Received: 16 July 2025 | Accepted: 17 December 2025

DOI: 10.1111/jfir.70038

ORIGINAL ARTICLE

The Journal of Financial Research

Strategic technology talent acquisition and firm value: A cross-industry examination

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Abstract

Technology-driven transformation compels firms to invest in both physical and human capital, particularly information technology (IT) talent. Using LinkUp job posting data, we examine how IT talent acquisition signals strategic intent and affects firm value. We find that IT hiring improves operational efficiency through automation in low-tech sectors and fosters innovation in high-tech sectors. These mechanisms reveal distinct pathways through which technology talent shapes firm dynamics. Moreover, IT hiring influences financial performance, risk management, organizational culture, and strategic decisions. Our results offer new insights into how strategic IT talent acquisition drives value creation and informs managerial and policy choices.

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 (IT), innovate processes, and adopt transformative tools to enhance productivity (e.g., Abis & Veldkamp, 2024; Acemoglu & Autor, 2011).[1] Knowledge capital, a key driver of innovation, accounts for 40%–50% of firms' market value,[2] with contributions varying across industries over time (e.g., Belo et al., 2022).[3] Although prior research has firmly established the role of capital–skill complementarity in enhancing firm value (e.g., Duffy et al., 2004; Kogan et al., 2021; Krusell et al., 2000), relatively little attention has been paid to how firms' current technology hiring decisions signal strategic repositioning efforts that extend beyond their existing technology stock. Accordingly, the extent to which IT talent hiring influences firm value across diverse industry landscapes remains an important, yet underexplored, question.[4]

This article introduces a novel method to capture a firm's strategic technology investment by focusing on IT-related hiring activity, based on detailed hiring position data from LinkUp, which is a high-quality, reliable job listing dataset sourced directly from employer websites, capturing over 57,000 unique companies hiring positions from 2007 to 2023. Unlike traditional indicators based on accumulated technology stock, such as patent counts or research and development (R&D) expenditures, our approach captures firms' current strategic intent and willingness to expand their IT capabilities. Because LinkUp pulls data directly from employer websites, it offers a real-time snapshot of the job market and serves as a highly reliable source 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 approach makes LinkUp more precise and minimizes the need for extensive data cleaning by ensuring that the data represent active and valid job openings while eliminating duplicates, expired listings, and other noise commonly found in aggregated sources such as Burning Glass (e.g., Babina et al., 2024; Fedyk & Hodson, 2023). Accordingly, our measurement allows us to capture a firm's IT talent hiring with greater precision and to relate it systematically to its valuation, strategies, and culture.

Prior research highlights that IT human capital contributes to firm performance through productivity improvements, innovation, and digital transformation (e.g., Bharadwaj, 2000; Brynjolfsson & Hitt, 2000; Tambe et al., 2012). However, the magnitude of these benefits likely differs across industries depending on their existing level of technological sophistication. High-tech firms already possess advanced digital infrastructures and specialized IT expertise, which may limit the marginal performance gains from additional IT hiring. In contrast, low-tech firms, often operating with more traditional production processes and lower digital integration, stand to benefit more substantially from new IT talent. Incremental IT hiring in these settings can yield significant improvements in automation, efficiency, and data-driven decision-making by modernizing operations from a lower technological baseline (e.g., Aral & Weill, 2007). We therefore expect the valuation effects of IT talent hiring to vary between high-tech and low-tech industries, and the valuation effects of IT talent acquisition to be more pronounced in low-tech industries, where IT hiring serves as a key driver of technological upgrading and strategic renewal.

[1]Abis and Veldkamp (2024) analyze how big data technologies reshape the relation among data, labor, and knowledge creation, indicating that big data technologies 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 aggregate stock market value dynamics. Belo et al. (2022) document that physical capital accounts for 22%–30% of a firm's market value, installed labor force accounts for 23%–27%, knowledge capital accounts for 38%–47%, and brand capital accounts for the remaining 5%–9%. Thus, on average, nonphysical 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%–43% and 21%–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%–18% and 20%–22%, respectively. In contrast, in high-skill industries, the contribution is 21%–24% and 43%–51%, respectively.

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

To evaluate these predictions, we begin by examining how strategic investment in technology talent influences a firm's value, with particular attention to industry heterogeneity. Industry classification is central to our analysis, as hiring rates for skilled employees and firm valuations differ systematically between high- and low-tech sectors. To classify firms, we use two approaches. We first classify sectors into three groups guided by B. H. Hall and Vopel (1996), Hatzichronoglou (1997), and Markusen et al. (2008): high tech (high technology/knowledge intensive), medium tech (medium skilled), and low tech (low skilled). This classification groups industries by underlying technologies to capture differences in innovation opportunities and appropriability. Their taxonomy links directly to R&D and market value, recognizing that innovation rents vary systematically across sectors. High-tech industries (e.g., computers, electronics, pharmaceuticals, medical instruments, aerospace) are characterized by rapid product cycles and high R&D intensity, medium-tech industries (e.g., chemicals, petroleum refining, machinery, motor vehicles) rely on more mature processes, and low-tech industries (e.g., manufacturing, food & tobacco, textiles, wood/furniture, paper, resource extraction, toys, musical instruments, jewelry) exhibit limited R&D and slower innovation. This approach provides a systematic framework for analyzing technological investments across industries. Although this classification predates recent technological advancements, it remains a valuable historical benchmark for understanding baseline industry structures. Recognizing potential changes in the technological landscape, we complement this method with a machine-learning-based K-Means Clustering approach, using firm-level IT hiring rates, R&D intensity, and capital intensity. This dual approach ensures that our industry groups remain robust and reflective of both traditional and contemporary technological factors.[5]

Our results reveal no significant relation between IT talent hiring and firm valuation metrics for high-tech firms, whereas higher IT talent investment significantly boosts market valuation (e.g., price earnings [P/E] and enterprise value divided by earnings before interest, taxes, depreciation, and amortization ratio [EV/EBITDA] ratios) of low-tech firms in traditional industries, such as manufacturing and resource extraction. The effect is economically meaningful: A 1 *SD* increase in *IT Talent Rate* is associated with an approximately 21.5% increase relative to the mean P/E ratio in low-tech industries. Similarly, the same increase in *IT Talent Rate* corresponds to an estimated 20.7% increase relative to the mean EV/EBITDA ratio. These results highlight the divergent 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., Duffy et al., 2004; Griliches, 1969; Krusell et al., 2000).

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) may be more likely to hire IT talent, reflecting their greater resources or prestige. Additionally, unobserved factors such as market conditions could simultaneously influence both IT talent hiring and firm valuation, confounding the relation. 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 as 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 positive and significant relation, 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 the authors 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

[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.

[6]For instance, Griliches (1969) and Autor et al. (2020) 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 more susceptible to automation.

process, directly shaping the technologies and processes that drive the sector's competitive advantage. To examine the possible mechanism, we create two separate measures: composite automation ratio (CAR) and automation potential index (API), as proxies of a firm's automation level, and examine the relation 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 capital expenditures (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 positive and significant relation among low-tech firms, whereas the relation 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 relations 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 low-tech firms. 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 effect 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., Anderson et al., 2025; Doukas & Zhang, 2021), 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 used to build a strategic talent buffer. Skilled managers ensure this strategy remains purposeful rather than excessive. The magnitude of the effect is economically meaningful: IT talent hiring increases by approximately 5.7% when a firm maintains a strategic human capital buffer and managerial ability rises by 1 percentage point. Given the long-term nature of IT investment, we further examine cumulative IT hiring over the next 5 years, minimizing short-term labor market fluctuations. This approach confirms that managerial ability significantly drives long-term IT investment, whereas 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 are not merely technological decisions but also cultural commitments that align closely with firms' organizational values. IT professionals help firms 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. Although the immediate financial effect 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 article 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 on the literature documenting the role of knowledge capital in driving firm growth (e.g., Abis & Veldkamp, 2024; Autor & Dorn, 2013; Babina et al., 2024; Belo et al., 2022) and provide additional evidence that IT talent acquisition enables low-tech 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 article introduces a distinctive approach to measuring firms' technology-based human capital by focusing on their willingness to hire technological professionals. Our key contribution lies in shifting the focus from the stock of IT employees to the flow of IT hiring, thereby examining how the intensity of IT talent acquisition influences firm value (e.g., Babina et al., 2024; Tuzel & Zhang, 2021). This dynamic perspective is valuable, as it emphasizes flows rather than levels and introduces a novel dataset (LinkUp), which remains relatively unexplored in the finance literature. Furthermore, our study highlights firms' strategic intent to invest in IT capabilities through the lens of hiring flows. This perspective offers early insights into firms' dynamic technology repositioning efforts. By capturing firms' ongoing commitment to technology talent investment, our measure reflects strategic priorities more directly than traditional proxies. Previous studies primarily rely on firm-level cost items, such as R&D and selling, general, and administrative (SG&A) expenses, to quantify intangible capital, including knowledge and human capital (e.g., Belo et al., 2022; Crouzet & Eberly, 2019; Eisfeldt & Papanikolaou, 2013; Eisfeldt et al., 2020; Peters & Taylor, 2017). More recent studies have turned to datasets such as Burning Glass to capture AI-related job postings. In contrast, our methodology employs firm-level recruitment data from LinkUp to measure technology-related intangibles, offering novel insights into the dynamics of IT talent acquisition and its impact on firm value. Importantly, LinkUp offers greater precision and minimizes the need for extensive data cleaning by ensuring the data reflect active, valid job openings while eliminating duplicates, expired listings, and the noise commonly associated with aggregated datasets.

Finally, our article provides one of the first pieces of systematic evidence on how a firm's managerial ability moderates the relation 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 et al., 2019), financial technology (fintech) innovation (Chen et al., 2019), loan underwriting (e.g., Fuster et al., 2022; Jansen et al., 2024), and financial analysis (e.g., Cao et al., 2024), from the labor market resource perspective by using employees' resumes to develop the labor resource. Our article focuses on a firm's technology talent hiring and firm activities from the firm's recruitment perspective, using hiring position descriptions to better capitalize on the firm's talent investment. We provide evidence that firms with high managerial ability tend to hire more IT talent to maintain a strategic human capital buffer, ensuring access to the human capital needed to address unforeseen opportunities or challenges. We also contribute new empirical evidence on the significance of knowledge capital investment through the lens of firm characteristics. Although prior research predominantly employs econometric models, such as production functions, to establish mathematical relations between knowledge input (proxied by R&D) and firm output (e.g., Belo et al., 2017; Duffy et al., 2004; Griliches, 1969; Krusell et al., 2000), our study extends this literature by using practical market data to link talent hiring with firm culture. We suggest that greater IT hiring is positively associated with firm value. This finding is consistent with the notion that IT professionals may contribute through channels such as teamwork, innovation, and quality improvements, although we do not directly test these mechanisms (e.g., Bharadwaj, 2000; Kaplan & Lee, 2024; Li et al., 2021). Thus, IT hiring represents an indirect strategic investment in cultivating teamwork, innovation, and excellence as enduring cultural attributes, rather than merely an expansion of human capital.

2 | LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

In this section, we synthesize 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 and managerial ability

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. Labor market efficiency is captured by a firm's ability to align labor reserves with potential shortfalls. Ghaly et al. (2017) emphasize the positive association between long-term institutional investors and labor investment efficiency, asserting that effective governance can mitigate inefficiencies of overinvesting in 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 the Tax Cuts and Jobs Act 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 because of increased severance pay and litigation risks (e.g., Krusell et al., 2000).

Research also highlights that workforce strategies such as maintaining a human capital buffer can generate an enduring competitive advantage, and an undersupply of talent constrains innovation and growth (e.g., Campbell et al., 2012; Liu et al., 2014; Nohria & Gulati, 1996). Recent contributions 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 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 among 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). Wright et al. (2014) argue that highly competent managers are more adept at implementing strategies that balance strategic human capital buffer and labor undersupply, 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 relation between labor market efficiency and managerial ability, showing that low-ability managers tend to over- or underinvest in human capital hiring, whereas high-ability managers strategically create a human capital buffer to drive future firm performance. Furthermore, Sabah et al. (2025) 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 affects 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, the literature predominantly examines the causes, consequences, and mechanisms of firms' labor investment inefficiencies. There is a notable lack of research exploring the relation between talent hiring and labor investment efficiency, particularly how managerial ability influences this relation. 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 article addresses this important research gap.

[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 from the authors.

2.2 | Technology talent and firm value

Previous research highlights the importance of nonphysical capital inputs as key determinants of firm value, particularly intangible capital's role in understanding aggregate stock market evaluations (e.g., R. E. Hall, 2001; McGrattan & Prescott, 2001; 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. Tambe (2014) 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 relation 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 life cycle of specific technologies, leading to potential overinvestment in popular but transient innovations. Ghaly et al. (2017) compare this phenomenon to fads and bubbles, where overexuberant 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 of the variation in IT talent hiring. B. H. 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.

Finally, 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, Chen et al. (2016) 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 relation.

2.3 | Hypothesis development

The literature on IT talent investment has primarily focused on stocks of intangible capital, such as accumulated R&D, patent portfolios, or measures of organizational capital, which show that technology capital is an important driver of firm valuation and innovation outcomes. At the same time, the productivity literature emphasizes that the value of IT talent is highly contingent on complementary assets and organizational context. This suggests that the flow of IT hiring, which captures firms' near-term strategic intent to build technological capabilities, may convey information to investors that differs from traditional stock-based measures.

These insights motivate our view that the market response to IT hiring should vary systematically by industry technology intensity. The literature on capital–skilled complementarity and market expectations indicates that IT hiring generates stronger contemporaneous valuation effects in low-tech industries. In such settings, incremental IT talent can create unanticipated automation and efficiency gains, consistent with evidence that IT disproportionately substitutes for routine tasks in less technology-intensive sectors (e.g., Acemoglu & Restrepo, 2018; Autor et al., 2003). Because IT-driven modernization is less expected in these industries, investors may interpret hiring shocks as more informative about future performance (e.g., Ewens & Rhodes-Kropf, 2015). By contrast, in high-tech industries, where IT hiring is routine and largely anticipated, additional hiring is less likely to surprise markets (Fama, 1998). Instead, its benefits are more indirect, influencing valuation through long-term channels such as R&D intensity and innovation outcomes (e.g., Bresnahan et al., 2002; Tambe et al., 2012). Based on this reasoning, we state the following hypotheses:

H1. IT talent hiring exerts different valuation effects in high-tech industries compared to low-tech industries.

H2. Firms in low-tech industries experience stronger positive valuation responses to IT hiring, as incremental IT talent enhances automation and efficiency in ways not fully anticipated by investors.

H3. Firms in high-tech industries exhibit muted contemporaneous valuation responses to IT hiring because investors expect ongoing IT investment. The benefits of IT hiring in these industries are more likely to manifest indirectly through increased R&D intensity and innovation output.

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. Using 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:

$$\omega_{IT} = \frac{\#\ \textit{of IT} - \textit{related positions}}{\#\ \textit{of total new hiring of the firm}}. \tag{1}$$

Intuitively, this measure captures how correlated IT employee hiring is with the firm's total new hiring. To refine the dataset, we exclude all international and private companies, resulting in a final sample of 4,318 firms and 34,331 firm-year observations.

3.2 | Sample selection and variable definition

We gather firm-level financial data for all firm-year observations with *IT Talent Rate* data from Compustat and equity market data from the Center for Research in Security Prices (CRSP). The control variables used in our regressions are: *Firm Size*, measured as total assets in billions; *Capital Intensity*, calculated as the firm's CapEx scaled by total assets; *Leverage*, determined by the firm's total debt ratio; *Payout*, represented by the dividend payout ratio[8]; *ROA* (return on assets), estimated as the firm's net income divided by total assets at the beginning of the year; *Tobin's Q*, measured as the ratio of the firm's market value of equity plus the book value of debt, divided by the book value of total assets; and *Firm Age*, measured based on the firm's IPO year, or if IPO data are unavailable, the first year the firm appears in the Compustat database.[9]

Panel A of Table 1 reports summary statistics for all 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 average *IT Talent Rate* across all 48 industries using the Fama–French 48-industry classification during the whole sample period (2007–2023). Panel B shows that among industries, the *IT Talent Rate* of tobacco products (0.363%), steel works, etc. (0.378%), and nonmetallic 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 presents summary statistics for firm-specific characteristics by industry group. Compared with their counterparts, high-tech firms invest more in IT talent and are larger and younger. Furthermore, low-tech firms are more capital intensive, and high-tech firms are likely to focus more on intangible assets (e.g., software). Finally, high-tech firms exhibit higher average valuations, as reflected in metrics such as the P/E ratio, EV/EBITDA ratio, and Tobin's Q, consistent with stronger growth expectations and innovation potential.

4 | EMPIRICAL RESULTS

In this section, we explore our baseline hypothesis regarding the impact of IT talent investment on firm value across various industry groups. Then, to address endogeneity concerns, we employ a 2SLS approach. Furthermore, we investigate the underlying mechanisms through which IT talent investment influences firms differently across distinct industry segments. To address concerns about potential serial correlation and dynamic panel bias arising from including all lagged dependent variables, we cluster standard errors at the firm level.[10]

[8]Our baseline payout measure is the dividend payout ratio (Dividends/Net Income), the standard definition in corporate finance. Because this ratio can be unstable or undefined when earnings are small or nonpositive, we also compute dividends/total assets (Div/TA) as an alternative scaling, following Fama and French (2002). Our findings are highly consistent.

[9]All 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.

[10]We also estimate key specifications, excluding lagged dependent variables, and find that our main results remain qualitatively unchanged. These alternative specifications are available upon request from the authors.

TABLE 1 Summary statistics.

Panel A: Summary statistics of key firm-level variables

Variable	Obs.	Mean	*SD*	10%	Median	90%
IT Talent Rate	34,331	1.897	4.307	0	0.57	4.87
P/E Ratio	33,786	20.977	44.274	6.444	18.119	54.745
EV/EBITDA	32,867	8.322	28.499	4.529	8.749	21.949
Firm Size	33,900	22.655	83.180	0.177	2.448	36.506
Capital Intensity	32,867	0.034	0.039	0.001	0.021	0.081
R&D Intensity	18,881	0.085	0.132	0.000	0.031	0.239
Leverage	33,725	0.272	0.235	0.007	0.232	0.583
Payout	31,421	0.541	1.697	0.001	0.289	1.600
ROA	32,975	−0.021	0.201	−0.215	0.024	0.118
Tobin's Q	31,785	2.271	1.832	1.000	1.632	4.259
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			Medium tech			Low tech		
Variable	Mean	*SD*	Median	Mean	*SD*	Median	Mean	*SD*	Median
IT Talent Rate	2.340	5.263	0.750	1.478	3.065	0.530	1.241	2.546	0.630
P/E Ratio	30.329	43.239	17.940	26.244	34.439	18.164	26.720	34.814	19.239
EV/EBITDA	12.703	14.522	9.780	10.622	10.078	9.269	11.405	9.693	10.430
Firm Size	52.755	144.281	4.617	15.806	45.679	3.287	19.239	32.256	6.087
Capital Intensity	0.020	0.028	0.011	0.046	0.042	0.033	0.049	0.035	0.041
R&D Intensity	0.092	0.121	0.057	0.022	0.034	0.012	0.014	0.039	0.006
Leverage	0.213	0.217	0.145	0.283	0.203	0.259	0.339	0.200	0.322
Payout	0.671	1.724	0.468	0.635	1.546	0.435	0.686	1.601	0.602
ROA	0.003	0.167	0.019	0.040	0.105	0.049	0.043	0.094	0.043

TABLE 1 (Continued)

Panel C: Summary statistics of key firm-level variables by industry groups

Variable	High tech Mean	High tech *SD*	High tech Median	Medium tech Mean	Medium tech *SD*	Medium tech Median	Low tech Mean	Low tech *SD*	Low tech Median
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

Note: Panel A provides descriptive statistics for key firm-level variables for the whole sample. The sample consists of all public companies in the United States with hiring data. The hiring data are collected from LinkUp Job Market Data from 2007 to 2023. Panel B presents 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 summary statistics for each industry group: high tech, medium tech, and low tech. Variables are defined in the Appendix.

4.1 | IT talent investment and firm value

We focus on P/E and EV/EBITDA ratios to analyze the relation between IT talent investment and firm value. P/E reflects market expectations regarding a company's growth potential and profitability.[11] At the same time, EV/EBITDA, which is measured as enterprise value (sum of market capitalization, total debt, preferred equity, minority interest excluding cash and equivalents) divided by EBITDA, provides a comprehensive measure of a company's value, factoring in its operational earnings while eliminating the effects of capital structure and noncash expenses.

A significant divergence in valuation metrics is expected between high- 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 because of 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 B. H. Hall and Vopel (1996), we classify sectors into three groups based on technological requirements and skill intensity: high tech (high technology/knowledge intensive), medium tech, and low tech. This systematic approach provides a clear and logical framework for analyzing technological investments across industries.[12]

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 R&D 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.[13] Table 2 reports the relation between IT

[11]When *P/E Ratio* is used as the dependent variable, we exclude firm years with nonpositive earnings, as negative P/E ratios are not economically meaningful.

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

[13]We also compute 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, and the bottom three are tobacco products, steel works, etc., and nonmetallic and industrial metal mining. The industries are then equally divided into three groups (16 industries each): high tech, medium tech, and low tech. The results using this method are highly consistent with the results from the other two grouping methods.

TABLE 2 IT talent investment and firm value.

	P/E Ratio				*EV/EBITDA*			
	All	High tech	Medium tech	Low tech	All	High tech	Medium tech	Low tech
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Industry groups based on B. H. Hall and Vopel (1996)								
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)
Firm 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)
Firm 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 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 2 (Continued)

	P/E Ratio				*EV/EBITDA*			
	All	**High tech**	**Medium tech**	**Low tech**	**All**	**High tech**	**Medium tech**	**Low tech**
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Industry FE	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
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								
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)
Firm 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)
Firm 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)

(Continues)

TABLE 2 (Continued)

	P/E Ratio				*EV/EBITDA*			
	All	**High tech**	**Medium tech**	**Low tech**	**All**	**High tech**	**Medium tech**	**Low tech**
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
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 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	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
Obs.	22,084	11,701	3,508	6,839	21,913	11,512	3,514	6,851

Note: This table reports the regression results of the following model:

$$\textit{Firm Value Measure}_{it} = \beta_0 + \beta_1 \textit{IT Talent Rate}_{it-1} + \beta_2 \textit{Firm Size}_{it-1} + \beta_3 \textit{Capital Intensity}_{it-1} + \beta_4 \textit{Leverage}_{it-1} + \beta_5 \textit{Payout}_{it-1} + \beta_6 \textit{ROA}_{it-1} + \beta_7 \textit{Tobin's Q}_{it-1} + \beta_8 \textit{Firm Age}_{it} + \varepsilon_{it}.$$

The dependent variable is firm value measure, for which we use both the firm's *P/E Ratio* and *EV/EBITDA*. The main independent variable is *IT Talent Rate*. Variables are defined in the Appendix. 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. Panel A reports the results by grouping the industries following B. H. Hall and Vopel (1996). Panel B uses K-Means Clustering based on *IT Talent Rate*, *R&D Intensity*, and *Capital Intensity* to group all Fama–French 48 industries into three groups. We also control for industry fixed effects, following the Fama–French 48-industry classification, and year fixed effects. Standard errors, reported in parentheses, are clustered at the firm level.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

talent investment and firm value across industries. The dependent variables are the firm's *P/E ratio* and *EV/EBITDA*,[14,15] and the primary independent variable is the firm's *IT Talent Rate*.[16]

First, as shown in Columns 1 and 5 of Panel A in Table 2, we find no significant relation between IT talent hiring and P/E or EV/EBITDA ratios for all companies in the sample. However, in Columns 2–4 and 6–8, the results derived from the two classification methods demonstrate high consistency. Specifically, for high-tech firms, no significant relation 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 and EV/EBITDA ratios. The effect is economically efficient. A 1 *SD* increase in *IT Talent Rate* (4.307 percentage points) is associated with an approximately 21.5% increase relative to the mean P/E ratio (1.047 × 4.307 ÷ 20.977). Similarly, the same increase in *IT Talent Rate* corresponds to an estimated 20.7% increase relative to the mean EV/EBITDA ratio (0.399 × 4.307 ÷ 8.322). These relative magnitudes indicate that IT talent acquisition has economically meaningful effects on firm value, particularly in low-tech industries. The findings for medium-tech firms present mixed results, falling between the two extremes.

We find a similar pattern in Panel B of Table 2 when industries are classified using K-Means Clustering. The effect of IT hiring is particularly strong in low-tech industries. A 1 *SD* increase in *IT Talent Rate* is associated with approximately a 26.2% increase relative to the mean P/E ratio. For the EV/EBITDA ratio, the corresponding effect in low-tech industries is a 19.3% increase relative to the mean ratio. These results again underscore the economically meaningful role of IT talent acquisition in enhancing firm value, particularly among firms operating in less technology-intensive sectors. By contrast, the effects are weaker in medium- and high-tech industries, where the estimated coefficients are small or statistically insignificant, suggesting that the marginal value of additional IT hiring is limited in firms already heavily reliant on technology.

Several potential rationales may exist to explain the differences in the relation between tech-related hiring and valuation metrics (*P/E Ratio* and *EV/EBITDA*) in low-skilled industries and high-tech or knowledge-intensive industries. First, in low-skilled industries such as manufacturing, food & tobacco, and wood/furniture, 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.

Second, 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.[17] Those changes can directly enhance financial valuations and lead to

[14]The number of firm-year observations is smaller under the B. H. Hall and Vopel (1997) classification because this taxonomy requires a stable SIC/NAICS mapping. Observations with missing or ambiguous industry codes or lacking the variables needed for lagged terms are dropped. By contrast, K-Means Clustering uses only observed firm-year characteristics (IT hiring intensity, R&D intensity, capital intensity), so it retains the full set of observations.

[15]We also explore *Tobin's Q* as the dependent variable (excluding its lag term from the controls) and find IT hiring remains positive and significant in all groups, with the effect strongest in low-tech industries (4.229, $p < 0.01$), followed by medium-tech (1.241, $p < 0.05$) and high-tech (0.887, $p < 0.10$) industries. These consistent results confirm that IT hiring raises firm value. We nonetheless *EV/EBITDA* and *P/E Ratio* in the baseline because they more directly capture efficiency and earnings channels, whereas *Tobin's Q*, being broader and slower moving, yields smaller magnitudes.

[16]A potential concern is that because Tobin's Q captures firms' valuation and growth opportunities, controlling for it in regressions where other valuation multiples (such as *P/E Ratio* or *EV/EBITDA*) serve as the dependent variable may constitute overcontrolling, as Tobin's Q itself embeds similar information. To address this issue, we reestimate all baseline specifications excluding Tobin's Q. The results remain qualitatively unchanged in terms of both magnitude and significance, confirming that our findings are not an artifact of including Tobin's Q. We therefore retain lagged Tobin's Q in our main models, consistent with prior corporate finance studies, to better capture firms' prior growth opportunities while ensuring robustness to its exclusion.

measurable impacts on EBITDA and investor sentiment. Knesl (2023) explores technological advancements that allow capital to displace labor and affect firm valuation. Zhang (2019) also documents that firms tend to replace routine-task labor with machines 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.

Finally, our measure, based on the flow of IT-related hiring, captures firms' active strategic adjustments toward technological adaptation, rather than reflecting their existing IT capabilities. This distinction is particularly meaningful. In low-tech industries, new IT hiring often signals a significant strategic pivot that can materially alter a firm's future trajectory. By contrast, in high-tech sectors where substantial IT capital already exists, marginal increases in hiring flows are less informative to market participants. Accordingly, the muted valuation response observed in high-tech industries likely reflects the market's endogenous expectations of continued IT investment in these firms.

Overall, the results in Table 2 underscore the differing roles that tech-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, tech-related hiring shows no significant valuation effects because of existing investor expectations.[18]

4.2 | Endogeneity analysis using 2SLS

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 relation. To address this issue, we employ the 2SLS method. In line Babina et al. (2024), who employ the regional supply of AI-trained university graduates as an IV for AI investment, 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.[19] Each institution is mapped to its corresponding state, and this information is merged with firm-level data based on the location of the firm's headquarters. The use of the supply of local CS graduates as an instrument for IT hiring is motivated by the geographically constrained nature of early-career labor markets. Because of relocation frictions and compensation constraints, firms predominantly hire local IT talent, making the availability of nearby CS graduates a strong predictor of IT hiring behavior. Importantly, the supply of CS graduates is unlikely to affect firm valuation directly beyond its impact through labor availability, particularly after accounting for state fixed effects and firm-level fundamentals. To further validate the exclusion restriction, we

[17]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 et al. (2024). These studies paint a picture of automation as a double-edged sword: It boosts firm efficiency and valuation while reshaping labor markets.

[18]As an additional robustness test, we estimate specifications with firm fixed effects in place of industry fixed effects (the results are available upon request from the authors). The coefficients on *IT Talent Rate* remain positive but are less precisely estimated. The high-tech group shows no significant effect (*P/E Ratio* = 0.141, $p = 0.544$; *EV/EBITDA* = 0.157, $p = 0.295$), and the low-tech group continues to display economically meaningful and statistically significant results (*P/E Ratio* = 1.014, $p < 0.10$; *EV/EBITDA* = 0.293, $p < 0.10$). This pattern is consistent with our baseline findings that IT hiring has stronger valuation implications in low-tech firms. The weaker significance under firm fixed effects reflects the limited within-firm variation in IT hiring once time-invariant firm characteristics are absorbed. We therefore retain industry and year fixed effects in our main specification, which better capture sectoral dynamics and preserve precision, but the firm fixed effect results further support our interpretation.

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

conducted robustness tests by regressing firm valuation directly on the supply of CS graduates and found no significant relation, suggesting that our instrument meets the necessary validity conditions.[20]

Table 3 presents the results of the 2SLS regression analysis examining the impact of IT talent hiring on firm valuation across high-, medium-, 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 positive and significant relation between CS graduate availability and IT talent hiring. Columns 2–4 report the second-stage results, where firm value is measured by *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 *EV/EBITDA* as an alternative valuation measure in Columns 5–7, 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 relation 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 | Underlying mechanism of the impact of IT talent investment on firm value

In this section, we investigate the mechanism underlying 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).[21] 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 measures to capture a firm's automation level. First, following Cheng et al. (2024), we construct automation measures but extend their framework with additional adjustments to better capture firm-level heterogeneity. Specifically, we employ property, plant, and equipment (PP&E) as a proxy for automation-related capital, recognizing that it also contains assets such as buildings that are not directly tied to automation. This limitation implies our estimates may be conservative, but PP&E remains the most accessible standardized measure of long-lived assets across firms (e.g., Mazumder & Pugachev, 2025). We further normalize capital by employment and adjust for age, which reduces bias from firm size or life-cycle effects. 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 because the 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:

$$\textit{Adjusted Capital Intensity}_{j,t} = \frac{\textit{Net PP \& E}_{j,t}}{\textit{Total Employees}_{j,t}} \times \frac{1}{(1 + \textit{Average Age of Capital}_{j,t})}. \tag{2}$$

[20]When implementing the 2SLS regressions, the number of observations reduced from approximately 22,000 firm-years in the baseline regressions to about 16,000 in the IV regressions. The reasons include the following: First, information on the annual supply of CS graduates is not available for all state-year combinations, particularly for earlier years or for smaller private institutions, which results in missing coverage. Second, firm headquarters locations could not always be reliably matched to state-level graduation data, leading to further sample attrition. Third, because the instrument is specified in logarithmic form, state-years with zero graduates were necessarily excluded. Finally, we include state fixed effects, and requiring complete data on all firm-level controls further reduces the usable sample. Taken together, these factors explain why the effective sample size in the IV regressions is smaller than in our baseline regressions.

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

TABLE 3 Endogeneity analysis using 2SLS analysis.

Variable	Stage 1 *IT Talent Rate*$_{t-1}$ (1)	Stage 2 *P/E Ratio* High tech (2)	Medium tech (3)	Low tech (4)	*EV/EBITDA* High tech (5)	Medium tech (6)	Low tech (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)
Firm 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)
Firm 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 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	No	No	No	No
R^2	0.091	0.229	0.239	0.236	0.193	0.413	0.294
Obs.	16,256	3,495	4,489	1,907	3,424	4,505	1,910
F-value	25.6						

Note: This table presents the results of a two-stage least squares (2SLS) analysis addressing endogeneity, where Stage 1 uses lagged *CS Graduates* to predict *IT Talent Rate* and Stage 2 focuses on the effect of the fitted values on firm values, measured by *P/E Ratio* and *EV/EBITDA*, across high-tech, medium-tech, and low-tech industries. Variables are defined in the Appendix. We also control for industry fixed effects, following the Fama–French 48-industry classification, year fixed effects, and state fixed effects (in Stage 1). We report on the *F*-value for Stage 1. Standard errors, reported in parentheses, are clustered at the firm level.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

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. To capture workforce dynamics, we incorporate employee turnover, proxied by changes in firm-level employment from year $t-1$ to year t, scaled by average employment. Although this measure does not distinguish voluntary exits from new hiring, it effectively reflects net human capital replacement, which is directly relevant for automation's labor-saving role. High turnover suggests disruptive restructuring, whereas 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:

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

We 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), following the method employed by Lovelace et al. (2022), we convert *API* to *Adjusted Capital Intensity*, *CapEx per Employee*, and *Employee Turnover* into *Z*-scores, ensuring consistency across firms and sectors.[22] Unlike *CAR*, which can be distorted by extreme values, *API* normalizes the distribution, balancing positive indicators (capital investment) and negative indicators (turnover) to provide a more comprehensive and unbiased assessment of firm automation potential:

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

Both *CAR* and *API* 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. Taken together, they provide complementary insights into firm-level automation potential.

We then analyze the relation between the firm's IT talent investment and its automation level, overall and across different industry groups. Table 4 reports the results.

The results in Columns 1 and 5 of Table 4 show a positive and significant relation between IT talent hiring and firm automation levels. However, when firms are categorized into three industry groups, the positive relation remains significant for low-tech firms, supporting our hypothesis that IT-related hiring primarily enhances cost control and operational efficiency in these sectors. In high-tech sectors, as shown in Columns 2 and 6, the relation is insignificant, whereas the results for medium-tech sectors fall between the two extremes. The effects of IT hiring on automation outcomes are economically substantial, particularly in low-tech industries. A 1 *SD* increase in *IT Talent Rate* is associated with an 11.1-point rise in *CAR* (2.582×4.307), which corresponds to about a 64% increase relative to mean *CAR* ($11.1 \div 17.36 = 0.64$). For *API*, the same increase yields a 2.1-point gain (0.487×4.307), equivalent to roughly a 25% increase relative to mean *API* ($2.1 \div 8.3 = 0.25$). In contrast, the effects are moderate in medium-tech industries and statistically insignificant in high-tech industries, suggesting that IT hiring plays a transformative role in advancing automation in low-tech industries, where technology capabilities are relatively scarce, but has limited marginal effects in high-tech firms that are already operating at the technology frontier.

[22]Lovelace et al. (2022) use *Z*-scores to standardize continuous predictor variables in regression models. This *Z*-score transformation allows us to interpret the impact of high versus low levels of a given variable.

TABLE 4 IT talent investment and firm automation level.

	CAR				API			
	All	High tech	Medium tech	Low tech	All	High tech	Medium tech	Low tech
Variable	(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)
Firm 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)
Firm 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 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	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
Obs.	21,183	4,728	6,321	2,941	21,183	4,728	6,321	2,941

Note: This table reports the regression results of the following model:

$$\textit{Firm Automation Level}_{it} = \beta_0 + \beta_1 \textit{IT Talent Rate}_{it-1} + \beta_2 \textit{Firm Size}_{it-1} + \beta_3 \textit{Capital Intensity}_{it-1} + \beta_4 \textit{Leverage}_{it-1} + \beta_5 \textit{Payout}_{it-1} + \beta_6 \textit{ROA}_{it-1} + \beta_7 \textit{Tobin's } Q_{it-1} + \beta_8 \textit{Firm Age}_{it} + \varepsilon_{it}.$$

The dependent variable is the firm automation level, for which we use both *CAR* and *API*. The main independent variable is *IT Talent Rate*. Variables are defined in the Appendix. We report the results by grouping the industries following B. H. Hall and Vopel (1996). We also control for industry fixed effects, following the Fama–French 48 industry classification, and year fixed effects. Standard errors, reported in parentheses, are clustered at the firm level.

**p* < 0.10; ***p* < 0.05; ****p* < 0.01.

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 R&D 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 relation 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. Table 5 presents the findings.[23]

First, the result in Column 1 of Table 5 reveals a positive relation between *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-, medium-, and low-tech groups, as reported in Columns 2–4, respectively, the positive relation between *IT Talent Rate* and *R&D Intensity* remains significant for high- and medium-tech firms but is insignificant for low-tech firms. The effects of IT hiring on firms' innovative activity are economically meaningful. A 1 *SD* increase in *IT Talent Rate* predicts approximately a 12% increase relative to mean *R&D Intensity* across all firms. The corresponding effects are about 8.5% in high-tech firms and 9.9% in medium-tech firms. By contrast, the effect in low-tech firms is negligible. These results support 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 Columns 5–8 of Table 5, indicate that, on average, greater R&D intensity is associated with higher firm value, as reflected in the P/E ratio. Notably, this positive correlation is primarily evident in high-tech firms, whereas no significant effects are observed for medium- or low-tech firms. The economic impact of *R&D Intensity* on *P/E Ratio* is modest overall but more pronounced in high-tech industries: A 1 *SD* increase in *R&D Intensity* (0.132) corresponds to an approximately 0.54% increase relative to mean *P/E Ratio* among high-tech firms ($1.251 \times 0.132 \div 30.329 = 0.0054$; Column 6). The corresponding effects in medium- and low-tech industries are small and statistically insignificant. We observe the same pattern when using *EV/EBITDA* as the dependent variable.[24]

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

5 | FURTHER ANALYSIS

This subsequent analysis redirects our attention toward investigating the relation between tech 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.

[23]In this analysis, when R&D is used as an outcome variable, firm-years with missing R&D data are excluded. Following prior studies (e.g., Chan et al., 2001), we do not impute missing values as zero, because this would conflate nondisclosure with true zero spending, introduce measurement error, and bias coefficients toward zero. Restricting the sample to nonmissing R&D ensures a more reliable test of the mechanism. However, when we retain observations with missing R&D values by imputing them as zero, our main inferences remain unchanged.

[24]We also employ *EV/EBITDA* as an alternative dependent variable to measure firm value, and our inference remains unchanged. Specifically, the coefficient on high-tech industries is 0.316 ($t = 3.15$), whereas the coefficient on low-tech industries is insignificant (-0.019, $t = -0.29$). The economic effect is meaningful: Although the overall impact of R&D intensity on EV/EBITDA is modest, it is considerably more pronounced in high-tech industries. A 1 *SD* increase in *R&D Intensity* (0.132) is associated with approximately a 0.042-point increase in *EV/EBITDA* (0.316×0.132), which corresponds to about a 0.5% increase relative to mean *EV/EBITDA* for high-tech firms ($0.042 \div 8.322 = 0.005$). The corresponding effects in other sectors are negligible or statistically insignificant.

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

	R&D intensity				*P/E ratio*			
	All	High tech	Medium tech	Low tech	All	High tech	Medium tech	Low tech
Variable	(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)
Firm 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)
Firm 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 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	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
Obs.	13,581	3,803	3,585	1,333	13,533	3,796	3,545	1,327

Note: This table reports the regression results using *R&D Intensity* (Columns 1–4) and *P/E Ratio* (Columns 5–8) as dependent variables. The main independent variable for Columns 1–4 is *IT Talent Rate* in the previous year, and for Columns 5–8 is *R&D Intensity* in the previous year. Variables are defined in the Appendix. We put all industries into three groups following B. H. Hall and Vopel (1996), based on their reliance on technology, and run the regression within each industry group. We also control for industry fixed effects, following the Fama–French 48-industry classification, and year fixed effects. Standard errors, reported in parentheses, are clustered at the firm level.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

5.1 | IT talent investment, labor market efficiency, and managerial ability

Building on the findings from the previous section, tech 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, the capacity to balance strategic labor buffering with the risks of human capital undersupply, plays a critical role in shaping IT talent investment.[25] Liu et al. (2014) demonstrate that firms' internal workforce strategies, such as maintaining a strategic human capital buffer, play a critical role in shaping their long-term sustainable competitive advantage, whereas insufficient human capital can lead to foregone opportunities for innovation (e.g., Campbell et al., 2012; Nohria & Gulati, 1996). Therefore, a purposeful IT talent reserve 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 (e.g., Kryscynski et al., 2021; Nyberg et al., 2014). 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 the human capital slack 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 excess human capital capacity 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):

$$\begin{aligned} Net\ Hire_{it} = {} & \beta_0 + \beta_1 Sales\ Growth_{it-1} + \beta_2 Sales\ Growth_{it} + \beta_3\, \Delta ROA_{it-1} + \beta_4\, \Delta ROA_{it} + \beta_5 ROA_{it} + \beta_6 Return_{it} \\ & + \beta_7 Firm\quad Size\_R_{it-1} + \beta_8 Quick_{it-1} + \beta_9\, \Delta Quick_{it-1} + \beta_{10}\, \Delta Quick_{it} + \beta_{11} Leverage_{it-1} \\ & + \beta_{12} Lossbin1_{it-1} + \beta_{13} Lossbin2_{it-1} + \beta_{14} Lossbin3_{it-1} + \beta_{15} Lossbin4_{it-1} + \beta_{16} Lossbin5_{it-1} \\ & + Industry\ FE, \end{aligned} \tag{5}$$

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-year total assets; *Return* is the annual stock return; *Firm Size_R* is the log of market value of equity at the beginning of the year, ranked into percentiles; *Quick* is the quick ratio; *Leverage* 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 residuals from Regression (5) serve as our measure of labor market efficiency: Positive values indicate strategic labor buffering, whereas negative values reflect human capital undersupply. Based on this measure, we construct a binary indicator variable, *Strategic Human Capital Buffering*, which equals 1 if the firm maintains a strategic human capital buffer and 0 if the firm operates below its required human capital level.

To investigate the relation among IT talent investment, labor market efficiency, and managerial ability, we conduct regressions using *IT Talent Rate* as the dependent variable. *MA-Score*, *Strategic Human Capital Buffering*, and the interactive variable *MA-Score × Strategic Human Capital Buffering* are the main independent variables, alongside control variables. Both industry and year fixed effects are incorporated to control unobserved heterogeneity. Table 6 presents the results.

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

[25]Prior research on labor market efficiency frequently characterizes firms' staffing imbalances using the terms "overhiring" and "underhiring" (e.g., Nohria & Gulati, 1996; Pinnuck & Lillis, 2007). Building on this line of work, we introduce the concept of strategic human capital buffering to denote how managerial ability influences firms' talent reserve strategies. This framing emphasizes intentionality, highlighting that managers may deliberately maintain a buffer of human capital to preserve flexibility and support long-term strategic objectives, rather than viewing deviations in hiring solely as inefficiencies.

TABLE 6 IT talent investment, labor market efficiency, and managerial ability.

Variable	*IT talent rate* (1)	(2)	(3)	*5-Year IT talent rate* (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)
Strategic Human Capital Buffering		0.006***	0.006***		0.002	0.002
		(0.002)	(0.002)		(0.002)	(0.002)
MA-Score × Strategic Human Capital Buffering			0.057*** (0.013)			0.014 (0.011)
Firm 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)
Firm 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 FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.673	0.678	0.045	0.104	0.017	0.014
Obs.	20,063	4,062	4,062	11,197	2,774	2,774

Note: This table reports the regression results of the following model:

$$\begin{aligned} IT\ Talent\ Rate_{it} = {} & \beta_0 + \beta_1 MA-Score_{it} + \beta_2 Strategic\ Human\ Capital\ Buffering_{it} \\ & + \beta_3 (MA-Score \times Strategic\ Human\ Capital\ Buffering)_{it} + \beta_4 Firm\ Size_{it-1} + \beta_5 Capital\ Intensity_{it-1} \\ & + \beta_6 Leverage_{it-1} + \beta_7 Payout_{it-1} + \beta_8 ROA_{it-1} + \beta_9 Tobin's\ Q_{it-1} + \beta_{10} Firm\ Age_{it} + \varepsilon_{it}. \end{aligned}$$

The dependent variable for Columns 1–3 is *IT Talent Rate*, and for Columns 4–6 is *5-Year IT Talent Rate*. The main independent variables are *MA-Score*, *Strategic Human Capital Buffering*, and the interaction of *MA-Score* and *Strategic Human Capital Buffering*. Variables are defined in the Appendix. We also control for industry fixed effects, following the Fama–French 48-industry classification, and year fixed effects. Standard errors, reported in parentheses, are clustered at the firm level.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Anderson et al. (2025), who suggest that managers with higher abilities are more capable of acquiring and using resources efficiently than those with lower abilities, showing that low-ability managers tend to over- or underinvest, whereas high-ability managers strategically overinvest to sustain and prop up future firm performance.

Moreover, the empirical results in Column 2 of Table 6 suggest that firms identified as strategic human capital buffers are more likely to allocate resources toward IT talent new hiring. Notably, in Column 3, the positive and highly significant interaction term *MA-Score × Strategic Human Capital Buffering* indicates that firms with both high managerial ability and a tendency to maintain a strategic human capital buffer 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 maintaining a strategic human capital buffer 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.[26]

Because 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 5 years as the dependent variable, aligning with the cumulative nature of IT adoption. The results, presented in Columns 4–6 of Table 6, reveal a positive and significant effect of managerial ability on long-term IT talent investment. In contrast, strategic human capital buffering is positively signed but statistically insignificant. This pattern suggests that firms rely more heavily on managerial ability to guide strategic IT talent acquisition, whereas external labor conditions may not independently sustain long-term IT workforce expansion.[27]

5.2 | IT talent investment and corporate culture

Next, we investigate the influence of firm IT talent investment on firm culture. The 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, and 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.

Our corporate culture data are obtained from Li et al. (2021). 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 question and answer (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,

[26]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), whereas for the bottom 20% group, the coefficient is positive but not significant (0.015, *t*-value = 0.58). These findings suggest an asymmetric relation 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 from the authors.

[27]We also carry out examinations where the total IT talent hiring as a proportion of overall hiring across various intervals (e.g., 2 years, 3 years) serves as the dependent variable. Our conclusions remain consistent.

effective communication, and cooperative efforts across teams to achieve shared goals. We report the results in Table 7 and treat each cultural value as the dependent variable in Columns 1–5.[28]

The findings in Table 7 reflect how IT talent investments align with specific organizational cultural values. We find that IT talent investment is positively correlated with firm integrity, which indicates that technology professionals can implement transparent information systems and compliance infrastructures that enhance accountability, reduce information asymmetry, and support ethical decision-making across the organization. We also 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. Additionally, we 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 effect of IT talent on values like respect can be explained by their less direct connection to IT-related activities. Respect is often shaped by broader organizational ethics, leadership, and interpersonal dynamics, and is 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. To study performance implications beyond valuation multiples, we analyze three outcomes that capture distinct dimensions of firm performance: *Alpha* estimated from a Fama–French (1993) three-factor model (abnormal stock performance), *Volatility* (risk), and *Gross Profit Margin* (operational efficiency). *IT Centric* is equal to 1 if a firm's *IT Talent Rate* exceeds its industry median in year *t*, which delivers an interpretable, industry-relative benchmark and a portfolio-implementable signal. To enhance design transparency, we report specifications separately for contemporaneous and lagged IT measures (rather than including both in the same regression), reflecting the notion that operational outcomes may react more quickly whereas capital market outcomes typically adjust with a lag. We also replace the industry and year fixed effects with industry-year fixed effects. This specification fully absorbs any shocks common to firms in the same industry during a given year (e.g., industry-specific demand shifts, regulation, or technology adoption waves), which could otherwise bias our results. Table 8 presents the results.

The results in Columns 1–4 of Table 8 show that high IT talent investment in the current year has no significant relation with firm *Alpha*, indicating no immediate effect on financial returns. However, compared to industry peers, higher IT talent investment in the prior year demonstrates a positive and significant relation 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 5–8 indicate that IT talent investment reduces volatility (enhances stability). Although 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 reduction (stabilizing) impact. Firms with high IT talent investment in the prior year experience reduced stock return volatility, suggesting that IT talent reduces uncertainty and enhances operational predictability. Finally, the economic effects of *IT Centricity* are substantial. On average, IT-centric firms earn approximately 0.5 percentage

[28]Given the persistence of corporate culture, we exclude lagged culture values from our main specifications to avoid spurious correlations and dynamic panel bias. Instead, we directly examine how IT talent investment predicts subsequent changes in corporate culture. Untabulated results show that including lagged culture yields consistent conclusions, but with mechanically inflated R^2, so we refrain from emphasizing them in the main text.

TABLE 7 IT talent investment and corporate culture.

Variable	Integrity (1)	Teamwork (2)	Innovation (3)	Respect (4)	Quality (5)
IT Talent Rate$_{t-1}$	0.840***	2.548***	8.387***	0.588	2.048***
	(0.280)	(0.323)	(0.715)	(0.453)	(0.363)
Firm Size$_{t-1}$	0.115***	0.013	0.605***	−0.313***	−0.030
	(0.015)	(0.017)	(0.037)	(0.024)	(0.019)
Capital Intensity$_{t-1}$	−1.985***	−2.873***	−3.748***	−5.182***	3.701***
	(0.301)	(0.347)	(0.768)	(0.486)	(0.389)
Leverage$_{t-1}$	−0.037	−0.545***	−1.363***	−0.690***	−0.374***
	(0.052)	(0.060)	(0.133)	(0.084)	(0.067)
Payout$_{t-1}$	0.004	0.005	0.021	0.000	0.016**
	(0.006)	(0.007)	(0.015)	(0.009)	(0.007)
ROA$_{t-1}$	−0.196	−1.253***	−1.315***	−0.033	−0.757***
	(0.132)	(0.152)	(0.338)	(0.214)	(0.171)
Tobin's Q$_{t-1}$	0.015**	0.084***	0.382***	0.171***	0.083***
	(0.007)	(0.009)	(0.019)	(0.012)	(0.010)
Firm Age	0.002	−0.162***	−0.472***	−0.025	−0.163***
	(0.030)	(0.035)	(0.078)	(0.049)	(0.039)
Constant	1.900***	2.138***	1.753***	3.721***	2.171***
	(0.087)	(0.100)	(0.221)	(0.140)	(0.112)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
R^2	0.104	0.110	0.110	0.100	0.067
Obs.	11,354	11,354	11,354	11,354	11,354

Note: This table reports the regression results of the following model:

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

The dependent variable is *Corporate Culture*. Following Li et al. (2020), we examine five corporate culture factors: integrity, teamwork, innovation, respect, and quality. The main independent variable is *IT Talent Rate*. Variables are defined in the Appendix. We also control for industry fixed effects, following the Fama–French 48-industry classification, and year fixed effects. Standard errors, reported in parentheses, are clustered at the firm level.

*p < 0.10; **p < 0.05; ***p < 0.01.

points higher stock abnormal returns than non-IT-centric firms, while also experiencing about a 1.5 percentage point reduction in return volatility.

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 (e.g., Bushee, 1997; Della Croce et al., 2011). To test this hypothesis, we analyze changes in institutional investor holdings for IT-centric firms. Our

TABLE 8 IT-centric firms' performance.

Variable	*Alpha*				*Volatility*				*Gross profit margin*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IT Centric$_t$	−0.350	0.003			−0.004	0.001			0.027***	0.026***		
	(0.276)	(0.222)			(0.004)	(0.004)			(0.003)	(0.003)		
IT Centric$_{t-1}$			0.521*	0.415*			−0.015***	−0.007*			0.026***	0.027***
			(0.287)	(0.225)			(0.004)	(0.004)			(0.003)	(0.003)
Firm Size$_{t-1}$	−1.722**	−0.259*	−1.081	−0.306*	−0.101***	−0.087***	−0.081***	−0.082***	0.001	0.000	0.003	0.003
	(0.793)	(0.154)	(0.853)	(0.158)	(0.010)	(0.003)	(0.011)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Capital Intensity$_{t-1}$	−1.952	−3.527	1.528	−1.516	0.055	0.229***	0.100	0.205***	−0.033	−0.006	−0.040	−0.005
	(5.449)	(3.297)	(5.925)	(3.440)	(0.080)	(0.054)	(0.085)	(0.058)	(0.046)	(0.048)	(0.049)	(0.051)
Leverage$_{t-1}$	−1.111	−0.099	−2.332*	−0.670	0.255***	0.143***	0.241***	0.132***	0.051***	0.051***	0.039***	0.039***
	(1.253)	(0.670)	(1.314)	(0.676)	(0.016)	(0.009)	(0.017)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)
Payout$_{t-1}$	−0.031	−0.067	−0.046	−0.077	−0.001	−0.006***	−0.001	−0.006***	0.002*	0.002*	0.001	0.001
	(0.074)	(0.070)	(0.075)	(0.070)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ROA$_{t-1}$	0.150	2.685**	−0.767	1.702	−0.385***	−0.546***	−0.385***	−0.570***	0.304***	0.303***	0.298***	0.298***
	(1.641)	(1.369)	(1.747)	(1.449)	(0.017)	(0.012)	(0.019)	(0.013)	(0.011)	(0.012)	(0.012)	(0.012)
Tobin's Q$_{t-1}$	−0.937***	−0.288***	−0.966***	−0.290***	−0.009***	−0.012***	−0.006***	−0.011***	0.027***	0.027***	0.027***	0.027***
	(0.186)	(0.110)	(0.191)	(0.109)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Age	−6.156	0.058	−8.074	0.081	0.029	−0.082***	0.003	−0.086***	−0.008*	−0.008*	−0.014***	−0.013***
	(5.233)	(0.835)	(6.015)	(0.860)	(0.023)	(0.005)	(0.025)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.168*	6.013	0.234**	5.382	0.601***	0.790***	0.800**	0.926***	0.313**	0.363***	0.302***	0.367***
	(0.087)	(5.112)	(0.101)	(4.929)	(0.039)	(0.114)	(0.042)	(0.112)	(0.015)	(0.102)	(0.016)	(0.099)

TABLE 8 (Continued)

Variable	*Alpha* (1)	(2)	(3)	(4)	*Volatility* (5)	(6)	(7)	(8)	*Gross profit margin* (9)	(10)	(11)	(12)
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry-by-year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.141	0.166	0.146	0.174	0.378	0.329	0.327	0.335	0.156	0.069	0.189	0.076
Obs.	5,563	5,563	4,975	4,975	23,493	23,493	20,520	20,520	24,636	24,636	21,470	21,470

Note: This table reports the regression results of the following model:

$$\textit{Firm Performance}_{it} = \beta_0 + \beta_1 \textit{IT Centric}_i + \beta_2 \textit{Size}_{it-1} + \beta_3 \textit{Capital Intensity}_{it-1} + \beta_4 \textit{Leverage}_{it-1} + \beta_5 \textit{Payout}_{it-1} + \beta_6 \textit{ROA}_{it-1} + \beta_7 \textit{Tobin's } Q_{it-1} + \beta_8 \textit{Age}_{it} + \varepsilon_{it}$$

The dependent variable measures firm performance based on *Alpha*, *Volatility*, and *Gross Profit Margin*. The main independent variable is *IT Centric*. Variables are defined in the Appendix. We also control for industry fixed effects, following the Fama–French 48-industry classification, year fixed effects, and the interactive term. Standard errors, reported in parentheses, are clustered at the firm level.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

untabulated results indicate a significant increase in both the number of institutional investors and the institutional ownership percentage for firms with IT talent hiring that is higher than industry peers. 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 *Gross Profit Margin*, as shown in Columns 9–12 of Table 8. The positive and highly significant coefficient for the current year's IT-centric status demonstrates that IT-centric firms enjoy a persistent profitability advantage. Economically, IT-centric firms are associated with a 2.6–2.7 percentage point increase in gross profit margin, both contemporaneously and with a 1-year lag, highlighting the durability of IT-driven operational gains.[29]

6 | CONCLUSION

Firms increasingly invest in skill-driven IT, 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 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.

Beyond industrywide patterns, we find that organizational factors, particularly managerial ability, modestly influence the intensity of IT hiring at the firm level. Additionally, investments in IT talent influence corporate strategies and culture. The long-term benefits of investing in IT talent are reflected in superior stock performance, enhanced operational efficiency, and reduced uncertainty, each contributing to a sustained competitive advantage.

Our findings 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 and firm automation. 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. Our 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.

ACKNOWLEDGMENTS

We thank Kevin Lu for his valuable assistance with data processing. We are grateful for insightful comments and suggestions from Seong Byun (SFA discussant) and Lei Chen (EFMA discussant); seminar participants at the

[29]We use an indicator for IT-centric firms rather than the continuous *IT Talent Rate*. The dummy provides a clearer interpretation and aligns with a portfolio-sorting framework that highlights economically meaningful differences between high- and low-IT investors. As a robustness check, we also reestimate all specifications with the continuous IT measure. The coefficients carry the same sign as the indicator results but are less statistically significant. We interpret this attenuation as reflecting (1) a threshold-type effect whereby performance improvements accrue only after IT hiring surpasses a salient benchmark and (2) greater measurement noise in the continuous variable that is mitigated when focusing on industry-relative extremes.

Research Hour at the Williamson College of Business Administration, Youngstown State University; and conference participants at the Academy of Finance Annual Meeting, the European Financial Management Association Conference, and the Southern Finance Association Conference.

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How to cite this article: Dong, F., Doukas, J. A., & Zhang, R. G. (2025). Strategic technology talent acquisition and firm value: A cross-industry examination. *Journal of Financial Research*, 1–34. https://doi.org/10.1111/jfir.70038

APPENDIX: 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 years t to $t + 4$ scaled by the total number of new hires for each firm from year t to year $t + 4$.
P/E Ratio	Firm's market capitalization divided by net income, excluding firm-years with nonpositive earnings ((PRCC_F × CSHO)/NI)
Enterprise Value	Sum of market capitalization, total debt, preferred equity, and minority interest, less cash and equivalents ((PRCC_F × CSHO) + (DLTT + DLC) + Pref + MIB − CHE)

(Continues)

Variable	Definition
EV/EBITDA	Firm's enterprise value divided by earnings before interest, taxes, depreciation, and amortization (EBITDA) (EV/EBITDA)
MA-Score	Managerial ability level of the firm, measured following Demerjian et al. (2012)
Strategic Human Capital Buffering	Equals 1 if the firm maintains a strategic human capital buffer and 0 if the firm operates below its required human capital level, based on the model of Pinnuck and Lillis (2007)
Firm Size	Log value of the firm's total assets (AT)
Capital Intensity	Firm's capital expenditures (CapEx) scaled by the firm's total assets (CAPX/AT)
Leverage	Firm's total debt ratio ((DLTT + DLC)/AT)
Payout	Dividend payout ratio of the firm (DVC/NI)
ROA	Firm's return on total assets (NI/(($AT_t + AT_{t-1}$)/2))
Tobin's Q	Measured as the ratio of the firm's market value of equity plus the book value of debt, divided by the book value of total assets ((PRCC_F × CSHO + DLTT + DLC)/AT)
Firm Age	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	Log value of total computer science 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	Total R&D expenses divided by total assets (XRD/AT)
Average Age of Capital	Firm's net property, plant, and equipment (PP&E) over depreciation expenses (PPENT/DP)
Adjusted Capital Intensity	Firm's net PP&E over number of total employees, scaled by 1 plus *Average Age of Capital* ((PPENT/EMP) × (1 + PPENT/DP))
CapEx per Employee	Firm's CapEx scaled by number of the firm's total employees (CAPX/EMP)
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, measured as 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	Firm's total cash divided by total assets (CHE/AT)
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	Includes five corporate culture factors: innovation, integrity, quality, respect, and teamwork, following Li et al. (2021)
IT Centric	Dummy variable equal to 1 if a firm's *IT Talent Rate* exceeds the annual industry median based on Fama–French 48-industry classification, and 0 otherwise
Alpha	Estimated using Fama–French five-factor model
Volatility	Annualized stock return standard deviation
Gross Profit Margin	Subtract the cost of goods sold (COGS) from net sales and divide by sales ((SALE − COGS)/SALE)