn new tools and techniques
- Proven abilities to take initiative and be innovative
- Able to work in a team environment and on individual projects/tasks with a high level of independence
- Strong sense of ownership and accountability
- Excellent written and verbal communication skills

JOB TITLE: Financial Analyst - Corrosion Protection

ORGANIZATION: Corrpro Companies, Inc.

JOB LOCATION: US-TX-Houston

POSITION TYPE: Full-Time

JOB DESCRIPTION:
The Financial Analyst role is critical finance role for the Corrosion Protection Platform (CPP or the Platform), reporting directly to the VP of Operational Finance for the Platform. The successful candidate will partner closely with Platform leadership across all disciplines, including sales, operations, and controllership to support the budgeting, forecasting, management reporting, and financial analysis processes for CPP and its respective business units. Assess current reporting systems/tools and support efforts to improve business intelligence and reporting capabilities at the local and Platform level. Develop, review, and refine key performance indicators and performance dashboards for each business unit to support critical business decisions Generate and interpret complex financial analyses, including economic/project support, cash flow conversion and forecasting, and return on investment calculations Support Platforms annual budgeting process for full financials, including P&L, capex, and balance sheet through historical and operational metrics Support quarterly forecasting efforts, including developing processes for expanded forecasting in the areas of capital spending, working capital metrics, and ROIC Develop trends or other ad hoc analyses to test forecast assumptions and understand risks and opportunities to the forecast Partner with Sales and Strategy/Corporate Development on market analyses to corroborate forecast assumptions with market drivers and a detailed understanding of the sales funnel Support and test various bonus compensation calculations based on actual and forecasted performance Play a key role in the longer-term implementation of a company-wide forecasting software Perform other duties as assigned

QUALIFICATIONS:

- Bachelor degree in Accounting, Economics, or Finance
- Required 3-5 years of progressively increasing responsibilities in FP&A/Accounting/Finance CPA or MBA
- Preferred Oil and gas sector and/or capital projects experience strongly preferred Operational experience with JD Edwards, Hyperion, and Data Access Studio
- Preferred familiarity with U.S. GAAP and current SEC rules and reporting requirements
- Advanced Microsoft Excel (including ability to mine large sets of data) and PowerPoint skills
- Ability to think creatively, highly-driven and self-motivated Strong attention to detail
- Ability to research and analyze detailed information as well as summarize key message points for executive-level management

JOB TITLE: Financial Analyst

ORGANIZATION: ResMed

JOB LOCATION: San Diego, CA

POSITION TYPE: Full-Time

JOB DESCRIPTION:
This position will be responsible for designing, building and maintaining financial reports, graphs and presentations globally at all levels of the commercial organization and will report to the Finance Manager. This will require becoming familiar with how financial data is generated and consumed across the business. Financial/data analyst will also be involved in the expense allocation process including the creation and maintenance of allocation rules and inputs. Financial/data analyst may also conduct research to determine the best means of obtaining and transforming data into management reports and dashboards. Assist in gathering and interpreting reporting requirements from internal business customers. Assist in designing, standardizing and automating dashboards and reports using a variety of systems. Troubleshoot, validate, and test new and existing reports to ensure data completeness and consistency. Maintain report lists and distribution lists and keep them up to date. Generate and distribute reports in a timely manner according to a predetermined schedule, including daily, monthly, quarterly and annual reports. Assist in generating presentations and reporting packages involving revenue and expense for budget, forecast and actuals. Become a subject matter expert within FP&A on TM1, Cognos, Tableau and other sources of data/reporting.

QUALIFICATIONS:

- Familiar with financial reporting and concepts and also have significant technical proficiencies
- Proficiencies should include advanced excel knowledge including complex formulas and some VBA, SQL or other equivalent basic programing knowledge. Previous experience with financial and reporting systems such as TM1, Cognos, Oracle, Tableau or equivalent is a plus.
- Ability to plan, execute and deliver on projects in a timely manner and to multi-task on varying projects and initiatives with external driven deadlines that may shift during the course of the project
- Strong technical, planning, analytical and problem-solving skills with a high level of demonstrated quantitative, system thinking and finance skills
- Detail-oriented, organized and thorough with desire for continuous improvement
- Ability to understand new business and financial models quickly with less than full information
- Performs well under pressure in both team and individual settings
- Collaborative work style
- Enthusiastically makes contributions and takes satisfaction in team accomplishments
- Ability to build relationship and trust with local and remote colleagues

JOB TITLE: IT Auditor Staff

ORGANIZATION: AERONAUTICS COMPANY

JOB LOCATION: City Fort Worth

POSITION TYPE: Full-Time

JOB DESCRIPTION:
Performs IT and business systems audits reviewing a variety of platforms, operating systems, applications, and processes. Will be responsible to gain a working understanding of the business processes under review, an understanding of and relationship to related requirements and to communicate clearly defined issues. Accountable to comprehend and assess procedures and work instruction to actual process in place. Will work with functional management to provide recommendations for resolution, develop solutions to complex problems which require the regular use of ingenuity and innovation, determine a course of corrective action and present audit results to senior-level management. Auditor may handle multiple complex tasks and will be a team player. Auditor must clearly document assignment while adhering to the Institute of Internal Audit Standards.

QUALIFICATIONS:
- A professional, with working experience in information technology (IT) platforms and applications.
- Good analytical and organizational skills. Initiative to understand and learn various applications, databases and interfaces. MS Office applications, specifically Excel for analytics and databases.
- Ability to clearly and concisely communicate ideas orally and in writing.
- Customer service orientated.
- Familiar with basic auditing principles.
- Able to take instruction and perform independently.
- Personable, a team player and can easily adapt to change. Flexible and willing to learn new processes.
- SAP expertise
- Certified Information Systems Auditor
- Certified Internal Auditor
- Experience in TeamMate audit software
- Experience in ACL or similar audit analytic software
- Data mining expertise
- Knowledge of FAR, DFAR, CAS, EVM, MMAS, Estimating, Procurement, and MRP systems is a plus.

Appendix C
Variable Definitions

Variable	Definition
Firm digitalization variable	
Digitalization	Ranked score for the total number of digital-related words disclosed in a firm's 10-K filing in a year. It is set as 1 (2) [3] if the total number of digital-related words is not zero and is in the bottom (middle) [top] tercile of the sample distribution in year *t*. Digital-related words are those listed in Appendix A. It is set as 0 if there are no digital-related words disclosed in a firm's 10-K filing.
Accountant variables	
Accountants	The number of job postings for accountants divided by the total number of job postings for a firm in a year. Accountants are those with an SOC code of 13-2000 and 43-3000, after excluding 13-2021 Property Appraisers and Assessors, 13-2041 Credit Analysts, 13-2052 Personal Financial Advisors, 13-2053 Insurance Underwriters, 13-2071 Credit Counselors, 13-2072 Loan Officers, 13-2081 Tax Examiners and Collectors, and Revenue Agents, 43-3041 Gambling Cage Workers, and 43-3071 Tellers.
$Accountants^{FS}$	The number of job postings for financial specialists divided by the total number of job postings for a firm in a year. Financial specialists are those with an SOC code of 13-2000, after excluding 13-2021, 13-2041, 13-2052, 13-2053, 13-2071, 13-2072, and 13-2081.
$Accountants^{FC}$	The number of job postings for financial clerks divided by the total number of job postings for a firm in a year. Financial clerks are those with an SOC code of 43-3000, after excluding 43-3041 and 43-3071.
$Digital\ Skills^{Acct}$ ($Digital\ Skills^{FS}$) [$Digital\ Skills^{FC}$]	The number of job postings for accountants (financial specialists) [financial clerks] requiring at least one digital skill divided by the total number of job postings for accountants (financial specialists) [financial clerks] from a firm in a year. Appendix B lists the keywords used to identify digital skills.
$Social\ Skills^{FS}$	The number of job postings for financial specialists that require social skills divided by the total number of job postings for financial specialists from a firm in a year. Social skills refer to those under the "communication," "teamwork," "collaboration," "negotiation," and "presentation" skill clusters identified by Burning Glass (Deming and Kahn 2018).
$Financial\ Skills^{FS}$	The number of job postings for financial specialists that require at least one financial skill divided by the total number of job postings for financial specialists for a firm in a year. Financial skills refer to those under the "finance" and "internal control" skill clusters identified by Burning Glass (Gao et al. 2020).
$Accounting\ Major^{FS}$	The number of job postings for financial specialists requiring an accounting major divided by the total number of job postings for financial specialists for a firm in a year.
$General\ Ability^{FS}$	The number of job postings for financial specialists requiring a Certified Public Accountant (CPA) designation, a Bachelor's degree, and work experience divided by the total number of job postings for financial specialists for a firm in a year.

Control variables for analysis of the demand for accountants and their skills	
Size	Natural logarithm of total assets.
Age	Firm age, calculated as the current year minus the first year the firm appeared in Compustat.
ROA	Income before extraordinary items divided by total assets.
Leverage	Total debts divided by total assets.
MTB	The market value of equity divided by the book value of equity.
Sales Growth	Current year's sales minus last year's sales divided by last year's sales.
R&D	Research and development expenditures scaled by total assets; it is set as zero if the value of research and development expenditures is missing.
SG&A	SG&A expense scaled by total assets; it is set as zero if the value of SG&A is missing.
CAPEX	Capital expenditures scaled by total assets.
Return	Stock returns of a firm over a year.
RetVolt	The standard deviation of daily stock returns for a firm over the fiscal year.

Additional variables for the financial reporting quality analysis	
DA	Discretionary accruals estimated from the Modified Jones model (Jones 1991; Dechow et al. 1995). Specifically, *DA* is the residual estimated from the following regression model: $\frac{ACCR_{i,t}}{TA_{i,t-1}} = \beta_1 \frac{1}{TA_{i,t-1}} + \beta_2 \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \beta_3 \frac{PPE_{i,t}}{TA_{i,t-1}} + \varepsilon_{i,t}$, where *ACCR* is total accruals, defined as earnings before extraordinary items and discontinued operations minus operating cash flows, *TA* is total assets, ΔREV is the change in sales, ΔREC is the change in accounts receivable, and *PPE* is gross property, plant, and equipment. The regression model is estimated by industry-year that has at least 20 observations (industries being defined based on 2-digit SIC codes). We multiply this value by 100 for readability.
DD	Discretionary working capital accruals, estimated from a modified version of the cross-sectional Dechow and Dichev (2002) model (McNichols 2002; Francis et al. 2005). Specifically, *DD* is the residual estimated from the following model: $WCA_{i,t} = \beta_0 + \beta_1 CFO_{i,t-1} + \beta_2 CFO_{i,t} + \beta_3 CFO_{i,t+1} + \beta_4 \Delta REV_{i,t} + \beta_5 PPE_{i,t} + \varepsilon_{i,t}$, where *WCA* is working capital accruals, measured as the change in non-cash current assets minus the change in current liabilities (other than short-term debt and tax payable), *CFO* is operating cash flow, ΔREV is the change in sales, and *PPE* is gross property, plant, and equipment, all scaled by lagged total assets. The regression model is estimated by industry-years with at least 20 observations (industries being defined based on 2-digit SIC codes). We multiple this value by 100 for readability.
DR	Discretionary revenues, estimated from the model developed by McNichols and Stubben (2008) and Stubben (2010). *DR* is the residual estimated from the following model: $\frac{\Delta AR_{i,t}}{TA_{i,t-1}} = \beta_1 \frac{1}{TA_{i,t-1}} + \beta_2 \frac{\Delta REV_{i,t}}{TA_{i,t-1}} + \varepsilon_{i,t}$, where ΔAR is the annual change in accounts receivable, ΔREV is the annual change in sales, and *TA* is total assets. The regression model is estimated by industry-year that has at least 20 observations (industries being defined based on 2-digit SIC codes). We multiply this value by 100 for readability.

FRQ_PC	A composite financial reporting quality measure based on the first principal component generated from a principal analysis of *DA*, *DD*, and *DR*.
$Digital\ Skills^{NonAcct}$	The number of job postings for positions other than accountant positions that require at least one digital skill divided by the total number of job postings for positions other than accountant positions. Appendix B lists the keywords used to identify digital skills.
$Other\ Skills^{FS}$	The number of job postings for financial specialists that require social skills, financial skills, or accounting majors divided by the total number of job postings for financial specialists for a firm in a year.

Variables for the salary analysis, measured at the job posting level

Salary	The natural logarithm of annual salary (in $) specified in the job posting.
Digital Skills ($Digital\ Skills_t^{FS}$) [$Digital\ Skills_t^{FC}$]	An indicator variable that equals one if the job posting requires at least one digital skill (and the job posting is for a financial specialist [financial clerks]), and zero otherwise.
Num Skills	The total number of skills required by the job posting.
Social Skills	An indicator variable that equals one if the job posting requires at least one social skill, and zero otherwise.
Financial skills	An indicator variable that equals one if the job posting requires at least one financial skill, and zero otherwise.
Accounting Major	An indicator variable that equals one if the job posting requires an accounting major, and zero otherwise.
General Ability	An indicator variable that equals one if the job posting requires a Certified Public Accountant (CPA) designation, a Bachelor's degree, and work experience, and zero otherwise.

Appendix D Accountant Job Positions Distribution

This appendix presents the distributions of top 20 accountant job positions for financial specialists and financial clerks in our sample. Financial specialists are those with SOC of 13-2000 (excluding 13-2021, 13-2041, 13-2052, 13-2053, 13-2071, 13-2072, 13-2081). Financial clerks are those with SOC of 43-3000 (excluding 43-3041, and 43-3071).

Panel A: Financial specialists (N=114,340)

Titles	%
Financial Analyst	5.27%
Senior Financial Analyst	4.58%
Senior Accountant	2.70%
Staff Accountant	2.55%
Accountant	2.27%
Pricing Analyst	0.95%
Senior Internal Auditor	0.90%
Cost Accountant	0.86%
Internal Auditor	0.76%
Senior Auditor	0.63%
Financial Analyst II	0.61%
Finance Analyst	0.59%
Tax Accountant	0.49%
Senior Tax Accountant	0.47%
Senior Tax Analyst	0.45%
Accountant II	0.44%
Mult Func Financial Analyst Asc	0.44%
Treasury Analyst	0.41%
Principal Financial Analyst	0.39%
Financial Analyst I	0.38%
Other	73.51%

Panel B: Financial clerks (N=58,824)

Titles	%
Buyer Assistant	4.29%
Accounts Receivable Clerk	3.02%
Accounts Receivable Specialist	2.08%
Accounting Clerk	1.95%
Accounts Payable Clerk	1.87%
Accounts Payable Specialist	1.55%
Back Up Scan	1.55%
Accounts Receivable Representative	1.32%
Billing Specialist	1.30%
Payroll Specialist	1.26%
Accounting Assistant	1.16%
Site Accounting Representative	0.81%
Accounting Associate	0.74%
Payroll Administrator	0.74%
Reimbursement Specialist	0.74%
Billing Clerk	0.73%
College Student Non-Technician	0.67%
Collections Specialist	0.67%
Payroll Coordinator	0.65%
Payroll Analyst	0.63%
Other	72.26%

TABLE 1
Sample Selection and Distributions

This table presents the sample selection procedure and the annual and industry distributions. The final sample includes 7,050 firm-years between 2011 and 2019. Firms with digitalization refer to the observations with $Digitalization_{t-1} > 0$ in a year. Firms requiring digital skills from accountants refer to the observations with $Digital\ Skills_{t}^{Acct} > 0$ in a year.

Panel A: Sample selection

	# of firm-years	# of unique firms
Firm-years in Compustat between 2010 and 2019	85,902	13,411
Less:		
Financial and utility industry (SIC 6000-6999, 4900-4949)	21,133	3,038
Technology firms	14,679	2,523
Firm-years without Burning Glass data	37,948	7,257
Firm-years with missing data for calculating related variables	4,514	2,182
Singleton firms	578	578
Total	7,050	1,333

Panel B: Sample distribution by year

Year	# of firms (1)	# of firms with digitalization (2)	Digitalization percent (3) = (2)/(1)	# of firms requiring digital skills from accountants (4)	Digital skills accountant percent (5) = (4)/(1)
2011	639	55	9%	137	21%
2012	698	84	12%	181	26%
2013	749	100	13%	202	27%
2014	760	114	15%	222	29%
2015	768	153	20%	229	30%
2016	795	262	33%	265	33%
2017	832	252	30%	284	34%
2018	936	288	31%	330	35%
2019	873	398	46%	339	39%
Total	7,050	1,706	24%	2,189	31%

TABLE 1 (cont'd)

Panel C: Sample distribution by Fama–French industries

Because we exclude utility and financial firms, the sample only includes firms in 10 Fama–French industries.

Industry	# of firm-years	# of firm-years with digitalization	Digitalization percent	# of firm-years requiring digital skills from accountants	Digital skills accountant percent
	(1)	(2)	(3) = (2)/(1)	(4)	(5) = (4)/(1)
Consumer Nondurables	619	207	33%	241	39%
Consumer Durables	266	57	21%	70	26%
Manufacturing	926	249	27%	321	35%
Oil, Gas, and Coal Extraction and Products	557	51	9%	156	28%
Chemicals and Allied Products	276	37	13%	106	38%
Business Equipment	206	101	49%	84	41%
Telephone and Television Transmission	137	68	50%	53	39%
Wholesale and Retail	1,070	418	39%	403	38%
Healthcare, Medical Equipment, and Drugs	1,857	487	26%	394	21%
Other	1,136	373	33%	361	32%
Total	7,050	2,048	29%	2,189	31%

Panel D: Job postings distribution by year

Year	# of accounting job postings	# of accounting postings requiring digital skills	Digital skills accountant percent	Average # of digital skills required per accounting job posting requiring digital skills
	(1)	(2)	(3) = (2)/(1)	(4)
2011	12,991	1,295	10%	1.5
2012	14,821	1,305	9%	1.5
2013	17,248	1,679	10%	1.6
2014	18,469	1,759	10%	1.8
2015	21,841	2,287	10%	1.9
2016	20,276	2,556	13%	1.8
2017	20,579	2,945	14%	1.8
2018	23,335	3,420	15%	1.9
2019	23,604	3,642	15%	2.1
Total	173,164	20,888	12%	1.8

TABLE 2
Descriptive Statistics

This table reports the summary statistics of the variables used in the analyses The sample includes 7,050 firm-years between 2011 and 2019. Please see Appendix C for variable definitions.

Variable	N	Mean	Std. Dev.	Q25	Median	Q75
Variables used in the analysis of the demand for accounts and accountants' digital skills						
$Digitalization_{t-1}$	7,050	0.385	0.771	0.000	0.000	0.000
$Accountants_{t}$	7,050	0.043	0.082	0.000	0.018	0.046
$Accountants_{t}^{FS}$	7,050	0.030	0.068	0.000	0.007	0.030
$Accountants_{t}^{FC}$	7,050	0.012	0.033	0.000	0.001	0.011
$Digital\ Skills_{t}^{Acct}$	7,050	0.069	0.162	0.000	0.000	0.059
$Digital\ Skills_{t}^{FS}$	7,050	0.085	0.188	0.000	0.000	0.077
$Digital\ Skills_{t}^{FC}$	7,050	0.014	0.070	0.000	0.000	0.000
$Size_{t-1}$	7,050	7.021	2.024	5.612	7.059	8.428
Age_{t-1}	7,050	24.810	17.970	10.000	20.000	34.000
ROA_{t-1}	7,050	-0.050	0.268	-0.038	0.037	0.078
$Leverage_{t-1}$	7,050	0.258	0.225	0.066	0.229	0.380
MTB_{t-1}	7,050	3.458	8.304	1.350	2.392	4.233
$Sales\ Growth_{t-1}$	7,050	0.172	0.662	-0.010	0.062	0.172
$R\&D_{t-1}$	7,050	0.076	0.170	0.000	0.000	0.045
$SG\&A_{t-1}$	7,050	0.273	0.297	0.060	0.178	0.393
$CAPEX_{t-1}$	7,050	0.055	0.065	0.017	0.034	0.066
$Return_{t-1}$	7,050	0.188	0.633	-0.163	0.087	0.360
$RetVol_{t-1}$	7,050	0.028	0.014	0.017	0.024	0.034
Financial reporting quality variables						
DA_{t}	5,728	1.126	9.093	-2.173	1.825	5.465
DD_{t}	5,728	0.080	4.990	-2.068	0.089	2.286
DR_{t}	5,728	-0.190	2.976	-1.337	-0.317	0.767
FRQ_PC_{t}	5,728	0.001	0.989	-0.431	0.022	0.436

TABLE 3
Firm Digitalization and Accounting Jobs

This table reports the results of the regressions of the number of job postings for accountants (*Accountants*, $Accountants_t^{FS}$, $Accountants_t^{FC}$) on the extent of firm digitalization (*Digitalization*). Please see Appendix C for the variable definitions. We include but do not report the intercepts. The sample includes 7,050 firm-years in the period of 2011-2019. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)
Dependent Variable =	$Accountants_t$	$Accountants_t^{FS}$	$Accountants_t^{FC}$
***Digitalization** t-1*	**-0.001**	**0.001**	**-0.002****
	(-0.60)	**(0.88)**	**(-2.56)**
$Size_{t-1}$	0.004	0.003	0.000
	(1.01)	(1.03)	(0.16)
Age_{t-1}	0.004	-0.002	0.005
	(0.65)	(-0.56)	(1.35)
ROA_{t-1}	0.005	0.006	0.002
	(0.49)	(0.71)	(0.42)
$Leverage_{t-1}$	-0.002	0.004	-0.005
	(-0.17)	(0.42)	(-1.14)
MTB_{t-1}	0.000	0.000	0.000
	(0.93)	(0.24)	(0.55)
$Sales\ Growth_{t-1}$	0.001	0.000	0.000
	(0.39)	(0.28)	(0.37)
$R\&D_{t-1}$	0.010	0.007	0.002
	(0.47)	(0.38)	(0.26)
$SG\&A_{t-1}$	-0.003	-0.007	0.003
	(-0.37)	(-1.09)	(0.69)
$CAPEX_{t-1}$	-0.059	-0.047	-0.013
	(-1.62)	(-1.47)	(-0.98)
$Return_{t-1}$	-0.002	-0.001	-0.001
	(-0.89)	(-0.60)	(-0.72)
$RetVolt_{t-1}$	0.058	0.122	-0.065
	(0.31)	(0.73)	(-1.04)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	7,050	7,050	7,050
Adj. R^2	0.27	0.25	0.22

TABLE 4
Firm Digitalization and Accountants' Digital Skills

This table reports the results of the regressions of digitization skills required for accounting jobs (*Digital Skills*^{Acct}, *Digital Skills*^{FS}, and *Digital Skills*^{FC}) on the extent of firm digitalization (*Digitalization*). Please see Appendix C for the variable definitions. We include but do not report the intercepts. The sample includes 7,050 firm-years in the period of 2011-2019. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)
Dependent Variable =	*Digital Skills* $_t^{Acct}$	*Digital Skills* $_t^{FS}$	*Digital Skills* $_t^{FC}$
Digitalization $_{t\text{-}1}$	**0.007***	**0.011****	**-0.002**
	(1.87)	**(2.33)**	**(-1.22)**
Size $_{t\text{-}1}$	0.004	0.008	0.006**
	(0.65)	(1.02)	(1.99)
Age $_{t\text{-}1}$	-0.032	-0.021	-0.014
	(-1.37)	(-0.84)	(-1.42)
ROA $_{t\text{-}1}$	0.002	0.000	-0.005
	(0.14)	(0.01)	(-1.34)
Leverage $_{t\text{-}1}$	-0.005	-0.007	-0.000
	(-0.32)	(-0.38)	(-0.01)
MTB $_{t\text{-}1}$	0.000	0.000	0.000
	(0.30)	(0.04)	(0.91)
Sales Growth $_{t\text{-}1}$	0.001	0.001	0.001
	(0.25)	(0.33)	(1.15)
R&D $_{t\text{-}1}$	-0.021	-0.038	0.006
	(-0.76)	(-1.15)	(1.20)
SG&A $_{t\text{-}1}$	-0.011	-0.010	-0.004
	(-0.58)	(-0.46)	(-1.12)
CAPEX $_{t\text{-}1}$	-0.011	0.028	-0.031
	(-0.23)	(0.52)	(-1.28)
Return $_{t\text{-}1}$	0.008**	0.009**	0.001
	(2.15)	(2.18)	(0.53)
RetVolt $_{t\text{-}1}$	0.005	0.147	-0.078
	(0.02)	(0.50)	(-0.72)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	7,050	7,050	7,050
Adj. R^2	0.36	0.35	0.37

TABLE 5
Firm Digitalization and Other Skills of Accountants

This table reports the results of the regressions of other skills required of financial specialists (*Social Skills*^{FS}, *Financial Skills*^{FS}, *Accounting Major*^{FS}, *General Ability*^{FS}) on the extent of firm digitalization (*Digitalization*). Please see Appendix C for the variable definitions. We include but do not report the intercepts and fixed effects. The sample includes 7,050 firm-years in the period of 2011-2019. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)	(4)
Dependent Variable =	*Social Skills* $_t^{FS}$	*Financial Skills* $_t^{FS}$	*Accounting Major* $_t^{FS}$	*General Ability* $_t^{FS}$
Digitalization $_{t\text{-}1}$	**-0.003**	**-0.013**	**-0.008**	**-0.007**
	(-0.44)	**(-1.51)**	**(-0.92)**	**(-1.46)**
Size $_{t\text{-}1}$	0.087***	0.107***	0.053***	0.022**
	(5.16)	(6.08)	(3.43)	(1.98)
Age $_{t\text{-}1}$	0.032	0.039	0.048	-0.001
	(0.84)	(1.09)	(1.30)	(-0.04)
ROA $_{t\text{-}1}$	0.006	-0.005	0.034	0.002
	(0.15)	(-0.14)	(0.93)	(0.09)
Leverage $_{t\text{-}1}$	0.023	0.004	0.044	0.036
	(0.47)	(0.08)	(0.92)	(1.02)
MTB $_{t\text{-}1}$	0.000	0.000	0.000	0.000
	(0.66)	(0.11)	(0.45)	(0.53)
Sales Growth $_{t\text{-}1}$	-0.002	-0.004	-0.004	-0.009*
	(-0.21)	(-0.57)	(-0.49)	(-1.74)
R&D $_{t\text{-}1}$	0.027	0.017	0.054	0.054
	(0.32)	(0.19)	(0.62)	(0.89)
SG&A $_{t\text{-}1}$	-0.017	-0.039	-0.033	-0.032
	(-0.39)	(-0.87)	(-0.70)	(-1.11)
CAPEX $_{t\text{-}1}$	-0.017	-0.065	0.008	-0.005
	(-0.11)	(-0.42)	(0.05)	(-0.05)
Return $_{t\text{-}1}$	0.002	0.005	0.005	-0.002
	(0.28)	(0.53)	(0.55)	(-0.27)
RetVolt $_{t\text{-}1}$	1.004	0.999	0.949	0.689
	(1.55)	(1.37)	(1.43)	(1.48)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	7,050	7,050	7,050	7,050
Adj. R^2	0.44	0.52	0.42	0.30

TABLE 6
Firm Digitalization, Accountants' Digital Skills, and Financial Reporting Quality

This table reports the results of the regressions of financial reporting quality on the extent of firm digitalization (*Digitalization*) and financial specialists' digital skills (*Digital Skills^{FS}*). Panel A is based on the individual measures of financial reporting quality (*DA*, *DD*, or *DR*), and Panel B is based on the composite measure (*FRQ_PC*). Please see Appendix C for the variable definitions. We include but do not report the intercepts and fixed effects. The sample includes 5,728 firm-years in the period of 2011-2019. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed tests.

Panel A: Individual measures of financial reporting quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable =	DA_t	DA_t	DA_t	DD_t	DD_t	DD_t	DR_t	DR_t	DR_t
$Digitalization_{t-1}$	0.000		0.153	0.004		0.129	-0.048		0.038
	(0.00)		(0.65)	(0.03)		(0.90)	(-0.60)		(0.41)
$Digital\ Skills^{FS}_{t-1}$		0.161	1.001		-0.311	0.359		-0.441	0.019
		(0.23)	(1.34)		(-0.77)	(0.76)		(-1.49)	(0.06)
$Digitalization_{t-1} \times Digital\ Skills^{FS}_{t-1}$			**-1.321***			**-1.053*****			**-0.718****
			(-1.79)			**(-3.16)**			**(-2.34)**
$Size_{t-1}$	0.388	0.386	0.383	-0.251	-0.247	-0.249	-1.179***	-1.172***	-1.174***
	(0.72)	(0.72)	(0.71)	(-0.89)	(-0.87)	(-0.88)	(-6.63)	(-6.61)	(-6.62)
Age_{t-1}	-0.428	-0.426	-0.387	-0.356	-0.360	-0.328	0.230	0.229	0.246
	(-0.32)	(-0.31)	(-0.28)	(-0.64)	(-0.65)	(-0.59)	(0.68)	(0.68)	(0.73)
ROA_{t-1}	-0.291	-0.289	-0.276	2.360**	2.357**	2.369**	1.447**	1.449**	1.451**
	(-0.17)	(-0.17)	(-0.16)	(2.49)	(2.48)	(2.50)	(2.50)	(2.50)	(2.51)
$Leverage_{t-1}$	0.043	0.044	0.074	1.326	1.325	1.350	-0.042	-0.035	-0.026
	(0.03)	(0.03)	(0.04)	(1.35)	(1.36)	(1.38)	(-0.07)	(-0.06)	(-0.05)
MTB_{t-1}	-0.010	-0.010	-0.009	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(-0.48)	(-0.48)	(-0.46)	(-0.28)	(-0.27)	(-0.24)	(-0.47)	(-0.43)	(-0.41)
$Sales\ Growth_{t-1}$	0.411	0.411	0.410	0.186	0.185	0.184	0.066	0.063	0.063
	(1.43)	(1.43)	(1.42)	(0.97)	(0.96)	(0.96)	(0.65)	(0.62)	(0.62)
$R\&D_{t-1}$	-3.233	-3.234	-3.249	4.584**	4.587**	4.574**	0.570	0.569	0.565

	(-0.90)	(-0.90)	(-0.91)	(2.35)	(2.36)	(2.35)	(0.55)	(0.55)	(0.54)
SG&A $_{t\text{-}1}$	3.422*	3.419*	3.423*	-0.673	-0.667	-0.664	-0.709	-0.701	-0.698
	(1.92)	(1.92)	(1.92)	(-0.63)	(-0.63)	(-0.62)	(-1.63)	(-1.62)	(-1.61)
CAPEX $_{t\text{-}1}$	0.468	0.469	0.417	3.696*	3.698*	3.652*	-0.064	-0.100	-0.096
	(0.12)	(0.12)	(0.11)	(1.95)	(1.94)	(1.93)	(-0.05)	(-0.07)	(-0.07)
Return $_{t\text{-}1}$	0.817**	0.818**	0.830**	-0.025	-0.026	-0.017	0.032	0.030	0.037
	(2.51)	(2.51)	(2.55)	(-0.15)	(-0.15)	(-0.10)	(0.31)	(0.30)	(0.36)
RetVolt $_{t\text{-}1}$	-16.398	-16.369	-16.062	11.143	11.089	11.331	2.694	2.592	2.781
	(-0.69)	(-0.69)	(-0.68)	(0.77)	(0.77)	(0.79)	(0.34)	(0.32)	(0.35)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,728	5,728	5,728	5,728	5,728	5,728	5,728	5,728	5,728
Adj. R^2	0.24	0.24	0.24	0.06	0.06	0.06	0.19	0.19	0.19

TABLE 6 (cont'd)

Panel B: The composite measure of financial reporting quality

	(1)	(2)	(3)
Dependent Variable =	FRQ_PC_t	FRQ_PC_t	FRQ_PC_t
$Digitalization_{t-1}$	-0.006		0.026
	(-0.23)		(0.91)
$Digital\ Skills_{t-1}^{FS}$		-0.082	0.088
		(-0.97)	(0.99)
Digitalization $_{t-1}$ **×** ***Digital Skills*** $_{t-1}^{FS}$			**-0.267*****
			(-3.32)
$Size_{t-1}$	-0.161***	-0.160***	-0.161***
	(-2.88)	(-2.87)	(-2.88)
Age_{t-1}	-0.027	-0.028	-0.020
	(-0.21)	(-0.21)	(-0.15)
ROA_{t-1}	0.416**	0.416**	0.418**
	(2.19)	(2.19)	(2.20)
$Leverage_{t-1}$	0.132	0.132	0.138
	(0.73)	(0.74)	(0.77)
MTB_{t-1}	-0.001	-0.001	-0.001
	(-0.58)	(-0.56)	(-0.53)
$Sales\ Growth_{t-1}$	0.048	0.047	0.047
	(1.26)	(1.25)	(1.24)
$R\&D_{t-1}$	0.382	0.382	0.379
	(0.96)	(0.96)	(0.95)
$SG\&A_{t-1}$	0.007	0.009	0.010
	(0.04)	(0.04)	(0.05)
$CAPEX_{t-1}$	0.391	0.386	0.380
	(0.99)	(0.98)	(0.97)
$Return_{t-1}$	0.042	0.042	0.044
	(1.26)	(1.26)	(1.34)
$RetVol_{t-1}$	0.678	0.661	0.725
	(0.24)	(0.24)	(0.26)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	5,728	5,728	5,728
Adj. R^2	0.10	0.10	0.11

TABLE 7
Cross-Sectional Analysis

This table reports the results of the regressions of financial reporting quality measures (*DA, DD, DR, FRQ_PC*) on the extent of firm digitalization (*Digitalization*) and financial specialists' digital skills (*Digital Skills^{FS}*) in subsamples. High *FV* (Low *FV*) represents firms that have total fair-value amount greater than (smaller or equal to) the sample median for a year. Total fair value amount, *FV*, is the sum of the absolute value of Level-2 fair value assets and liabilities, and Level-3 fair value assets and liabilities, divided by the sum of total assets and liabilities. Please see Appendix C for other variable definitions. We include but do not report the intercepts and fixed effects. The sample includes 3,814 firm-years with available information in the period of 2011-2019. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed tests.

Dependent Variable =	*DA$_t$*		*DD$_t$*		*DR$_t$*		*FRQ_PC$_t$*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample Partitions	High *FV*	Low *FV*	High *FV*	Low *FV*	High *FV*	Low *FV*	High *FV*	Low *FV*
Digitalization$_{t-1}$	0.674	-0.052	0.425	0.032	-0.031	0.154	0.073	0.023
	(1.35)	(-0.15)	(1.53)	(0.13)	(-0.16)	(1.05)	(1.19)	(0.52)
Digital Skills$^{FS}_{t-1}$	-0.452	0.261	0.169	0.859	0.117	0.197	0.013	0.131
	(-0.29)	(0.19)	(0.15)	(1.04)	(0.17)	(0.42)	(0.05)	(0.83)
Digitalization$_{t-1}$ × Digital Skills$^{FS}_{t-1}$	**-1.148**	**-0.399**	**-2.213*** **	**-0.393**	**-1.542** **	**-0.481**	**-0.507** **	**-0.129**
	(-0.56)	**(-0.48)**	**(-2.59)**	**(-0.75)**	**(-2.01)**	**(-1.23)**	**(-2.25)**	**(-1.24)**
P-value for tests on diff. between High and Low	0.30		0.00		0.06		0.01	
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,910	1,904	1,910	1,904	1,910	1,904	1,910	1,904
Adj. R^2	0.16	0.33	0.01	0.03	0.23	0.25	0.03	0.12

TABLE 8
Digitalization, Accountants' Digital Skills, and Financial Reporting Quality—Controlling for Other Employees' Digital Skills and Accountants' Other Skills

This table reports the results of the regressions of financial reporting quality (*DA*, *DD*, *DR*, and *FRQ_PC*) on the extent of firm digitalization (*Digitalization*) and financial specialists' digital skills ($Digital\ Skills^{FS}$) when we control for non-accounting employees' digital skills and financial specialists' other skills. Panel A presents the results when we control for non-accounting employees' digital skills ($Digital\ Skills^{NonAcct}$). Panel B presents the results when we control for financial specialists' financial skills, social skills, and accounting majors ($Other\ Skills^{FS}$). Panel C presents the results when we control for the general ability of financial specialists ($General\ Ability^{FS}$). Please see Appendix C for the variable definitions. We include but do not report the intercepts, control variables, and fixed effects. The sample includes 5,728 firm-years in the period of 2011-2019. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed tests.

Panel A: Controlling for non-accounting employees' digital skills

Variable	(1) DA_t	(2) DD_t	(3) DR_t	(4) FRQ_PC_t
$Digitalization_{t-1}$	0.201	0.158	-0.028	0.022
	(0.83)	(1.06)	(-0.31)	(0.78)
$Digital\ Skills^{FS}_{t-1}$	0.865	0.283	0.136	0.089
	(1.15)	(0.58)	(0.45)	(0.98)
$\boldsymbol{Digitalization_{t-1} \times Digital\ Skills^{FS}_{t-1}}$	**-1.175**	**-0.962****	**-0.970*****	**-0.283*****
	(-1.42)	**(-2.53)**	**(-2.76)**	**(-3.04)**
$Digital\ Skills^{NonAcct}_{t-1}$	1.863	0.993	-0.987	0.063
	(1.19)	(0.92)	(-1.53)	(0.31)
$Digitalization_{t-1} \times Digital\ Skills^{NonAcct}_{t-1}$	-0.789	-0.471	1.047**	0.051
	(-0.68)	(-0.68)	(2.33)	(0.35)
Control Variables	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,728	5,728	5,728	5,728
Adj. R^2	0.24	0.06	0.20	0.10

TABLE 8 (Cont'd)

Panel B: Controlling for other skills of financial specialists

Variable	(1) DA_t	(2) DD_t	(3) DR_t	(4) FRQ_PC_t
$Digitalization_{t-1}$	-0.128	0.290	0.083	0.034
	(-0.38)	(1.28)	(0.65)	(0.79)
$Digital\ Skills^{FS}_{t-1}$	0.853	0.096	0.071	0.061
	(1.10)	(0.19)	(0.22)	(0.64)
$Digitalization_{t-1} \times Digital\ Skills^{FS}_{t-1}$	**-1.692****	**-0.816****	**-0.660****	**-0.253*****
	(-2.08)	**(-2.31)**	**(-2.05)**	**(-2.92)**
$Other\ Skills^{FS}_{t-1}$	0.371	0.435*	-0.111	0.048
	(0.87)	(1.74)	(-0.74)	(0.93)
$Digitalization_{t-1} \times Other\ Skills^{FS}_{t-1}$	0.497	-0.274	-0.081	-0.014
	(1.33)	(-1.07)	(-0.59)	(-0.29)
Control Variables	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,728	5,728	5,728	5,728
Adj. R^2	0.24	0.06	0.19	0.11

Panel C: Controlling for general ability of financial specialists

Variables	(1) DA_t	(2) DD_t	(3) DR_t	(4) FRQ_PC_t
$Digitalization_{t-1}$	0.031	0.132	-0.011	0.014
	(0.12)	(0.81)	(-0.11)	(0.43)
$Digital\ Skills^{FS}_{t-1}$	0.905	0.354	0.107	0.095
	(1.19)	(0.74)	(0.36)	(1.04)
$Digitalization_{t-1} \times Digital\ Skills^{FS}_{t-1}$	**-1.408***	**-1.048*****	**-0.799****	**-0.281*****
	(-1.86)	**(-3.12)**	**(-2.58)**	**(-3.45)**
$General\ Ability^{FS}_{t-1}$	0.830	0.032	-0.524**	-0.025
	(1.22)	(0.09)	(-2.22)	(-0.33)
$Digitalization_{t-1} \times General\ Ability^{FS}_{t-1}$	0.763	-0.022	0.306	0.076
	(1.05)	(-0.06)	(1.24)	(0.98)
Control Variables	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,728	5,728	5,728	5,728
Adj. R^2	0.24	0.06	0.20	0.11

TABLE 9
Coarsened Exact Matching Analysis

This table presents the results of coarsened exact matching (CEM) analysis. CEM is to reduce imbalance between digitalized (*Digitalization* > 0) and non-digitalized (*Digitalization* = 0) firms based on all control variables used in Equation (1). To ensure that we retain a reasonable number of digitalized firms, we create four equally spaced cutoff points for all covariates used in the matching procedure. Please see Appendix C for variable definitions. We include but do not report intercepts, control variables, and fixed effects. The sample includes 5,835 (4,743) firm-years for the analysis of the demand for accountants and their skills (financial reporting quality) in the period of 2011-2019. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable =	$Accountants_t$	$Accountants_t^{FS}$	$Accountants_t^{FC}$	$Digital\ Skills_t^{FS}$	DA_t	DD_t	DR_t	FRQ_PC_t
$Digitalization_{t\text{-}1}$	**-0.001**	**0.001**	**-0.002***	**0.011***	0.261	0.055	0.112	0.033
	(-0.52)	**(0.71)**	**(-1.75)**	**(1.88)**	(0.98)	(0.33)	(1.03)	(1.03)
$Digital\ Skills_{t\text{-}1}^{FS}$					1.362	0.235	0.117	0.107
					(1.62)	(0.49)	(0.31)	(1.18)
$Digitalization_{t\text{-}1} \times Digital\ Skills_{t\text{-}1}^{FS}$					**-1.490***	**-0.810****	**-0.509**	**-0.223****
					(-1.94)	**(-2.27)**	**(-1.41)**	**(-2.53)**
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,835	5,835	5,835	5,835	4,743	4,743	4,743	4,743
Adj. R^2	0.34	0.30	0.33	0.37	0.33	0.18	0.10	0.22

TABLE 10
Frank (2000) ITCV Analysis

This table presents the results from an assessment of the impact of unobservable confounding variables based on the Frank (2000) methodology, with the dependent variable of *Digital Skills* ^{FS} in Panel A and financial reporting quality measures (*DA*, *DD*, *DR*, and *FRQ_PC*) in Panel B. For each independent variable, an impact statistic (*ITCV*) measures the minimum impact of a confounding variable that would be needed to render the coefficient statistically insignificant. The *ITCV* is defined as the product of the correlation between *Digitalization* (*Digitalization* × *Digital Skills*^{FS}) and the confounding variable and the correlation between *Digital Skills*^{FS} (*DA, DD, DR,* and *FRQ_PC*) in Panel A (Panel B) and the confounding variable. To assess the likelihood that such a variable exists, *Impact* indicates the impact of the inclusion of each control variable on the coefficient on *Digital Skills* ^{Acct} (*DA, DD, DR,* and *FRQ_PC*) in Panel A (Panel B).

Panel A: Analyses of Digital Skills ^{FS}

Dependent Variable =	*Digital Skills* $_t^{FS}$	
	(1)	(2)
	ITCV	*Impact*
Digitalization $_{t-1}$	0.034	
Size $_{t-1}$		0.000
Age $_{t-1}$		0.005
ROA $_{t-1}$		0.004
Leverage $_{t-1}$		0.000
MTB $_{t-1}$		0.000
Sale Growth $_{t-1}$		0.003
R&D $_{t-1}$		0.003
SG&A $_{t-1}$		0.000
CAPEX $_{t-1}$		0.000
Return $_{t-1}$		-0.001
RetVolt $_{t-1}$		0.001

TABLE 10 (Cont'd)

Panel B: Analyses of DA, DD, DR, and FRQ_PC

Dependent Variable =	DA_t		DD_t		DR_t		FRQ_PC_t	
	ITCV	*Impact*	*ITCV*	*Impact*	*ITCV*	*Impact*	*ITCV*	*Impact*
$Digitalization_{t\text{-}1} \times Digital\ Skills^{FS}_{t\text{-}1}$	0.007		0.024		-0.011		0.022	
$Size_{t\text{-}1}$		0.000		-.0003		-0.0001		-0.0001
$Age_{t\text{-}1}$		0.000		-.0003		0.0001		0.0001
$ROA_{t\text{-}1}$		0.000		0.0010		-0.0002		-0.0001
$Leverage_{t\text{-}1}$		0.000		-0.0002		0.000		-0.0001
$MTB_{t\text{-}1}$		0.000		0.000		0.000		0.000
$Sale\ Growth_{t\text{-}1}$		-0.0004		-0.0003		-0.0002		-0.0001
$R\&D_{t\text{-}1}$		0.0001		-0.0013		-0.0001		-0.0001
$SG\&A_{t\text{-}1}$		0.000		-0.0001		0.000		0.000
$CAPEX_{t\text{-}1}$		0.000		-0.0004		0.000		-0.0001
$Return_{t\text{-}1}$		-0.0001		0.0002		0.000		-0.0001
$RetVolt_{t\text{-}1}$		0.000		0.000		0.000		0.000

TABLE 11
Alternative Definitions of Firm Digitalization

This table reports the results of the regressions of digitization skills required for financial specialist jobs (*Digital Skills*^{FS}) on the extent of firm digitalization (*Digitalization Unique* and *Digitalization Sent*) and the regressions of financial reporting quality (*DA*, *DD*, *DR*, and *FRQ_PC*) on the extent of firm digitalization and employee skillsets. Please see Appendix C for the variable definitions. We include but do not report the intercepts and fixed effects. The sample includes 7,050 (5,728) firm-years for the analysis of the demand for accountants and their skills (financial reporting quality) in the period of 2011-2019. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed tests.

Panel A: Alternative definition of digitalization using unique digital-related terms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable =	$Accountants_t$	$Accountants^{FS}_t$	$Accountants^{FC}_t$	Digital $Skills^{FS}_t$	DA_t	DD_t	DR_t	FRQ_PC_t
Digitalization Unique $_{t-1}$	**-0.003**	**-0.000**	**-0.002****	**0.014*****	0.072	0.114	0.020	0.018
	(-1.62)	**(-0.32)**	**(-2.16)**	**(2.82)**	(0.30)	(0.80)	(0.20)	(0.63)
Digital Skills $^{FS}_{t-1}$					0.942	0.253	-0.046	0.066
					(1.28)	(0.55)	(-0.16)	(0.75)
Digitalization Unique $_{t-1}$ × ***Digital Skills*** $^{FS}_{t-1}$					**-1.271****	**-0.923*****	**-0.640***	**-0.241*****
					(-2.09)	**(-2.80)**	**(-1.96)**	**(-3.23)**
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,050	7,050	7,050	7,050	5,728	5,728	5,728	5,728
Adj. R^2	0.27	0.25	0.22	0.35	0.24	0.06	0.19	0.11

TABLE 11 (Cont'd)

Panel B: Alternative definition of digitalization using the number of sentences with digital-related terms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable =	$Accountants_t$	$Accountants_t^{FS}$	$Accountants_t^{FC}$	$Digital\ Skills_t^{FS}$	DA_t	DD_t	DR_t	FRQ_PC_t
Digitalization Sent $_{t-1}$	**-0.000**	**0.001**	**-0.001*****	**0.005****	0.013	-0.027	0.030	0.002
	(-0.09)	**(1.18)**	**(-2.83)**	**(2.42)**	(0.13)	(-0.45)	(0.78)	(0.15)
Digital Skills $_{t-1}^{FS}$					0.729	0.128	-0.056	0.042
					(1.04)	(0.29)	(-0.19)	(0.48)
Digitalization Sent $_{t-1}$ × ***Digital Skills*** $_{t-1}^{FS}$					**-0.403***	**-0.307****	**-0.277****	**-0.087*****
					(-1.75)	**(-2.40)**	**(-2.28)**	**(-2.96)**
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,050	7,050	7,050	7,050	5,728	5,728	5,728	5,728
Adj. R^2	0.27	0.25	0.22	0.35	0.24	0.06	0.19	0.11

TABLE 12
Digital Skills and Salary

This table reports the results of the regressions of the natural logarithm of annual salary (*Salary*) on the digital skills (*Digital Skills*) by a job posting for accountants, financial specialists, and financial clerks. Please see Appendix C for the variable definitions. We include but do not report the intercepts and fixed effects. The sample includes 5,013 job postings for accountants in the period of 2011-2019. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed tests.

	Accountants	Financial Specialists	Financial Clerks
	(1)	(2)	(3)
Dependent Variable =	$Salary_t$	$Salary_t$	$Salary_t$
Digital Skills $_t$	**0.186*** **	**0.104*** **	**0.167*** **
	(9.32)	**(5.00)**	**(3.25)**
Num Skills $_t$	0.004***	0.000	0.010***
	(4.05)	(0.35)	(6.48)
Social Skills $_t$	-0.024*	-0.022	-0.031*
	(-1.77)	(-1.26)	(-1.73)
Financial Skills $_t$	0.147***	0.186***	0.035
	(8.12)	(6.62)	(1.65)
Accounting Major $_t$	0.120***	-0.039**	0.095***
	(8.64)	(-2.33)	(4.18)
General Ability $_t$	0.203***	0.124***	-0.068
	(10.53)	(6.42)	(-0.65)
Size $_{t-1}$	-0.081**	-0.042	-0.098
	(-2.05)	(-0.81)	(-1.64)
Age $_{t-1}$	0.028	-0.043	0.116**
	(0.83)	(-1.12)	(2.14)
ROA $_{t-1}$	0.123	-0.400	0.796***
	(0.68)	(-1.57)	(3.52)
Leverage $_{t-1}$	-0.336***	-0.373***	0.164
	(-3.34)	(-2.82)	(1.17)
MTB $_{t-1}$	0.000	-0.001	0.003**
	(0.29)	(-1.25)	(2.46)
Sales Growth $_{t-1}$	-0.013	-0.101	0.100
	(-0.19)	(-1.12)	(1.06)
R&D $_{t-1}$	-3.387**	-3.774**	-3.522
	(-2.55)	(-2.33)	(-1.28)
SG&A $_{t-1}$	-0.103	0.214	-0.361
	(-0.70)	(1.11)	(-1.42)
CAPEX $_{t-1}$	-0.189	0.370	-0.905*
	(-0.50)	(0.74)	(-1.90)
Return $_{t-1}$	0.018	0.041	-0.003

	(0.83)	(1.43)	(-0.10)
RetVolt $_{t-1}$	2.849	9.235***	-0.259
	(1.35)	(2.82)	(-0.10)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	5,013	2,686	2,224
Adj. R^2	0.47	0.42	0.38