Does Greater Access to Employees with Information Technology Capability Improve Financial Reporting Quality?

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Abstract: We examine the association between a firm's access to information technology (IT) capable labor and financial reporting quality (*FRQ*). We proxy for access to IT capable labor using workforce measures in the Metropolitan Statistical Area (MSA) where the firm is headquartered, including: (1) number of IT-related college degrees relative to total workforce; (2) level of education of IT graduates; (3) income level of IT graduates; and (4) a composite measure. We find that firms in MSAs with a greater IT competent labor force are associated with a significantly lower current and future probability of an internal control material weakness and financial misstatement. In terms of economic significance, we document that a one-standard-deviation increase in the IT human capability measures is associated with a 10 to 29.3 percent decrease in the probability of a firm experiencing a material weakness and a 6.2 to 18 percent decrease in the probability of a firm experiencing a financial misstatement, respectively. This study contributes to the IT business value research, as well as to the emerging literature stream examining the influence of geographic labor characteristics on firm-level outcomes.

INTRODUCTION

In this study, we examine whether companies with greater access to information technology (IT) capable human capital demonstrate higher quality financial reporting. This investigation is particularly important since many corporations today continue to face challenges of human error, exponential growth in data sources and volume, as well as ineffective technology (BlackLine 2019).[1] Additionally, organizations continue to lack adequate human expertise to use IT effectively (PWC 2012; Ismail 2017). For example, in the 2018 CIO Survey by KPMG and Harvey Nash USA, almost two-thirds of chief information officers (CIOs) report that a lack of IT talent and skill in employees are holding back their organization (KPMG and Harvey Nash 2018). As one executive in the survey noted, "IT strategy isn't complete unless there are the people to make it happen (KPMG and Harvey Nash 2018)."

A recent 2019 survey (titled *Mistrust in the Numbers*) by BlackLine (NASDAQ: BL) of over 1,100 C-level executives and finance professionals depicts the ongoing problem with financial reporting quality. Nearly 70% of global business leaders and finance professionals affirm that their company has made a significant business decision based on inaccurate financial accounting data. Over half (55%) of respondents are *not* completely confident they can identify financial errors before reporting financial results. Finally, a mere 38% of finance professionals claim that they completely trust the accuracy of their financial accounting data.

The quality of employees matter for financial reporting quality. The 2018 global fraud report by the Association of Certified Fraud Examiner (ACFE) show that tips are almost three times more likely than the next monitoring source (i.e., internal audit) to detect occupational fraud;

[1] See the 2019 global survey by BlackLine. https://www.blackline.com/resources/whitepapers/mistrust-in-the-numbers/.

more than half (53%) of all tips are provided by the company's own employees.[2] Academic studies highlight the key role of employees in the financial reporting process. For example, Dyck, Morse, and Zingales (2010) show that employees play a bigger role in uncovering corporate frauds in the U.S. compared to external auditors, regulators, and the media. Call, Kedia, and Rajgopal (2016) document that misreporting firms grant more stock options to "rank and file" employees during the misreporting period. Their findings illustrate that management recognizes the ability of employees to detect wrongdoing and so they try to give employees incentives to remain quiet about irregularities. More recently, the work by Call et al. (2017) uses the average workforce education level in MSA(s) where the firm operates as a proxy for overall employee quality, finding that higher employee quality contributes to higher financial reporting quality.

We build upon this stream of research by investigating specifically the IT-related education and competency level of the workforce. We proxy for the firm's access to IT capable workers in three ways[3]: (1) the average IT education level (i.e., undergraduate or graduate studies) in the MSA where the firm is headquartered, (2) the average number of workers with IT degrees in the company's MSA, and (3) the average salary level of IT employees in the company's MSA. Using these measures, we examine whether access to a high IT capable workforce is associated with better financial reporting outcomes.

We posit that firms with greater access to IT competent labor are associated with higher financial reporting quality. In businesses today, IT is such an integral aspect of the financial reporting process and pervasively affects the quality of accounting information (Lim et al. 2011; Masli et al. 2011; Chen et al. 2014; Ashraf, Michas, and Russomanno 2019). IT provides an

[2] https://www.acfe.com/report-to-the-nations/2018/default.aspx
[3] In the testing, we also use a composite measure of these three measures. We discuss this further in the Methodology section.

automated and computerized means for firms to record, process, store, and report accounting data (AICPA 2006, Ashraf et al. 2019). The American Accounting Association (2020) states that "the importance of accounting information systems is vital, given the essentially total reliance of accounting and auditing on computerized information systems." The organization also notes that accounting systems do not operate in isolation because IT plays a ubiquitous role in all aspects of the lives of individuals and organizations (American Accounting Association 2020).

The 2019 global survey by BlackLine report that of the top executives who did not completely trust the accuracy of their financial data, human error topped the list of reasons for the mistrust. Call et al. (2017) suggest that higher educated employees provide higher quality inputs into the financial reporting process, which then generates reliable financial disclosures. In this setting, we argue that the IT capability of workers critically influences the quality of information input into the financial reporting system. Employees with higher IT competency use technology more effectively. Hence, workers with greater IT skills should be more capable of using the underlying accounting information systems to reduce input errors and to generate higher-quality inputs, leading to higher financial reporting quality. Even if the IT skilled worker is not directly inputting the information, he or she is able to assist, guide, or train other employees to use the accounting system effectively. For example, in the process of gathering and generating financial accounting data, more IT capable employees are able to demonstrate to colleagues how to use the software features correctly. Additionally, IT competent employees are more capable of detecting errors and glitches in the system. Overall, a more IT-savvy workforce would help ensure that the accounting IT system is being utilized appropriately.

Greater access to IT capable employees can also improve the company's ability to identify and uncover intentional financial misreporting. Top management and corporate insiders can take advantage of integrated IT systems to make opportunistic and discretionary accounting decisions that lower financial reporting quality. For example, Brazel and Zhang (2008) note that ERP systems provide management with unprecedented access to real-time accounting information, which aids better decision-making. At the same time, however, having greater access and control over financial accounting data gives management more opportunity to manage earnings (Brazel and Zhang 2008). IT capable employees can serve as a counterbalance. The work by Call et al. (2016) indicates that employees have the ability to uncover unsavory practices happening inside the company. In this case, IT-savvy employees have an understanding of the inner-workings of the IT system and hence, are more likely to recognize when activities occurring in or decisions made in the accounting IT system appear suspicious and potentially fraudulent. Furthermore, Glaeser and Saks (2006) show that educated individuals are more proactive than less educated individuals in monitoring and preventing corruption. In this setting, IT educated employees are more willing and able to monitor irregularities in the accounting system as well as to prevent misuses of IT.

Companies often have internal mechanisms (e.g., the internal audit function) to detect and prevent financial misreporting. In doing so, companies increasingly rely on the use of technology-based audit techniques, which are automated audit tools such as generalized audit software, computerized audit programs, and computer-assisted audit techniques (IIA IPPF 2016). If companies have greater access to IT capable workers, they have a better chance of recruiting employees who can use technology-based audit techniques competently.

To conduct the study, we use data from the United States Census Bureau's American Community Survey (ACS) to obtain average IT education, number of IT graduates, and IT salary levels of each MSA. We examine the association between these three IT labor force quality measures and financial reporting quality. In the models, we control for various MSA-level variables (including non-IT related education of the overall workforce) as well as company-specific factors that may affect financial reporting quality.

We examine the association between IT capability of the workforce and two attributes of financial reporting quality – the propensity to report a material weakness in internal controls and the likelihood of a firm misstating its financial statements. We provide evidence suggesting that companies headquartered in MSAs with higher average levels of IT degrees, IT education, and IT wages are associated with a lower likelihood of both reporting a material weakness and misstating financial statements in the current and future periods. Interestingly, we do not find consistent associations between the non-IT education level of employees and financial reporting quality. We next provide corroborating evidence by showing that the results are robust to the inclusion of firm fixed effects, as well as by documenting that firms that relocate to an MSA with a higher-quality IT workforce are associated with increased financial reporting quality. We conclude that access to employees with higher education in IT, in particular, matters for financial reporting quality.

Our study makes several contributions. We contribute to the research on the business value of IT, which is a significant stream of research in the information systems (IS) and accounting information systems (AIS) literatures. Given the importance of IT capability, there is great interest in how IT capability is measured (Lim et al. 2011; Masli et al. 2011; Yoon 2011). We introduce a new measure of IT capability that is associated with firm outcomes. We contribute to the line of work investigating whether and how IT resources and capabilities affect the company's business outcomes (Kobelsky et al. 2008; Lim et al. 2011; Masli et al. 2011; Kim et al. 2018). Academics and practitioners advocate that human resources with superior IT capability should be considered a valuable asset that contributes to business value (Ross et al. 1996; Bharadwaj 2000; Melville et al. 2004). We extend the IT business value literature by developing an empirical proxy of the IT capability of employees. We show that access to a workforce with higher IT education and competency facilitates companies to generate higher financial reporting quality.

Our study adds to the emerging literature investigating the influence of MSA-level characteristics on corporate-specific outcomes. For example, McGuire et al. (2012) document that companies headquartered in highly religious MSAs have better financial reporting quality. Call, et al. (2017) investigate the education level of the overall workforce and find that companies headquartered in MSAs with higher average employee education levels have higher mandatory and voluntary disclosure quality. In this work, we focus on the IT education of employees, which represents a specialized component of labor competency. Controlling for the non-IT education level of the overall workforce, we find that having access to more IT educated and qualified workers contributes to higher financial reporting quality.

Our work should also be informative to business executives, managers, human resource departments, boards of directors, and other business practitioners. Given the importance of IT on business strategy and financial reporting processes, managers ought to continuously monitor the availability of labor with high IT competency in their area. We conclude that having access to employees with high IT competency matters for the financial reporting process.

The remainder of the paper is organized as follows: Section II provides background and develops the hypotheses. Section III describes the research design and empirical models. Section IV provides empirical results, and Section V concludes this study.

BACKGROUND AND HYPOTHESES DEVELOPMENT

Prior literature on MSA level characteristics and corporate outcomes

There is a stream of literature in the economics and finance disciplines, suggesting that the social environment where a firm is headquartered affects firm outcomes and relationships with various stakeholders (Hilary and Hui 2009). Recently, accounting research has begun to investigate the association between social and environmental factors and outcomes for the firm and its stakeholders. For example, Jha and Chen (2014) find that firms in high social capital areas pay lower audit fees, while Beck et al. (2018) find that the human capital of the region in which the auditor is located is associated with higher audit quality. McGuire et al. (2012) examine the impact of religion on financial reporting quality and find that firms in religious areas are less likely to engage in financial reporting irregularities. Boone et al. (2013) find that religiosity is associated with less tax avoidance, while Callen and Fang (2015) find that firms in religious areas exhibit lower levels of stock price crash risk.

Most closely related to the current study, Call et al. (2017) investigate the role that the education level of the MSA (a proxy for the firm's broader workforce) has on financial reporting and disclosure quality. Call et al. (2017) find that firms headquartered in MSAs with higher levels of education are associated with higher quality financial reporting. They conclude that the workforce prepares the accounting information and provides the internal data that form the basis for the company's financial reporting choices; the MSA education level is a reasonable proxy for the education level of a firm's workforce. This study extends this line of inquiry by investigating the effects of MSA level IT education, which is a specialized element of general labor skill.

IT human capital as a valuable resource

The resource-based view of the firm suggests that firm-specific resources and skills, that are rare and difficult to duplicate, contribute to the firm's competitive advantage and performance

(Barney 1991; Mata et al. 1995). Applying the resource-based perspective to IT, Bharadwaj (2000) argues that investments and spending in IT do not necessarily produce competitive advantages since competitors easily duplicate such investments; rather, it is the firm's development of unique IT resources and competencies that translates IT to business value (Bharadwaj 2000; Melville et al. 2004). She defines the "ability to mobilize and deploy IT-based resources" as IT capability (Bharadwaj 2000, p. 171). Bharadwaj (2000) continues by defining three resources that contribute to IT capability: 1) tangible IT infrastructure; 2) human IT resources; and 3) intangible IT resources. This has spawned several streams of research investigating the contribution of IT capability on firm business value and firm performance.

Because IT human competencies are largely unobservable, there is a dearth of archival research on the business impact of human IT capability. However, competent IT human skills have long been suggested as a key source of competitive advantage given that such resources are valuable and are heterogenously distributed across firms (Ross et al. 1996; Bharadwaj 2000; Melville et al. 2004). These skills include knowledge to build IT applications using available technology and to effectively utilize IT to make products or provide services (Capon and Glazer 1987; Mata et al. 1995). Bharadwaj (2000; p. 173) particularly notes that "firms with strong human IT resources are able to (1) integrate the IT and business planning processes more effectively, (2) conceive of and develop reliable and cost effective applications that support the business needs of the firm faster than competition, (3) communicate and work with business units more efficiently, and (4) anticipate future business needs of the firm and innovate valuable new product features before competitors."

In their IT integrative model of IT business value, Melville et al. (2004) offer human capital as a key resource, referring to the IT expertise and knowledge of its workforce. Examples of this expertise include the development of software and applications, integration of multiple systems, and maintenance of existing IT systems (Melville et al. 2004). They clarify that human IT expertise may be associated with the whole IT infrastructure of the organization, reside locally within individual business units, or be associated with specific business applications (Melville et al. 2004).

Practitioners also value the human capital of IT. For example, Ross et al. (1996) interviewed fifty top executives about their IT management practices. Respondents indicated that the human asset is an essential component of overall IT assets. They define valuable human assets as employees that solve business problems and address business opportunities through the utilization of information technology (Ross et al. 1996). In sum, despite its importance in theory and practice, the human capital resource of IT capability has been largely unexplored.

Hypothesis development

Recent research has investigated the role that a firm's workforce plays in financial reporting quality. Dyck et al. (2010) examine a large sample of alleged corporate fraud in large US companies and find that the firm's employees often uncover corporate wrongdoing, more so than other governance mechanisms (i.e., auditors, regulators, etc.). The 2018 ACFE global fraud report shows that tips are the number one source of occupational fraud detection and the majority of tips come from employees. Call et al. (2016) provide evidence that managers are aware of employees' ability to uncover and report misconduct because executives grant more stock options to employees in periods of misreporting. Further, Call et al. (2017) suggest that having higher quality employees (i.e., more educated employees) improves financial reporting quality because these employees input fewer errors into the accounting system and are more likely to recognize when a transaction appears irregular and possibly fraudulent.

The positive link between employee quality and financial reporting quality should be more salient for a workforce that has higher IT competency. The overall financial reporting process is integrally linked to the underlying accounting information systems and technology that initiate, record, process, and report business transaction data used in financial statement generation (Tucker 2001; ITGI 2004; Li et al. 2012). IT capable employees are more proficient in using IT and ought to make fewer errors when processing data within the accounting information system. IT competent employees are also able to support other employees in using the accounting system more proficiently. For example, IT skilled employees are able to demonstrate to coworkers who are inputting data how to use the software features correctly. Employees adept in IT are also more proficient in detecting errors and anomalies in the system.

Top management and corporate insiders can use integrated IT systems to make opportunistic and discretionary accounting decisions that lower financial reporting quality (Brazel and Dang 2008). IT capable employees can help offset this activity. The findings by Dyck et al. (2010) and Call et al. (2016) suggest that employees have the ability to expose unsavory business conduct happening in the organization. In this setting, IT proficient employees have a good comprehension about the inner-workings of the IT system and thus, are more likely to recognize irregular activities in the accounting IT system. Furthermore, Glaeser and Saks (2006) show that when individuals suspect corruption, those who are more educated are more willing and able to take action compared to those who are less educated. In the current case, IT educated workers will be more proactive, relative to less IT educated workers, in uncovering irregularities in the accounting system and in preventing the misuse of IT.

Nowadays, companies rely more and more on the use of technology-based audit techniques to detect and prevent misreporting. Internal audit functions make use of a variety of technology tools, such as generalized audit software, computerized audit programs, and computer-assisted audit techniques (IIA IPPF 2016). If companies have greater access to IT educated workers, they can better engage employees who are competent in operating such technologies. The hypothesis is as follows:

> **H: Access to IT competent labor is positively associated with financial reporting quality.**

RESEARCH DESIGN

Sample Selection

We retrieve all firm-level financial data for firms covered in Compustat from 2009-2016. We restrict the sample to firms with positive sales and assets above $10 million. After merging the sample with Audit Analytics, we retain 25,452 firm-year observations. We then merge this dataset with the MSA statistics, yielding the final sample of 19,470 firm-year observations.[4]

Measuring IT capability of a firm's workforce

Given that the IT capability of employees at the firm level is unobservable, we proxy for a firm-level IT capability by measuring the IT capability of individuals at the MSA level. We access the ACS data collected and administered by the US Census Bureau. Given the interval of the decennial census conducted in the US (2000, 2010, and expected in 2020), the ACS survey has been conducted annually to collect household-level data for each MSA. ACS data require extensive processing to make it easily accessible, so we follow prior research and gather data from the University of Minnesota's Integrated Public Use Microdata Series (IPUMS–USA; Call et al. 2017).[5] IPUMS provides economic data on households and individuals in non-decennial census years.

[4] The number of observations decreases when the dependent variables are measured in year *t+1* and *t+2*.
[5] See https://usa.ipums.org/usa/index.shtml.

Call et al. (2017) note that IPUMS employment data is inherently limited to the period 2005-2011, so we base the analysis of IT quality workforce on the place of residence instead of the place of employment. We gather information on the place of residence from IPUMS data item *MET2013*.[6] We use the individual's employment MSA (IPUMS data item *PWMETRO*) to identify the individual's location when *MET2013* data is unavailable. At this point, we acknowledge that it is not uncommon for employees to travel within city limits and even beyond, yet we would argue that it is unlikely that those individuals leave one MSA to travel to their place of work located in another MSA. Therefore, we believe that choosing the MSA of residence to determine the quality of the IT labor workforce is appropriate in the vast majority of cases.

We compute the level of IT capability per MSA using three distinct but related measures of the quality of the IT labor force. First, we compute the average number of individuals holding an IT or IT-related degree, weighted by the survey sampling weights[7] (*PERWT*). We argue that the higher the number of qualified IT graduates per MSA, the easier it is for firms to fill vacant positions, which should contribute to higher IT capability. Second, we calculate the average level of education of IT graduates (*IT_EDU*), weighted by the survey sampling weights. While *IT_DEG* affects how likely firms are able to meet their quantitative demand for IT graduates in a given MSA, we believe that the level of education of IT graduates (undergraduate vs. graduate studies) measures the quality of those graduates, thereby capturing a different dimension of IT workforce quality. Third, we calculate the average income level of IT graduates, *IT_WAGES,* weighted by the survey sampling weights. We believe that the third measure captures a combination of an

[6] Call et al. (2017) use IPUMS data item *METAREA* for missing *PWMETRO* items which is only available for the time period 2005-2011. For the identification of place of residence, we use the most recent delineation of MSAs published by The Office of Management and Budget (OMB) as described by IPUMS data item *MET2013*.
[7] The survey sampling weights (*PERWT*) indicate the number of individuals living in the U.S. who are similar to the survey respondent in terms of socio-economic characteristics. Sampling weights are determined by IPUMS.

individual IT graduate's experience and importance within the firm. That is, more important and more experienced IT employees likely receive higher salaries compared to less talented and less experienced employees. Taken together, we argue that the three measures of IT workforce quality measure similar, yet distinct, dimensions of the quality of IT labor supply within any given MSA. We illustrate the computation of the IT-capability measures per MSA in Appendix A. We also compute a composite IT score by applying principal component analysis to the preceding variables (*IT_COMP*).[8] Figure 1 provides a graphical representation of the average number of IT graduates per division in the sample. As expected, the Pacific and the South Atlantic Divisions have the highest concentration of individuals with at least one IT degree.

Insert Figure 1 here

IPUMS provides information about the workforce status (active vs. an inactive member of the workforce), so we follow prior literature (Call et al. 2017) and only include information on individuals actively participating in the workforce. We retrieve the most current MSA and delineation data from the US Census Bureau to get a list of all US Counties that are part of an MSA.[9] We then retrieve all currently active ZIP codes per county as published by the United States Postal Service's (USPS), providing us with detailed and most current data of the complete universe of US ZIP codes and their corresponding MSAs.[10,11] Given that each county can only belong to one single MSA, we can match each city to its corresponding MSA, if the county to which the city belongs to is part of an MSA.

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[8] We use the Kaiser-Meyer-Olkin (KMO) test to measure the suitability of the data for the use of PCA. The KMO test yields a mean 0.737 for the *MW* and *Misstatement* samples. A statistic above 0.5 is desirable (Cerny and Kaiser 1977).
[9] The OMB delineates MSAs and micropolitan statistical areas (MISA) according to most current standards that are applied to all US Census Bureau data. Per definition, any one county can belong to only one MSA or MISA, or neither. See https://www.census.gov/programs-surveys/metro-micro/about/omb-standards.html for more detailed information about the definitions of MSAs and MISAs.
[10] The delineation data published by the OMB and used in the analyses are current as of August 2017.
[11] Some ZIP codes span multiple counties. Using United States Postal Services (USPS) data, we are able to assign the county to the ZIP code it most closely belongs to.

Research Design

The hypothesis predicts a positive association between a firm's access to high-quality IT labor and financial reporting quality. We proxy for financial reporting quality employing two direct and unambiguous measures, material weakness *(MW)* and misstatement of financial reports (*MISSTATE)*. We test the hypothesis by estimating the following two regression models with clustered standard errors by firm:

$$MW_{i,t-t+2} = \alpha_0 + \beta_1 IT\_C + \Sigma\beta_k MSAControls + \Sigma\theta_j FirmControls + \Sigma\mu_m IndustryFE + \Sigma\rho_n YearFE + \varepsilon_{i,t} \quad (1)$$

$$MISSTATE_{i,t-t+2} = \alpha_0 + \beta_1 IT\_C + \Sigma\beta_k MSAControls + \Sigma\theta_j FirmControls + \Sigma\mu_m IndustryFE + \Sigma\rho_n YearFE + \varepsilon_{i,t} \quad (2)$$

We estimate Eq. (1) - (2) using logistic regression, and we assess statistical significance throughout the paper using two-tailed *p*-values. We include industry and year fixed effects. *IT_C* refers to the IT quality measures, *IT_DEG*, *IT_EDUC*, *IT_WAGES*, and *IT_COMP*. *MSAControls* refers to control variables that are measured for each MSA. *FirmControls* includes firm-specific control variables. We report regression results for both models for the current period (*t*) and the two following periods (*t+1* and *t+2*).

We control for a variety of MSA-based variables. Specifically, we control for the natural logarithm of the number of total IT graduates per MSA (*IT_LNPOP*), as well as for the overall education level (*GEN_EDU*). To control for the difference in income levels between IT graduates and the overall population, we include *INC_DIFF* measured as the average income level of IT graduates divided by the average income level of the general population excluding IT graduates. We also include *BUS_DEG* to ensure that the results are not driven by other business-related college degrees, such as accounting, finance, or management degrees.

To control for the overall economic environment per MSA, we consider several factors, such as the consumer price index (*CPI*), unemployment rate (*UNEMPLOYMENT*), number of new housing starts (*NEWHOUSING*), and a summary measure for an MSA's economic condition, that is the state coincident index (*SCI*). We also include the average profitability and earnings volatility per MSA (*MSAROA* and *MSAROAVOL*). Prior research notes a positive relationship between the level of religiosity and financial reporting quality (McGuire et al. 2012; Dyreng et al. 2012). We, therefore, control for the level of religious adherence by including *RELIGIOUS*. We generally expect a positive sign for *RELIGIOUS*. Finally, we include the number of survey respondents whose occupation is that of a reporter (*REPORTER*), as prior research identifies the level of press coverage as a monitoring device (Miller, 2006). Besides the direction of *RELIGIOUS*, we do not predict the sign or magnitude of any other MSA-level control variable.

The set of firm-level control variables for Eq. (1) - (2) is based on prior literature (e.g., Roy 1952; Simunic 1980; Dechow and Dichev 2002; Palmrose and Scholz 2004; Hay et al. 2006; Ashbaugh-Skaife et al. 2007; Doyle et al. 2007b; Hribar and Nichols 2007; Hoitash et al. 2009; Hoitash and Hoitash 2018) and described in detail in Appendix A.

EMPIRICAL RESULTS

Descriptive statistics and correlations

We present in Table 1 descriptive summary statistics. We document a mean value of approximately 0.022 for *IT_DEG*, meaning that, on average, 2.2 percent of the total workforce among all MSAs hold an IT degree. The mean education level of these IT graduates (*IT_EDU*) equals approximately 10.3.[12] The mean (median) income level of these IT graduates (*IT_WAGES*) equals $83,000 ($82,000) over the sample period 2009-2016.

[12] An education level of 10 equals 4 years of college and a level of 11 equals 5+ years of college. See Appendix A for a detailed explanation of education levels.

Insert Table 1 here

Table 2 presents correlations among the MSA variables. *IT_DEG*, *IT_EDU*, and *IT_WAGES* exhibit significant correlations with most MSA variables. Specifically, *IT_DEG* is positively correlated with *IT_EDU*, *IT_WAGES*, *GEN_EDU*, *BUS_DEG*, *IT_LNPOP*, *INC_DIFF*, *SCI*, and *MSAROAVOL*. *IT_DEG* exhibits negative and significant correlations with *CPI*, *RELIGIOUS*, *UNEMPLOYMENT*, and *MSAROA*. *IT_EDU* and *IT_WAGES* exhibit similar correlations. See Appendix A for variable definitions.

Insert Table 2 here

Main results

For the hypothesis, we regress measures of *FRQ* on the independent variables of interests and sets of MSA level variables and firm-specific controls. Consistent with prior research (Call et al. 2017), we document a positive association between the overall education level (*GEN_EDU*) including IT-related education and *FRQ* (Table 3, Panel A). This positive association persists with *FRQ* measured in *t+1* (Table 3, Panel B). In columns two to five of Table 3, Panels A-C, we separate the IT-related education (*IT_EDU*) from the general education and find that the overall education level excluding IT (*GEN_EDU_NOIT*) becomes mostly insignificant in explaining variation in *FRQ*, while all of the IT human capability measures including the IT-specific education level (*IT_EDU*) become highly predictive. We note that, in year *t*, all IT human capability measures are negatively and statistically significantly associated with *FRQ*. For year *t+1* and *t+2* (Table 3, Panels B and C), we document that three of the four IT human capital measures (*IT_EDU* is not statistically significant) are negatively associated with *MW*. In economic terms, we observe a one-standard-deviation increase in *IT_DEG* is associated with a 29.3 percent decrease in the probability of experiencing a material weakness. Similarly, a one-standard-deviation increase in *IT_EDU (IT_WAGES)* is associated with a ten (23.7) percent decrease in the probability of reporting a material weakness. Finally, a one-standard-deviation increase in *IT_COMP* is associated with a 26.8 percent decrease in the probability of a firm reporting a material weakness.

Insert Table 3, Panel A here

Insert Table 3, Panel B here

Insert Table 3, Panel C here

Again, we document in column one of Tabel 4, Panels A-C, a positive association between the general education level (*GEN_EDU*) and *FRQ*. When separating the IT-specific education from the general education level, the general education level (*GEN_EDU_NOIT*) becomes mostly insignificant, suggesting that it is the average education level of IT graduates as compared to the average education level of the overall workforce that explains variation in *FRQ*. Besides, we continue to observe significant effects of the IT human capability measures on *FRQ* proxied by *MISSTATE*. Specifically, we document that a one-standard-deviation increase in the IT human capital measures is associated with a 6.2 to 18 percent decrease in the probability of a firm reporting a misstatement, respectively. This relation appears to be the strongest in year *t* as only *IT_DEG*, *IT_EDU*, and *IT_COMP* are negative and significant in *t+1* and *IT_DEG* and *IT_COMP* in *t+2*, respectively. Together, we find strong support for the central hypothesis positing a positive association between greater access to IT capable labor and *FRQ*.

Insert Table 4, Panel A here

Insert Table 4, Panel B here

Insert Table 4, Panel C here

Robustness tests and additional analyses

IT core employees or support staff?

Generally, IT employees can assume different functions in an organization, e.g., that of a core-employee, as it is the case in high-tech firms or that of support staff, as is the case in non-high-tech firms. Following the definition of high-tech firms in Krishnan and Yang (2009)[13], we examine whether the observed effects in the principal analysis are concentrated among high-tech firms (*HIGHTECH*). Ex-ante, we do not predict whether the asserted relation between access to IT capable labor and *FRQ* applies equally to high-tech and non-high-tech firms. To examine the differential effect, we include a dummy variable indicating the presence of a high-tech firm in each of the main regressions (Eq. 1-2) and interact that dummy with the IT human capability measures. We merely observe a significant interaction between *HIGHTECH* and both *IT_EDU* (p<0.10) and *IT_WAGES* (p<0.05) on *MW*, and *HIGHTECH* and *IT_WAGES* (p<0.10) on *MISSTATE*. Together, we do not find substantial evidence suggesting a differential effect between high-tech and non-high-tech firms.

Excluding ambiguous IT and IT-related college degrees

We conduct a number of tests to examine the robustness of the findings. We acknowledge that some degrees may be interpreted as business degrees rather than IT degrees.[14] We exclude those degrees with differing IPUMS degree identification numbers.[15] We exclude potentially ambiguous degrees, such as *Communication Technologies* (IPUMS data item DEGFIELDD #2001), *Computer Engineering* (IPUMS data item DEGFIELDD or DEGFIELD2D #2407), *Mathematics and Computer Science* (IPUMS data item DEGFIELDD or DEGFIELD2D #4005), and *Management Information Systems and Statistics* (IPUMS data item DEGFIELDD or

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[13] Krishnan and Yang (2009) identify high-tech firms as being part of the following 3-digit SIC-codes: 283, 284, 357, 366, 367, 371, 382, 384, or 737.
[14] IPUMS assigns '21' for the first two digits of data item *DEGFIELD or DEGFIELD2* to identify *Computer and Information Sciences* degrees.
[15] IPUMS assigns '62' for the first two digits of data item *DEGFIELD or DEGFIELD2* to identify *Business* degrees.

DEGFIELD2D #6212). After dropping these degrees, we find that the results remain qualitatively unchanged.

Combinations of IT and business degree

Next, we examine whether the observed effects are concentrated among specific combinations of IT degrees and other, business or non-business-related degrees. We concentrate the analysis on differences among individuals holding both an IT degree and a business degree, graduates that hold an IT degree and a non-business degree, and individuals holding any IT degree. We find no evidence that the results are driven by those graduates holding both an IT degree and a business degree. We neither find evidence that the combination of IT degree and non-business degree is driving the results. We conclude that holding any IT degree, whether combined with a business or non-business degree, drives the findings.

Controlling for InformationWeek 500

Several studies use the *InformationWeek* 500 rankings to measure firm-specific IT capability (e.g., Kim, Song, Stratopoulous 2018). There is a concern that the results documenting an association between employee IT competency and firm performance and financial reporting quality are predominantly driven by the company's inclusion in the *InformationWeek* 500 list. To allay this concern, we re-estimate the tests controlling for the presence on the *InformationWeek* 500 list of technology leaders. After doing so, the inferences remain unchanged.

Firm-fixed effects

Similar to the changes in headquarters analysis, we run firm-fixed effects regression models. In Table 5, we document that *IT_DEG*, *IT_EDU*, and *IT_COMP* load negatively and statistically significantly on *MW* (with p-values ranging from $p<0.05$ to $p<0.01$). In Table 6, we find results suggesting a change in *IT_DEG* and *IT_EDU* being associated with a decrease in *MISSTATE* (with p-values at $p<0.05$). Together, results from the firm-fixed effects regression models provide support that within-firm changes in the IT human capability measures over time are associated with *FRQ*.

Insert Table 5 here

Insert Table 6 here

Changes analysis - location changes

We next address a potential correlated omitted variable bias by examining firms that change their headquarters during the sample period. Call et al. (2017) argue that firms unlikely change their headquarters primarily for the quality of the workforce. We test whether firms that changed their headquarters during the sample period experienced a change in *FRQ*. We conduct the analysis by by comparing the two years before the change to the two years after the change in headquarters.[16] We obtain data on changes in headquarters among MSAs from Bill McDonald's publicly available data.[17] Similar to Call et al. (2017), we run the following model:

$$\begin{aligned} DV_{i,t} = {} & \alpha_0 + \beta_1 POST_{i,t} + \beta_2 IT\_LABOR\_INCREASING\_RELOCATION_{i,t} \\ & + \beta_3\, POST \times IT\_LABOR\_INCREASING\_RELOCATION_{i,t} + \Sigma\beta_k MSAControls_{i,t} \\ & + \Sigma\theta_j FirmControls_{i,t} + \Sigma\mu_m IndustryFE + \varepsilon_{i,t} \qquad (3) \end{aligned}$$

DV stands for the set of dependent variables proxying for *FRQ*. *POST* is a dummy variable that equals one for the period after the change in headquarters. *IT_LABOR_INCREASING_RELOCATION* is a dummy variable that equals one if the firm moves to a headquarter with a higher quality IT workforce, zero otherwise. We drop the year of the change in headquarters. We control for all MSA and firm-specific variables. If the relocation in headquarters to an MSA with a higher-quality IT workforce is associated with an increase in *FRQ*, then we expect the coefficient on the interaction of *POST* and

[16] We require at least one observation before and one observation after the change in headquarters.
[17] See https://sraf.nd.edu/data/.

IT_LABOR_INCREASING_RELOCATION (β_3) to be negative and statistically significant. We identify 287 firms that changed their headquarters during 2009-2016, yielding a sample of 665 firm-year observaions (331 observations before and 334 observations after the change in headquarters). Out of the 287 firms that changed their headquarters during the sample period, 138 firms moved to an MSA with a higher-quality IT workforce, while 149 firms relocated to an MSA with a lower quality IT workforce. Despite the very small sample size, we find (untabulated) evidence of a change in headquarters being associated with a decrease in *MISSTATE* (at p<0.05). Overall, the changes in headquarters analysis allows us to address a potential endogeneity concern by showing that firms moving to higher IT capable MSAs are associated with an increase in *FRQ*.

Shocks to local IT labor markets

We identify temporary shocks to the supply of local IT labor to provide more robust statistical evidence on the relationship between having access to IT capable labor and *FRQ*. We argue that significant layoffs by high-tech firms increase access to IT human capital for other, non-high-tech firms in the same MSA. To detect temporary shocks to IT labor access, we identify significant changes in the total number of employees by high-tech firms, i.e., firms in which IT workers are considered core-employees as compared to mere support staff. Given that approximately thirty percent of the firms in the sample are high-tech firms, we must examine substantial changes to allow us to observe an effect of an increase in IT labor supply for non-high-tech firms on *FRQ*. We compute labor supply shocks as the cumulative percentage change of employees of high-tech employees per MSA as a percentage of the prior year's total number of high-tech employees. We then examine at what shock- size to the local IT labor market non-high-tech firms can benefit from in the form of increased *FRQ*. For this analysis, we utilize propensity score matching (PSM) to identify control firms with similar characteristics.

In using PSM, we employ a first stage logit and match firms based on the entire set of firm-level and MSA-level controls. Consistent with prior research, we use a caliper of 0.03 and impose common support.[18] We match the set of firms that experienced a shock to local IT labor supply (treatment firms) with control firms in MSAs that did not experience a shock to the IT labor supply during the sample period. We then use the two years before as well as two years following the shock as the pre- and post-periods. Finally, to reduce noise, we exclude from the final PSM sample the year of the shock and remove high-tech firms.

Consistent with the primary regressions, the dependent variables are *MW* and *MISSTATE*. the independent variable of interest is the difference-in-differences (DID) estimator capturing the differential effect between firms experiencing a shock to IT labor supply and their counterparts in the control group over time. For the *MISSTATE* sample, we document (untabulated) a positive and statistically significant coefficient on the DID estimator at shock-sizes beginning at 13 percent (p<0.01). This effect remains constant between 14 percent (p<0.01) over 21 percent (p<0.01) to 28 percent (p<0.05). We do not observe a statistically significant effect beyond a shock-size of 33 percent (p<0.05), likely because of a steep decline in sample size at a shock-size of 34 percent (N=147). For the *MW* sample, we observe inconsistent results that do not allow us to draw conclusions with desired statistical certainty.

Overall, the DID estimation allows us to minimize the influence of extraneous variables and omitted variables bias while providing strong support for the central hypothesis.

CONCLUSION

We investigate the association between the information technology (IT) capability of a firm's workforce and *FRQ*. We find that firms with access to higher IT capable employees are associated

[18] the inferences remain unchanged when we utilize a caliper between 0.01 and 0.05. The ROC of the first stage logit is above 0.869, which is above the minimum suggested threshold of 0.7.

with higher *FRQ*. While we attempt to address as many limitations as possible through empirical analysis, the study is subject to limitations. Specifically, we do not measure a firm's specific workforce, so to the extent that a firm is not reliant on the local population for its workforce, the measures may not be well specified.

Our findings should be of interest to business practitioners as well as academics in several different fields. For information system researchers, we present an archival measure of employee IT competency obtained through IT education levels in MSAs. For accounting and finance academics, we provide evidence that employee and workforce factors, particularly those pertaining to IT capability, are associated with financial reporting outcomes.

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APPENDIX A – ILLUSTRATION OF CALCULATING AN MSA'S IT-CAPABILITY MEASURES

RECORD	YEAR	CBSA_NAME	MET2013	PERWT	EDUC	DEGFIELD	INCWAGE	LABFORCE
1	2013	San Jose-Sunnyvale-Santa Clara, CA	41940	25.00	10	Computer & IS	153,000	2
2	2013	San Jose-Sunnyvale-Santa Clara, CA	41940	256.00	2	N/A	35,000	2
3	2013	San Jose-Sunnyvale-Santa Clara, CA	41940	194.00	2	N/A	24,100	2
4	2013	San Jose-Sunnyvale-Santa Clara, CA	41940	74.00	8	N/A	50,000	2
5	2013	San Jose-Sunnyvale-Santa Clara, CA	41940	72.00	11	Engineering	100.000	2
6	2013	San Jose-Sunnyvale-Santa Clara, CA	41940	66.00	10	Business	50,000	2
7	2013	San Jose-Sunnyvale-Santa Clara, CA	41940	5.00	11	Computer & IS	130,000	2
8	2013	San Jose-Sunnyvale-Santa Clara, CA	41940	62.00	5	N/A	35,000	2
9	2013	San Jose-Sunnyvale-Santa Clara, CA	41940	26.00	11	Computer & IS	85,000	2
10	2013	San Jose-Sunnyvale-Santa Clara, CA	41940	119.00	6	N/A	15,000	2
…	...	...	…	…	…	…	…	…

$$^{a}IT\_DEG_{MSA,t} = \frac{\sum_{i=1}^{N} IT\_DEG_i * PERWT_i}{\sum_{i=1}^{N} PERWT_i} = \frac{1*25+1*5+1*26}{(25+256+194+74+72+66+5+62+26+119)} = \frac{56}{899} = 0.0623$$

$$^{b}IT\_EDU_{MSA,t} = \frac{\sum_{i=1}^{N} IT\_EDU_i * PERWT_i}{\sum_{i=1}^{N} PERWT_i} = \frac{10*25+11*5+11*26}{(25+5+26)} = \frac{591}{56} = 10.554$$

$$^{c}IT\_WAGES_{MSA,t} = \frac{\sum_{i=1}^{N} IT\_WAGES_i * PERWT_i}{\sum_{i=1}^{N} PERWT_i} = \frac{25*153{,}000+5*130{,}000+26*85{,}000}{(25+5+26)} = \frac{6{,}110{,}000}{56} = \$109{,}107.14$$

[a] *IT_DEG* is computed as the total number of IT graduates divided by the total number of the active workforce (*LABFORCE*=2). We calculate *IT_Degree* based on IPUMS data items DEGFIELD, DEGFIELD2, DEGFIELDD, and DEGFIELD2D. To get the number of total IT graduates per MSA, we sum up the survey weights (PERWT) per MSA for those individuals that hold an IT degree.
[b] *IT_EDU* is computed as the average education level for IT graduates per MSA. *EDUC* ranges from 1-11, whereas 0=N/A or no schooling, 1= Nursery school to grade 4, 2=Grade 5-8, 3=Grade 9, 4==Grade 10, 5=Grade 11, 6=Grade 12, 7=1 completed year of college, 8=2 completed years of college, 9=3 completed years of college, 10=4 completed years of college, 11=5+ completed years of college.
[c] *IT_WAGES* is computed as the average income level for IT graduates. Note that *IT_EDU* and *IT_WAGES* have the same denominator as both measures compute a specific average for IT graduates only.

APPENDIX B – Variable Definitions

Financial Reporting Quality

$MW_{i,t\text{-}t+2}$	=	a dummy variable that equals 1 if firm *i* in year *t* disclosed a material weakness in its reports on SOX Section 302/404, 0 otherwise [Audit Analytics].
$MISSTATE_{i,t\text{-}t+2}$	=	a dummy variable that equals 1 if firm *i* subsequently restated its financial report, 0 otherwise [Audit Analytics].

Variables of interest

$IT\_DEG_{i,t}$	=	the overall quality of the workforce concerning IT for MSA *i* in year *t*. Individuals holding more than one IT degree are counted only once in computing this measure. See appendix A for a detailed illustration of how this variable is computed [IPUMS].
$IT\_EDU_{i,t}$	=	the overall quality of education for individuals with an IT or IT-related degree for MSA *i* in year *t*. See appendix A for a detailed illustration of how this variable is computed [IPUMS].
$IT\_WAGES_{i,t}$	=	the level of wages of individuals holding an IT or IT-related degree for MSA *i* in year *t*. We obtain income information from the ACS. All wages data are weighted by sample weights reported in IPUMS. See appendix A for a detailed illustration of how this variable is computed [IPUMS].
$IT\_COMP_{i,t}$	=	the composite score computed from applying principal component analysis to the IT human capital measures *IT_DEG*, *IT_DEU*, and *IT_WAGES* for MSA *i* in year *t* [IPUMS].

MSA control variables

$GEN\_EDU_{i,t}$	=	the weighted-average education level per ACS respondent for MSA *i* in year *t*. This variable is coded following Call et al. (2017). We exclude individuals holding an IT degree, and we count individuals holding more than one business degree only once in computing this measure.
$BUS\_DEG\_NOFIN_{i,t}$	=	a measure for the quality of workforce concerning overall business education excluding finance graduates for MSA *i* in year *t*.
$BUS\_DEG_{i,t}$	=	a measure for the quality of workforce concerning overall business education, including accounting, finance, and other business-related degrees for MSA *i* in year *t*. We exclude individuals holding an IT degree, and we count individuals holding more than one business degree only once in computing this measure. [IPUMS].

$GEN\_EDU\_NOFIN_{i,t}$	=	the weighted-average education level per ACS respondent excluding finance graduates for MSA *i* in year *t*. This variable is coded in the same way as in Call et al. (2017).
$IT\_LNPOP_{i,t}$	=	the natural log of the number of IT graduates for MSA *i* in year *t* [IPUMS].
$INC\_DIFF_{i,t}$	=	a measure capturing the relation between income levels of IT graduates and the overall income level for MSA *i* in year *t*. This measure is computed as the average income level of IT graduates in MSA *i*, divided by the overall income level in MSA *i*. We obtain wages information from the ACS. All wages data are weighted by sample weights reported in IPUMS [IPUMS].
$RELIGIOUS_{i}$	=	the percentage of religious population per MSA *i*. We obtain data from the 2010 Religious Congregations and Membership Study (RCMS) through The Association of Religion Data Archives (ARDA).
$REPORTERS_{i,t}$	=	the number of survey respondents who identify themselves as "News Analysts, Reporters, and Correspondents" as reported in IPUMS Occupation Code 2810 for MSA *i* in year *t* [IPUMS].
$UNEMPLOYMENT_{i,t}$	=	the unemployment level for MSA *i* in year *t*. We obtain unemployment data from the Bureau of Labor Statistics.
$SCI_{i,t}$	=	the coincident index per state in which the MSA *i* is located, in year *t*. This index is an indicator of the current state of economic activity. The index is a metric that includes manufacturing activities, inventory levels, and level of new business startups, to name a few.
$CPI_{i,t}$	=	the consumer price index for MSA *i* in year *t*. We obtain CPI data from the Bureau of Labor Statistics. In case of unavailable price information, we use the regional CPI (i.e., Northeast, Midwest, South, and West) for "Class B/C" areas, which is defined as populations between 50 thousand and 1.5 million. This is consistent with Call et al. (2017).
$MSAROA_{i,t}$	=	the mean *ROA* for firms located in MSA *i* in year *t* [Compustat].
$MSAROAVOL_{i,t}$	=	the average earnings volatility computed as the running standard deviation of *ROA* over the most recent 5 periods for MSA *i* in year *t*. This variable requires at least three non-missing observations over the most recent five periods to be computed [Compustat].
Other control variables		
$SEGMENT_{i,t}$	=	the sum of business segments reported by firm *i* in year *t* (Compustat Segments File).

$FOREIGN_{i,t}$	=	a dummy-variable that equals 1 if firm *i* in year *t* reports any foreign currency exchange (FCA), 0 otherwise [Compustat].
$SIZE_{i,t}$	=	the natural log of total assets (AT) reported by firm *i* in year *t* [Compustat].
$LOSS_{i,t}$	=	a dummy variable that equals 1 if firm *i* reports negative net income (NI) in year *t*, 0 otherwise [Compustat].
$GC_{i,t}$	=	a dummy-variable that equals 1 if firm *i* in year *t* reports an adverse going-concern opinion, 0 otherwise [Audit Analytics].
$DISTRESS_{i,t}$	=	the level of financial distress, defined as the decile rank of the Altman's Z-score (Ashbaugh-Skaife et al. 2007) [Compustat].
$EXT\_GROWTH_{i,t}$	=	a dummy variable that equals 1 if the annual industry adjusted sales growth for firm *i* in year *t* falls in the top quintile, 0 otherwise (Doyle et al. 2007a) [Compustat].
$NEW\_EQUITY_{i,t}$	=	a dummy variable that equals 1 if firm *i* issued new common or preferred stock (SSTK) in period *t*, but not in period *t-1*, 0 otherwise [Compustat].
$NEW\_DEBT_{i,t}$	=	a dummy variable that equals 1 if firm *i* issued long-term debt (DLTIS) in period *t*, but not in period *t-1*, 0 otherwise [Compustat].
$STD\_CFLOW_{i,t}$	=	the standard deviation of cash flows from operations (OANCF) for firm *i* in year *t*, calculated over five years with at least three non-missing observations [Compustat].
$STD\_SALE_{i,t}$	=	the standard deviation of sales (SALE) for firm *i* in year *t*, calculated over five years with at least three non-missing observations [Compustat].
$LEVERAGE_{i,t}$	=	long term assets (DLTT) divided by total assets (AT) for firm *i* in year *t* [Compustat].
$RESTRUCTURE_{i,t}$	=	an indicator variable that equals 1 if firm *i* restructured its operations in year *t* (non-missing Compustat values for RCP, RCD, RCA, or RCEPS), 0 otherwise [Compustat].
$SPECIAL_{i,t}$	=	special items (SPI) divided by total assets (AT) for firm *i* in year *t* [Compustat].
$FIRM\_AGE_{i,t}$	=	the number of years firm *i* in year *t* has Compustat data [Compustat].
$LITIGIOUS_{i,t}$	=	a dummy-variable that equals 1 if firm *i* in year *t* operates within a high-risk litigation industry, defined as SEC codes 2833-2836, 3570-3577, 3600-3674, 5200-5961, or 7370, 0 otherwise (Hoitash and Hoitash 2018) [Compustat].
$BIG4_{i,t}$	=	an indicator variable that equals 1 if firm *i* is audited by a big-4 audit firm in year *t*, 0 otherwise [Audit Analytics].

$lnAF_{i,t}$	=	the natural log of audit fees for firm *i* in year *t* [Audit Analytics].
$lnNAF_{i,t}$	=	the natural log of non-audit fees for firm *i* in year *t* [Audit Analytics].
$HIGHTECH_{i,t}$	=	a dummy variable that equals 1 if firm *i* in year *t* is part of the following 3-digit SIC codes: 283, 284, 357, 366, 367, 371, 382, 384, or 737 (Krishnan and Yang 2009) [Compustat].

Figure 1 – Average Number of IT-Graduates per Division (2009-2016)

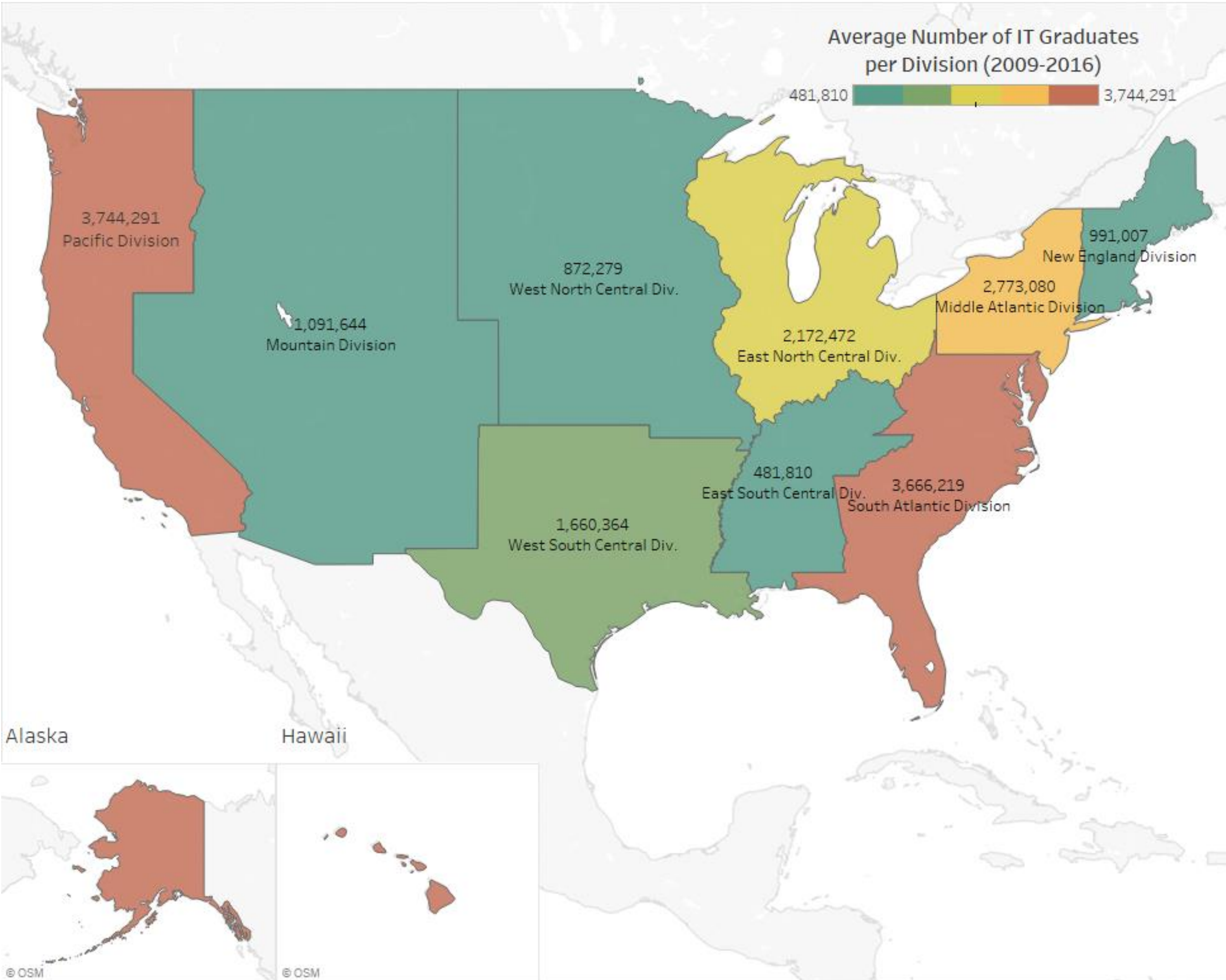

Table 1: Descriptive Statistics

Final sample composition – *MW* and *MISSTATE*	N	mean	sd	25%	50%	75%
MW	19470	0.084	0.277	0	0	0
MISSTATE	19470	0.170	0.375	0	0	0
IT_DEG	19470	0.022	0.014	0.015	0.019	0.023
IT_EDU	19470	10.297	0.086	10.249	10.299	10.343
IT_WAGES	19470	83,000	16,000	74,000	82,000	91,000
IT_COMP	19470	0.101	1.555	-0.736	-0.151	0.732
GEN_EDU	19470	7.674	0.337	7.416	7.701	7.9
BUS_DEG	19470	0.083	0.014	0.073	0.086	0.093
GEN_EDU_NOIT	19470	7.617	0.321	7.373	7.654	7.841
BUS_DEG_NOIT	19470	0.080	0.013	0.071	0.083	0.09
IT_LNPOP	19470	10.539	1.330	9.792	10.884	11.49
INC_DIFF	19470	1.858	0.203	1.733	1.835	1.969
RELIGIOUS	19470	0.497	0.080	0.442	0.514	0.555
REPORTERS	19470	91.716	126.489	13	30	85
UNEMPLOYMENT	19470	0.072	0.021	0.053	0.072	0.087
SCI	19470	106.540	11.297	97.503	104.479	114.387
CPI	19470	201.097	46.407	145.443	217.5	240.864
MSAROA	19470	-0.024	0.066	-0.046	-0.018	0.015
MSAROAVOL	19470	0.150	0.289	0.07	0.103	0.155
SEGMENT	19470	2.323	1.676	1	1	3
FOREIGN	19470	0.307	0.461	0	0	1
SIZE	19470	6.742	2.113	5.257	6.755	8.188
LOSS	19470	0.306	0.461	0	0	1
GC	19470	0.019	0.138	0	0	0
DISTRESS	19470	0.096	0.295	0	0	0
EXT_GROWTH	19470	0.191	0.393	0	0	0
NEW_EQUITY	19470	0.061	0.240	0	0	0
NEW_DEBT	19470	0.112	0.316	0	0	0
STD_CFLOW	19470	182.586	1,340.916	8.93	29.318	95.157
STD_SALE	19470	508.319	1,776.631	23.808	85.779	310.778
INV_REC	19470	0.225	0.192	0.068	0.18	0.326
RECVB_TO	19470	18.074	154.092	4.322	6.434	10.248
LEVERAGE	19470	0.196	0.196	0.003	0.157	0.321
RESTRUCTURE	19470	0.304	0.460	0	0	1
SPECIAL	19470	-0.011	0.110	-0.011	-0.001	0
FIRM_AGE	19470	21.567	16.713	8	17	29
LITIGIOUS	19470	0.253	0.435	0.000	0	1
BIG4	19470	0.759	0.428	1.000	1	1
LnAF	19470	13.91	1.21	13.163	13.924	14.66
LnNAF	19470	11.83	1.81	10.639	11.886	13.064

Table 2: Correlations among MSA variables

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*
MW																
MISSTATE	**0.20**															
IT_DEG	0.00	**-0.04**														
IT_EDU	0.01	**-0.02**	**0.67**													
IT_WAGES	**0.02**	**-0.04**	**0.73**	**0.67**												
IT_COMP	0.01	**-0.04**	**0.91**	**0.87**	**0.90**											
BUS_DEG_NOIT	0.00	**-0.02**	**0.24**	**0.30**	**0.43**	**0.36**										
GEN_EDU_NOIT	0.00	**-0.04**	**0.56**	**0.53**	**0.62**	**0.64**	**0.56**									
IT_LNPOP	**0.03**	0.01	**0.39**	**0.42**	**0.46**	**0.47**	**0.57**	**0.36**								
INC_DIFF	0.01	0.01	**0.28**	**0.16**	**0.49**	**0.35**	**-0.15**	**-0.03**	**-0.06**							
RELIGIOUS	**-0.02**	**-0.02**	**-0.25**	**-0.05**	**-0.08**	**-0.14**	**0.25**	**-0.11**	**0.13**	**-0.25**						
REPORTERS	0.00	0.00	-0.01	**0.19**	**0.18**	**0.13**	**0.30**	**0.16**	**0.67**	**-0.23**	**0.28**					
UNEMPLOYMENT	**-0.05**	**0.07**	**-0.22**	**-0.13**	**-0.38**	**-0.27**	**-0.29**	**-0.36**	**-0.05**	0.00	**-0.06**	**0.05**				
SCI	**0.07**	**-0.07**	**0.20**	**0.09**	**0.33**	**0.24**	**0.16**	**0.07**	**0.09**	**0.11**	-0.01	**-0.09**	**-0.83**			
CPI	**0.02**	0.00	**-0.07**	**0.11**	**0.19**	**0.08**	**0.39**	**0.20**	**0.67**	**-0.09**	**0.17**	**0.53**	**-0.06**	**0.13**		
MSAROA	**-0.03**	0.01	**-0.22**	**-0.22**	**-0.30**	**-0.27**	**0.02**	**-0.22**	**-0.19**	**-0.07**	**0.20**	**-0.07**	**0.15**	**-0.23**	**-0.25**	
MSAROLVOL	**0.04**	0.01	**0.06**	**0.04**	**0.05**	**0.06**	**-0.05**	**0.02**	**0.05**	0.01	**-0.16**	**0.02**	**-0.03**	**0.07**	**-0.03**	**-0.15**

Table 2 presents correlations among MSA-level variables and the variables of interest. Bold correlations are significantly different from zero at $p<0.05$.

TABLE 3 – PANEL A

IT Capability of Employees and Material Weakness (*MW*) measured in year *t*.

	(1)			(2)			(3)			(4)			(5)		
	MW			*MW*			*MW*			*MW*			*MW*		
	Coeff.	t-stat.		Coeff.	t-stat.		Coeff.	t-stat.		Coeff.	t-stat.		Coeff.	t-stat.	
IT_DEG				-27.041	-5.02	***									
IT_EDU							-1.314	-2.24	**						
IT_WAGES										-0.186	-3.22	***			
IT_COMP													-0.213	-4.39	***
GEN_EDU_NOIT				0.361	1.37		-0.121	-0.50		0.168	0.62		0.340	1.24	
BUS_DEG_NOIT				-8.130	-1.67	*	-3.605	-0.75		-2.050	-0.42		-5.422	-1.11	
GEN_EDU	-0.416	-1.95	*												
BUS_DEG	-1.616	-0.36													
IT_LNPOP	0.124	2.03	**	0.330	4.46	***	0.144	2.26	**	0.169	2.59	***	0.254	3.54	***
INC_DIFF	-0.140	-0.76		0.164	0.87		-0.075	-0.39		0.608	2.00	**	0.374	1.71	*
RELIGIOUS	-0.503	-0.80		-0.525	-0.85		-0.273	-0.44		-0.119	-0.19		-0.175	-0.29	
REPORTERS	-0.001	-2.20	**	-0.002	-3.40	***	-0.001	-2.28	**	-0.001	-1.83	*	-0.001	-2.63	***
UNEMPLOYMENT	0.000	0.25		0.000	0.48		0.000	0.72		0.000	0.82		0.000	0.88	
SCI	-3.797	-0.86		1.455	0.32		-1.047	-0.23		-1.488	-0.33		0.855	0.19	
CPI	-0.007	-0.62		0.007	0.66		-0.002	-0.19		0.001	0.12		0.004	0.40	
MSAROA	-0.001	-0.80		-0.005	-3.50	***	-0.001	-1.20		-0.002	-1.57		-0.003	-2.65	***
MSAROAVOL	1.140	2.06	**	1.177	2.11	**	1.136	2.04	**	0.859	1.52		0.934	1.64	
SEGMENT	0.152	1.83	*	0.134	1.62		0.156	1.89	*	0.165	1.98	**	0.150	1.81	*
FOREIGN	-0.005	-0.17		-0.008	-0.30		-0.005	-0.18		-0.005	-0.19		-0.007	-0.26	
SIZE	0.006	0.07		0.001	0.01		0.006	0.07		0.004	0.04		0.004	0.05	
LOSS	-0.550	-10.59	***	-0.551	-10.63	***	-0.553	-10.61	***	-0.554	-10.61	***	-0.555	-10.65	***
GC	0.434	5.44	***	0.444	5.59	***	0.435	5.46	***	0.441	5.55	***	0.442	5.57	***
DISTRESS	0.734	4.13	***	0.725	4.05	***	0.728	4.08	***	0.722	4.02	***	0.717	3.99	***
EXT_GROWT	0.026	0.20		0.029	0.23		0.024	0.18		0.025	0.19		0.025	0.19	
NEW_EQUITY	0.236	3.34	***	0.240	3.41	***	0.236	3.35	***	0.240	3.40	***	0.240	3.41	***
NEW_DEBT	0.084	0.84		0.081	0.80		0.082	0.81		0.079	0.78		0.077	0.76	
STD_CFLOW	-0.145	-1.71	*	-0.137	-1.63		-0.145	-1.72	*	-0.144	-1.70	*	-0.141	-1.67	*
STD_SALE	0.000	2.76	***	0.000	2.81	***	0.000	2.77	***	0.000	2.76	***	0.000	2.79	***
INV_REC	0.000	-0.74		0.000	-0.83		0.000	-0.75		0.000	-0.76		0.000	-0.79	
RECVB_TO	0.325	1.36		0.320	1.34		0.323	1.35		0.316	1.31		0.314	1.31	
LEVERAGE	-0.001	-1.02		-0.001	-1.04		-0.001	-1.04		-0.001	-1.05		-0.001	-1.07	
RESTRUCTURE	0.652	2.82	***	0.618	2.68	***	0.646	2.79	***	0.630	2.72	***	0.616	2.66	***
SPECIAL	-0.083	-0.99		-0.081	-0.97		-0.086	-1.02		-0.091	-1.09		-0.087	-1.04	
FIRM_AGE	-1.337	-3.14	***	-1.262	-3.00	***	-1.327	-3.13	***	-1.321	-3.12	***	-1.282	-3.04	***
LITIGIOUS	-0.016	-4.96	***	-0.016	-5.10	***	-0.016	-5.01	***	-0.016	-5.11	***	-0.016	-5.15	***
BIG4	-0.193	-1.76	*	-0.147	-1.34		-0.186	-1.70	*	-0.185	-1.69	*	-0.161	-1.47	
lnAF	-0.805	-7.83	***	-0.817	-7.94	***	-0.814	-7.91	***	-0.810	-7.89	***	-0.818	-7.96	***
lnNAF	0.927	11.70	***	0.951	11.94	***	0.937	11.73	***	0.948	11.81	***	0.957	11.92	***
_cons	-0.008	-0.32		-0.009	-0.37		-0.009	-0.34		-0.010	-0.38		-0.010	-0.40	
	-7.772	-3.17	***	-16.643	-5.51	***	2.502	0.46		-13.811	-4.53	***	-17.057	-5.20	***
Year and Indystry FE?	Yes			Yes			Yes			Yes			Yes		
N	19470			19470			19470			19470			19470		
Pseudo r-squared	0.116			0.121			0.117			0.118			0.119		

Table 3 – Panel A presents the estimated coefficients and associated significance levels for Eq. (1) with *MW* measured at year *t*. See Appendix B for variable definitions. We include year and industry fixed effects, and standard errors are clustered at the firm level. All independent, non-logarithmic continuous variables are winsorized at the top and bottom 1%. T-statistics are displayed in parentheses, and we consistently report two-tailed t-tests. *, **, and *** denote significance levels at $p<0.10$, $p<0.05$, and $p<0.01$.

TABLE 3 – PANEL B

IT Capability of Employees and Material Weakness (*MW*) measured at year *t+1*.

	(1)		(2)		(3)		(4)		(5)	
	MW		*MW*		*MW*		*MW*		*MW*	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
IT_DEG			-28.853	-4.73 ***						
IT_EDU					-1.310	-2.25 **				
IT_WAGES							-0.210	-3.53 ***		
IT_COMP									-0.222	-4.34 ***
GEN_EDU	-0.406	-1.78 *								
GEN_EDU_NOIT			0.421	1.46	-0.111	-0.43	0.243	0.85	0.383	1.32
All other controls?	Yes		Yes		Yes		Yes		Yes	
Year and Indystry FE?	Yes		Yes		Yes		Yes		Yes	
N	16076		16076		16076		16076		16076	
Pseudo r-squared	0.095		0.099		0.095		0.097		0.098	

Table 3 – Panel B presents the estimated coefficients and associated significance levels for Eq. (1) with *MW* measured at year *t+1*. See Appendix B for variable definitions. We include year and industry fixed effects, and standard errors are clustered at the firm level. All independent, non-logarithmic continuous variables are winsorized at the top and bottom 1%. T-statistics are displayed in parentheses, and we consistently report two-tailed t-tests. *, **, and *** denote significance levels at $p<0.10$, $p<0.05$, and $p<0.01$.

TABLE 3 – PANEL C

IT Capability of Employees and Material Weakness (*MW*) measured at year *t+2*.

	(1)		(2)		(3)		(4)		(5)	
	MW		*MW*		*MW*		*MW*		*MW*	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
IT_DEG			-31.179	-4.09 ***						
IT_EDU					-1.454	-2.26 **				
IT_WAGES							-0.278	-4.18 ***		
IT_COMP									-0.253	-4.25 ***
GEN_EDU	-0.371	-1.48								
GEN_EDU_NOIT			0.482	1.50	-0.042	-0.15	0.444	1.40	0.512	1.57
All other controls?	Yes		Yes		Yes		Yes		Yes	
Year and Indystry FE?	Yes		Yes		Yes		Yes		Yes	
N	12943		12943		12943		12943		12943	
Pseudo r-squared	0.070		0.074		0.071		0.073		0.074	

Table 3 – Panel C presents the estimated coefficients and associated significance levels for Eq. (1) with *MW* measured at year *t+2*. See Appendix B for variable definitions. We include year and industry fixed effects, and standard errors are clustered at the firm level. All independent, non-logarithmic continuous variables are winsorized at the top and bottom 1%. T-statistics are displayed in parentheses, and we consistently report two-tailed t-tests. *, **, and *** denote significance levels at $p<0.10$, $p<0.05$, and $p<0.01$.

TABLE 4 – PANEL A
IT Capability of Employees and Material Weakness (*MW*) measured at year *t*.

	(1)		(2)		(3)		(4)		(5)	
	MISSTATE		*MISSTATE*		*MISSTATE*		*MISSTATE*		*MISSTATE*	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
IT_DEG			-16.782	-3.45 ***						
IT_EDU					-0.876	-2.13 **				
IT_WAGES							-0.082	-1.70 *		
IT_COMP									-0.125	-3.07 ***
GEN_EDU_NOIT			0.028	0.14	-0.250	-1.32	-0.171	-0.78	0.001	0.00
BUS_DEG_NOIT			-2.700	-0.70	-0.279	-0.07	0.839	0.22	-1.168	-0.30
GEN_EDU	-0.414	-2.38 **								
BUS_DEG	0.252	0.07								
IT_LNPOP	0.074	1.45	0.182	2.87 ***	0.084	1.60	0.083	1.56	0.137	2.33 **
INC_DIFF	-0.055	-0.42	0.081	0.61	-0.015	-0.11	0.260	1.14	0.213	1.35
RELIGIOUS	-0.937	-1.84 *	-0.966	-1.91 *	-0.819	-1.61	-0.760	-1.48	-0.758	-1.50
REPORTERS	0.000	-0.73	-0.001	-1.43	0.000	-0.70	0.000	-0.44	0.000	-0.88
UNEMPLOYMENT	0.000	-0.46	0.000	-0.34	0.000	-0.19	0.000	-0.16	0.000	-0.06
SCI	-3.088	-0.86	0.202	0.06	-1.635	-0.45	-1.949	-0.54	-0.443	-0.12
CPI	-0.005	-0.52	0.004	0.45	-0.003	-0.27	-0.001	-0.12	0.002	0.17
MSAROA	0.000	-0.04	-0.002	-1.78 *	0.000	-0.32	0.000	-0.38	-0.001	-1.19
MSAROAVOL	-0.241	-0.50	-0.256	-0.53	-0.280	-0.58	-0.377	-0.77	-0.386	-0.78
SEGMENT	0.059	0.65	0.047	0.52	0.062	0.67	0.065	0.71	0.058	0.63
FOREIGN	0.104	0.54	0.095	0.49	0.100	0.52	0.102	0.53	0.095	0.49
SIZE	0.000	-0.36	0.000	-0.37	0.000	-0.36	0.000	-0.37	0.000	-0.37
LOSS	0.030	1.38	0.028	1.32	0.030	1.37	0.029	1.33	0.028	1.31
GC	0.007	0.10	0.006	0.08	0.009	0.12	0.007	0.09	0.009	0.12
DISTRESS	-0.098	-2.65 ***	-0.097	-2.64 ***	-0.099	-2.70 ***	-0.099	-2.70 ***	-0.100	-2.72 ***
EXT_GROWT	0.116	1.82 *	0.119	1.87 *	0.116	1.82 *	0.119	1.86 *	0.119	1.87 *
NEW_EQUITY	0.026	0.15	0.019	0.10	0.018	0.10	0.020	0.11	0.012	0.06
NEW_DEBT	-0.069	-0.66	-0.068	-0.66	-0.069	-0.67	-0.069	-0.67	-0.068	-0.66
STD_CFLOW	0.211	3.67 ***	0.211	3.67 ***	0.211	3.68 ***	0.212	3.70 ***	0.212	3.69 ***
STD_SALE	-0.002	-0.02	-0.006	-0.08	-0.005	-0.06	-0.005	-0.06	-0.008	-0.10
INV_REC	0.054	0.93	0.057	1.00	0.053	0.93	0.054	0.93	0.055	0.96
RECVB_TO	0.000	-0.28	0.000	-0.28	0.000	-0.28	0.000	-0.28	0.000	-0.28
LEVERAGE	0.000	-1.16	0.000	-1.21	0.000	-1.16	0.000	-1.16	0.000	-1.19
RESTRUCTURE	0.663	3.66 ***	0.645	3.57 ***	0.657	3.63 ***	0.655	3.61 ***	0.642	3.55 ***
SPECIAL	0.135	2.10 **	0.137	2.13 **	0.133	2.07 **	0.130	2.02 **	0.132	2.06 **
FIRM_AGE	-0.226	-0.71	-0.198	-0.67	-0.224	-0.71	-0.217	-0.70	-0.205	-0.68
LITIGIOUS	-0.008	-3.41 ***	-0.008	-3.53 ***	-0.008	-3.47 ***	-0.008	-3.48 ***	-0.009	-3.56 ***
BIG4	-0.057	-0.61	-0.024	-0.25	-0.052	-0.55	-0.054	-0.57	-0.035	-0.38
lnAF	0.000	0.00	-0.003	-0.04	-0.005	-0.05	-0.002	-0.02	-0.007	-0.07
lnNAF	0.232	3.91 ***	0.241	4.05 ***	0.238	4.01 ***	0.241	4.03 ***	0.247	4.14 ***
_cons	0.054	2.61 ***	0.054	2.59 ***	0.054	2.60 ***	0.054	2.60 ***	0.053	2.58 ***
	-1.294	-0.63	-6.312	-2.55 **	5.885	1.40	-3.819	-1.53	-6.383	-2.46 **
Year and Indystry FE?	Yes		Yes		Yes		Yes		Yes	
N	19470		19470		19470		19470		19470	
Pseudo r-squared	0.031		0.033		0.032		0.032		0.032	

Table 4 – Panel A presents the estimated coefficients and associated significance levels for Eq. (2) with *MISSTATE* measured at year *t*. See Appendix B for variable definitions. We include year and industry fixed effects, and standard errors are clustered at the firm level. All independent, non-logarithmic continuous variables are winsorized at the top and bottom 1%. T-statistics are displayed in parentheses, and we consistently report two-tailed t-tests. *, **, and *** denote significance levels at $p<0.10$, $p<0.05$, and $p<0.01$.

TABLE 4 – PANEL B

IT Capability of Employees and Material Weakness (*MW*) measured at year *t+1*.

	(1)			(2)			(3)			(4)			(5)		
	MISSTATE			*MISSTATE*			*MISSTATE*			*MISSTATE*			*MISSTATE*		
	Coeff.	t-stat.		Coeff.	t-stat.		Coeff.	t-stat.		Coeff.	t-stat.		Coeff.	t-stat.	
IT_DEG				-17.629	-3.04	***									
IT_EDU							-0.778	-1.72	*						
IT_WAGES										-0.085	-1.54				
IT_COMP													-0.123	-2.63	***
GEN_EDU	-0.478	-2.48	**												
GEN_EDU_NOIT				-0.027	-0.12		-0.339	-1.62		-0.241	-1.00		-0.085	-0.36	
All other controls?	Yes			Yes			Yes			Yes			Yes		
Year and Indystry FE?	Yes			Yes			Yes			Yes			Yes		
N	16101			16101			16101			16101			16101		
Pseudo r-squared	0.031			0.033			0.031			0.031			0.032		

Table 4 – Panel B presents the estimated coefficients and associated significance levels for Eq. (2) with *MISSTATE* measured at year *t+1*. See Appendix B for variable definitions. We include year and industry fixed effects, and standard errors are clustered at the firm level. All independent, non-logarithmic continuous variables are winsorized at the top and bottom 1%. T-statistics are displayed in parentheses, and we consistently report two-tailed t-tests. *, **, and *** denote significance levels at $p<0.10$, $p<0.05$, and $p<0.01$.

TABLE 4 – PANEL C

IT Capability of Employees and Material Weakness (*MW*) measured at year *t+2*.

	(1)		(2)		(3)		(4)		(5)	
	MISSTATE		*MISSTATE*		*MISSTATE*		*MISSTATE*		*MISSTATE*	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
IT_DEG			-18.046	-2.68 ***						
IT_EDU					-0.510	-1.00				
IT_WAGES							-0.097	-1.36		
IT_COMP									-0.114	-2.12 **
GEN_EDU	-0.497	-2.34 **								
GEN_EDU_NOIT			-0.051	-0.19	-0.403	-1.69 *	-0.243	-0.89	-0.143	-0.52
All other controls?	Yes		Yes		Yes		Yes		Yes	
Year and Indystry FE?	Yes		Yes		Yes		Yes		Yes	
N	12963		12963		12963		12963		12963	
Pseudo r-squared	0.036		0.038		0.036		0.037		0.037	

Table 4 – Panel C presents the estimated coefficients and associated significance levels for Eq. (2) with *MISSTATE* measured at year *t+2*. See Appendix B for variable definitions. We include year and industry fixed effects, and standard errors are clustered at the firm level. All independent, non-logarithmic continuous variables are winsorized at the top and bottom 1%. T-statistics are displayed in parentheses, and we consistently report two-tailed t-tests. *, **, and *** denote significance levels at $p<0.10$, $p<0.05$, and $p<0.01$.

TABLE 5
Firm fixed effects regression for *MW*.

	(1) *MW* Coeff.	t-stat.		(2) *MW* Coeff.	t-stat.		(3) *MW* Coeff.	t-stat.		(4) *MW* Coeff.	t-stat.	
IT_DEG	-35.063	-2.42	**									
IT_EDU				-1.968	-2.07	**						
IT_WAGES							-0.160	-1.09				
IT_COMP										-0.332	-2.81	***
All other controls?	Yes			Yes			Yes			Yes		
Firm fixed effects?	Yes			Yes			Yes			Yes		
N	3966			3966			3966			3966		
Pseudo r-squared	0.146			0.145			0.144			0.147		

Table 5 presents the estimated coefficients and associated significance levels for Eq. (1). See Appendix B for variable definitions. We include firm fixed effects. All independent, non-logarithmic continuous variables are winsorized at the top and bottom 1%. T-statistics are displayed in parentheses, and we consistently report two-tailed t-tests. *, **, and *** denote significance levels at $p<0.10$, $p<0.05$, and $p<0.01$.

TABLE 6
Firm fixed effects regression for *MISSTATE*.

	(1)			(2)		(3)			(4)	
	MISSTATE			*MISSTATE*		*MISSTATE*			*MISSTATE*	
	Coeff.	t-stat.		Coeff.	t-stat.	Coeff.	t-stat.		Coeff.	t-stat.
IT_DEG	-29.217	-2.55	**							
IT_EDU				0.284	0.45					
IT_WAGES						-0.275	-2.44	**		
IT_COMP									-0.093	-1.15
All other controls?	Yes			Yes		Yes			Yes	
Firm fixed effects?	Yes			Yes		Yes			Yes	
N	6469			6469		6469			6469	
Pseudo r-squared	0.075			0.074		0.075			0.074	

Table 6 presents the estimated coefficients and associated significance levels for Eq. (2). See Appendix B for variable definitions. We include firm fixed effects. All independent, non-logarithmic continuous variables are winsorized at the top and bottom 1%. T-statistics are displayed in parentheses, and we consistently report two-tailed t-tests. *, **, and *** denote significance levels at $p<0.10$, $p<0.05$, and $p<0.01$.