How Valuable is Technology Talent Hiring?

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Abstract

This study investigates the impact of technology talent hiring on firm performance, utilizing data from LinkUp on employer hiring positions. Our findings indicate that, in low-tech industries, technology talent hiring primarily enhances efficiency and cost control through automation, while in high-tech industries, IT talent plays a pivotal role in driving innovation, thus strengthening competitive advantage. Additionally, we identify that managerial ability is a critical determinant of IT talent acquisition, influencing financial performance, risk management, cultural adaptation, and strategic decisions. These findings underscore the strategic importance of IT talent in shaping firm dynamics, providing valuable guidance for managers, policymakers, and investors.

Keywords: Technology Talent Hiring, Automation, Innovation, Firm Valuation

JEL Classification: G12; G32; G34; M12; M41

"An investment in knowledge pays the best interest."

—— Benjamin Franklin

1. INTRODUCTION

Technology is reshaping the world at an unprecedented pace, compelling firms to invest heavily in skill-driven information technology, innovate processes, and adopt transformative tools to enhance productivity (e.g., Acemoglu & Autor, 2011; Abis & Veldkamp, 2024).[1] Previous academic research highlights the capital-skill complementary hypothesis, suggesting technology not only complements but also substitutes labor to create firm value (e.g., Krusell, Ohanian, Ríos-Rull, & Violante, 2000; Duffy, Papageorgiou, & Perez-Sebastian, 2004; Kogan, Papanikolaou, Schmidt, & Seegmiller, 2021). Moreover, knowledge capital, a key driver of innovation, accounts for 40%-50% of firms' market value,[2] with contributions varying across industries over time (Belo, Gala, Salomao, & Vitorino, 2022).[3] Accordingly, the extent to which the hiring of information technology (IT) professionals shapes firm value across diverse industry landscapes, as well as the willingness of firms to pursue such hiring practices, warrants further investigation.[4]

This paper introduces a novel method to capture a firm's investment in technology talent based on unique hiring position data from LinkUp, a high-quality, reliable job listing dataset sourced directly from employer websites, capturing over 57,000 unique companies hiring positions from 2007 to 2023. Because it pulls directly from employer sites, LinkUp

[1] Abis and Veldkamp (2024) analyze how big data technologies reshape the relationship between data, labor, and knowledge creation, indicating that big data technologies will significantly alter long-term output, factor shares, and income distribution. For instance, they predict a 5% decline in labor's share of income in the investment management industry, a shift comparable in magnitude to the Industrial Revolution.

[2] Merz and Yashiv (2007) show that labor matters for understanding the aggregate stock market value dynamics. Belo, Gala, Salomao, and Vitorino (2022) document that physical capital accounts for 22 to 30% of a firm's market value, installed labor force accounts for 23 to 27%, knowledge capital accounts for 38 to 47%, and brand capital accounts for the remaining 5 to 9%. Thus, on average, non-physical capital inputs account for most firms' market value, with a share between 70% and 80%.

[3] As shown in Belo et al. (2022), the contribution of physical capital to firm value is higher in low-skill industries than in high-skill industries, with ranges of 40 to 43 % and 21 to 30 %, respectively. Related, the contribution of labor and knowledge capital for firm value increases with the average labor-skill level of the industry. In low-skill industries, the contribution of labor and knowledge capital is, on average, only 14 to 18% and 20 to 22%, respectively. In contrast, in high-skill industries, the contribution is 21 to 24% and 43 to 51%, respectively.

[4] Our paper focuses on information technology talent hiring, as defined in section 3.1. The terms "technology talent hiring," "IT talent hiring," and "tech hiring" are interchangeable in this paper.

provides a real-time snapshot of the job market, making it highly reliable for immediate labor market analysis. It avoids aggregating from job boards, where listings may be reposted multiple times by different recruiters, leading to duplicates and redundancies. This makes LinkUp more precise and reduces the need for extensive data cleaning, ensuring that the data represents active and valid job openings, eliminating duplicates, expired listings, and noise often found in aggregated data, such as Burning Glass job posting data, used in previous literature (e.g., Babina, Fedyk, He, & Hodson, 2024; Fedyk & Hodson, 2023). Therefore, our distinctive measurement allows us to capture a firm's IT talent hiring precisely and relate it to its valuation, strategies, and culture.

We begin our analysis by examining how significant investment in technology talent impacts a firm's value, especially within specific industries. Industry classification is central to our analysis, as hiring rates for skilled employees and firm valuations differ systematically between high- and low-technology sectors. To classify firms, we use two approaches. We first classify sectors into three groups based on technological requirements and skill intensity, guided by Hall and Vopel (1996): High-tech (high-technology/knowledge-intensive), Med-tech (medium-skilled), and Low-tech (low-skilled). This approach provides a systematic framework for analyzing technological investments across industries. To ensure robustness, we also use the K-Means clustering method, a machine learning algorithm used for partitioning data into distinct clusters based on IT-Related Hiring Rate, R&D Intensity, and Capital Intensity, to group all Fama-French 48 industries into three groups. Together, 3these methods offer a reliable foundation for evaluating IT talent hiring across diverse industry contexts.[5]

Our results reveal no significant relationship between IT talent hiring and firm valuation metrics for High-tech firms, while higher IT talent investment in the prior year significantly boosts market valuation (e.g., P/E and EV/EBITDA ratios) of Low-tech firms in traditional industries, such as manufacturing and resource extraction. The effect is economically meaningful; when a low-tech firm expands its IT workforce by 1%, the P/E ratio rises by around 1.047%, while the EV/EBITDA ratio improves by 0.399%. These

[5] Following Belo et al. (2017), we also split the sample into low and high-skill industries based on the industry-level average fraction of workers classified as high-skilled workers in each industry. Our inference does not change.

results highlight the differing roles of tech-related hiring across industries, confirming that the substitution elasticity between technology and unskilled labor exceeds that between technology and skilled labor (e.g., Griliches, 1969; Krusell, Ohanian, Ríos-Rull, & Violante, 2000; Duffy, Papageorgiou, & Perez-Sebastian, 2004).

One potential endogeneity concern is the possibility of reversed causality or omitted variable bias. Specifically, firms with higher valuations (e.g., higher P/E and EV/EBITDA ratios) might naturally hire more IT talent due to more excellent resources or prestige. Additionally, unobserved factors such as market conditions could simultaneously influence both IT talent hiring and firm valuation, confounding the relationship. To address these concerns, we employ the Two-Stage Least Squares (2SLS) method, using the logarithm of the total number of Computer Science (CS) major graduates in the same state as the firm's headquarters as an instrumental variable (IV). This IV is a strong predictor of IT hiring rates since the availability of local CS talent influences hiring decisions. However, it is unlikely to affect firm valuation directly, satisfying the exclusion restriction. The results establish a causal relationship, demonstrating that a higher IT hiring rate increases firm value, mitigating endogeneity concerns.

Next, we perform two analyses to investigate the underlying mechanisms through which hiring technology talent exerts varying impacts across industries. Autor and Dorn (2013) show that automation displaces routine jobs while boosting demand for high-skill roles and emphasize how automation boosts firm efficiency. Therefore, we hypothesize that in low-tech industries, the impact of IT hires is mainly on improving firm efficiency and cost control (i.e., automation).[6] In comparison, IT talent plays a critical role in high-tech industries' innovation process, directly shaping the technologies and processes that drive the sector's competitive advantage. To examine the possible mechanism, we create two separate measures, the Composite Automation Ratio (CAR) and the Automation Potential Index (API), as proxies of a firm's automation level and examine the relationship between a firm's IT talent hiring and automation level. The CAR reflects a firm's automation intensity by combining capital investment per employee, capital age, and

[6] For instance, Griliches (1969), and Autor, Dorn, Katz, Patterson, & Van Reenen (2020) also indicate that the rise of automation, artificial intelligence, and digital platforms has made firms more productive while reducing the reliance on routine task labor, especially in sectors that are more susceptible to automation.

capital expenditure (CapEx), adjusted for employee turnover. Higher CAR values indicate greater automation potential with stable workforce conditions. The API standardizes adjusted capital intensity, CapEx per employee, and turnover into z-scores, allowing for cross-firm and cross-industry comparisons while reducing the influence of extreme values and providing a relative measure of automation potential, where higher values suggest increased technological adoption and capital-driven efficiency. The results from both measures, consistent with our hypothesis, reveal a significant positive relationship among low-tech firms, while the relationship remains insignificant for high-tech firms. Conversely, we examine the mechanism through which technology talent hiring influences high-tech firms. Our analysis shows that, on average, prior IT-talent hiring positively affects a firm's R&D intensity, and higher past R&D intensity enhances firm value, as measured by the P/E ratio. However, the positive relationships between past IT-talent hiring and R&D intensity and between R&D intensity and firm value are predominantly observed in high-tech firms, with no significant effect identified for firms in low-tech sectors. Therefore, our findings reveal that tech-related hiring fulfills distinct roles across industries: in low-tech sectors, it signals strategic shifts, enhancing operational and financial performance through automation and increasing firm valuation, whereas in high-tech sectors, it constitutes an inherent expectation within R&D activities, exerting minimal impact on firm valuation.

We also analyze how managerial ability and labor market efficiency influence firms' IT talent hiring, by enhancing their knowledge capital. Managerial ability reflects leadership capacity to navigate technological advancements (e.g., Doukas & Zhang, 2021; Anderson, Sherer, & Yu, 2025), enabling firms to identify and leverage IT talent for competitive advantage. We find that firms with strong managerial ability are more likely to invest in IT talent. Labor market efficiency also shapes IT hiring, with over-hiring often used to build a talent buffer. Skilled managers ensure this strategy remains purposeful rather than excessive. Our results show that a 1% increase in managerial ability leads to a 5.7% rise in IT hiring during over-hiring periods. Given the long-term nature of IT investment, we further examine cumulative IT hiring over the next five years, minimizing short-term labor market fluctuations. This approach confirms that managerial ability significantly drives long-term IT investment, while labor market efficiency has a positive but insignificant effect, underscoring the dominant role of leadership over external market conditions.

In addition to influencing firm value and corporate strategies, our results demonstrate that IT talent investments align closely with organizational cultural values. IT professionals foster teamwork through their inherently collaborative work processes and drive innovation by introducing and implementing transformative technologies. Moreover, IT talent significantly enhances quality by developing systems and processes that improve operational accuracy, efficiency, and reliability, embedding high standards across all organizational functions.

Our final set of investigations sheds light on the performance outcomes of firms with IT talent investments that exceed those of their industry peers. Our analysis indicates that firms with significant IT talent investments outperform their industry peers over time, demonstrating superior stock performance, enhanced operational efficiency, and reduced uncertainty. While the immediate financial impact of IT investments may be limited, their long-term benefits are substantial, driving improved resource management, operational predictability, and profitability. These findings underscore the strategic value of IT talent as a critical determinant of sustained firm performance and competitive advantage.

This paper makes a significant contribution by bridging the gap between automation, labor economics, and financial markets, demonstrating that technology talent hiring serves distinct functions across industries. Our findings build upon prior literature documenting the role of knowledge capital in driving firm growth (e.g., Autor & Dorn, 2013; Belo et al., 2022; Abis & Veldkamp, 2024; Babina et al., 2024) and provide additional evidence that IT talent acquisition enables low-technology firms to achieve a strategic competitive advantage by facilitating increased automation, thereby improving operational efficiency and overall firm performance. Conversely, in high-tech sectors, IT talent hiring is an inherent aspect of R&D activities, exerting a limited influence on firm valuation. The findings also provide a fresh perspective on the broader economic implications of IT talent hiring, suggesting that investors should consider labor composition when evaluating firms' value.

Moreover, methodologically, our paper provides a unique approach to measuring a firm's technology-based human capital by focusing on its perspective and willingness to hire technological professionals rather than non-technology labor (non-IT intensive) employees. This approach captures a firm's commitment to technology talent investment as a reflection of its strategic priorities. Previous studies primarily rely on firm-level cost items, such as R&D and SG&A, to quantify intangible capital, including knowledge and human capital (e.g., Eisfeldt & Papanikolaou, 2013; Peters & Taylor, 2017; Crouzet & Eberly, 2019; Eisfeldt, Kim, & Papanikolaou, 2020; Belo et al., 2022). Recent studies have measured AI technologies using various database resources, such as Burning Glass job posting data. In contrast, our methodology utilizes firm-level recruitment data from LinkUp to directly capture technology-related intangibles, providing novel insights into the dynamics of technology talent acquisition and its influence on firm value. Notably, LinkUp offers greater precision and minimizes the need for extensive data cleaning by ensuring the data reflects active, valid job openings while eliminating duplicates, expired listings, and the noise commonly associated with aggregated datasets.

Finally, our paper provides one of the first pieces of systematic evidence on how a firm's managerial ability moderates the relationship between labor investment efficiency and technology talent hiring. Recent work has made progress in examining the impact of technologies on firm activities in various specific settings, such as Robo-advising (D'Acunto, Prabhala & Rossi, 2019), fintech innovation (Chen, Wu, & Yang, 2019), loan underwriting (e.g., Fuster, Goldsmith-Pinkham, Ramadorai & Walther, 2022; Jansen, Nguyen, & Shams, 2024), and financial analyst (e.g., Cao, Jiang, Wang, & Yang, 2024), from the labor market resource perspective by using employee resume to develop the labor resource. Our paper focuses on a firm's technology talent hiring and firm activities from the firm recruitment perspective by using the hiring position description, which can better capitalize on the firm's talent investment. We provide evidence that firms tend to over-hire to build a talent buffer, ensuring access to the human capital needed to address unforeseen opportunities or challenges, and that managerial ability enhances the effectiveness of labor market practices in fostering IT talent investment. We contribute new empirical evidence on the significance of knowledge capital investment through the lens of firm characteristics as well. While prior research predominantly employs econometric models, such as production functions, to establish mathematical relationships between knowledge input (proxied by R&D) and firm output (e.g., Belo, Li, Lin, & Zhao, 2017; Duffy et al., 2004; Griliches, 1969; Krusell, et al., 2000), our study extends this literature by utilizing practical market data to link talent hiring with firm culture. We demonstrate that IT professionals foster teamwork, drive innovation, and significantly enhance quality by implementing systems and processes that improve operational effectiveness.

The rest of the paper proceeds as follows. Section 2 discusses related literature. Section 3 presents the definitions of the data and variables. Section 4 introduces empirical results. Section 5 explores several further empirical analyses. Finally, Section 6 concludes.

2. LITERATURE REVIEW

The following section synthesizes existing research on technology talent and its implications for firm value and performance. This review aims to provide a comprehensive understanding of how IT talent hiring shapes firm dynamics and strategies across industries.

2.1 Labor Market Efficiency

The concept of labor as a long-term investment has been extensively analyzed, with scholars highlighting its role as both a driver of firm value and a potential source of agency problems. Ghaly et al. (2020) emphasize the positive association between long-term institutional investors and labor investment efficiency, asserting that effective governance can mitigate inefficiencies such as over-hiring. Khedmati et al. (2020) find that increases in independent directors with ties to the CEO are associated with decreased labor investment efficiency. Meanwhile, Kaplan and Lee (2024) demonstrate that labor investment efficiency decreased for US-based firms after the enactment of Tax Cuts and Job Acts and suggest that the mechanism behind the decrease is that increases in agency costs arising from high cash holdings lead the managers to seek a quiet life.[7] Labor adjustment costs, particularly for skilled employees, exacerbate inefficiencies due to

[7] Consistent with prior research (e.g., Donangelo, 2014; Ghaly et al., 2017), our untabulated empirical results document that firms with significant IT talent investments tend to maintain higher cash holdings to mitigate risks associated with skilled employee mobility. Moreover, state labor credit policies, which provide financial incentives to support high-skill job creation, moderate this effect. Firms in states with stronger labor credit policies hold less cash when investing in IT talent, as these states' policies reduce hiring costs and turnover risks. Our findings underscore the interplay between IT talent strategies and financial resource management, shaped by external labor market incentives. The results are available upon request.

increased severance pay and litigation risks (Krusell et al., 2000).

Recent contributions further refine our understanding of managerial ability and its influence on labor market efficiency. Thakor (2021) explores the interplay between short-termism and managerial talent, finding that firms pursuing long-term projects attract and retain more skilled managers, thus enhancing firm value. This perspective complements prior work by Doukas and Zhang (2021), who underscore the importance of managerial ability in anticipating and adapting to technological advancements. Collectively, these studies establish a robust link between managerial skill, labor market practices, and the strategic alignment of IT talent acquisition. Managerial ability also interacts with labor market conditions in complex ways (e.g., Anderson et al., 2025). Liu et al. (2022) argue that highly competent managers are more adept at implementing strategies that balance over-hiring and under-hiring, mitigating the risks associated with labor market volatility. Their analysis highlights the importance of managerial decision-making in optimizing resource allocation in competitive environments. Anderson et al.(2025) provide evidence that there is a nonlinear relationship between labor market efficiency and managerial ability, showing that low-ability managers tend to over- or underinvest, while high-ability managers strategically overinvest to drive future firm performance. Furthermore, Sabah et al. (2022) provide evidence that effective talent retention strategies amplify managerial capability, creating synergies that enhance firm productivity and value. In addition, Edmans (2012) demonstrates the link between job satisfaction and firm value, suggesting that employees' well-being directly impacts managerial effectiveness and firm outcomes. This finding aligns with the broader emphasis on managerial talent as a key determinant of organizational success. These studies collectively point to the significant role that managerial ability plays in shaping labor investment strategies and overall firm performance.

However, existing literature predominantly examines the causes, consequences, and mechanisms of firms' labor investment inefficiencies. There is a notable lack of research exploring the relationship between talent hiring and labor investment efficiency, particularly how managerial ability influences this relationship. With the growing integration of new technologies into business operations, understanding the interplay among labor market efficiency, managerial ability, and IT talent hiring has become a crucial area of inquiry. This paper addresses this important research gap.

2.2 Technology Talent and Firm Value

Previous research highlights the importance of non-physical capital inputs as key determinants of firm value, particularly intangible capital's role in understanding aggregate stock market evaluations (e.g., Hall, 2001; McGrattan & Prescott, 2000; Vitorino, 2014). Belo et al. (2022) decompose firm value into multiple capital inputs, demonstrating that knowledge capital—a cumulative investment in innovation—is vital for market valuation. The elasticity of substitution between capital equipment and unskilled labor, as highlighted by Griliches (1969), further underscores the unique role of skilled IT talent in enhancing productivity and operational efficiency. Rock (2021) advances this discourse by examining the returns to investments in AI talent, showing that firms leveraging such expertise achieve significant financial gains. Similarly, Babina et al. (2024) emphasize the transformative impact of AI-skilled employees on firm growth and product innovation, using job postings data to quantify the demand for technological skills.

The relationship between technical skills and firm returns, however, is conceptually ambiguous. On the one hand, skilled employees enhance productivity, potentially leading to positive firm returns if the market underprices their contributions, akin to other intangibles. Furthermore, technically skilled employees introduce a mobility risk premium, as their high mobility can amplify a firm's exposure to systematic risks (e.g., Donangelo, 2014). On the other hand, the demand for technical skills often fluctuates with the lifecycle of specific technologies, leading to potential over-investment in popular but transient innovations. Ghaly et al. (2017) compare this phenomenon to fads and bubbles, where over-exuberant expectations result in negative future returns as tangible benefits fall short.

Empirical studies illustrate these dynamics. For instance, Fedyk and Hodson (2023) document that technical skills, while correlated with higher firm valuations, often predict systematically lower future returns when they align with popular but overvalued technologies. These findings align with evidence of boom-and-bust cycles in demand for technical skills among employers and employees. Similarly, Krusell et al. (2000) examine the elasticity of substitution between capital equipment and labor, finding that skilled labor complements capital equipment more effectively than unskilled labor. This capital-skill complementarity implies that growth in capital stock increases the marginal productivity of skilled labor, further emphasizing its value.

Another research focus is the valuation impact variation of IT talent hiring. Hall and Vopel (1996) find that the market valuation of innovative output (measured by R&D expenditures) is higher for firms with a larger market share, suggesting that these firms benefit more significantly from their innovations. Kaplan and Rauh (2013) underscore how integrating skilled labor in mature industries can signal strategic pivots, boosting investor confidence.

Last, the cultural implications of technology talent hiring extend beyond operational outcomes, shaping firm innovation, teamwork, and adaptability. Bharadwaj (2000) links IT capabilities to structural and cultural shifts, arguing that technological investments foster a collaborative and innovation-centric environment. Li et al. (2021) quantify the influence of IT talent on corporate culture, demonstrating its alignment with values such as quality and teamwork. Adding to this discourse, Allison et al. (2023) explore the intersection of gender, technology, and labor, finding that gender diversity enhances firm performance when coupled with technological advancements. Their study underlines the importance of inclusive hiring practices in maximizing the strategic value of IT talent, providing actionable insights for firms navigating global labor markets. Further evidence of the interaction between culture and talent is provided by Kaplan and Lee (2024), who note that labor investment efficiency directly influences a firm's cultural adaptability. Effective management of IT talent aligns corporate goals with evolving workforce expectations, ensuring sustained innovation and competitive advantage. This intersection highlights technological investments' transformative role in shaping financial and cultural aspects of firm performance.

In summary, the literature highlights the multifaceted role of IT talent in driving firm value and organizational success. By bridging technological expertise, cultural alignment, and strategic labor market practices, firms can secure a competitive edge while fostering long-term growth and resilience. Notably, there remains a lack of empirical evidence regarding the role of technology talent hiring across different industries and the underlying mechanisms that drive this relationship.

Building on this foundation, our study focuses on firms' recruitment strategies for technology employees across industries and their subsequent impact on firm value. Unlike prior research, which predominantly examines labor supply characteristics, we explore firms' willingness to hire IT talent from a demand-side perspective. This perspective bridges gaps in understanding the strategic interplay between labor market dynamics and firm performance, offering insights into the valuation effects of technology-driven hiring decisions.

3. DATA, VARIABLE DEFINITIONS, AND DESCRIPTIVE STATISTICS

3.1 Measuring a Firm's IT Talent Hiring

We propose a new measure of a firm's investment in technology talent based on firm hiring position data. We collect data from LinkUp, a high-quality, reliable job listing dataset sourced directly from employer websites. Utilizing a proprietary process, the platform gathers, verifies, and enriches job data, and the dataset includes new postings, removed listings, and captured updates. With job content validated and job durations included, LinkUp's dataset is particularly valuable for studies requiring accurate and up-to-date insights into hiring trends. The raw dataset comprises over 57,000 unique company IDs from 2007 to 2023.

Each job listing includes detailed information such as an occupation code (with 1,203 unique job codes), job title, description, and job hash. We systematically screen job codes and descriptions to identify IT-related positions using the following criteria: (1) job titles (e.g., IT Manager), (2) programming languages (e.g., JavaScript), (3) technologies and tools (e.g., HTML/CSS), (4) databases and data processing tools (e.g., MySQL), (5) operating systems (e.g., Linux), (6) domain knowledge and methodologies (e.g., Cybersecurity), and (7) specialized certifications (e.g., CISSP).

To measure a firm's IT talent hiring, we create a variable, *IT Talent Rate*, by calculating the number of IT-related new hires scaled by the total new hires of the firm within that year.

$$\omega_{IT} = \frac{\#\ of\ IT\ related\ positions}{\#\ of\ total\ new\ hiring\ of\ the\ firm} \quad (1)$$

Intuitively, this measure captures how correlated IT employee hiring is with the firm's total new hiring. For example, if a firm has a value of 0.06, it means that 6% of its job postings are related to high-tech talent hiring.

To refine the dataset, we exclude all international and private companies, and the final sample consists of 4,318 firms and 34,332 firm-year observations.

3.2 Sample Selection and Variable Definition

We gather firm-level financial data for all the firm-year observations with the *IT Talent Rate* data from Compustat and equity market data from CRSP. The control variables used in our regressions include firm size, measured as total assets in billions; capital intensity, calculated as the firm’s capital expenditures (CapEx) scaled by its total assets; leverage, determined by the firm’s total debt ratio; payout, represented by the dividend payout ratio; ROA (return on assets), estimated as the firm’s net income divided by total assets at the beginning of the year; Tobin's Q, which is the firm’s annual Tobin’s Q ratio; and firm age, measured based on the firm’s IPO year, or if IPO data is unavailable, the first year the firm appears in the Compustat database.[8]

Table 1 Panel A reports the summary statistics for all the variables. Our sample's mean and median *IT Talent Rate* are 1.897% and 0.57%, respectively, with a standard deviation of 4.307%. We also calculate the average *IT Talent Rate* across all 48 industries using the Fama-French 48-Industry Classification during the whole sample period (2007 to 2023). Panel B of Table 1 shows that among the industries, the *IT Talent Rate* of tobacco products (0.363%), steel works, etc. (0.378%), and non-metallic and industrial metal mining (0.415%) exhibit the lowest rates. In contrast, the highest rates are observed in Defense (3.804%), Electronic Equipment (4.997%), and Computers (5.237%). Panel C of Table 1 presents the summary statistics of firm-specific characteristics by the industry groups. Compared with their counterparts, we find that high-tech firms invest more in IT talent and are larger and younger. Furthermore, low-tech firms are more capital-intensive, and high-

[8] All the control variables are winsorized at the top and bottom 1% in the following regressions to reduce the outlier influence and enhance the robustness of the analysis.

tech firms are likely to focus more on intangible assets (e.g., software). Finally, High-tech firms have higher average valuations (2.12 vs. 1.82), reflecting growth expectations and innovation potential, and they distribute more to shareholders than low-tech firms.

[Insert Table 1 about here]

4. EMPIRICAL RESULTS

This section explores our baseline hypothesis on the impact of IT talent investment on firm value across various industry groups. Then, to address endogeneity concerns, we employ a two-stage least squares (2SLS) approach. Furthermore, we investigate the underlying mechanisms through which IT talent investment influences firms differently across distinct industry segments.

4.1 IT Talent Investment and Firm Value

We focus on P/E and EV/EBITDA ratios to analyze the relationship between IT talent investment and firm value. P/E reflects market expectations regarding a company's growth potential and profitability. At the same time, EV/EBITDA provides a comprehensive measure of a company's value, factoring in its operational earnings while eliminating the effects of capital structure and non-cash expenses.

A significant divergence in valuation metrics is expected between high-tech and low-tech firms, driven by their distinct business models and market dynamics. High-tech companies, often in their growth phases, tend to exhibit higher P/E and EV/EBITDA ratios due to their significant revenue expansion and market optimism about their innovative potential. In contrast, low-tech companies typically operate in more mature industries with stable but slower growth. Their lower valuations often reflect market skepticism about their ability to adapt to technological disruptions and maintain competitive edges. For these reasons, we categorize firms into three groups using two distinct methods. First, guided by Hall and Vopel (1996), we classify sectors into three groups based on technological requirements and skill intensity: High-tech group (high-technology/knowledge-intensive), Med-tech group, and Low-tech group. This systematic approach provides a clear and logical framework for analyzing technological investments across industries.[9]

To ensure the robustness of our results, we also use K-Means Clustering, a machine learning algorithm, based on three key variables, IT Talent Rate, R&D Intensity, and Capital Intensity, as an alternative industry classification method. These variables provide a comprehensive and reliable basis for grouping industries. IT Talent Rate reflects the proportion of IT-related hires, capturing technological dependence and digital workforce integration within an industry. R&D Intensity measures the focus on innovation, indicating how much industries prioritize research and development for maintaining competitiveness. Capital Intensity assesses reliance on physical capital, highlighting structural differences in operational investment. Together, these variables account for technological adoption, innovation, and resource allocation patterns, offering a robust and nuanced classification.[10] Table 2 reports the relationship between IT talent investment and firm value across industries. The dependent variables are the firm's *P/E ratio* and *EV/EBITDA*, and the primary independent variable is the firm's prior year's *IT Talent Rate*.

[Insert Table 2 about here]

Firstly, as shown in columns (1) and (5) of Panels A and B, we find no significant relationship between the prior year's IT talent hiring and the current year's P/E or EV/EBITDA for all companies in the sample. However, in columns (2) to (4) and (6) to (8), the results derived from the two classification methods demonstrate high consistency. Specifically, for High-tech firms, no significant relationship is observed between IT talent hiring and firm valuation metrics. In contrast, for low-tech firms, which primarily operate in traditional industries characterized by physical production, manufacturing, or resource extraction, higher IT talent investment in the prior year significantly increases their P/E ratios and EV/EBITDA ratios. The effect is economically efficient. When the firm hires

[9] The summary statistics for firms within each industry, based on the first measure, are presented in Table 1, Panel C. The summary statistics using the second measure are largely consistent with those obtained from the first measure.

[10] we also compute the average IT Talent Rate for each of the Fama-French 48 industries and rank them in descending order. The top three industries are Computers, Electronic Equipment, and Defense, while the bottom three are Tobacco Products, Steel Works, Etc., and Non-Metallic and Industrial Metal Mining. The industries are then equally divided into three groups (16 industries each): High-tech, Med-tech, and Low-tech. The results using this method are highly consistent with the results from the other two grouping methods.

1% more IT talent, the P/E ratio increases by about 1.047%, and EV/EBITDA improves by 0.399%. The findings for Mid-tech firms present mixed results, falling between the two extremes.

Two explanations exist to rationalize the differences in the relationship between tech-related hiring and valuation metrics (*P/E* and *EV/EBITDA*) in low-skilled industries and high-technology or knowledge-intensive industries. Firstly, in low-skilled industries such as Basic Materials, Consumer Staples, and Utilities, technology-related hiring often serves as a differentiator, which signals automation and modernization, as these industries are traditionally not associated with technological advancement. Therefore, our findings provide evidence that tech hiring signals a strategic shift toward digital transformation or automation, positioning firms to gain a competitive edge. This drives investor expectations for future growth or improved margins, leading to higher valuations. In contrast, tech-related hiring is often considered the norm for high-tech or knowledge-intensive industries. Technology is already embedded in firm valuations in these sectors, as firms are expected to continuously invest in and hire tech roles. Consequently, incremental increases in tech hiring do not significantly alter investor expectations or valuations. Moreover, the marginal utility of additional tech-related hiring is lower in industries already highly dependent on technology, and the structural dynamics of high-tech industries make factors such as R&D effectiveness, market positioning, or regulatory changes more critical than increasing tech hiring.

Secondly, in low-tech industries, tech adoption can transform value chains by automating production processes or optimizing supply chains, contributing to operational efficiency, including cost reduction, improved productivity, and better resource management.[11] Those changes can directly enhance financial valuations and lead to measurable impacts on EBITDA and investor sentiment. Knesl (2023) explores technological advancements that allow capital to displace labor and impact firm valuation. Zhang (2019) also documents that firms tend to replace routine-task labor with machines

[11] The contemporary literature on workplace automation and firm efficiency includes studies by Autor and Dorn (2013), Acemoglu and Restrepo (2018), Zhang (2019), Knesl (2023), and Bates, Du, and Wang (2024). These studies paint a picture of automation as a double-edged sword: it boosts firm efficiency and valuation while reshaping labor markets.

in response to unfavorable aggregate shocks. Conversely, in High-tech industries, shorter innovation cycles mean that investor attention is focused on disruptive IT breakthroughs (i.e., electric vehicles, blockchain and cryptocurrencies, AI and machine learning, 3D printing, cloud computing, and autonomous driving) rather than increases in new IT-related hiring.

Overall, the results in Table 2 underscore the differing roles of technology-related hiring plays across industries. In low-skilled industries, tech-related hiring signals a strategic shift with clear operational and financial benefits, driving higher valuations. In contrast, in high-tech industries, technology talent hiring shows no significant valuation effects due to existing investor expectations.

4.2 Endogeneity Analysis Using 2SLS Analysis

A key endogeneity issue in this study arises from potential reverse causality or omitted variable bias. Firms with higher valuations might attract more IT talent because of their superior financial resources, strong reputation, or ability to provide better compensation. This creates the possibility that the observed link between IT talent hiring, and firm value is driven by reverse causality. Additionally, unobserved factors, like market dynamics or industry-specific disruptions, may simultaneously influence both IT talent hiring rates and firm valuations, confounding the causal relationship. To address this issue, we employ the 2SLS method. We use the logarithm of the total number of CS graduates from higher education institutions—both private and public—per year in the same state as the firm's headquarters as an IV.[12] Each institution is mapped to its corresponding state, and this information is merged with the firm data based on the location of the firm’s headquarters. This IV is appropriate because the local supply of CS graduates is an important determinant of IT hiring, influencing the availability of skilled local labor for firms. At the same time, the CS graduate supply is unlikely to directly affect firm valuation, aside from its indirect impact through IT talent acquisition. By leveraging this IV, we isolate the causal relationship between managerial ability and IT hiring, addressing concerns about potential endogeneity.

[12] Data on CS graduates is obtained from https://datausa.io/. which provides detailed information on graduate numbers by institution.

[Insert Table 3 about here]

Table 3 presents the results of the 2SLS regression analysis examining the impact of IT talent hiring on firm valuation across high-tech, medium-tech, and low-tech industries. The first-stage F-statistic of 25.6 indicates that the instrument (CS graduates) is strong. The first-stage results in Column (1) confirm a significant positive relationship between CS graduate availability and IT talent hiring. Columns (2) to (4) report the second-stage results, where firm value is measured by the P/E ratio. The findings reveal that IT talent hiring has a positive and significant effect on firm value in low-tech industries, with a coefficient of 13.411, significant at the 5% level, suggesting that markets reward low-tech firms with tech talent acquisition. A similar pattern emerges when using the EV/EBITDA ratio as an alternative valuation measure in Columns (5) to (7), where IT talent hiring remains positively associated with firm value (coefficient = 4.276, $p < 0.1$). After instrumenting technology talent hiring, the results demonstrate that there is still a positive relationship between IT talent hiring and firm valuation in low-tech firms. We thus confirm that endogenous issues do not drive our empirical conclusion.

4.3 The Underlying Mechanism of the Impact of IT Talent Investment on Firm Value

This section investigates the underlying mechanism of our hypothesis, which posits that tech-related hiring has distinct implications across industries. Specifically, we argue that in low-tech sectors, technology hiring signals strategic transformation and enhances operational efficiency and firm valuation through increased automation (e.g., Autor & Dorn, 2013).[13]In contrast, IT hiring plays a crucial role in high-tech industries by driving innovation and shaping technological advancements, thus sustaining a competitive advantage without significantly altering investors' expectations.

We use two different measures to capture a firm's automation level. First, we estimate the adjusted capital intensity using net PP&E per employee adjusted by the average age of capital, as shown in Equation (2). The rationale is that a higher value of net PP&E per employee suggests more tangible resources supporting each worker, often indicating automation potential. However, the average age of capital should be adjusted since the

[13] Autor and Dorn (2013) find that automation displaces routine jobs while amplifying demand for high-skill roles and boosting efficiency.

measure should ensure that it reflects not only capital quantity but also its modernization. Without this adjustment, firms with outdated assets might appear capital-intensive despite limited automation potential. By penalizing older capital and favoring newer investments, the measure more accurately captures a firm's commitment to technological advancement and provides a balanced comparison across firms and industries.

$$Adjusted\ Capital\ Intensity_{j,t} = \frac{Net\ PP\&E_{j,t}}{Total\ Employees_{j,t}} \times \frac{1}{(1+Average\ Age\ of\ Capital_{j,t})} \quad (2)$$

Meanwhile, CapEx per employee is a crucial indicator of firm automation because it reflects ongoing investment in technology and equipment relative to the workforce size. Higher CapEx per employee suggests a firm's commitment to modernizing operations and enhancing productivity through technology, making it a forward-looking measure of automation intensity. Employee turnover is also crucial when measuring firm automation because it reflects workforce stability, which can signal how firms adapt to technological change. High turnover suggests disruptive restructuring, while low turnover indicates smoother integration and stable workforce management, boosting the score. It also controls for short-term shocks, ensuring the measures highlight firms achieving sustainable automation rather than those relying solely on capital investment with excessive labor displacement. Thus, we form our first measure, Composite Automation Ratio (CAR), as shown in Equation (3). Higher CAR values indicate firms investing in capital and technology while maintaining workforce stability, enhancing automation potential.

$$CAR_{j,t} = \frac{Adjusted\ Capital\ Intensity_{j,t} + CapEx\ per\ Employee_{j,t}}{(1+Employee\ Turnover_{j,t})} \quad (3)$$

We also use another alternative measure, the Automation Potential Index (API), to facilitate cross-firm and cross-industry comparisons by standardizing key components. As defined in Equation (4), API converts Adjusted Capital Intensity, CapEx per Employee, and Employee Turnover into z-scores, ensuring consistency across firms and sectors. Unlike CAR, which can be distorted by extreme values, API normalizes the distribution, balancing positive indicators (capital investment) and negative ones (turnover) to provide a more comprehensive and unbiased assessment of firm automation potential.

$$API_{j,t} = \frac{Z(Adjusted\ Capital\ Intensity_{j,t}) + Z(CapEx\ per\ Employee_{j,t}) - Z(Employee\ Turnover_{j,t})}{3} \quad (4)$$

Both CAR and API measures leverage commonly available financial and employment data from firm-level databases, ensuring accessibility and ease of implementation. CAR provides a firm-specific, investment-focused perspective, capturing how capital investment and workforce dynamics reflect automation adoption. In contrast, API standardizes these components for cross-firm and cross-industry comparisons, offering a more balanced and robust measure. Together, they provide complementary insights into firm-level automation potential.

We then analyze the relationship between the firm's prior IT talent investment and the firm's automation level, overall and across different industry groups. The result is reported in Table 4.

[Insert Table 4 about here]

The results in Table 4, columns (1) and (5), show a positive and significant relationship between prior IT talent hiring and firm automation levels. However, when firms are categorized into three industry groups, the positive relationship remains significant for low-tech firms, supporting our hypothesis that tech-related hiring primarily enhances cost control and operational efficiency in these sectors. In high-tech sectors, as shown in columns (2) and (6), the relationship is insignificant, while the results for med-tech sectors fall between the two extremes.

Next, we examine whether firms' valuations across different industries are influenced by their past R&D outcomes. IT professionals are pivotal in driving innovation and technological development, which are core research and development components. IT talent contributes directly to the development of new technologies, products, and services, which are typically funded through R&D budgets. Additionally, advanced IT skills enhance the efficiency and accuracy of R&D activities, such as data analysis, simulation, and prototyping, which require significant resource allocation. Thus, one should expect that IT talent investment is closely related to a firm's R&D expenses. We examine the relationship between investments in IT talent and the firm's R&D intensity, measured as total R&D expenses divided by the total assets for each firm within each year. The findings are presented in Table 5.

[Insert Table 5 about here]

First of all, the result in Table 5 column (1) reveals a positive relationship between the lagged IT Talent Rate and R&D intensity, which confirms that IT talent is both a resource and a driver of R&D outcomes, making investment in IT capabilities a critical determinant of overall R&D spending. However, when sorting all firms into High-tech, Med-tech, and Low-tech groups, as reported in columns (2) to (4), the positive relationship between IT Talent Rate and R&D intensity remains significant for High- and Med-tech firms but insignificant for Low-tech ones. The results are economically meaningful: a 1% increase in IT talent rate is associated with a 0.167% increase in R&D intensity, which supports our baseline argument, indicating that IT talent drives innovation in high-tech firms and enhances operational efficiency in low-tech firms by facilitating automation.

To strengthen this argument, we analyze whether firm valuations across various industries are affected by their historical R&D performance. The results, presented in Table 5, columns (5) through (8), indicate that, on average, greater R&D intensity in the past is associated with higher firm value, as reflected in the P/E ratio. Notably, this positive correlation is primarily evident in high-tech firms, while no significant effects are observed for med-tech or low-tech firms.

Overall, the results in Tables 4 and 5 confirm our hypotheses that the underlying mechanism of tech talent hiring affects firm valuations (P/E, EV/EBITDA) differently across industries. In low-skilled sectors, tech hiring signals automation and modernization, driving investor expectations for growth and higher valuations. In contrast, technology talent hiring drives innovation in high-tech industries, but since ongoing investment in IT is already factored into valuations, incremental increases in tech talent have a limited impact as investors in these industries tend to focus more on disruptive innovations.

5. FURTHER ANALYSIS

This subsequent analysis redirects our attention towards investigating the relationship between technology talent acquisition and organizational strategies. We begin by identifying the extent to which managerial capability and labor market efficiency influence the hiring of IT-related talent. Subsequently, we investigate the impact of IT talent acquisition on firm strategies, with a particular focus on corporate culture and performance outcomes in firms whose IT talent investments surpass those of their industry peers.

5.1 IT Talent Investment, Labor Market Efficiency, and Managerial Ability

Building on the findings from the previous section, technology talent hiring emerges as a critical component of firms' strategic development. Firms are increasingly positioned to identify and capitalize on strategies for acquiring strategic human capital. Managerial ability reflects a firm's leadership capacity to anticipate and adapt to technological advancements, enabling managers to evaluate the demand for IT talent strategically and align hiring decisions with the firm's long-term objectives. Consequently, firms with strong managerial capabilities are expected to exhibit a heightened propensity to invest in IT-related talent relative to their industry peers.

Labor market efficiency, particularly the ability to balance over-hiring and under-hiring, also plays a critical role in shaping IT talent investment. While over-hiring can traditionally lead to resource inefficiencies and under-hiring may result in missed opportunities for innovation, a purposeful over-hiring strategy reflects the availability of sufficient corporate resources to adopt a proactive stance. Firms employing this approach can build a talent buffer, ensuring access to the human capital needed to address unforeseen opportunities or challenges. This strategy is especially crucial in IT, where talent shortages and intense competition often hinder firms from acquiring skilled professionals when required. Meanwhile, high managerial ability further enhances the effectiveness of over-hiring by ensuring that such practices are strategic rather than excessive. Together, these elements establish a comprehensive framework for IT talent investment, with managerial ability offering strategic direction and over-hiring providing the adaptability needed to capitalize on technological opportunities.

We use *MA-Score*, developed by Demerjian et al. (2012), to measure the firm's managerial ability. The *MA-Score* quantifies managerial ability by isolating management-specific efficiency from factors like firm size or industry conditions. Using Data Envelopment Analysis, it measures a firm's resource-conversion efficiency, then adjusts for external factors to reflect only the managerial contribution. To assess a firm's labor market efficiency, we follow the model of Pinnuck and Lillis (2007):

$$\begin{aligned} Net\ Hire_{it} = {} & \beta_0 + \beta_1 Sales\ Growth_{it-1} + \beta_2 Sales\ Growth_{it} + \beta_3 \Delta ROA_{it-1} + \beta_4 \Delta ROA_{it} + \beta_5 ROA_{it} \\ & + \beta_6 Return_{it} + \beta_7 Size_{R_{it-1}} + \beta_8 Quick_{it-1} + \beta_9 \Delta Quick_{it-1} + \beta_{10} \Delta Quick_{it} \end{aligned}$$

$$+ \beta_{11} Lev_{it-1} + \beta_{12} Lossbin1_{it-1} + \beta_{13} Lossbin2_{it-1} + \beta_{14} Lossbin3_{it-1}$$
$$+ \beta_{15} Lossbin4_{it-1} + \beta_{16} Lossbin5_{it-1} + Industry\ FEs \quad (1)$$

Where *Net Hire* is the percentage change in employees; *Sales Growth* is the percentage change in sales; *ROA* is net income scaled by beginning of the year total assets; *Return* is the annual stock return; *Size_R* is the log of market value of equity at the beginning of the year, ranked into percentiles; *Quick* is the quick ratio; *Lev* is the ratio of long-term debt to total assets at the beginning of the year; and the *Lossbin* variables are indicators for each 0.005 interval of prior year *ROA* from 0 to -0.025. The residual estimates from regression (1) are used to measure labor market efficiency; above zero indicates over-hiring, and below zero indicates under-hiring. Then, we create a dummy variable, *Over Hiring*, which equals one if the firm is over-hiring and zero if the firm is under-hiring.

To investigate the relationship between IT talent investment, labor market efficiency, and managerial ability, we conduct regressions using *IT Talent Rate* as the dependent variable. *MA-Score*, *Over Hiring*, and the interactive variable, *MA*Over Hiring*, are the main independent variables, alongside control variables. Both industry and year-fixed effects are incorporated to control unobserved heterogeneity. The results are presented in Table 6.

[Insert Table 6 about here]

Along with our expectations, the positive and significant coefficient across all models indicates that firms with higher managerial ability are more inclined to invest in IT talent. This highlights the role of strong managerial competence in driving strategic investments in technology and talent. Our empirical results align with those of Anderson et al. (2025), who suggest that managers with higher abilities are more capable of acquiring and utilizing resources efficiently than those with lower abilities, showing that low-ability managers tend to over- or under-invest, while high-ability managers strategically overinvest to sustain and prop up future firm performance.

Moreover, the empirical results in column (2) suggest that firms identified as over-hiring are more likely to allocate resources toward IT-talent new hiring. Notably, in column (3), the positive and highly significant interaction term, *MA*Over Hiring*, indicates that firms with both high managerial ability and a tendency to over-hire are particularly strong investors in IT talent. The magnitude of the effects is economically meaningful, with a 5.7% increase in IT talent hiring when a firm is over hiring and a managerial ability increase of 1%. This result suggests a complementary effect, where managerial ability enhances the effectiveness of labor market practices by adopting expansionary IT talent employment strategies.[14]

Since IT hiring often represents strategic, long-term investments that evolve gradually, we conduct another analysis using total IT talent hiring as a proportion of total hiring over the next five years as the dependent variable, aligning with the cumulative nature of IT adoption. The results, presented in Table 2, columns (4) to (6), reveal a significant positive impact of managerial ability on long-term IT talent investment, while labor market efficiency shows a positive but insignificant relationship. This suggests that firms depend more on managerial ability for strategic IT talent acquisition, whereas external market conditions may cause short-term fluctuations but fail to drive sustained IT workforce expansion.[15]

5.2 IT Talent Investment and Corporate Culture

Next, we investigate the influence of firm IT Talent investment on firm culture. Previous literature, especially in management, has argued that investing in IT talent can profoundly shape a firm's culture by fostering innovation, adaptability, and collaboration. For instance, Bharadwaj (2000) highlights how IT capabilities drive structural and cultural shifts, while Orlikowski and Barley (2001) emphasize technology's impact on institutional norms and practices. Ravichandran and Lertwongsatien (2005) explore technology's role in strategic decision-making and cultural adaptation, and Galliers and Leidner (2003) underscore IT's strategic influence on organizational behavior. Therefore, we investigate how more IT-capable employees shape corporate culture.

[14] We also perform a subgroup analysis by running regression analyses separately for firms in the top 20% and bottom 20% of MA-Score. For the top 20% group, the coefficient is positive and significant (0.017, t-value = 3.57), while for the bottom 20% group, the coefficient is positive but not significant (0.015, t-value = 0.58). These findings suggest an asymmetric relationship between managerial ability and IT talent investment, where the positive association is primarily driven by firms with managers of relatively high managerial ability. The results are available upon request.

[15] We also carry out examinations where the total IT talent hiring as a proportion of overall hiring across various time intervals (e.g., two years, three years) serves as the dependent variable. Our conclusions remain consistent.

Our corporate culture data are obtained from Li et al. (2020). The authors estimate corporate culture elements using a machine learning-based word embedding model trained on 209,480 earnings call transcripts. They define five cultural values—innovation, integrity, quality, respect, and teamwork—using seed words derived from S&P 500 firms' websites. The model identifies contextually related words, creating a culture dictionary for each value. Cultural scores are calculated by weighting the frequency of dictionary words in earnings call Q&A sections, ensuring relevance to firm operations and minimizing self-promotion biases. The five elements measure different aspects of the firm: *Innovation* reflects a firm's commitment to creativity, experimentation, and the development of new ideas, technologies, and products; *Integrity* represents adherence to ethical principles, accountability, and transparent decision-making in organizational behavior; *Quality* emphasizes delivering superior products or services that meet or exceed customer expectations; *Respect* highlights the value of diversity, inclusion, and fair treatment of all stakeholders, including employees and customers; and *Teamwork* captures collaboration, effective communication, and cooperative efforts across teams to achieve shared goals. We report the results in Table 7, and each cultural value is treated as the dependent variable in columns (1) to (5). Given the stability of corporate culture and its minimal year-to-year variation, the prior year's cultural level is included as a control variable.

[Insert Table 7 about here]

The findings in Table 7 reflect how IT talent investments align with specific organizational cultural values. We provide evidence that IT professionals drive teamwork through the collaborative nature of their work, as IT projects often require cross-functional efforts, bringing together diverse teams to achieve shared goals. We also find that innovation thrives in organizations with strong IT talent, as these professionals introduce and implement cutting-edge technologies, enabling transformative changes in products, services, and processes. Their expertise fosters a culture where innovation becomes a central organizational value. Furthermore, IT talent contributes significantly to quality by implementing systems and processes that enhance operational accuracy, efficiency, and reliability, embedding high standards across functions. However, the limited impact of IT talent on values like integrity and respect can be explained by their less direct connection to IT-related activities. These values are often shaped by broader organizational ethics, leadership, and interpersonal dynamics and are less influenced by IT investments.

5.3 Performance Implications of IT-centric Firms

Babina et al. (2024) reveal that AI adoption drives firm growth and innovation, suggesting that firms investing in AI experience significant growth in sales, employment, and market valuations. However, AI-driven growth is concentrated in larger "superstar" firms. Accordingly, in this section, we investigate how IT talent hiring influences firm performance by benchmarking high-IT talent investment firms against their industry counterparts. In other words, we want to test if firms with higher than industry average investment in technology talent yield superior performance than their competitors in the same industry and whether investors could benefit by investing in those IT-centric firms. To conduct this analysis, we create a dummy variable, *IT-Centric*, set to one if a firm's *IT Talent Rate* exceeds the industry median annually, based on Fama-French 48 industry classifications, and zero otherwise. Our analysis focuses on three key factors to assess firm-level return, risk, and operational efficiency: *Alpha* is estimated using the Fama-French 5-factor model; *Volatility* represents the variability in stock returns; and *Gross Profit Margin* reflects operational efficiency. We present the results in Table 8.

[Insert Table 8 about here]

The results in Table 8, columns (1) to (3), show that high IT talent investment in the current year has a negative but statistically insignificant relationship with firm Alpha, indicating no immediate impact on financial returns. However, compared to industry peers, higher IT talent investment in the prior year demonstrates a positive and significant relationship with *Alpha*. This finding suggests that the performance advantages of IT talent investment, compared to industry peers with lower IT investment, emerge over time, driving improved stock performance and firm-specific returns beyond market expectations. Meanwhile, the results for *Volatility* in columns (4) to (6) indicate that IT talent investment reduces volatility (enhances stability). While the influence of the current year's stock volatility is insignificant, the negative and significant coefficient for prior-year IT-centric status highlights a delayed reducing (stabilizing) impact. Firms with high IT talent investment in the prior year experienced reduced stock return volatility, suggesting that IT talent reduces uncertainty and enhances operational predictability.

The observed changes in stock returns and volatility may be driven by shifts in the composition of the investor base. High technology investment, while increasing firm costs in the short term due to the expense of IT-related talent hiring, delivers long-term value and higher growth potential. As a result, IT-centric firms become more attractive to long-term, value-oriented investors, such as institutional investors (Bushee, 1997; Della Croce, Stewart, & Yermo, 2011). To test this hypothesis, we analyzed changes in institutional investor holdings for IT-centric firms. Our untabulated results indicate a significant increase in both the number of institutional investors and the institutional ownership percentage for firms with higher-than-industry-peer IT talent hiring.[16] Simultaneously, the Herfindahl–Hirschman index for institutional investors decreases significantly, suggesting diversification of the institutional investor base in the current and subsequent years. This shift underscores the alignment of IT talent investment with the preferences of long-term, growth-focused investors.

Furthermore, IT talent investment has immediate and sustained effects on the *Gross Profit Margin*, as shown in columns (7) to (9). The positive and highly significant coefficient for the current year's IT-centric status demonstrates that firms with high IT talent investment experience higher operational efficiency in the same year. The positive and significant coefficient for prior-year IT-centric status also underscores that the benefits of IT talent investment persist, continuing to improve operational performance through better resource management and process optimization.

6. CONCLUSION

Firms increasingly invest in skill-driven information technology, adopting innovative practices and advanced tools to enhance productivity. Our findings reveal that investments in technology talent have different impacts across industries. In low-tech industries, such hires signal strategic shifts that lead to significant operational and financial benefits, driving higher valuations. In contrast, technology talent hiring in high-tech industries is seen as an expectation, with minimal effects on valuation. To explore the underlying

[16] These results are available upon request.

mechanisms driving the differential impacts, we construct two firm automation measures. Our findings reveal that, in low-tech industries, IT hires primarily contribute to improving efficiency and cost control through automation. Conversely, in high-tech industries, IT talent plays a crucial role in fostering innovation, thereby enhancing competitive advantage. In other words, our evidence suggests that IT talent fuels innovation in high-tech firms while driving operational efficiency and automation in low-tech firms.

This paper also reveals that firms with high managerial ability tend to over-hire IT talent, emphasizing the crucial role of managerial skill in optimizing labor market practices through increased IT talent recruitment. Additionally, we find that investments in IT talent impact corporate strategies and culture. Firms with substantial IT talent investments typically maintain higher cash reserves to manage risks related to the mobility of skilled employees. These investments also align with cultural values, promoting teamwork, driving innovation, and improving quality through enhanced systems and processes. The long-term benefits of investing in IT talent are reflected in superior stock performance, increased operational efficiency, and reduced uncertainty—all contributing to a sustained competitive advantage.

The findings of this paper offer substantial practical value for managers, policymakers, and investors. For managers, the study underscores the importance of strategic IT talent hiring as a key driver of firm value, particularly in low-tech industries where such investments enhance operational efficiency, innovation, and profitability. Policymakers can use the insights to shape labor credit policies that support IT hiring, thereby incentivizing technological advancements, especially in traditionally low-innovation sectors. For investors, the research highlights the valuation effects of IT hiring, suggesting that firms with significant IT talent investments, especially in low-tech industries, present opportunities for long-term value creation. The study's focus on the diverse roles of IT talent across industries highlights the need for tailored strategies that align with sector-specific dynamics, emphasizing the crucial role of technology-driven human capital in driving firm competitiveness and sustainable growth.

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Table 1 Summary Statistics

Panel A provides the descriptive statistics of the key firm-level variables for the whole sample. The sample consists of all public companies in the U.S. with hiring data. The hiring data are collected from LinkUp Job Market Data from 2007 to 2023. *IT Talent Rate* is measured as the number of IT-related new hires scaled by the total number of new hires for each firm each year. The other key variables, which are collected from Compustat, contain: *Firm Size*, which is the total assets of the firm in billions; *Capital Intensity*, which is estimated as the firm's CapEx scaled by the firm's total assets; *Leverage*, which is measured by the firm's total debt ratio; *Payout*, which is the dividend payout ratio of the firm; *ROA* is estimated as net income over total assets at the beginning of the year; *Tobin's Q*, which is the firm's annual Tobin's Q ratio; and *Firm Age*, which is measured based on the firm's IPO year (if the IPO year data is missing, we use the first year when the firm has data in Compustat). Panel B shows the top (bottom) three industries, based on the Fama-French 48-Industry Classification, with the highest (lowest) average IT Talent Rate during the sample period. Panel C reports the summary statistics for each industry group: High-Tech, Med-Tech, and Low-Tech.

Panel A: Summary Statistics of Key Firm-Level Variables

	Obs	**Mean**	**Std. Dev.**	**10%**	**Median**	**90%**
IT Talent Rate	34,331	1.897	4.307	0	0.57	4.87
Firm Size	33,900	31.608	183.017	0.177	2.448	36.506
Capital Intensity	32,867	0.035	0.045	0.001	0.021	0.081
Leverage	33,725	0.283	0.389	0.007	0.232	0.583
Payout	31,421	0.627	19.291	-0.088	0.289	1.6
ROA	32,975	-0.034	0.922	-0.215	0.024	0.118
Tobin's Q	31,785	3.976	175.963	0.981	1.501	3.946
Firm Age	34,331	23.287	18.9	3	19	55

Panel B: IT Talent Rate for Top and Bottom Industries

	IT Talent Rate	**Industry name**
Lowest industries	0.363%	Tobacco Products
	0.378%	Steel Works Etc
	0.415%	Non-Metallic and Industrial Metal Mining
Highest industries	3.804%	Defense
	4.997%	Electronic Equipment
	5.237%	Computers

Panel C: Summary Statistics of Key Firm-Level Variables by Industry Groups

	High-Tech			**Med-Tech**			**Low-Tech**		
Variable	**Mean**	**Std. Dev.**	**Median**	**Mean**	**Std. Dev.**	**Median**	**Mean**	**Std. Dev.**	**Median**
IT Talent Rate	2.340	5.263	0.750	1.478	3.065	0.530	1.241	2.546	0.630
Firm Size	84.956	337.325	4.617	15.857	46.488	3.287	19.238	32.255	6.087
Capital Intensity	0.020	0.030	0.011	0.047	0.050	0.033	0.049	0.038	0.041
Leverage	0.815	194.164	0.469	0.579	32.197	0.568	0.695	19.407	0.810
Payout	0.838	11.091	0.468	0.835	16.372	0.435	0.444	13.401	0.602
ROA	0.020	1.669	0.019	0.041	0.121	0.049	0.042	0.121	0.043
Tobin's Q	2.121	3.376	1.418	1.855	1.406	1.484	1.823	1.194	1.442
Firm Age	29.189	13.866	26.000	35.854	17.800	30.000	41.161	19.573	38.000

Table 2 IT talent investment and firm value

This table reports the regression results of the following model:

$$\begin{aligned} Firm\ Value\ Measure_{it} \\ = \beta_0 + \beta_1 IT\ Talent\ Rate_{it-1} + \beta_2 Size_{it-1} + \beta_3 Capital\ Intensity_{it-1} + \beta_4 Leverage_{it-1} + \beta_5 Payout_{it-1} + \beta_6 ROA_{it-1} \\ + \beta_7 Tobin's\ Q_{it-1} + \beta_8 Age_{it} + \varepsilon_{it} \end{aligned}$$

The dependent variable is firm value measures, for which we use both the firm's P/E ratio and EV/EBITDA ratio. The main independent variable is *IT Talent Rate*, which is measured as the number of IT-related new hires scaled by the total number of new hires for each firm within each year. We further use two methods to group all industries into three groups based on their reliance on technology and run the regression within each industry group. In panel A, we report the results by grouping the industries following Hall and Vopel (1996). In Panel B, we use K-Means clustering based on IT Talent Rate, R&D Intensity, and Capital Intensity to group all Fama-French 48 industries into three groups. Appendix 1A provides all the variable definitions. We also control for industry-fixed effects, following the Fama-French 48-Industry Classification, and year-fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Industry groups based on Hall and Vopel (1996)

	P/E Ratio				EV/EBITDA			
Variables	**All**	**High-Tech**	**Med-Tech**	**Low-Tech**	**All**	**High-Tech**	**Med-Tech**	**Low-Tech**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
IT Talent Rate$_{t-1}$	0.084	0.213	0.433**	1.047**	0.072	0.111	-0.046	0.399***
	(0.111)	(0.170)	(0.215)	(0.519)	(0.053)	(0.073)	(0.075)	(0.152)
Size$_{t-1}$	0.008	0.004	0.013	0.067***	0.003	0.000	0.006**	0.019***
	(0.006)	(0.012)	(0.009)	(0.013)	(0.003)	(0.005)	(0.003)	(0.004)
Capital Intensity$_{t-1}$	0.184	0.318	0.018	0.507*	-0.06	-0.436***	-0.250***	-0.208**
	(0.119)	(0.347)	(0.157)	(0.306)	(0.057)	(0.147)	(0.055)	(0.090)
Leverage$_{t-1}$	-0.019	0.046	-0.115***	-0.150***	0.035***	0.046**	0.020*	-0.026*
	(0.020)	(0.048)	(0.032)	(0.054)	(0.010)	(0.020)	(0.011)	(0.016)
Payout$_{t-1}$	0.022***	0.020***	0.007**	0.015***	0.002	0.003	0.003**	-0.001
	(0.002)	(0.005)	(0.004)	(0.006)	(0.001)	(0.002)	(0.001)	(0.002)
ROA$_{t-1}$	0.352***	0.428***	0.154**	-0.222*	0.279***	0.296***	-0.008	0.055
	(0.027)	(0.060)	(0.066)	(0.129)	(0.013)	(0.026)	(0.023)	(0.038)
Tobin's Q$_{t-1}$	0.003	0.034***	0.038***	0.066***	0.004***	0.014***	0.024***	0.022***
	(0.002)	(0.005)	(0.006)	(0.009)	(0.001)	(0.002)	(0.002)	(0.003)
Age	0.089***	0.068	-0.034	-0.037	0.029***	-0.006	-0.032***	-0.037***
	(0.012)	(0.052)	(0.028)	(0.043)	(0.006)	(0.022)	(0.010)	(0.013)
Constant	-0.102***	-0.147*	0.027	-0.326***	-0.010	0.035	0.049**	0.036
	(0.038)	(0.087)	(0.057)	(0.101)	(0.018)	(0.037)	(0.020)	(0.030)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.325	0.302	0.197	0.160	0.153	0.140	0.465	0.288
# of Obs	22,084	5,166	6,378	2,969	21,913	5,070	6,391	2,975

Panel B: Industry groups based on K-Means Clustering

	P/E Ratio				EV/EBITDA			
Variables	**All**	**High-Tech**	**Med-Tech**	**Low-Tech**	**All**	**High-Tech**	**Med-Tech**	**Low-Tech**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
IT Talent Rate$_{t-1}$	0.084	0.029	-0.055	1.277***	0.072	0.065	-0.125	0.377***
	(0.111)	(0.138)	(0.298)	(0.362)	(0.053)	(0.070)	(0.126)	(0.142)
Size$_{t-1}$	0.008	0.000	0.036***	0.007	0.003	-0.001	-0.001	0.014***
	(0.006)	(0.009)	(0.011)	(0.010)	(0.003)	(0.004)	(0.005)	(0.004)
Capital Intensity$_{t-1}$	0.184	0.436**	-0.022	-0.076	-0.060	-0.152	-0.027	0.016
	(0.119)	(0.218)	(0.162)	(0.195)	(0.057)	(0.111)	(0.068)	(0.075)
Leverage$_{t-1}$	-0.019	-0.014	-0.018	-0.047	0.035***	0.024	0.041**	0.038***
	(0.020)	(0.030)	(0.043)	(0.032)	(0.010)	(0.015)	(0.018)	(0.012)
Payout$_{t-1}$	0.022***	0.028***	0.018***	0.007*	0.002	0.003	0.000	0.000
	(0.002)	(0.004)	(0.005)	(0.004)	(0.001)	(0.002)	(0.002)	(0.001)
ROA$_{t-1}$	0.352***	0.360***	0.169***	0.356***	0.279***	0.326***	0.105***	0.090***
	(0.027)	(0.036)	(0.062)	(0.059)	(0.013)	(0.018)	(0.026)	(0.023)
Tobin's Q$_{t-1}$	0.003	-0.005	0.035***	0.027***	0.004**	-0.002	0.019***	0.023***
	(0.002)	(0.003)	(0.008)	(0.005)	(0.001)	(0.002)	(0.003)	(0.002)
Age	0.089***	0.134***	0.004	0.050***	0.029***	0.052***	0.017*	-0.007
	(0.012)	(0.018)	(0.024)	(0.019)	(0.006)	(0.009)	(0.010)	(0.007)
Constant	-0.102***	-0.106*	-0.153*	-0.084	-0.010	-0.013	-0.011	-0.025
	(0.038)	(0.058)	(0.080)	(0.060)	(0.018)	(0.030)	(0.034)	(0.023)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.325	0.281	0.723	0.038	0.153	0.132	0.588	0.405
# of Obs	22,084	11,701	3,508	6,839	21,913	11,512	3,514	6,851

Table 3 Endogeneity Analysis Using Two-Stage Least Squares (2SLS) Analysis

This table presents the results of a 2SLS analysis addressing endogeneity, with stage 1 using lagged CS Graduates to predict IT Talent Rate and stage 2 focusing on the effect of the fitted values on firm values, measured by P/E ratio and EV/EBITDA ratio, across High-Tech, Med-Tech, and Low-Tech industries. *CS Graduates* is the log value of total CS major students graduated from the same state of the firm's headquarters in each year, and the data are collected from https://datausa.io/; *IT Talent Rate* is measured as the number of IT-related new hiring scaled by the total number of new hiring for each firm within each year. Appendix 1A provides all the variable definitions. We also control for industry-fixed effects, following the Fama-French 48-Industry Classification, and year-fixed effects. We report the F value for stage 1. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Stage 1	***Stage 2***			***Stage 2***		
		P/E Ratio			**EV/EBITDA**		
Variables	**IT Talent Rate$_{t-1}$**	**High-Tech**	**Med-Tech**	**Low-Tech**	**High-Tech**	**Med-Tech**	**Low-Tech**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
CS Graduates$_{t-1}$	0.002***						
	(0.001)						
Fitted Value		-0.973	6.589	13.411**	-1.854	4.294	4.276*
		(10.381)	(7.577)	(5.923)	(4.393)	(2.692)	(2.206)
Size$_{t-1}$	0.007***	0.019	-0.024	-0.014	0.017	-0.026	0.008
	(0.000)	(0.075)	(0.053)	(0.043)	(0.032)	(0.019)	(0.016)
Capital Intensity$_{t-1}$	-0.006	-0.035	0.028	-0.008	-0.666***	-0.238***	-0.327***
	(0.008)	(0.468)	(0.201)	(0.226)	(0.197)	(0.071)	(0.084)
Leverage$_{t-1}$	-0.006***	0.086	-0.096	-0.098*	0.030	0.042**	-0.030
	(0.001)	(0.086)	(0.059)	(0.053)	(0.036)	(0.021)	(0.020)
Payout$_{t-1}$	0.000**	0.018**	0.010**	0.012***	0.000	0.004**	-0.004**
	(0.000)	(0.008)	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)
ROA$_{t-1}$	-0.006***	0.466***	0.221**	-0.170*	0.328***	0.055	0.071*
	(0.002)	(0.105)	(0.098)	(0.101)	(0.044)	(0.035)	(0.037)
Tobin's Q$_{t-1}$	0.002***	0.040*	0.025	0.034**	0.020**	0.015***	0.017***
	(0.000)	(0.021)	(0.016)	(0.013)	(0.009)	(0.006)	(0.005)
Age	-0.004***	0.080	-0.069	-0.062	-0.032	-0.024	-0.050***
	(0.001)	(0.087)	(0.049)	(0.046)	(0.037)	(0.017)	(0.017)
Constant	0.074***	-0.123	0.185***	-1.077**	0.116**	0.099***	-0.265
	(0.024)	(0.114)	(0.071)	(0.537)	(0.048)	(0.025)	(0.200)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.091	0.229	0.239	0.236	0.193	0.413	0.294
# of Obs	16,256	3,495	4,489	1,907	3,424	4,505	1,910
F value	25.6						

Table 4 IT talent investment and firm automation level

This table reports the regression results of the following model:

$$Firm\ Automation\ Level_{it} = \beta_0 + \beta_1 IT\ Talent\ Rate_{it-1} + \beta_2 Size_{it-1} + \beta_3 Capital\ Intensity_{it-1} + \beta_4 Leverage_{it-1} + \beta_5 Payout_{it-1} + \beta_6 ROA_{it-1} + \beta_7 Tobin's\ Q_{it-1} + \beta_8 Age_{it} + \varepsilon_{it}$$

The dependent variable is the firm automation level, for which we use both the Composite Automation Ratio (CAR) and Automation Potential Index (API) measures. The main independent variable is the *IT Talent Rate,* which is measured as the number of IT-related new hires, scaled by the total number of new hires for each firm within each year. We further report the results by grouping the industries following Hall and Vopel (1996). Appendix 1A provides all the variable definitions. We also control for industry-fixed effects, following the Fama-French 48-Industry Classification, and year-fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Composite Automation Ratio (CAR)				**Automation Potential Index (API)**			
Variables	**All**	**High-Tech**	**Med-Tech**	**Low-Tech**	**All**	**High-Tech**	**Med-Tech**	**Low-Tech**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
IT Talent Rate$_{t-1}$	1.055***	0.224	1.222***	2.582***	0.078**	0.029	0.121*	0.487***
	(0.148)	(0.188)	(0.347)	(0.659)	(0.034)	(0.044)	(0.071)	(0.172)
Size$_{t-1}$	0.396***	0.375***	0.374***	0.399***	0.026***	0.025***	0.031***	0.024***
	(0.008)	(0.014)	(0.014)	(0.017)	(0.002)	(0.003)	(0.003)	(0.004)
Capital Intensity$_{t-1}$	10.216***	8.168***	11.266***	9.112***	0.355***	0.360***	0.495***	0.143
	(0.158)	(0.382)	(0.258)	(0.390)	(0.036)	(0.090)	(0.052)	(0.102)
Leverage$_{t-1}$	0.401***	0.579***	0.609***	0.395***	0.038***	0.022*	0.018	-0.074***
	(0.027)	(0.055)	(0.053)	(0.068)	(0.006)	(0.013)	(0.011)	(0.018)
Payout$_{t-1}$	-0.003	0.001	-0.003	0.004	0.002**	0.002*	0.003***	-0.004**
	(0.003)	(0.006)	(0.006)	(0.007)	(0.001)	(0.001)	(0.001)	(0.002)
ROA$_{t-1}$	0.031	-0.008	0.026	0.298*	0.135***	0.109***	0.149***	0.148***
	(0.036)	(0.068)	(0.108)	(0.163)	(0.008)	(0.016)	(0.022)	(0.043)
Tobin's Q$_{t-1}$	-0.024***	-0.019***	-0.062***	0.000	-0.012***	-0.008***	-0.004**	-0.008***
	(0.003)	(0.006)	(0.009)	(0.012)	(0.001)	(0.001)	(0.002)	(0.003)
Age	-0.351***	-0.339***	-0.254***	-0.136**	0.051***	0.036**	0.020**	0.027*
	(0.016)	(0.060)	(0.045)	(0.055)	(0.004)	(0.014)	(0.009)	(0.014)
Constant	1.768***	2.046***	1.469***	1.641***	-0.095***	-0.060***	-0.080***	0.001
	(0.052)	(0.098)	(0.094)	(0.129)	(0.012)	(0.023)	(0.019)	(0.034)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.503	0.428	0.339	0.513	0.630	0.341	0.534	0.314
# of Obs	21,183	4,728	6,321	2,941	21,183	4,728	6,321	2,941

Table 5 IT talent investment, R&D expenses, and firm valuation

This table reports the regression results using *R&D Intensity* (in columns (1) to (4)), which is measured as total R&D expenses divided by the total assets for each firm within each year, and *P/E Ratio* (in columns (5) to (8)) as dependent variables. The main independent variable for columns (1) to (4) is *IT Talent Rate* in the previous year, which is measured as the number of IT-related new hiring scaled by the total number of new hiring for each firm within each year, and for columns (5) to (8) is *R&D Intensity* in the previous year. We further put all industries into three groups following Hall and Vopel (1996), based on their reliability on technology, and run the regression within each industry group. Appendix 1A provides all the variable definitions. We also control for industry-fixed effects, following the Fama-French 48-Industry Classification, and year-fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	R&D Intensity				**P/E Ratio**			
	All	**High-Tech**	**Med-Tech**	**Low-Tech**	**All**	**High-Tech**	**Med-Tech**	**Low-Tech**
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
IT Talent Rate$_{t-1}$	0.230***	0.167***	0.195***	0.032				
	(0.017)	(0.023)	(0.017)	(0.048)				
R&D Intensity$_{t-1}$					0.458***	1.251***	-0.107	-0.695
					(0.082)	(0.146)	(0.293)	(0.550)
Size$_{t-1}$	-0.013***	-0.015***	-0.001	-0.005***	0.006	0.026	0.002	0.071***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.008)	(0.016)	(0.012)	(0.021)
Capital Intensity$_{t-1}$	-0.147***	-0.036	0.010	-0.005	-0.057	-0.139	-0.220	0.497
	(0.022)	(0.049)	(0.016)	(0.027)	(0.187)	(0.417)	(0.280)	(0.509)
Leverage$_{t-1}$	-0.065***	-0.025***	-0.028***	-0.015***	-0.019	-0.008	-0.120***	-0.110
	(0.003)	(0.007)	(0.003)	(0.004)	(0.028)	(0.062)	(0.047)	(0.081)
Payout$_{t-1}$	0.001**	0.001*	0.000	0.001*	0.026***	0.019***	0.007	0.014*
	(0.000)	(0.001)	(0.000)	(0.000)	(0.003)	(0.007)	(0.005)	(0.008)
ROA$_{t-1}$	-0.261***	-0.246***	-0.062***	-0.127***	0.462***	0.756***	0.199**	-0.097
	(0.004)	(0.008)	(0.005)	(0.010)	(0.040)	(0.080)	(0.096)	(0.202)
Tobin's Q$_{t-1}$	0.009***	0.012***	0.006***	0.010***	-0.007**	0.012*	0.034***	0.059***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.003)	(0.006)	(0.008)	(0.014)
Age	-0.008***	-0.010	-0.019***	0.010***	0.123***	0.138**	-0.034	0.026
	(0.002)	(0.008)	(0.002)	(0.003)	(0.017)	(0.067)	(0.041)	(0.066)
Constant	0.111***	0.144***	0.050***	0.010	-0.133**	-0.348***	0.080	-0.335**
	(0.007)	(0.013)	(0.004)	(0.008)	(0.053)	(0.108)	(0.079)	(0.154)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.335	0.327	0.158	0.221	0.200	0.053	0.317	0.156
# of Obs	13,581	3,803	3,585	1,333	13,533	3,796	3,545	1,327

Table 6 IT talent investment, labor market efficiency, and managerial ability

This table reports the regression results of the following model:

$$\begin{aligned} IT\ Talent\ Rate_{it} &= \beta_0 + \beta_1 MA - Score_{it} + \beta_2 Over\ Hiring_t + \beta_3 MA - Score * Over\ Hiring_t \\ &+ \beta_4 Size_{it-1} + \beta_5 Capital\ Intensity_{it-1} + \beta_6 Leverage_{it-1} + \beta_7 Payout_{it-1} \\ &+ \beta_8 ROA_{it-1} + \beta_9 Tobin's\ Q_{it-1} + \beta_{10} Age_{it} + \varepsilon_{it} \end{aligned}$$

The dependent variable for columns (1) to (3) is *IT Talent Rate*, which is measured as the number of IT-related new hires scaled by the total number of new hires for each firm within each year. The dependent variable for columns (4) to (6) is the *5-Year IT Talent Rate*, which is measured as the total number of IT-related new hiring in year t to t+4 scaled by the total number of new hiring for each firm from year t to year t+4. The main independent variables are *MA-Score*, which is measured following Demerjian et al. (2012); Over-hiring, which is based on the model of Pinnuck and Lillis (2007) and equals one if the firm is over-hiring and zero if the firm is under-hiring; and the interaction of *MA-Score* and *Over Hiring*. Appendix 1A provides all the variable definitions. We also control for industry-fixed effects, following the Fama-French 48-Industry Classification, and year-fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	IT Talent Rate			**5-Year IT Talent Rate**		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
MA-Score	0.012***	0.021***	0.014***	0.010***	0.017***	0.015***
	(0.002)	(0.005)	(0.005)	(0.002)	(0.004)	(0.004)
Over Hiring		0.006***	0.006***		0.002	0.002
		(0.002)	(0.002)		(0.002)	(0.002)
MA*Over Hiring			0.057***			0.014
			(0.013)			(0.011)
$Size_{t-1}$	0.006***	0.008***	0.008***	0.006***	0.008***	0.008***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Capital $Intensity_{t-1}$	-0.010	0.099***	0.092***	-0.015**	0.078***	0.076***
	(0.008)	(0.021)	(0.021)	(0.007)	(0.019)	(0.019)
$Leverage_{t-1}$	-0.005***	0.007	0.006	-0.006***	0.018***	0.018***
	(0.002)	(0.004)	(0.004)	(0.001)	(0.004)	(0.004)
$Payout_{t-1}$	-0.000	-0.000	-0.000	0.000	0.000	0.000
	(0.00)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA_{t-1}	-0.0008	-0.009	-0.009	0.000	-0.025***	-0.025***
	(0.002)	(0.008)	(0.008)	(0.002)	(0.008)	(0.008)
Tobin's Q_{t-1}	0.001***	0.003***	0.003***	0.002***	0.001**	0.001**
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Age	-0.003***	-0.009*	-0.008	-0.006***	-0.026***	-0.026***
	(0.001)	(0.005)	(0.005)	(0.001)	(0.005)	(0.005)
Constant	0.005*	-0.014	-0.014	0.007***	0.024***	0.024***
	(0.003)	(0.009)	(0.009)	(0.002)	(0.008)	(0.008)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.673	0.678	0.045	0.104	0.017	0.014
# of Obs	20,063	4,062	4,062	11,197	2,774	2,774

Table 7 IT talent investment and corporate culture

This table reports the regression results of the following model:

$$Corporate\ Culture_{it} = \beta_0 + \beta_1 IT\ Talent\ Rate_{it-1} + \beta_2 Corporate\ Culture_{it-1} + \beta_3 Size_{it-1} + \beta_4 Capital\ Intensity_{it-1} + \beta_5 Leverage_{it-1} + \beta_6 Payout_{it-1} + \beta_7 ROA_{it-1} + \beta_8 Tobin's\ Q_{it-1} + \beta_9 Age_{it} + \varepsilon_{it}$$

The dependent variable is *Corporate Culture*. Following Li et al.. (2020), we examine five corporate culture factors: *innovation, integrity, quality, respect*, and *teamwork*. The main independent variables are *IT Talent Rate*, which is measured as the number of IT-related new hires scaled by the total number of new hires for each firm within each year, and the lag term of the culture factor. Appendix 1A provides all the variable definitions. We also control for industry-fixed effects, following the Fama-French 48-Industry Classification, and year-fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Integrity	Teamwork	Innovation	Respect	Quality
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
IT Talent Rate$_{t-1}$	0.175	0.763***	1.532***	-0.105	0.674***
	(0.196)	(0.221)	(0.385)	(0.282)	(0.208)
Integrity$_{t-1}$	0.555***				
	(0.007)				
Teamwork$_{t-1}$		0.638***			
		(0.007)			
Innovation$_{t-1}$			0.776***		
			(0.006)		
Respect$_{t-1}$				0.705***	
				(0.006)	
Quality$_{t-1}$					0.736***
					(0.006)
Size$_{t-1}$	0.046***	-0.028**	0.137***	-0.088***	-0.023*
	(0.011)	(0.012)	(0.022)	(0.016)	(0.012)
Capital Intensity$_{t-1}$	-0.785***	-0.795***	-1.175***	-1.934***	0.534**
	(0.219)	(0.248)	(0.428)	(0.316)	(0.233)
Leverage$_{t-1}$	-0.064*	-0.234***	-0.216***	-0.181***	-0.038
	(0.037)	(0.042)	(0.073)	(0.054)	(0.040)
Payout$_{t-1}$	0.001	0.003	-0.001	0.001	0.004
	(0.004)	(0.005)	(0.008)	(0.006)	(0.005)
ROA$_{t-1}$	-0.119**	-0.479***	-0.037	0.010	-0.065
	(0.058)	(0.067)	(0.114)	(0.084)	(0.062)
Tobin's Q$_{t-1}$	0.014**	0.032***	0.070***	0.053***	0.015***
	(0.005)	(0.005)	(0.010)	(0.007)	(0.005)
Age	-0.006	-0.059**	-0.130***	0.028	-0.047*
	(0.022)	(0.025)	(0.044)	(0.032)	(0.024)
Constant	0.900***	0.894***	0.240*	0.941***	0.544***
	(0.067)	(0.076)	(0.129)	(0.098)	(0.071)
Year FEs	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.973	0.977	0.993	0.992	0.990
# of Obs	14,640	14,640	14,640	14,640	14,640

Table 8 IT-centric firms' performance

This table reports the regression results of the following model:

$$\begin{aligned} Firm\ Performance_{it} &= \beta_0 + \beta_1 IT\ Centric_{it} + \beta_2 IT\ Centric_{it-1} + \beta_3 Size_{it-1} + \beta_4 Capital\ Intensity_{it-1} + \beta_5 Leverage_{it-1} + \beta_6 Payout_{it-1} \\ &+ \beta_7 ROA_{it-1} + \beta_8 Tobin's\ Q_{it-1} + \beta_9 Age_{it} + \varepsilon_{it} \end{aligned}$$

The dependent variable measures firm performance based on Alpha, which is estimated using the Fama-French 5-factor model; Volatility, which measures the variability in stock returns; and Gross Profit Margin, which is calculated by subtracting the cost of goods sold (COGS) from net sales and dividing by sales. The main independent variable, *IT-Centric*, is a dummy variable set to 1 if a firm's IT Talent Rate exceeds the annual industry median based on Fama-French 48 industry classifications, and zero otherwise. Appendix 1A provides all the variable definitions. We also control for industry-fixed effects, following the Fama-French 48-Industry Classification, and year-fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Alpha			**Volatility**			**Gross Profit Margin**		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
IT Centric$_t$	-0.350		-0.448	-0.004		0.000	0.027***		0.022***
	(0.276)		(0.293)	(0.004)		(0.004)	(0.003)		(0.004)
IT Centric$_{t-1}$		0.521*	0.568**		-0.015***	-0.015***		0.026***	0.017***
		(0.287)	(0.288)		(0.004)	(0.004)		(0.003)	(0.004)
Size$_{t-1}$	-1.722**	-1.081	-1.073	-0.101***	-0.081***	-0.081***	0.001	0.003	0.000
	(0.793)	(0.853)	(0.853)	(0.010)	(0.011)	(0.011)	(0.002)	(0.002)	(0.003)
Capital Intensity$_{t-1}$	-1.952	1.528	1.504	0.055	0.100	0.100	-0.033	-0.040	-0.033
	(5.449)	(5.925)	(5.924)	(0.080)	(0.085)	(0.085)	(0.046)	(0.049)	(0.049)
Leverage$_{t-1}$	-1.111	-2.332*	-2.337*	0.255***	0.241***	0.241***	0.051***	0.039***	0.040***
	(1.253)	(1.314)	(1.314)	(0.016)	(0.017)	(0.017)	(0.008)	(0.008)	(0.008)
Payout$_{t-1}$	-0.031	-0.046	-0.047	-0.001	-0.001	-0.001	0.002*	0.001	0.002
	(0.074)	(0.075)	(0.075)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ROA$_{t-1}$	0.150	-0.767	-0.731	-0.385***	-0.385***	-0.385***	0.304***	0.298***	0.297***
	(1.641)	(1.747)	(1.747)	(0.017)	(0.019)	(0.019)	(0.011)	(0.012)	(0.012)
Tobin's Q$_{t-1}$	-0.937***	-0.966***	-0.967***	-0.009***	-0.006***	-0.006***	0.027***	0.027***	0.027***
	(0.186)	(0.191)	(0.191)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Age	-6.156	-8.074	-8.057	0.029	0.003	0.003	-0.008*	-0.014***	-0.013***
	(5.233)	(6.015)	(6.014)	(0.023)	(0.025)	(0.025)	(0.005)	(0.005)	(0.005)
Constant	0.168*	0.234**	0.236**	0.601***	0.800**	0.800***	0.313**	0.302***	0.302***
	(0.087)	(0.101)	(0.101)	(0.039)	(0.042)	(0.042)	(0.015)	(0.016)	(0.016)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.141	0.146	0.146	0.378	0.327	0.327	0.156	0.189	0.192
# of Obs	5,563	4,975	4,975	23,493	20,520	20,520	24,636	21,470	21,470

Appendix 1A Variable Definitions

Variable	Definition
IT Talent Rate	Measured as the number of IT-related new hires scaled by the total number of new hires for each firm each year. The hiring data are collected from LinkUp Job Market Data from 2007 to 2023.
5-Year IT Talent Rate	Measured as the total number of IT-related new hires in year t to t+4 scaled by the total number of new hires for each firm from year t to year t+4.
MA-Score	The managerial ability level of the firm, measured following Demerjian et al. (2012).
Over Hiring	Dummy variable, which is based on the model of Pinnuck and Lillis (2007) and equals one if the firm is over-hiring and zero if the firm is under-hiring.
Size	The log value of the firm's total assets.
Capital Intensity	The firm's Capital Expenditure (CapEx) scaled by the firm's total assets.
Leverage	The firm's total debt ratio.
Payout	The dividend payout ratio of the firm.
ROA	The firm's return on total assets.
Tobin's Q	The firm's annual Tobin's Q ratio.
Firm Age	The difference between the firm's IPO year and current year (if the IPO information is missing, the age is estimated based on the first year when the firm appears in the Compustat database).
CS Graduates	The log value of total CS major students graduated from the same state of the firm's headquarters in each year, and the data are collected from https://datausa.io/
R&D Intensity	The total R&D expenses are divided by the total assets.
Average Age of Capital	The firm's net Property, Plant, and Equipment (PP&E) over depreciation expenses.
Adjusted Capital Intensity	The firm's net PP&E over the number of total employees, scaled by 1 plus Average Age of Capital.
CapEx per Employee	The firm's CapEx scaled by the number of the firm's total employees.
CAR	Composite Automation Ratio, measured as the sum of Adjusted Capital Intensity and CapEx per Employee over 1 plus Average Age of Capital
API	Automation Potential Index, the sum of the z-score standardizations of Adjusted Capital Intensity and CapEx per Employee minus the z-score standardization of Employee Turnover, divided by 3.
Cash Holdings	The firm's total cash divided by the total assets.
State Grade	Measures each state's labor credit policies based on the quality of its economic development subsidies, particularly hiring-credit programs, from Mattera et al. (2011).
Corporate Culture	Include five corporate culture factors: innovation, integrity, quality, respect, and teamwork, following Li et al. (2020).
IT Centric	Dummy variable, which is set to 1 if a firm's IT Talent Rate exceeds the annual industry median based on Fama-French 48 industry classifications, and 0 otherwise.
Alpha	Estimated using Fama-French 5-factor model.
Volatility	The annualized stock return standard deviation.
Gross Profit Margin	Subtract the cost of goods sold (COGS) from net sales and divide by sales.