Tech Trailblazers: How Chief Technology Officers Elevate Corporate Innovation Efficiency?

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Abstract

This study investigates the influence of Chief Technology Officers (CTOs) on corporate innovation efficiency, measured through patents, citations, and patent market value scaled by R&D expenses. Drawing on the resource-based view and upper echelons theory, we find a substantial benefit to firms with a CTO, particularly when the CTO has a technological background. Moreover, CEOs with previous CTO experience lead to innovation efficiency. Our results maintain robustness across various alternative research designs, including propensity score matching, entropy balancing methods, Heckman model, Granger causality test, etc. In summary, our findings offer fresh insights into the important and nuanced impact of CTOs on corporate innovation performance.

Keywords: Innovation efficiency, CTO, executive qualification, CEO background

1. Introduction

"In today's digital landscape, the Chief Technology Officer (CTO) holds a vital role in driving technology strategy, innovation, and digital transformation within an organisation. With their technical expertise, strategic vision, leadership, and business acumen, the CTO is instrumental in shaping the organisation's technological future and achieving competitive success in the digital era."

- The Economic Times[1], October 13, 2023

According to the 2018 McKinsey research, given the rapidly increasing speed of technological advancements, every company needs a Chief Technology Officer (CTO) to stay abreast of new technologies and integrate them into their strategies and operating models. [2] As innovation and technology are closely intertwined, it is crucial for a CTO to be well-versed in the latest technology trends, possess innovation, and demonstrate leadership skills (not only in technology but also in innovation). In turn, companies that successfully incorporate the best technological innovation often emerge as the most successful. As a result, the latest heightened demand for CTOs in the market can be attributed to various factors, such as the growing emphasis on big data and artificial intelligence, the emergence of cryptocurrency and the metaverse, and the widespread adoption of blockchain technology (CTO Academy, 2021). [3] Nevertheless, despite the

[1] https://economictimes.indiatimes.com/jobs/c-suite/the-role-of-a-chief-technology-officer-cto-in-todays-digital-landscape/articleshow/100996331.cms?utm_source=contentofinterest&utm_medium=text&utm_campaign=cppst

[2] https://www.mckinsey.com/capabilities/operations/our-insights/why-you-need-a-cto-and-how-to-make-her-successful

[3] In response to the increasing strategic significance of technology, corporations initiated the integration of the CTO position into their top management teams. This trend emerged in the 1980s as businesses recognized the escalating importance of technology in their operations. Adler and Ferdows (1990) identified two primary reasons for introducing CTO positions: firstly, to provide strategic guidance for technical growth, particularly in situations where technology plays a critical role in competitive advantage; and secondly, to foster synergy among the

dizzily increasing demand and attention towards CTOs, the impact of their presence on innovation has not been thoroughly studied in accounting and finance literature.

In this study, we define innovation efficiency as a firm's capability to maximize innovation outputs given a certain amount of R&D inputs following extant studies (e.g., Cruz-Cázares et al. 2013; Hirshleifer, Hsu, and Li 2013). Thus, innovation efficiency considers both inputs and outputs and lies at the core of a firm's performance (Alegre and Chiva, 2008; Chiesa & Frattini, 2009; Song et al., 2007). Despite the importance of innovation efficiency, how it might be influenced by CTOs remains unknown. Therefore, to fill this gap, this study aims to examine whether and how the presence of CTOs and their related attributes affect firm innovation efficiency.

Drawing upon the resource-based view (RBV) and upper echelons theory, we posit that a CTO positioned as the most senior executive within top executive teams, holds the potential to advocate and prioritize limited resources allocation for technology advancement and influence firm innovation efficiency across various dimensions. On one hand, a CTO can spearhead a productive and efficient research department, elevating innovation efficiency through strategic planning, adept utilization of limited resources, and serving as a communication bridge. The responsibilities of a CTO encompass the monitoring and assessment of new technologies (Smith, 2003). Confronted with challenges in determining research direction and strategies, CTOs can enhance innovation efficiency by leveraging their professional judgment to select research projects with a high probability of success and substantial potential to add value to the company (Smith, 2003). Moreover, CTOs can collaborate closely with other C-suite executives, department heads, and teams to understand their technology needs and align technology initiatives with business

company's diverse technologies. They also defined the CTO's role as encompassing responsibilities across both product and process technologies (and in some cases, information technology), typically at both divisional and corporate levels. This definition has gained widespread acceptance among academia and practitioners (e.g., Medcof and Lee, 2017; Cetindamar and Pala, 2011; Van der Hoven et al., 2012).

objectives. The inclusion of a CTO in the top management team accelerate the communication among all executives and research departments, thereby reducing the information asymmetry and enhancing the transparency among within the organization. For instance, Zhong (2018) find that transparency can expedite innovation efficiency by assisting managers in selecting valuable projects and ensuring discipline throughout the execution process. Finally, the presence of CTOs can improve innovation efficiency by acquiring valuable information through external engagement. Effective leadership and communication skills are crucial for CTOs; they should inspire and motivate the technology team, convey the technology vision to stakeholders, and cultivate relationships across the organization. CTOs possess the ability to translate complex technical concepts into clear and understandable terms for non-technical stakeholders.

In contrast, one may argue that some CTOs, as technology enthusiasts, might be fixated on invention and disregard the cost-benefit aspect of research projects. Unlike other executive members, CTOs are often evaluated based on innovation outputs. Consequently, they may be highly motivated to invest more in R&D projects to increase the likelihood of achieving innovation outcomes, less concerning how much to spend and use their resources. In such a scenario, there is a risk that firms with CTOs might overinvest and, as a result, reduce innovation efficiency in spite of high innovation output. Therefore, we refrain from speculating on the direction of the impact of a CTO on firm innovation efficiency.

Furthermore, the upper echelons theory posits that individuals' characteristics and attributes, including educational background and career experience, influence corporate investment decisions (Hambrick & Mason, 1984). CTOs typically boast a robust educational background in science and engineering, which often enhances their understanding of technology and innovation (Tyler & Steensma, 1998). However, not all CTOs hold technology-related degrees.

In such cases, technological experience becomes significant.[4] On the other hand, individuals aiming to distinguish themselves within the tech industry might choose to complete an MBA course to enhance their management skills.[5] However, the impact of a business-related background on innovation efficiency remains unknown. On the input side, CTOs with exposure to business concepts may lean towards considering cost-benefit analyses given the limited resources and exhibit a more risk-averse attitude, potentially leading to a decrease in R&D input. On the output side, Finkelstein and Hambrick (1996) as well as Hambrick and Mason (1984) state that MBA programs are seen as offering little to enhance innovative or risk-taking skills in students. Consequently, the effect of a business background on innovation efficiency remains ambiguous, as both R&D input and output are expected to decrease. Therefore, in our second hypothesis, we explore the impact of CTO's qualification or background on firm innovation efficiency.

In this study, utilizing a sample of 30,604 firm-year observations spanning the years 2001 through 2016 (encompassing 3,817 unique firms), we find that 14.32% of firms employ CTOs. Among these, 72.86% have a technology background, and 31.32% of firm-year observations feature CTOs with a business education background. Our baseline regression indicates that firms with CTOs demonstrate superior innovation efficiency compared to firms without CTOs. These results suggest that firms with CTOs are more efficient in innovation than their counterparts without CTOs.

Next, we explore the impact of CTO qualifications on innovation efficiency. We find that a CTO with a technology background can enhance firm innovation efficiency, whereas CTOs with

[4] For example, Adam Duro, the CTO of Freebird Rides, began his tech career without a technology degree, but his over 15 years of tech-related work experience propelled him to the position of a CTO. As he mentioned in an interview, a successful technology career requires individuals to remain ambitious, continuously learn, and progress while on the job (No CS Degree, 2019).

[5] The Software Report website listed the top 25 software CTOs of 2022, with six of them holding an MBA (2022).

a business background cannot. Further, the presence of CTOs possessing both technology and business backgrounds improves firm innovation efficiency. In addition, a small number of CEOs were promoted from the CTO role, either within the corporation or from outside of the firm. [6] A CEO with substantial tech experience is more inclined to allocate resources towards the latest technologies and technological innovations. Our results are consistent with this conjecture: firm innovation efficiency is enhanced for the group of CEOs with prior CTO experience.

Besides CTO's and CEO's technology background, we explore two potential mechanisms though which CTOs may make a difference in corporate innovation efficiency. The first mechanism focuses on patent success rates, captured by a firm's ability to secure patent grants. The patent filing process is extremely complicated and challenging due to registry issues, backlogs, delays in trademark and patent registration, lack of experts in patent claims drafting, the cost of protection, Intellectual Property (IP) lawsuits, etc. As a result, not all patent applications can be granted; and the average success rate is approximately 68 percent during a sample period of 2000-2019. We conjecture that CTOs with patent and technology expertise may be able to lead R&D teams to navigate the application process successfully. We find that is the case; firms with CTOs significantly improve innovation efficiency by increasing patent success rates. In the second mechanism, we explore CTO social networks, similar to CEO social networks (Engelberg et al. 2013; Griffin et al. 2021), which connect organizations to external sources of knowledge sharing and communication to spillover, as a result benefit innovation efficiency. The size of CTO networks is measured by summing their professional, educational, and social connections. Our results indicate that a larger CTO network significantly enhances innovation efficiency, which could be attributed to CTOs' knowledge spillover. Finally, we conducted various robustness tests,

[6] Our final sample includes 485 firm-year observations with tech CEOs, among which, 129 have prior CEO experience.

including propensity score matching, entropy balanced matching methods, the Heckman model, and Granger causality test, all yielding consistent results that reaffirm the positive association between the presence of CTOs and firm innovation efficiency.

In essence, this study makes a dual contribution to the literature. First, it expands upon the existing literature on upper echelons theory by illustrating that a firm's performance is influenced by the characteristics of its senior management, aligning with consistent findings in related studies (Hambrick & Mason, 1984; Barker & Mueller, 2002; Galasso & Simcoe, 2011; Sunder et al., 2016; Shao et al., 2020). Additionally, we advance this literature by introducing the impact of the CTO existence, qualification, and experience on innovation efficiency and outcomes. To the best of our knowledge, this paper is the first to delve into the importance and economic value of CTOs within the context of accounting and finance literature.

Second, we contribute to the growing body of literature on corporate innovation efficiency. Innovation is recognized as a crucial competitive advantage for firm performance, contributing to long-term success (Zheng et al., 2020; Ahuja, Lampert, & Tandon, 2008; Tushman & O'Reilly, 1996). Our research extends this line of inquiry by identifying another vital determinant of corporate innovation efficiency and advocating for a corporate board setting that encourages firms to prioritize innovation. Companies are encouraged to recruit or promote a CTO as an integral member of their executive teams to guide research direction and uphold high standards, particularly in high-intensity research and development industries.

The remainder of the paper is organized as follows. Section 2 discusses the related literature and develops the hypotheses. Section 3 describes the sample construction, data, and methodology. Section 4 presents our summary statistics, empirical results, and additional analysis. Section 5 provides the conclusion.

2. Literature review and hypothesis development

2.1 Innovation efficiency

Previous researchers have extensively studied the consequences and benefits of innovation, as evidenced by long-term firm performance (Zheng et al, 2020; Ahuja, Lampert, & Tandon, 2008; Tushman & O'Reilly, 1996) and high growth rates (Martínez-Alonso, 2019). However, it is essential to note that intense R&D input does not necessarily guarantee an increase in innovative output. To achieve this, firms need to enhance efficiency, which can be gauged by the number of patents or citations scaled by R&D expenses. Hirshleifer, Hsu, and Li (2013) discovered that innovation efficiency strongly predicts future returns, even when accounting for firm characteristics and risks. In addition, Gao and Chou (2015) find that efficient innovation is associated with higher firm value.

On the other hand, some firms adopt a conservative strategy regarding R&D investments, often resulting in R&D facing underinvestment compared to other tangible assets. This R&D underinvestment can be attributed to three reasons: 1) the inherently risky nature of new research projects, 2) firms with financial constraints have limited resources (Brown et al, 2013; Hall, 2002), and 3) internal managerial incentives due to short-term performance targets may not align with the long-term goal, based on agency theory (Holmstrom, 1989). First, investing in R&D is inherently associated with high uncertainty and secrecy (Hall, 2002). Kothari et al. (2002) discovered that intangible R&D investments carry more risk than fixed capital investments. The outcomes of R&D investments often take many years to materialize, and even more time may be needed to translate innovation outcomes into profits. Moreover, during the transition from R&D expenses to innovative outcomes, the likelihood of failure is high. Recent estimates indicate that the failure rate for product development ranges from 24% to 48% and varies across industries (Castellion &

Markham, 2013). Next, since shareholders' expectations from the management are often driven by the increase in market prices, the executives such as the CEO are more motivated to meet short-term performance targets and as a result, are unwilling to bear the career consequences if innovation fails due to purely stochastic reasons (Hirshleifer, 1993; Kaplan & Minton, 2012). one may argue there is a positive relationship between the existence of a CTO and innovation efficiency. In many companies, the CTO, as an executive member, can advocate for the allocation of more resources to the R&D department, but the final decision is made by the entire executive team, especially the CEO. Therefore, apart from investing more in R&D expenditure, another approach to enhancing innovation output is to increase innovation efficiency.

2.2 CTOs and innovation efficiency

Extant studies have identified several contributors to firms' innovation efficiency; they find that innovation is more efficient when there is gender diversity in the R&D team (Xie, Zhou, Zong, and Lu 2020), CEO power and remuneration (Qiao and Fung 2016), CEOs with more outside directorship experience (Chen, Tee, and Chang 2022), etc. However, despite CTO being the lead of the R&D team, the association between CTOs and innovation efficiency has not yet been explored.

The impact of CTOs on innovation efficiency can be expected in two contrasting ways based on the resource-based view and upper echelons theory. The resource-based view suggests that firms possess resources to achieve and sustain competitive advantages (Wade and Hulland 2004). Among the limited resources, CTO’s knowledge is a key resource that can enable competitive advantages in innovation. This is especially the case because CTO skills are often developed over a long period and cannot be easily imitated by competitors (Bharadwaj 2000; Wade and Hulland 2004). Meanwhile, upper echelons theory (Carpenter et al. 2004; Hambrick 2007;

Hambrick and Mason 1984) emphasize the role of managers' background and observable characteristics such as age, functional track, career experiences, and education. Having CTOs with technology expertise elevates the firm's ability to use technology effectively for sustainable innovative advantage.

One the other hand, given that the expectations from and performance evaluation of CTOs are often directly tied with innovation outputs, firms with a CTO are more likely to invest in R&D projects to increase the chance of improving innovation output. No matter which R&D investment strategy a company adopts, there is no doubt that they all aim to improve innovation output. However, in such cases, there is a possibility that firms with CTOs may overinvest, leading to a decrease in R&D efficiency. Furthermore, some technology enthusiasts are so focused on inventions that they may extensively invest in R&D and concentrate on projects that carry a high chance of failure. Due to their potential disregard for the cost-benefit aspect, we argue that the presence of CTOs could impede firm innovation efficiency.

To the contrary, the presence of a CTO can enhance innovation efficiency in at least three ways. First, the primary responsibility of the CTO is to make strategic decisions regarding technology that can contribute to a firm's competitive advantages and benefit future growth. Specifically, the CTO monitors new technologies and selects research projects with a high probability of success and the potential to add value to the company (Smith, 2003). The importance of having a CTO can be exemplified in how decisions are made during a project's early phases. While it may be easy for a tech manager to decide to halt research when the cost of inventing a product outweighs its anticipated profit, this is not always the best approach. Due to the challenges in assessing whether a complex project will succeed, a CTO plays a critical role in assuring that the development of fundamental technologies can offer clear, competitive advantages for current and future businesses, according to O'Neill & Bridenbaugh (1992). Therefore, innovation efficiency improves when a CTO is involved with research projects, which likely results in an increase in the success rate.

Second, a CTO can improve innovation efficiency by increasing the transparency among the executives and research teams. Research by Zhong (2018) find that transparency can assist managers in selecting valuable projects and enforcing discipline throughout the execution process. By participating regular executive meetings, CTOs can effectively communicate with other executives, reducing the information asymmetry between board members, top management teams, and the research team, whereby accelerating innovation efficiency.

Finally, CTOs are expected to engage in outside activities and interact with the media, government, and academic and industry groups. As a result, CTO can create more opportunities, promote the company's innovation reputation and gather valuable feedback. Through communication with external parties, CTOs can obtain valuable information that helps determine the research direction and increases the success rate, thereby improving innovation efficiency. Consequently, the existence of a CTO can help improve innovation efficiency. Considering the two potential opposite relationships between CTO existence and innovation efficiency, our first hypothesis is set in a null form.

H1: *There is no relationship between the presence of a CTO and firm innovation efficiency.*

Upper echelons theory state that the expertise, career experience, and personal traits of senior management can predict organizational outcomes, such as strategic decisions and firm performance, including firm innovation (Hambrick & Mason, 1984; Hayward & Hambrick, 1997; Taylor et al, 2015). According to Tyler and Steensma (1998), managers educated in science and engineering possess a more comprehensive understanding of technology and innovation. Consequently, we expect that CTOs with a technology-related educational background can improve firm innovation efficiency.

However, it is essential to note that not all CTOs have tech-related degrees. A community known as "No CS Degree" shares inspiring interviews with self-taught engineers who lack official tech degrees. For instance, Adam Duro, the CTO at Freebird Rides, began working professionally without a computer science degree at the age of 17 (2019). Despite not having a formal tech education, he acquired a full set of tech-related knowledge and has been working as an engineer, manager, and executive for over 15 years. Therefore, we add CTOs with a technology background (through education or experience) to the second hypothesis.

H2a: *A CTO with technology background has no impact on firm innovation efficiency.*

To distinguish themselves among tech-savvy colleagues and progress to a tech lead or senior management role, individuals often choose to pursue an MBA or other business program to refine their management skills. A competent CTO is expected to bridge the gap between technology and business while demonstrating strong technical capabilities and industry knowledge. Despite the prevalence of CTOs with a business education background, research suggests that traditional MBA programs may not significantly enhance innovative or risk-taking skills (Finkelstein and Hambrick, 1996; Hambrick and Mason, 1984). In 2022, the Software Report highlighted the top 25 software CTOs, with six of them holding an MBA. However, executives with business training, including CEOs, may be perceived as less inclined to prioritize innovation through increased R&D spending, as MBA programs tend to emphasize analytical skills to prevent major mistakes or losses (Barker & Mueller, 2002). As CTOs augment their business knowledge, they may shift focus to the cost and benefit of research projects, potentially improving efficiency by reducing R&D input while maintaining the output. Yet, the impact of a business background on innovation efficiency remains unclear. Therefore, we set a null hypothesis to test the association between a CTO with a business education background and firm innovation efficiency.

H2b: *A CTO with a business background has no impact on firm innovation efficiency.*

Given its pivotal role in shaping organizational strategies (Minnick & Noga, 2010; Ting, 2013; Qiao & Fung, 2016), appointing a CEO with a tech background can prove advantageous for firms whose growth is closely tied to technology. As the primary leader, a CEO occupies a crucial role in decision-making processes. Prior studies have explored the association between various CEO characteristics and firm innovation input, output, and performance. For example, companies led by younger CEOs with significant stock ownership, advanced science-related degrees, and career experience in marketing, engineering, or R&D tend to exhibit higher R&D spending (Barker & Mueller, 2002). Shao, Zhao, Wang, and Jiang (2020) found that CEOs associated with universities or research institutions are often linked to increased innovation output and firm performance. CEOs with advanced science-related training are also predicted to engage in high R&D spending (Barker & Mueller, 2002). Moreover, CEOs with a background in technology are more likely to prioritize technological evolution as a long-term strategy, allocating resources to firm R&D input.

In addition, CEOs promoted from the CTO role are likely to prioritize technology and empathize with CTOs, making them more effective in fostering innovation. Consequently, we hypothesize that having a CEO with prior CTO experience may influence innovation efficiency.

H3: *The presence of a CEO with experience as a CTO has no impact on innovation efficiency.*

3. Sample, Variable Definitions, and Methodology

3.1 Sample selection and data

Our sample selection includes all the firm-year observations from the CRSP/Compustat Merged database over the period 2001-2016. We begin with the financial statement items from the CRSP/Compustat Merged database and exclude observations with missing values on total assets and sales revenue. Additionally, we remove firm-year observations with total assets and sales revenue lower than one million. Financial firms and regulated utilities are also excluded. Next, we match accounting data with the BoardEx database and limit the sample to firm-year observations with CEO records. The BoardEx database provides a complete historical profile for each director or executive, including employment history, education background, and social activities. If a firm does not have CEO data in BoardEx, we infer that all other director information is missing. To calculate our dependent variables, we use patent data compiled by the National Bureau of Economic Research (NBER), covering patents awarded through 2020 (Kogan, Papanikolaou, Seru, and Stoffman 2017). Due to the time gap between R&D expense input and actual patent output, our sample includes listed firms from 2001 to 2016, with the innovation efficiency measurement based on t+3, covering the period from 2004 to 2019. The final sample consists of 30,604 firm-year observations for 3,817 distinct firms used in our baseline regressions. Among these, there are 4,384 CTO observations during the sample periods. Table 1 presents the sample selection process and sample distribution by year and industry for CTO firms and non-CTO firms.

[Table 1 about here]

3.2 Variable measurement

3.2.1 Measuring innovation efficiency

Following Hirshleifer et al (2013), we use three proxies for innovation efficiency: the number of granted patents scaled by R&D capital ($IEPAT_{i,t+3}$), adjusted patent citations scaled by R&D expenses ($IECIT_{i,t+3}$), and value of granted patents scaled by R&D capital ($IEMKV_{i,t+3}$).

To clarify, we will introduce $IEPAT_{i,t}$ which is the ratio of firm i's patents granted in year t ($Patents_{i,t}$) scaled by its R&D capital. Following Chan et al (2001) and Lev et al (2005), we define R&D capital as the 5-year cumulative R&D expenses assuming an annual depreciation rate of 20% in the fiscal year ending in year t – 2:

$$IEPAT_{i,t} = \frac{Patents_{i,t}}{R\&D\ Capital} = \frac{Patents_{i,t}}{R\&D_{i,t-2}+0.8*R\&D_{i,t-3}+0.6*R\&D_{i,t-4}+0.4*R\&D_{i,t-5}+0.2*R\&D_{i,t-6}} \quad (1)$$

where $R\&D_{i,t-2}$ represents firm i's R&D expenses in the fiscal year ending in year t-2, and so on. We set missing R&D to zero. This patents-based innovation efficiency variable measure R&D efficiency in terms of patents granted per unit of R&D spending.

The second innovation efficiency measure is based on citations, which can better represent the technological or economic influence and importance (Hirshleifer et al, 2013). We define $IECIT_{i,t}$ as the adjusted number of citations in year t to firm i's patents granted over the previous 5 years scaled by the sum of corresponding R&D expenses:

$$IECIT_{i,t} = \frac{Adjusted\ Citations_{i,t}}{RD} = \frac{\sum_{j=1}^{5}\sum_{k=1}^{N_{t-j}} Citations_{ik}^{t-j}}{R\&D_{i,t-3}+R\&D_{i,t-4}+R\&D_{i,t-5}+R\&D_{i,t-6}+R\&D_{i,t-7}} \quad (2)$$

Where $Citations_{ik}^{t-j}$ is the number of citations received in year t by patent k, granted in year t-j (j=1-5) scaled by the average number of citations received in year t by all patents of the same class granted in year t-j, and N_{t-j} is the total number of patents granted in year t-j to firm i. Following prior literature, we only use citations obtained in the year before the forecast period by a firm's patents that were granted over the previous five years, therefore the innovation efficiency measure can be fully observable by investors at the time of their investments (Hirshleifer et al, 2013; Gu, 2005; Pandit et al, 2011).

Similar to patents-based innovation efficiency, $IEMKV_{i,t+3}$ is defined as values of firms' granted patents scaled by R&D capital. To measure the business value of firm patents, Kogan, Papanikolaou, Seru, and Stoffman(2017) utilized swings in stock prices on the days when patents are issued to the firm.

$$IEMKV_{i,t} = \frac{Value_{i,t}}{R\&D\ Capital} = \frac{Value_{i,t}}{R\&D_{i,t-2}+0.8*R\&D_{i,t-3}+0.6*R\&D_{i,t-4}+0.4*R\&D_{i,t-5}+0.2*R\&D_{i,t-6}} \quad (3)$$

They measure the economic value of patent k as the product of the estimated stock return due to the value of the patent multiplied by the market capitalization of the firm that is issued patent k on the day before the announcement of the patent insurance. If a company receives numerous patents on the same day, we equally assign each patent a portion of the total value.

3.2.2 Measuring CTO and other independent variables

We use directors' employment history from the BoardEx database to capture the existence of the CTO. We define $CTO_{i,t}$ as an indicator variable that takes the value of 1 if firm i has directors whose titles contain keywords including "CTO", "Chief Tech" in year t, and 0 otherwise[7]. To examine H2, we look at directors' educational background and employment histories. We define $BUSBACK_{i,t}$ equals one if the CTO in firm i in year t receives a business-related degree and/or have business-related working experience. When the qualification or the school's name includes keywords like business (including BBA and MBA), economics, accounting, finance, management, market, etc., we determine that the CTO receives a business-related degree. When the job title includes "finance", "account", "tax", "econ" etc., we consider it as a business-related experience.

[7] We also expand the CTO definition to CIO, whose titles include "CIO", "Chief Innovation", "Chief information". The main results are still hold.

In contrast, $TECHBACK_{i,t}$ is a binary variable that equals one if the CTO in firm i in year t receives a tech-related degree or has tech-related director employment experience. Following Malmendier and Tate (2008) and Galasso and Simcoe (2011), tech-related education is defined as undergraduate or graduate degrees in engineering, physics, operations research, chemistry, mathematics, biology, pharmacy, or other applied sciences, etc. Regarding tech-related experience, we check whether the CTO's past employment history contains any job titles including keywords like tech, engineer, sciences, computer, software, system, data, IT, pharmacy, biology, chemistry, physics, research, etc. In H3, we examine the relationship between the existence of CTO together with Tech CEO and innovation efficiency. We define $TECHCEO_{i,t}$ as a dummy variable that equals one if the CEO in firm i in year t worked as CTO in the past.

3.3 Methodology

To test H1, we run the following Ordinary Least Square (OLS) model:

$$IE_{i,t+3} = \beta_0 + \beta_1 CTO_{i,t} + \beta_2 FirmControls_{i,t} + \beta_3 CEOControls_{i,t} + IndustryFE + YearFE + \varepsilon_{i,t} \quad (4)$$

To test H2 on the effect of CTO qualification on the innovation efficiency, we run the following OLS model:

$$IE_{i,t+3} = \beta_0 + \beta_1 CTO_{i,t} + \beta_2 TECHBACK_{i,t} + \beta_3 FirmControls_{i,t} + \beta_4 CEOControls_{i,t} + IndustryFE + YearFE + \varepsilon_{i,t} \quad (5)$$

$$IE_{i,t+3} = \beta_0 + \beta_1 CTO_{i,t} + \beta_2 TECHBACK_{i,t} + \beta_3 BUSBACK_{i,t} + \beta_4 FirmControls_{i,t} + \beta_5 CEOControls_{i,t} + IndustryFE + YearFE + \varepsilon_{i,t} \quad (6)$$

$$IE_{i,t+3} = \beta_0 + \beta_1 CTO_{i,t} + \beta_2 TECHBACK_{i,t} + \beta_3 BUSBACK_{i,t} + \beta_4\, TECHBACK_{i,t} \times BUSBACK_{i,t} + \beta_5 FirmControls_{i,t} + \beta_6 CEOControls_{i,t} + IndustryFE + YearFE + \varepsilon_{i,t} \quad (7)$$

To test H3 on the effect of Tech CEO on the innovation efficiency, we run the following model:

$$IE_{i,t+3} = \beta_0 + \beta_1 CTO_{i,t} + \beta_2 TECHCEO_{i,t} + \beta_3 FirmControls_{i,t} + \beta_4 CEOControls_{i,t} + IndustryFE + YearFE + \varepsilon_{i,t} \quad (8)$$

Where i indexes firm and t indexes time. The dependent variables capture firm innovation efficiency outcomes: $IEPAT_{i,t+3}$, $IECIT_{i,t+3}$, and $IEMKV_{i,t+3}$. Since the innovation process generally takes multiple years and have on average 18 months pendency period, we use year t+3 to examine the effect of a firm's CTO existence on innovation efficiency (He and Tian 2013, Griffin et al. 2018).

We control firm characteristics and CEO-related characteristics that could impact a firm's innovation efficiency. Following the prior innovation literature (e.g., He & Tian, 2013), we control for firm characteristics that are important determinants of innovation activities. Our controls include firm size (The natural log of total assets), firm age (The natural log of one plus the firm age), profitability(return on assets), asset tangibility (net properties, plants, and equipment scaled by total assets), leverage, investments in tangible assets (capital expenditures over total assets), investments in intangible assets (R&D expenditures over total assets), growth opportunities (Tobin's Q), financial constraints (KZ index), industry concentration (the Herfindahl index based on sales), institutional ownership holdings (percentage of shares held by financial institutions), human capital (the natural log of one plus the number of employees), and Internal Control Material Weakness (an indicator which equals one if at least one internal control material weakness is reported in an audit report and otherwise zero).

In the regressions, we also control for CEO-specific variables that capture their age, tenure, and duality. We define CEO age as the natural log of one plus the CEO age in year t and measure

CEO tenure as the natural log of one plus the number of years a CEO is in office in year t. Duality is a dummy variable that equals one if the CEO is also the chairman of the board. This variable can capture CEO's structural power. Structural power assesses an executive's position in the organizational hierarchy and enables a CEO to resolve conflicts about strategy, acquisitions, organizational practices, and resource allocation in a way that is compatible with his or her preferences (Qiao & Fung, 2016). In addition, we include several control variables to control the effectiveness of corporate governance: Board Size (LNBOARD) and Audit Committee Size (LNAUDIT). Last, we add CIO to rule out a potential effect of CIO (Chief Information Office) on innovation efficiency (Shin et al. 2023). Industry fixed effects and year fixed effects are included in all regressions to account for industry-invariant characteristics and unobserved heterogeneity that varies over time, respectively. We cluster standard errors at the industry and year level. (Gow et al. 2010 and Petersen 2009).

4. Results

4.1 Descriptive statistics

Table 2 reports the descriptive statistics of our key variables. 4,384 firm-year observations contain CTO, which is 14.32% of observations. We observe significant variation in innovation efficiency between the two groups. The average $IEPAT_{i,t+3}$, $IECIT_{i,t+3}$, and $IEMVE_{i,t+3}$ for CTO firms are 0.0634, 0.065, and 0.4439, respectively. This number is more than twice as much as non-CTO firms (0.0311, 0.0282, and 0.1623). Among 4,384 CTO firms, 1,373 (31.32%) CTO have business-related background while 3,194 (72.86%) CTO have tech-related background. One may assume that a CTO has a technology background. However, as shown in the descriptive summary, only 73% of CTOs in our final sample have a technology education and/or tech director-level industry experience. 485 firm-year observations contain a Tech CEO in total, 184 of whom are from CTO firms and the rest are from non-CTO firms. CTO firms and non-CTO firms have a close average number in size, age, ROA, capital expenditure, and other control variables. From Table 2, we can see the obvious difference in investment strategy between CTO firms and non-CTO firms. The average $PPE_{i,t}$ and $RDEXP_{i,t}$ for CTO firms are 0.1469 and 0.0917, while the average $PPE_{i,t}$ and $RDEXP_{i,t}$ for non-CTO firms are 0.2481 and 0.0439, respectively. We can infer that non-CTO firms prefer investing in fixed assets and CTO firms are more willing to invest in R&D expenditure.

[Table 2 about here]

Table 3 presents the correlation matrix of our key variables, with Spearman's (Pearson's rank) correlation coefficients given in the lower (upper) triangle. The CTO and the Tech CEO are positively correlated with our proxies for firm innovation efficiency. CTO business background and tech background are also positively correlated with firm innovation efficiency. The results strongly provide support for all our three hypotheses.

[Table 3 about here]

4.2 Baseline empirical results

Table 4 reports the results of testing H1 on the impact of CTO on firm innovation efficiency by utilizing model 4. The first innovation efficiency proxy, $IEPAT_{i,t+3}$, is the ratio of firm i's patents granted scaled by its R&D capital in year t+3. The second innovation efficiency proxy ($IECIT_{i,t+3}$) is based on the innovation quality in year t+3. The last innovation efficiency proxy, $IEMKV_{i,t+3}$, is from the market value of innovation around grant date in year t+3. The results in Table 4 indicate significantly positive relations between the existence of a CTO and innovation efficiency . Specifically, the coefficient estimates of $IEPAT_{i,t+3}$, $IECIT_{i,t+3}$, and $IEMKV_{i,t+3}$ are 0.0170, 0.0174, and 0.1563, respectively. This suggests that firms with CTO are more efficient in innovation than non-CTO firms. For control variables, older firms, firms with lower leverage, higher R&D expenditure, higher growth probability (*TOBINQ*), higher financial constraints (*KZINDEX*), and higher CEO power (*DUALITY*) are associated with better innovation efficiency. In addition, the main results still hold after we control board size, the number of audit committee members and CIO. [8]

[Table 4 about here]

Table 5 presents the results on the relation between different CTO qualifications and firm innovation efficiency, estimated using ordinary least squares (OLS) model 5 – 7. We determine a CTO with a tech background if the CTO receives a tech-related education degree or if the CTO has practical technology working experience (e.g., tech director). Columns 1 through 3 report the effect of the CTO's technology background on corporate innovation efficiency. For $IEPAT_{i,t+3}$, the estimated coefficient on $TECHBACK_{i,t}$ is positive as expected, with a coefficient of 0.0052, and the coefficient on $TECHBACK_{i,t}$ is statistically significant (p-value < 0.05), suggesting that firms with CTOs from technology backgrounds enhance patent-based innovation efficiency performance. The coefficients in columns 2 and 3 are also positive. On the other hand, we define $BUSBACK_{i,t}$ as a dummy variable that equals one if the CTO receives an undergraduate or graduate business-related degree and/or has business-related working experience. Columns 4 through 6 report the effect of the CTO's technology and business qualification together on corporate innovation efficiency. Interesting, a CTO with a technology background is still positively associated with firm innovation efficiency, whereas a CTO with a business background is negatively associated with firm innovation efficiency. Overall, we can conclude that firm

[8] Columns 7-9 of table 4 show that the size of board and audit committee and the presence of CIO does not affect innovation efficiency. Our final sample includes 6,818 firm-year observations with CIO, among which 1,364 with both CTO and CIO.

innovation efficiency is enhanced by CTOs with a technology background, but not by CTOs with a business background.

Columns 7, 8, and 9 in Table 5 display the OLS results from regressing three innovation efficiency proxies on CTO from technology backgrounds, CTO from business backgrounds, and their interaction. In our sample, 1,122 CTOs have both tech and business backgrounds. The estimated coefficients of interaction ($TECHBACK_{i,t} \times BUSBACK_{i,t}$) on three innovation efficiency are positive in column 7, 8, and 9 (0.0105, 0.0105, and 0.0523, respectively), indicating that a CTO with both technology and business backgrounds can help improve companies' innovation efficiency albeit a CTO with a business background inhibits it.

[Table 5 about here]

To test H3, we continue to use OLS regression and add another key independent variable to $TECHCEO_{i,t}$, which is a binary variable that equals one if the CEO took a CTO role in the past and 0 otherwise. Table 6 reports the results of testing H3 with column 1 on $IEPAT_{i,t+3}$, column 2 on $IECIT_{i,t+3}$, and column 3 on $IEMKV_{i,t+3}$. The estimated coefficients of $TECHCEO_{i,t}$ on these three innovation efficiency proxies are significantly positive in all columns (0.0062, 0.0053, and 0.0154, respectively), confirming that innovation efficiency is increasing if having a CEO serving as a prior CTO . The estimated coefficients of $CTO_{i,t}$ in all three columns remain positive and significant, with economic magnitudes that are larger than the corresponding coefficients of $TECHCEO_{i,t}$, highlighting the importance of CTO existence.

[Table 6 about here]

4.3 Mechanism Analyses

We conduct two mechanisms to investigate how CTOs improve innovation efficiency. First, we examine the patent success rate, which is calculated as the ratio of the number of granted patents to the total number of patent applications. A higher patent success rate indicates the organization's ability not only to file more applications, but also to successfully secure their grants. By concentrating on this measure, we aim to examine the significance of CTOs in influencing the innovation process, as they can play a pivotal role in increasing the likelihood of patents being granted and, subsequently, enhancing innovation efficiency within the organization. Table 7 presents the results with $SUCCESSRATE_{i,t}$ as the dependent variable. The coefficient estimates of the $CTO_{i,t}$ are positive and statistically significant, demonstrating that firms with a CTO enhance corporate innovation efficiency by increasing patent success rates. In addition to the same control variable as in Table 4, we introduce an additional control variable, $PATACTIVITY_{i}$, which is an indicator variable that equals 1 if firm i has at least one patent during our sample period.

[Table 7 about here]

Another mechanism test involves the examination of CTO networks. CTOs often play a pivotal role in establishing connections between their organization and external sources of knowledge and expertise, including other industry experts, research institutions, or technology partners. By investigating CTOs' networks, we can assess whether these connections contribute to the enhancement of innovation efficiency. Similar to CEO network, we measure CTO network size by summing the CTO's professional, educational, and social connections to other CTOs and directors identified in the BoardEx dataset (Engelberg et al, 2013; Griffin et al, 2021). Table 8 examines the relationship between CTO networks and firm innovation efficiency. Through our analysis, we demonstrate that CTO's capacity to foster external connections and knowledge exchange can significantly bolster an organization's innovation.

[Table 8 about here]

5. Additional Analyses

5.1 Innovation Input and Output

Previous literature heavily uses innovation measurement by focusing on input and output separately. For example, Hsu, Tian, and Xu (2014) examine the relationship between financial market development and technological innovation, proxied by patent counts, patent citation, patent originality and generality, and industry-level R&D expense. We want to examine how the existence of a CTO affects technology innovation input and output separately as a supplement test. Following Hsu et al (2014), we construct one innovation input measure and three innovation output measure for additional analysis. Our sole innovation input measure is $RDEXP_{i,t+1}$, representing research and development (R&D) expenditure in year t+1 scaled by total assets at the end of fiscal year *t*. Our first innovation output measure, $LNPAT_{i,t+3}$, is the natural logarithm of one plus firm i's a total number of granted patents in year t+3. This innovation measure is straightforward to capture the quantity of innovation output. However, this variable cannot reflect the magnitude of innovation influence and importance. Therefore, our second innovation measure, $LNCIT_{i,t+3}$, is the natural logarithm of one plus firm i's a total number of citations received on the firm's patents in year t+3. Patent citations can reflect the influence of a patent, measuring the quality of inventions and the market value. In addition, we have third innovation measure, $LNMKV_{i,t+3}$, is the natural logarithm of one plus firm i's granted patents values in year t+3, following Kogan et al (2017).

On the input side, we use firm's research and development expenses scaled by total asset in year t+1. When a CTO assumes the role, the R&D expense in the subsequent year reflect the CTO's R&D policy. The coefficient estimates in Table 9 column 1 are positive and statistically significant at the 5% level, suggesting that firms with a CTO allocate more resources to R&D expenses compared to non-CTO firms.

For innovation output, we use two measurements to capture the quantity and quality of patents: $LNPAT_{i,t+3}$ and $LNCIT_{i,t+3}$. In year t+3, a CTO firm in our sample has on average 82.77 granted patents per year (and each patent receives 299.21 non-self citations), while non-CTO firms only have 8.74 patents per year on average and each patent receives 57.67 citations (untabulated). In addition, we use innovation value measurement ($LNMKV_{i,t+3}$) to capture the patent's market and economic significance following Kogan et al (2017).The average patent value of CTO firms are 931.90, which are also greater than those of non-CTO firms (176.91). Overall, CTO firms have better innovation quantity, quality, and values than non-CTO firms in the descriptive summary.

Table 9 displays the estimation results when we use three innovation variables as the dependent variable. First, we use 30,604 firm-year observations to test the effect of the existence of CTO on firm i's innovation in year t+3 after controlling for the firm and the CEO characteristics reported in Table 9 column 2 - 4. Positive numbers shown in $LNPAT_{t+3}$, $LNCIT_{t+3}$,and $LNMKV_{i,t+3}$ indicate better patent quantities and quality. The coefficients on CTO are significantly positive across all the innovation variables and are also economically significant. For example, the coefficient in column 2 (0.4691) suggests that firms with CTOs grant 46.91% more patents than non-CTO firms, and the estimated coefficient of CTO on $LNCIT_{i,t+3}$ (0.4772) indicate that patents from CTO firms have 47.72% more citations compared with those from non-CTO firms. Similarly, the coefficients on $LNMKV_{i,t+3}$ (0.6687) prove that firms with a CTO produce patents with better economic values. Overall, the results indicate that having a CTO is more likely to increase the firms' innovation output, influence, and values. According to Table 9 results, it is evident that companies with a CTO will invest more and generate better results compared to those without a CTO.

[Table 9 about here]

5.2 Propensity score matching

To control for observable differences between the two grounds and further mitigate endogeneity concerns, we use the propensity-score-matching approach to construct a control sample to test the H1. In the first stage of this analysis, we use the logit regression model to estimate the conditional odds of having a CTO including all control variables and calculate the propensity score for each firm using predicted probabilities. For each firm-year with CTO, we select one firm-year in the same industry with non-CTO firm-year observations (with no replacement) that has the closest distance in the propensity score. We successfully match 4,207 unique CTO firms with 4,248 non-CTO firms. We show the mean difference and t-test results before and after matching in Table 10 Panel A. We next repeat the estimation of Equation 4 using the propensity-score-matching sample. As shown in Table 10 Panel B, we find similar results to those using the full sample (Table 4). That is, the existence of a CTO accelerates firm innovation efficiency.

[Table 10 about here]

5.3 Entropy balancing tests

Entropy balancing is a relatively new matching technique that weights control sample units to achieve covariate balance, adjusting for random and systematic inequalities in the variable distributions between the treatment and control groups (Hainmueller 2012). Wilde (2017) listed two reasons why he uses the entropy balancing method. First, entropy balancing does not require design choices that can affect the composition of the control sample and then impact the results. Defond et al (2016) stated that PSM requires various design decisions, including whether to match with or without replacement, caliper width, the number of control companies matched to each treatment company, and the nonlinear factors included in the propensity score model. All of these decisions impact the content of the matched sample and, as a result, the findings reached from the

PSM analysis. Second, propensity score matching is a nearest-neighbor technique that imposes weights of 0 (i.e., discard the unit) or 1 (i.e., match the unit). Unlike that, entropy balancing is more flexible and allows observation weights to change gradually, conserving knowledge that enhances efficiency in later tests. Therefore, researchers can have larger samples.

We first get the matching weights based on firm control variables and then we conduct the regression using model 4 based on the weights. Table 11 presents the estimation results of Table 4 using the entropy balancing design. The coefficients of CTO on innovation efficiency stay significant and positive. This reinforces the evidence supporting our initial first hypotheses, which suggest that appointing a CTO enhances corporate innovation efficiency.

[Table 11 about here]

5.4 Heckman Model

To further address concerns about the endogeneity issue, we conduct robustness test using the Heckman model (Heckman 1979). In this approach, we compute the Inverse Mills Ratio (IMR) and incorporate it into our analysis. We consider two exogenous variables: industry level (defined as the ratio of firms operating in the same industry that have a CTO) and state level (measured as the ratio of firms operating in the same state that have a CTO). To calculate the IMR, we combine each exogenous variable with other control variables in Model 4 to predict the likelihood of a firm's decision in hiring a CTO. Despite the inclusion of the IMR, the results of this analysis are consistent with those presented in the main analysis. The findings are presented in Table 12, indicating that the coefficients on our variables of interest are positive and statistically significant across all columns. Overall, this analysis supports our hypothesis, suggesting a positive association between the presence of a CTO and firm innovation efficiency.

[Table 12 about here]

5.5 Granger Causality Test

To further investigate the nature of the relationship between CTOs and innovation efficiency, we conduct Granger causality tests (Granger 1969) between CTOs and innovation efficiency variables. In the contest of time-series data for two variables (X and Y), X is considered to “Granger-cause” Y if the lagged values of X are significant predictors of Y, incrementally to the lagged values of Y. In other words, values of X precede the values of Y. We test for Granger causality with the following regression:

$$IE_t = \sum_{i=1}^{n} \alpha_i \, IE_{t-i} + \sum_{i=1}^{m} \beta_i \, CTO_{t-i} \tag{9}$$

Where IE is the innovation efficiency proxy ($IEPAT_{i,t+3}$, $IECIT_{i,t+3}$, and $IEMKV_{i,t+3}$), and CTO is a dummy variable whether a firm has a CTO. If the coefficients on the lagged values of CTO are found to be significant in this equation, it can be concluded that the presence of CTOs Granger-causes innovation efficiency.

Table 13 presents the results of estimating model (9). We estimate model (9) separately for $IEPAT_{i,t+3}$ (Panel A), $IECIT_{i,t+3}$ (Panel B) and $IEMKV_{i,t+3}$ (Panel C). Due to the need for lagged values, a total of 21,821 firm-year of data are available for the estimation of model (9). Granger causality is assessed by testing the restriction that the coefficients on the lagged values of the CTO variable all equal zero, while the direction of the Granger causality is assessed by testing the restriction that the sum of coefficients on the lagged values of the CTO variables equals zero (Sanders 1996). Both restrictions are tested with a Chi-square test.

The results in Table 13 indicate that CTO Granger-cause $IEPAT_{i,t+3}$, $IECIT_{i,t+3}$, and $IEMKV_{i,t+3}$. The positive sign of the sum of the coefficients indicates that CTO has a positive lead relationship with innovation efficiency.

[Table 13 about here]

5.6 Firm-fixed effect

To address concerns regarding the endogeneity issue and assess the impact of CTO existence within firm variation, we conduct model 4 with firm fixed effect. The inclusion of firm fixed effects enables effective control for unobserved heterogeneity and time-invariant characteristics unique to each firm. This not only improves the precision of our parameter estimates but also alleviates potential endogeneity issues. Our results (not tabulated) remain consistent when incorporating both firm and year fixed effect, affirming that the presence of a CTO accelerates firm innovation efficiency.

6. Conclusion

This study examines the association between the existence of a CTO and innovation efficiency. We argue that the presence of a CTO improves firm innovation efficiency by increasing project success rates and reducing information asymmetry. Using a sample of 30,604 firm-year observations representing 3,817 unique firms from 2001 to 2016, we find evidence supporting our hypothesis that firms with a CTO exhibit higher innovation efficiency. The results remain robust when employing several alternative research designs, such as propensity score matching method, entropy balancing, Heckman models, Granger causality tests, etc. The regression coefficient on CTO with a technology background remains positive and significant, while CTO with a business background impedes firm innovation efficiency. Furthermore, considering the CEO as the major decision-maker, we also test whether CEOs with CTO experience is more likely to exhibit better innovation efficiency. Utilizing the same sample and controlling for firm and CEO characteristics, the results indicate that firms with CTO-experienced CEOs indeed demonstrate better innovation efficiency. Additionally, we conduct several cross-sectional analyses and find a positive and significant association between CTOs and firm innovation efficiency for firms in the high-intensity

R&D industry. This study contributes in two ways. Firstly, it adds to the existing literature on upper echelons theory by introducing the effect of CTO existence and CTO experience on innovative efficiency. Secondly, it contributes to the extensive literature on corporate innovation efficiency by providing support for the idea that CTOs, qualified CTOs, and CEOs with prior CTO experience can enhance firm innovation.

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Appendix A Variable Definitions

Dependent Variables

$IEPAT_{i\ t+3}$	=	The ratio of firm i's patents granted scaled by its R&D capital in year t+3. [R&D capital: The 5-year cumulative R&D expenses assuming an annual depreciation rate of 20% as in Chan, Lakonishok, and Sougiannis (2001) and Lev, Sarath, and Sougiannis (2005).]
$IECIT_{i,t+3}$	=	The adjusted number of citations occurring to firm i's patents filed over the previous 5 years (adjusted by average number of citations received in year t+3 by all patents of the same class over the previous 5 years) scaled by the sum of corresponding R&D expenses in year t+3.
$IEMKV_{i,t+3}$	=	The ratio of firm i's granted patents' value scaled by its R&D capital in year t+3.
$RDEXP_{i,t+1}$	=	Research and development (R&D) expenditure in year t+1 scaled by total assets at the end of fiscal year *t*, set to 0 if missing.
$LNPAT_{i,t+3}$	=	The natural logarithm of 1 plus firm i's total number of patents in year t+3.
$LNCIT_{i,t+3}$	=	The natural logarithm of 1 plus firm i's total number of citations received on the firm's patents in year t+3.
$LNMKV_{i,t+3}$	=	The natural logarithm of 1 plus firm i's total patents' value in year t+3.
$SUCCESSRATE_{i,t}$	=	The ratio of firm i's patent numbers scaled by its application number in year t.

Independent Variables

$CTO_{i,t}$	=	An indicator variable that takes a value of 1 if firm i have a Chief Technology Officer or equivalent director in year t; and 0 otherwise.
$TECHBACK_{i,t}$	=	An indicator variable that takes a value of 1 if firm i have a CTO with technology education or technology director-level practice background in year t; and 0 otherwise.
$BUSBACK_{i,t}$	=	An indicator variable that takes a value of 1 if firm i have a CTO with business education background or business-related working experience in year t; and 0 otherwise.
$TECHCEO_{i,t}$	=	An indicator variable that takes a value of 1 if firm i have a CEO with CTO career background in year t; and 0 otherwise.
$CTONETWORK_{i,t}$	=	The natural logarithm of 1 plus CTO's total number of networks in year t. The total number of networks equals the sum of professional network, educational network, and social connections.

Other Variables

$LNAT_{i,t}$	=	The natural log of firm i's total assets at the end of fiscal year t.
$LNFIRMAGE_{i,t}$	=	The natural log of 1 plus the firm i's age in year t, approximated by the number of years listed on Compustat Global.
$ROA_{i,t}$	=	Return on assets ratio, calculated as income before extraordinary items scaled by total assets at the end of fiscal year t.
$PPE_{i,t}$	=	Property, plant, and equipment scaled by total assets at the end of fiscal year t.
$LEV_{i,t}$	=	Firm *i*'s leverage ratio, defined as debt scaled by total assets at the end of fiscal year *t*.
$CAPEX_{i,t}$	=	Capital expenditure scaled by total assets at the end of fiscal year *t*.
$RDEXP_{i,t}$	=	Research and development (R&D) expenditure scaled by total assets at the end of fiscal year *t*, set to 0 if missing.
$TOBINQ_{i,t}$	=	The market value of assets divided by the book value of assets where the market value of assets equals the book value of assets plus the market value of common equity less the sum of the book value of common equity and balance sheet deferred taxes.
$KZINDEX_{i,t}$	=	Firm i's Kaplan and Zingales index measured at the end of fiscal year t, calculated as −1.002 * cash flow plus 0.283 * TobinQ plus 3.139 * Leverage minus 39.368 * dividends minus 1.315 * cash holdings

$HHI_{i,t}$	=	Herfindahl index of four-digit standard industrial classification (SIC) industry j where firm i belongs, measured at the end of fiscal year t. The index is based on the sales of all firms.
$HHI2_{i,t}$	=	$HHI_{i,t} \times HHI_{i,t}$.
$INSTOWN_{i,t}$	=	The institutional ownership in a firm, scaled by a firm's market capitalization.
$LNEMP_{i,t}$	=	The natural log of 1 plus the number of employees in firm i in year t
$LNCEOAGE_{i,t}$	=	The natural log of 1 plus firm i's CEO age in year t
$LNCEOTENURE_{i,t}$	=	The natural log of 1 plus the number of years since becoming CEO in firm i in year t
$DUALITY_{i,t}$	=	An indicator variable that takes a value of 1 if the CEO in firm i in year t is also the Chairman of the firm; and 0 otherwise.
$PATACTIVITY_{i}$	=	An indicator variable that takes a value of 1 if firm i have at least one patent in our sample period; and 0 otherwise.
$ICMW_{i,t}$	=	An indicator variable that takes a value of 1 if the firm i in year t contains at least one internal control material weakness in the auditor's report
$LNBOARD_{i,t}$	=	The natural log of 1 plus the number of board members in firm i in year t
$LNAUDIT_{i,t}$	=	The natural log of 1 plus the number of audit committee members in firm i in year t
$CIO_{i,t}$	=	An indicator variable that takes a value of 1 if firm i have a Chief Information/Innovation Officer or equivalent director in year t; and 0 otherwise.

Table 1 Sample Selection Procedure and Distribution

Panel A: Sample Selection

Sample	Firm-years
CRSP/Compustat Merged data over the period 2001–2016	97,664
Less:	
Firm-years missing total assets and net sales	10,876
Firm-years less than one million dollars in total assets and net sales	3,323
Firm-years with finance and utility industries	27,230
Firm-years missing director data from BoardEx	22,553
Firm-years without available control variables	3,078
Final sample (firm-years, 3,817 unique firms)	**30,604**

Panel B: Sample Distribution by Year

Year	CTO Sample	Non-CTO Sample	Total
2001	180	1,462	1,642
2002	191	1,575	1,766
2003	231	1,639	1,870
2004	256	1,792	2,048
2005	288	1,858	2,146
2006	293	1,845	2,138
2007	282	1,791	2,073
2008	289	1,702	1,991
2009	263	1,650	1,913
2010	267	1,599	1,866
2011	274	1,554	1,828
2012	295	1,519	1,814
2013	295	1,559	1,854
2014	316	1,581	1,897
2015	332	1,564	1,896
2016	332	1,530	1,862
Total	4,384	26,220	30,604

Panel C: Sample Distribution by Industry

Fama-French industry code (12 industries)	CTO Sample	Non-CTO Sample	Total
Consumer NonDurables -- Food, Tobacco, Textiles, Apparel, Leather, Toys	119	1,914	2,033
Consumer Durables -- Cars, TV's, Furniture, Household Appliances	151	785	936
Manufacturing -- Machinery, Trucks, Planes, Off Furn, Paper, Com Printing	487	3,855	4,342
Oil, Gas, and Coal Extraction and Products	51	1,499	1,550
Chemicals and Allied Products	154	926	1,080
Business Equipment -- Computers, Software, and Electronic Equipment	2,682	5,427	8,109
Wholesale, Retail, and Some Services (Laundries, Repair Shops)	141	3,988	4,129
Healthcare, Medical Equipment, and Drugs	322	4,055	4,377
Other -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment	277	3,771	4,048
Total	4,384	26,220	30,604

Table 2 Descriptive statistics

	CTO Firm					***Non CTO Firm***					***Test for mean difference***
	Mean	Std	P25	Median	P75	Mean	Std	P25	Median	P75	
Dependent variables											
$IEPAT_{i\ t+3}$	0.0634	0.1130	0	0	0.0805	0.0311	0.0900	0	0	0	-.0323***
$IECIT_{i\ t+3}$	0.0650	0.1399	0	0	0.0568	0.0282	0.0990	0	0	0	-.0368***
$IEMVE_{i\ \ t+3}$	0.4439	0.8246	0	0	0.4738	0.1623	0.5166	0	0	0	-.2816***
Independent variables											
$CTO_{i,t}$	1	0	1	1	1	0	0	0	0	0	/
$TECHBACK_{i,t}$	0.7286	0.4448	0	1	1	0	0	0	0	0	-.7286***
$BUSBACK_{i,t}$	0.3132	0.4638	0	0	1	0	0	0	0	0	-.3132***
$TECHCEO_{i,t}$	0.0420	0.2005	0	0	0	0.0115	0.1065	0	0	0	-.0305***
Control variables											
$LNAT_{i,t}$	6.6209	1.9669	5.1542	6.4091	8.0041	6.2010	1.8361	4.8716	6.1595	7.4895	-0.4199***
$LNFIRMAGE_{i,t}$	2.7280	0.8035	2.0794	2.7081	3.2958	2.8249	0.7526	2.3026	2.8332	3.4012	0.0969***
$ROA_{i,t}$	0.0682	0.1496	0.0250	0.0993	0.1512	0.0898	0.1454	0.0559	0.1129	0.1663	0.0216***
$PPE_{i,t}$	0.1407	0.1335	0.0498	0.0963	0.1810	0.2481	0.2250	0.0739	0.1721	0.3555	0.1074***
$LEV_{i,t}$	0.1469	0.1688	0	0.0927	0.2431	0.2020	0.1967	0.0092	0.1648	0.3226	0.0551***
$CAPEX_{i,t}$	0.0365	0.0350	0.0149	0.0258	0.0449	0.0474	0.0487	0.0159	0.0313	0.0593	0.0109***
$RDEXP_{i,t}$	0.0917	0.0876	0.0236	0.0739	0.1284	0.0439	0.0819	0	0.0016	0.0500	-0.0478***
$TOBINQ_{i,t}$	2.4117	1.4574	1.4068	1.9314	2.9328	1.9721	1.2868	1.1426	1.5411	2.3008	-0.4396***
$KZINDEX_{i,t}$	-9.9833	16.7544	-11.920	-4.3623	-0.7240	-7.7026	18.6154	-6.6724	-1.3670	0.4916	2.2807***
$HHI_{i,t}$	0.3420	0.2240	0.1711	0.2728	0.4263	0.3723	0.2326	0.1956	0.3006	0.4849	0.0303***
$HHI2_{i,t}$	0.1671	0.2275	0.0293	0.0744	0.1817	0.1927	0.2456	0.0383	0.0903	0.2351	0.0256***
$INSTOWN_{i,t}$	0.7424	0.2946	0.5742	0.8009	0.9522	0.6652	0.3408	0.3905	0.7302	0.9315	-0.0772***
$LNEMP_{i,t}$	1.4383	1.2994	0.3998	0.9422	2.2083	1.3435	1.1910	0.3347	1.0100	2.0660	-0.0948***
$LNCEOAGE_{i,t}$	4.0009	0.1419	3.9120	4.0073	4.0943	4.0323	0.1405	3.9318	4.0431	4.1271	0.0314***
$LNCEOTENURE_{i,t}$	1.2577	0.8026	0.6931	1.3863	1.7918	1.3934	0.8647	0.6931	1.3863	2.0794	0.1357***
$DUALITY_{i,t}$	0.5075	0.5000	0	1	1	0.5202	0.4996	0	1	1	0.0127
$ICMW_{i,t}$	0.0376	0.1903	0	0	0	0.0340	0.1813	0	0	0	-0.0036

Table 3 Correlation Matrix among selected variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) $IEPAT_{i\ t+3}$	1	**0.17**	**0.42**	**0.03**	**0.03**	0.00	0.00	**-0.03**	0.01	0.01	**-0.03**	**-0.04**	0.01	**0.02**	0.00	**0.02**	-0.01
(2) $IECIT_{i\ t+3}$	**0.64**	1	**0.03**	**0.04**	**0.04**	**0.01**	0.01	**-0.03**	**-0.03**	**-0.01**	**-0.02**	**-0.02**	**0.02**	**0.02**	0.00	0.00	-0.01
(3) $IEMVE_{i\ t+3}$	**0.99**	**0.64**	1	**0.05**	**0.05**	**0.03**	0.00	**0.11**	**0.04**	**0.03**	-0.01	**-0.01**	0.00	**0.07**	0.00	**0.01**	**0.04**
(4) $CTO_{i,t}$	**0.20**	**0.18**	**0.21**	1	**0.83**	**0.53**	**0.09**	**0.08**	**-0.04**	**-0.04**	**-0.17**	**-0.09**	**0.15**	**0.10**	0.01	**-0.05**	**0.08**
(5) $TECHBACK_{i,t}$	**0.19**	**0.17**	**0.20**	**0.83**	1	**0.51**	**0.07**	**0.10**	-0.01	**-0.03**	**-0.14**	**-0.08**	**0.13**	**0.08**	0.01	**-0.03**	**0.08**
(6) $BUSBACK_{i,t}$	**0.10**	**0.08**	**0.11**	**0.53**	**0.51**	1	**0.04**	**0.11**	**0.04**	0.00	**-0.07**	**-0.03**	**0.05**	**0.04**	0.00	**-0.02**	**0.06**
(7) $TECHCEO_{i,t}$	**0.06**	**0.07**	**0.06**	**0.09**	**0.07**	**0.04**	1	**-0.01**	**-0.03**	**-0.04**	**-0.06**	**-0.03**	**0.07**	**0.02**	0.00	**-0.05**	-0.01
(8) $LNAT_{i,t}$	**0.13**	**0.08**	**0.19**	**0.07**	**0.08**	**0.10**	**-0.01**	1	**0.31**	**0.32**	**0.19**	**0.25**	**-0.28**	**-0.12**	0.01	**0.01**	**0.51**
(9) $LNFIRMAGE_{i,t}$	**0.08**	**0.03**	**0.10**	**-0.05**	**-0.01**	**0.03**	**-0.03**	**0.30**	1	**0.19**	**0.07**	**0.02**	**-0.19**	**-0.19**	0.00	**0.17**	**0.10**
(10) $ROA_{i,t}$	0.00	**-0.03**	**0.02**	**-0.06**	**-0.04**	**0.01**	**-0.05**	**0.32**	**0.20**	1	**0.15**	0.00	**-0.60**	**-0.10**	**-0.03**	**0.07**	**0.21**
(11) $PPE_{i,t}$	**-0.11**	**-0.09**	**-0.10**	**-0.17**	**-0.13**	**-0.06**	**-0.07**	**0.22**	**0.16**	**0.27**	1	**0.25**	**-0.27**	**-0.16**	**0.02**	0.00	**-0.05**
(12) $LEV_{i,t}$	**-0.10**	**-0.11**	**-0.07**	**-0.10**	**-0.08**	**-0.03**	**-0.04**	**0.38**	**0.10**	**0.07**	**0.31**	1	**-0.12**	**-0.06**	**-0.03**	**0.02**	**0.04**
(13) $RDEXP_{i,t}$	**0.47**	**0.43**	**0.47**	**0.29**	**0.26**	**0.13**	**0.12**	**-0.23**	**-0.13**	**-0.30**	**-0.40**	**-0.31**	1	**0.33**	0.00	**-0.15**	**-0.09**
(14) $TOBINQ_{i,t}$	**0.20**	**0.13**	**0.22**	**0.14**	**0.12**	**0.07**	**0.03**	**-0.03**	**-0.16**	**0.25**	**-0.19**	**-0.21**	**0.34**	1	**-0.01**	**-0.10**	**0.02**
(15) $KZINDEX_{i,t}$	**-0.18**	**-0.14**	**-0.19**	**-0.14**	**-0.12**	**-0.07**	**-0.05**	**0.05**	**-0.04**	**-0.07**	**0.59**	**0.47**	**-0.31**	**-0.32**	1	**0.01**	0.00
(16) $HHI_{i,t}$	**-0.01**	**-0.03**	**-0.01**	**-0.06**	**-0.04**	**-0.02**	**-0.05**	0.00	**0.17**	**0.06**	**0.07**	**0.05**	**-0.14**	**-0.11**	**0.04**	1	**-0.06**
(17) $INSTOWN_{i,t}$	**0.11**	**0.10**	**0.13**	**0.07**	**0.08**	**0.05**	**-0.01**	**0.53**	**0.08**	**0.22**	**-0.02**	**0.08**	**-0.02**	**0.11**	**-0.07**	**-0.06**	1

Table 3 presents Pearson correlations (in the upper triangle) and Spearman correlations (in the lower triangle) among selected variables. Bold text indicates a statistical significance (p-value < 0.05). The sample comprises 4,384 firm-year observations for CTO firms and 26,220 firm-year observations for non-CTO firms as the final sample during the period from 2001 to 2016. All variable definitions are provided in Appendix A.

Table 4. The effect of Corporate Technology Officer on corporate innovation efficiency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. variable	$IEPAT_{i\ t+3}$	$IECIT_{i\ t+3}$	$IEMVE_{i\ t+3}$	$IEPAT_{i\ t+3}$	$IECIT_{i\ t+3}$	$IEMVE_{i\ t+3}$	$IEPAT_{i\ t+3}$	$IECIT_{i\ t+3}$	$IEMVE_{i\ t+3}$
$CTO_{i,t}$	**0.0170*** **	**0.0174** **	**0.1563*** **	**0.0179*** **	**0.0203*** **	**0.1718*** **	**0.0180*** **	**0.0203** **	**0.1723*** **
	(4.70)	**(2.17)**	**(2.77)**	**(5.38)**	**(2.62)**	**(2.65)**	**(5.33)**	**(2.57)**	**(2.63)**
$LNAT_{i,t}$	0.0046	0.0058	0.0972***	0.0041	0.0051	0.1046***	0.0042	0.0051	0.1050***
	(1.28)	(1.49)	(3.35)	(1.01)	(1.31)	(2.98)	(1.03)	(1.34)	(3.05)
$LNFIRMAGE_{i,t}$	0.0026*	0.0011	0.0364***	0.0020	0.0001	0.0324***	0.0020	0.0001	0.0326***
	(1.66)	(0.64)	(3.71)	(1.36)	(0.06)	(2.72)	(1.39)	(0.05)	(2.71)
$ROA_{i,t}$	0.0142*	-0.0035	0.0570*	0.0161	0.0047	0.0725	0.0162	0.0047	0.0729
	(1.70)	(-0.31)	(1.68)	(1.42)	(0.52)	(1.50)	(1.42)	(0.52)	(1.51)
$PPE_{i,t}$	-0.0163	-0.0083	-0.1752***	-0.0189	-0.0059	-0.2205***	-0.0190	-0.0058	-0.2224***
	(-1.39)	(-0.69)	(-3.13)	(-1.49)	(-0.44)	(-3.12)	(-1.49)	(-0.42)	(-3.12)
$LEV_{i,t}$	-0.0327***	-0.0315***	-0.1189***	-0.0339***	-0.0317***	-0.1356***	-0.0339***	-0.0317***	-0.1356***
	(-3.47)	(-3.41)	(-2.88)	(-3.50)	(-3.09)	(-2.82)	(-3.50)	(-3.09)	(-2.82)
$CAPEX_{i,t}$	0.0741	0.0510	0.3354	0.0857*	0.0421	0.3580	0.0859*	0.0420	0.3600
	(1.64)	(1.23)	(1.16)	(1.79)	(1.30)	(1.07)	(1.81)	(1.30)	(1.08)
$RDEXP_{i,t}$	0.0335	0.0877*	0.2859***	0.0266	0.0960*	0.2782**	0.0266	0.0960*	0.2784**
	(1.21)	(1.75)	(2.61)	(0.87)	(1.73)	(2.02)	(0.87)	(1.73)	(2.03)
$TOBINQ_{i,t}$	0.0060***	0.0043***	0.0866***	0.0061***	0.0040***	0.0968***	0.0061***	0.0040***	0.0969***
	(3.39)	(2.77)	(5.66)	(3.53)	(2.81)	(6.17)	(3.57)	(2.81)	(6.23)
$KZINDEX_{i,t}$	0.0001***	0.0001***	0.0007***	0.0001***	0.0001***	0.0010***	0.0001***	0.0001***	0.0010***
	(3.01)	(3.60)	(2.84)	(2.76)	(3.80)	(3.00)	(2.76)	(3.63)	(3.01)
$HHI_{i,t}$	0.0105	-0.0090	0.1137	0.0041	-0.0112	0.0338	0.0041	-0.0112	0.0344
	(0.24)	(-0.18)	(0.71)	(0.08)	(-0.21)	(0.19)	(0.08)	(-0.21)	(0.19)
$HHI2_{i,t}$	-0.0001	0.0078	0.0160	0.0061	0.0114	0.1101	0.0061	0.0115	0.1096
	(-0.00)	(0.17)	(0.11)	(0.13)	(0.24)	(0.70)	(0.13)	(0.24)	(0.69)
$INSTOWN_{i,t}$	-0.0048	0.0071*	-0.1322***	-0.0101	0.0032	-0.1757***	-0.0101	0.0032	-0.1754***
	(-0.82)	(1.94)	(-3.02)	(-1.43)	(0.55)	(-3.03)	(-1.42)	(0.54)	(-3.00)
$LNEMP_{i,t}$	-0.0026	-0.0046	0.0137	-0.0026	-0.0039	0.0139	-0.0026	-0.0040	0.0145
	(-0.73)	(-1.16)	(0.34)	(-0.70)	(-0.95)	(0.31)	(-0.68)	(-0.93)	(0.32)
$LNCEOAGE_{i,t}$	0.0042	0.0085	-0.0622	-0.0009	0.0100	-0.0922	-0.0010	0.0101	-0.0934
	(0.48)	(0.78)	(-1.08)	(-0.11)	(0.85)	(-1.38)	(-0.12)	(0.83)	(-1.35)
$LNCEOTENURE_{i,t}$	0.0013	0.0011	0.0106	0.0025*	0.0026	0.0160*	0.0025*	0.0026	0.0160*
	(1.09)	(0.84)	(1.16)	(1.79)	(1.61)	(1.86)	(1.77)	(1.61)	(1.83)
$DUALITY_{i,t}$	0.0041*	0.0016	0.0321	0.0051**	0.0020	0.0348	0.0051**	0.0020	0.0350
	(1.84)	(0.67)	(1.37)	(2.19)	(0.81)	(1.24)	(2.17)	(0.80)	(1.23)

$ICMW_{i,t}$	-0.0039**	0.0050*	-0.0503***	-0.0021**	0.0083**	-0.0460***	-0.0021**	0.0083**	-0.0461***
	(-2.41)	(1.82)	(-3.76)	(-2.50)	(2.48)	(-2.85)	(-2.53)	(2.48)	(-2.84)
$LNBOARD_{i,t}$				0.0059*	0.0047	0.0241	0.0059*	0.0047	0.0243
				(1.90)	(1.15)	(1.21)	(1.92)	(1.16)	(1.20)
$LNAUDIT_{i,t}$				0.0008	0.0009	0.0386	0.0009	0.0009	0.0390
				(0.07)	(0.12)	(0.70)	(0.08)	(0.12)	(0.71)
$CIO_{i,t}$							-0.0007	0.0007	-0.0091
							(-0.23)	(0.24)	(-0.36)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	30,604	30,604	30,604	25,194	25,194	25,194	25,194	25,194	25,194
Adj. R^2	0.0948	0.112	0.179	0.0968	0.114	0.185	0.0968	0.114	0.185

This table presents the results of testing the association between Corporate Technology Officer and corporate innovation efficiency. We use three proxies for corporate innovation efficiency as dependent variables in the analyses, that is, $IEPAT_{i\ t+3}$, $IECIT_{i\ t+3}$, and $IEMVE_{i\ t+3}$. *t*-statistics are reported in parentheses, based on standard errors clustered by year and industry. The sample comprises 4,384 firm-year observations for CTO firms and 26,220 firm-year observations for non-CTO firms as the final sample during the period from 2001 to 2016. Variable definitions are provided in Appendix A. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Table 5. The effect of Corporate Technology Officer qualification on corporate innovation efficiency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. variable	***IEPAT*** $_{i\ t+3}$	***IECIT*** $_{i\ t+3}$	***IEMVE*** $_{i\ t+3}$	***IEPAT*** $_{i\ t+3}$	***IECIT*** $_{i\ t+3}$	***IEMVE*** $_{i\ t+3}$	***IEPAT*** $_{i\ t+3}$	***IECIT*** $_{i\ t+3}$	***IEMVE*** $_{i\ t+3}$
CTO $_{i,t}$	**0.0051***	**0.0030****	**0.0270**	**0.0061*****	**0.0036*****	**0.0304****	**0.0079*****	**0.0053*****	**0.0390****
	(1.89)	**(2.13)**	**(1.64)**	**(2.89)**	**(2.93)**	**(2.04)**	**(2.86)**	**(3.49)**	**(2.21)**
TECHBACK $_{i,t}$	**0.0052****	**0.0032****	**0.0320*****	**0.0059****	**0.0036****	**0.0342*****	**0.0034**	**0.0011**	**0.0216**
	(2.24)	**(2.26)**	**(2.93)**	**(2.53)**	**(2.49)**	**(3.09)**	**(1.20)**	**(0.82)**	**(1.56)**
BUSBACK $_{i,t}$				**-0.0049**	**-0.0031***	**-0.0159**	**-0.0131*****	**-0.0113*****	**-0.0570*****
				(-1.62)	**(-1.79)**	**(-1.23)**	**(-4.99)**	**(-5.02)**	**(-4.02)**
TECHBACK* x *BUSBACK $_{i,t}$							**0.0105***	**0.0105*****	**0.0523***
							(1.87)	**(3.00)**	**(1.96)**
LNAT $_{i,t}$	0.0039*	0.0033**	0.0393***	0.0039*	0.0033**	0.0394***	0.0039*	0.0033**	0.0394***
	(1.86)	(2.14)	(2.97)	(1.85)	(2.13)	(2.97)	(1.86)	(2.14)	(2.97)
LNFIRMAGE $_{i,t}$	0.0033***	0.0017**	0.0226***	0.0034***	0.0017**	0.0228***	0.0034***	0.0017**	0.0228***
	(3.04)	(2.02)	(4.72)	(3.00)	(2.01)	(4.70)	(3.01)	(2.02)	(4.72)
ROA $_{i,t}$	0.0115*	-0.0023	0.0691***	0.0117*	-0.0022	0.0699***	0.0118*	-0.0021	0.0704***
	(1.73)	(-0.39)	(2.82)	(1.73)	(-0.38)	(2.85)	(1.75)	(-0.37)	(2.90)
PPE $_{i,t}$	-0.0082	-0.0016	-0.0622*	-0.0083	-0.0016	-0.0623*	-0.0082	-0.0015	-0.0618*
	(-1.13)	(-0.41)	(-1.95)	(-1.15)	(-0.42)	(-1.97)	(-1.14)	(-0.39)	(-1.96)
LEV $_{i,t}$	-0.0148***	-0.0106***	-0.0307*	-0.0148***	-0.0106***	-0.0307*	-0.0149***	-0.0106***	-0.0310*
	(-2.74)	(-3.10)	(-1.66)	(-2.75)	(-3.09)	(-1.66)	(-2.76)	(-3.11)	(-1.68)
CAPEX $_{i,t}$	0.0599***	0.0331**	0.2781***	0.0600***	0.0332**	0.2786***	0.0599***	0.0331**	0.2778***
	(2.94)	(2.38)	(3.03)	(2.93)	(2.36)	(3.03)	(2.92)	(2.34)	(3.01)
RDEXP $_{i,t}$	0.1287***	0.1203***	0.6198***	0.1284***	0.1201***	0.6188***	0.1281***	0.1198***	0.6173***
	(3.75)	(4.30)	(4.88)	(3.74)	(4.30)	(4.86)	(3.75)	(4.31)	(4.86)
TOBINQ $_{i,t}$	0.0036**	0.0011*	0.0372***	0.0036**	0.0011*	0.0372***	0.0036***	0.0011*	0.0373***
	(2.58)	(1.84)	(3.83)	(2.59)	(1.85)	(3.83)	(2.62)	(1.90)	(3.86)
KZINDEX $_{i,t}$	0.0001	0.0000	-0.0000	0.0001	0.0000	-0.0000	0.0001*	0.0000	-0.0000
	(1.62)	(1.03)	(-0.11)	(1.64)	(1.06)	(-0.10)	(1.67)	(1.08)	(-0.09)
HHI $_{i,t}$	-0.0045	-0.0019	-0.0135	-0.0042	-0.0017	-0.0127	-0.0045	-0.0020	-0.0141
	(-0.11)	(-0.08)	(-0.11)	(-0.10)	(-0.08)	(-0.10)	(-0.11)	(-0.09)	(-0.12)
HHI2 $_{i,t}$	0.0128	0.0055	0.0610	0.0125	0.0053	0.0600	0.0128	0.0057	0.0616
	(0.28)	(0.21)	(0.45)	(0.28)	(0.21)	(0.45)	(0.29)	(0.22)	(0.47)
INSTOWN $_{i,t}$	-0.0014	0.0024**	-0.0423***	-0.0015	0.0024**	-0.0426***	-0.0015	0.0024**	-0.0424***
	(-0.57)	(2.37)	(-2.91)	(-0.60)	(2.34)	(-2.90)	(-0.58)	(2.39)	(-2.91)

$LNEMP_{i,t}$	-0.0001	-0.0007	0.0102	-0.0000	-0.0007	0.0103	-0.0001	-0.0007	0.0102
	(-0.04)	(-0.55)	(0.90)	(-0.02)	(-0.54)	(0.92)	(-0.03)	(-0.55)	(0.91)
$LNCEOAGE_{i,t}$	0.0015	0.0036	-0.0207	0.0017	0.0037	-0.0203	0.0016	0.0036	-0.0207
	(0.30)	(1.21)	(-1.01)	(0.33)	(1.22)	(-0.99)	(0.31)	(1.21)	(-1.01)
$LNCEOTENURE_{i,t}$	0.0006	0.0002	0.0035	0.0006	0.0001	0.0034	0.0006	0.0002	0.0035
	(1.24)	(0.34)	(1.22)	(1.22)	(0.31)	(1.22)	(1.24)	(0.33)	(1.23)
$DUALITY_{i,t}$	0.0014*	0.0004	0.0120*	0.0014*	0.0004	0.0120*	0.0014*	0.0004	0.0122*
	(1.91)	(0.57)	(1.96)	(1.87)	(0.55)	(1.93)	(1.91)	(0.60)	(1.97)
$ICMW_{i,t}$	-0.0015	0.0010	-0.0128**	-0.0015	0.0010	-0.0128***	-0.0015	0.0010	-0.0128***
	(-1.33)	(1.23)	(-2.61)	(-1.33)	(1.24)	(-2.62)	(-1.33)	(1.24)	(-2.63)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	30,604	30,604	30,604	30,604	30,604	30,604	30,604	30,604	30,604
Adj. R^2	0.183	0.235	0.258	0.184	0.235	0.258	0.184	0.236	0.259

This table presents the results of testing the association between Corporate Technology Officer technological and educational qualification and corporate innovation efficiency. We use three proxies for corporate innovation efficiency as dependent variables in the analyses, that is, $IEPAT_{i\ t+3}$, $IECIT_{i\ t+3}$, and $IEMVE_{i\ t+3}$. *t*-statistics are reported in parentheses, based on standard errors clustered by year and industry. The sample comprises 4,384 firm-year observations for CTO firms and 26,220 firm-year observations for non-CTO firms as the final sample during the period from 2001 to 2016. Variable definitions are provided in Appendix A. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respective

Table 6. The effect of Corporate Technology Officer and Tech CEO on corporate innovation efficiency

	(1)	(2)	(3)
Dep. variable	***$IEPAT_{i\ t+3}$***	***$IECIT_{i\ t+3}$***	***$IEMVE_{i\ t+3}$***
$CTO_{i,t}$	**0.0088*****	**0.0052****	**0.0499*****
	(3.54)	**(2.58)**	**(4.01)**
$TECHCEO_{i,t}$	**0.0062****	**0.0053****	**0.0154**
	(2.23)	**(2.11)**	**(1.35)**
$LNAT_{i,t}$	0.0039*	0.0033**	0.0395***
	(1.86)	(2.14)	(2.96)
$LNFIRMAGE_{i,t}$	0.0034***	0.0017**	0.0229***
	(3.05)	(2.04)	(4.69)
$ROA_{i,t}$	0.0118*	-0.0022	0.0705***
	(1.77)	(-0.36)	(2.87)
$PPE_{i,t}$	-0.0082	-0.0015	-0.0619*
	(-1.14)	(-0.41)	(-1.96)
$LEV_{i,t}$	-0.0149***	-0.0106***	-0.0311*
	(-2.73)	(-3.11)	(-1.68)
$CAPEX_{i,t}$	0.0602***	0.0334**	0.2795***
	(2.95)	(2.39)	(3.04)
$RDEXP_{i,t}$	0.1287***	0.1200***	0.6239***
	(3.83)	(4.35)	(5.09)
$TOBINQ_{i,t}$	0.0036**	0.0011*	0.0371***
	(2.57)	(1.83)	(3.82)
$KZINDEX_{i,t}$	0.0001*	0.0000	-0.0000
	(1.66)	(1.09)	(-0.04)
$HHI_{i,t}$	-0.0045	-0.0019	-0.0140
	(-0.11)	(-0.08)	(-0.11)
$HHI2_{i,t}$	0.0132	0.0058	0.0628
	(0.29)	(0.22)	(0.46)
$INSTOWN_{i,t}$	-0.0013	0.0025**	-0.0420***
	(-0.53)	(2.43)	(-2.85)
$LNEMP_{i,t}$	-0.0001	-0.0007	0.0102
	(-0.05)	(-0.56)	(0.90)
$LNCEOAGE_{i,t}$	0.0016	0.0036	-0.0204
	(0.30)	(1.20)	(-0.99)
$LNCEOTENURE_{i,t}$	0.0006	0.0002	0.0036
	(1.29)	(0.38)	(1.25)
$DUALITY_{i,t}$	0.0014*	0.0004	0.0119*
	(1.93)	(0.58)	(1.90)
$ICMW_{i,t}$	-0.0016	0.0010	-0.0132***
	(-1.43)	(1.16)	(-2.71)
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Obs.	30,604	30,604	30,604
Adj. R^2	0.183	0.235	0.258

This table presents the results of testing the association between Corporate Technology Officer together with Tech CEO and corporate innovation efficiency. We use three proxies for corporate innovation efficiency as dependent variables in the analyses, that is, $IEPAT_{i\ t+3}$, $IECIT_{i\ t+3}$, and $IEMVE_{i\ t+3}$. *t*-statistics are reported in parentheses, based on standard errors clustered by year and industry. The sample comprises 4,384 firm-year observations for CTO firms and 26,220 firm-year observations for non-CTO firms as the final sample during the period from 2001 to 2016. Variable definitions are provided in Appendix A. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Table 7. The effect of Corporate Technology Officer on corporate patent success rate

	(1)	(2)
Dep. variable	$SUCCESSRATE_{,i\ t}$	$SUCCESSRATE_{i,t}$
$CTO_{i,t}$	0.0489***	0.0482***
	(3.70)	(3.90)
$PATACTIVITY_i$	0.2929***	0.2937***
	(11.09)	(11.15)
$LNAT_{i,t}$	0.0418***	0.0477***
	(4.91)	(3.95)
$LNFIRMAGE_{i,t}$	0.0190***	0.0176**
	(2.93)	(2.50)
$ROA_{i,t}$	0.0481**	0.0600**
	(2.01)	(2.16)
$PPE_{i,t}$	-0.0697*	-0.0789**
	(-1.86)	(-2.15)
$LEV_{i,t}$	-0.0524**	-0.0574**
	(-2.10)	(-2.44)
$CAPEX_{i,t}$	0.1572	0.1886*
	(1.49)	(1.68)
$RDEXP_{i,t}$	0.6500***	0.6672***
	(4.73)	(4.78)
$TOBINQ_{i,t}$	0.0043*	0.0049***
	(1.89)	(2.72)
$KZINDEX_{i,t}$	0.0002	0.0002
	(0.97)	(1.38)
$HHI_{i,t}$		0.0159
		(0.16)
$HHI2_{i,t}$		0.0074
		(0.08)
$INSTOWN_{i,t}$		-0.0390***
		(-4.81)
$LNEMP_{i,t}$		-0.0032
		(-0.24)
$LNCEOAGE_{i,t}$		0.0073
		(0.33)
$LNCEOTENURE_{i,t}$		-0.0008
		(-0.21)
$DUALITY_{i,t}$		0.0046
		(0.43)
$ICMW_{i,t}$		0.0131**
		(2.22)
Year FE	YES	YES
Industry FE	YES	YES
Obs.	30,604	30,604
Adj. R^2	0.354	0.355

This table presents the results of testing the association between Corporate Technology Officer together with Tech CEO and corporate innovation efficiency. We use three proxies for corporate innovation efficiency as dependent variables in the analyses, that is, $IEPAT_{i\ t+3}$, $IECIT_{i\ t+3}$, and $IEMVE_{i\ t+3}$. *t*-statistics are reported in parentheses, based on standard errors clustered by year and industry. The sample comprises 4,384 firm-year observations for CTO firms and 26,220 firm-year observations for non-CTO firms as the final sample during the period from 2001 to 2016. Variable definitions are provided in Appendix A. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Table 8. The effect of Corporate Technology Officer network on corporate innovation efficiency

	(1)	(2)	(3)
Dep. variable	***$IEPAT_{i\ t+3}$***	***$IECIT_{i\ t+3}$***	***$IEMVE_{i\ t+3}$***
$CTONETWORK_{i,t}$	0.0026***	0.0026**	0.0259***
	(5.25)	(2.24)	(2.84)
$LNAT_{i,t}$	0.0045	0.0057	0.0955***
	(1.26)	(1.47)	(3.30)
$LNFIRMAGE_{i,t}$	0.0025	0.0010	0.0358***
	(1.63)	(0.59)	(3.72)
$ROA_{i,t}$	0.0141*	-0.0037	0.0556
	(1.68)	(-0.32)	(1.65)
$PPE_{i,t}$	-0.0161	-0.0081	-0.1715***
	(-1.36)	(-0.67)	(-3.06)
$LEV_{i,t}$	-0.0327***	-0.0315***	-0.1177***
	(-3.47)	(-3.42)	(-2.83)
$CAPEX_{i,t}$	0.0728	0.0498	0.3198
	(1.62)	(1.21)	(1.11)
$RDEXP_{i,t}$	0.0328	0.0871*	0.2722**
	(1.17)	(1.72)	(2.48)
$TOBINQ_{i,t}$	0.0060***	0.0043***	0.0863***
	(3.39)	(2.77)	(5.64)
$KZINDEX_{i,t}$	0.0001***	0.0001***	0.0007***
	(2.99)	(3.59)	(2.86)
$HHI_{i,t}$	0.0100	-0.0095	0.1078
	(0.22)	(-0.19)	(0.68)
$HHI2_{i,t}$	0.0002	0.0080	0.0190
	(0.00)	(0.18)	(0.13)
$INSTOWN_{i,t}$	-0.0045	0.0074**	-0.1297***
	(-0.79)	(1.99)	(-2.98)
$LNEMP_{i,t}$	-0.0027	-0.0046	0.0130
	(-0.75)	(-1.19)	(0.33)
$LNCEOAGE_{i,t}$	0.0039	0.0081	-0.0644
	(0.45)	(0.75)	(-1.12)
$LNCEOTENURE_{i,t}$	0.0013	0.0012	0.0109
	(1.09)	(0.85)	(1.19)
$DUALITY_{i,t}$	0.0041*	0.0017	0.0324
	(1.86)	(0.69)	(1.42)
$ICMW_{i,t}$	-0.0038**	0.0051*	-0.0495***
	(-2.40)	(1.83)	(-3.75)
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Obs.	30,604	30,604	30,604
Adj. R^2	0.0950	0.112	0.181

This table presents the results of testing the association between Corporate Technology Officer together with Tech CEO and corporate innovation efficiency. We use three proxies for corporate innovation efficiency as dependent variables in the analyses, that is, $IEPAT_{i\ t+3}$, $IECIT_{i\ t+3}$, and $IEMVE_{i\ t+3}$. *t*-statistics are reported in parentheses, based on standard errors clustered by year and industry. The sample comprises 4,384 firm-year observations for CTO firms and 26,220 firm-year observations for non-CTO firms as the final sample during the period from 2001 to 2016. Variable definitions are provided in Appendix A. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Table 9 The effect of Corporate Technology Officer on corporate innovation input and output

	(1)	(2)	(3)	(4)
	Input	***Output***		
Dep. variable	$\boldsymbol{RDEXP_{i,t+1}}$	$\boldsymbol{LNPAT_{i\ t+3}}$	$\boldsymbol{LNCIT_{i\ t+3}}$	$\boldsymbol{LNMKV_{i\ t+3}}$
$\boldsymbol{CTO_{i,t}}$	0.0022***	0.4691***	0.4772***	0.6687***
	(2.88)	(4.12)	(2.99)	(3.80)
$LNAT_{i,t}$	0.0022***	0.3369***	0.3998***	0.6355***
	(2.67)	(3.16)	(3.12)	(3.90)
$LNFIRMAGE_{i,t}$	-0.0023*	0.1569***	0.1351***	0.2990***
	(-1.92)	(4.99)	(4.32)	(6.27)
$ROA_{i,t}$	0.0048	0.5723***	0.5146***	0.7938***
	(0.38)	(4.21)	(3.37)	(3.74)
$PPE_{i,t}$	0.0009	-0.5203***	-0.5355**	-0.8879***
	(0.74)	(-2.74)	(-2.25)	(-3.32)
$LEV_{i,t}$	-0.0109**	-0.4178***	-0.5119***	-0.5441***
	(-2.35)	(-3.34)	(-3.26)	(-4.08)
$CAPEX_{i,t}$	-0.0119**	1.3824**	1.6875*	2.0565**
	(-2.22)	(2.29)	(1.91)	(2.27)
$RDEXP_{i,t}$	0.8526***	3.7075***	4.1935***	5.5884***
	(66.66)	(7.38)	(6.54)	(8.79)
$TOBINQ_{i,t}$	0.0050***	0.0926***	0.1189***	0.2400***
	(3.91)	(4.62)	(4.16)	(6.99)
$KZINDEX_{i,t}$	-0.0001*	0.0011**	0.0014	0.0017*
	(-1.96)	(2.10)	(1.42)	(1.73)
$HHI_{i,t}$	-0.0084***	-0.1638	0.0087	-0.0921
	(-2.86)	(-0.36)	(0.01)	(-0.17)
$HHI2_{i,t}$	0.0074***	0.3635	0.2500	0.4501
	(3.01)	(0.80)	(0.43)	(0.79)
$INSTOWN_{i,t}$	-0.0000	-0.4248***	-0.3736***	-0.8067***
	(-0.02)	(-5.10)	(-4.24)	(-6.81)
$LNEMP_{i,t}$	-0.0028***	0.0377	0.0070	0.0692
	(-2.72)	(0.42)	(0.07)	(0.47)
$LNCEOAGE_{i,t}$	-0.0044***	-0.1235	-0.0397	-0.2990
	(-4.84)	(-0.76)	(-0.18)	(-1.31)
$LNCEOTENURE_{i,t}$	0.0003	0.0320	0.0340	0.0470
	(1.22)	(1.54)	(1.39)	(1.33)
$DUALITY_{i,t}$	0.0003	0.0655	0.0600	0.1128
	(0.58)	(1.29)	(1.09)	(1.38)
$ICMW_{i,t}$	-0.0028	-0.0958***	-0.1034**	-0.1817***
	(-1.49)	(-2.75)	(-2.33)	(-3.67)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Obs.	30,604	30,604	30,604	30,604
Adj. R^2	0.808	0.360	0.316	0.402

This table presents the results of testing the association between Corporate Technology Officer and corporate innovation. We use $RDEXP_{i,t+1}$ to proxy for innovation input and three proxies for corporate innovation output as dependent variables in the analyses, that is, $INPAT_{i\ t+3}$, $INCIT_{i\ t+3}$, and $INMVE_{i\ t+3}$. *t*-statistics are reported in parentheses, based on standard errors clustered by year and industry. The sample comprises 4,384 firm-year observations for CTO firms and 26,220 firm-year observations for non-CTO firms as the final sample during the period from 2001 to 2016. Variable definitions are provided in Appendix A. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Table 10 Panel A Propensity Score Matching

This table summarize our propensity score matching procedure. Variables are matched along log total assets (LNAT); log firm age (LNFIRMAGE); return on assets (ROA); property, plant, equipment scaled by total assets (PPE); leverage ratio (LEV); capital expenditure scaled by total assets (CAPEX); research and development expenditure scaled by total assets (RDEXP); the market value of assets divided by the book value of assets (TOBINQ); Kaplan and Zingales index (KZINDEX); Herfindahl index (HHI); the square of Herfindahl index (HHI2); the institutional ownership (INSTOWN); log the number of employees (LNEMP); log CEO age (LNCEOAGE); log CEO tenure (LNCEOTENURE); whether CEO is chairman of the company (DUALITY); whether the firm have internal control material weakness (ICMW). Refer to Appendix A for further variable definitions. The mean values, differences, and p-values for each variable are reported before and after matching. Continuous variables are winsorized at 2 percent tails.

	Before Matching				**After Matching**			
	Means				***Means***			
	CTO=1	***CTO=0***	***Difference***	***p-value***	***CTO=1***	***CTO=0***	***Difference***	***p-value***
$LNAT_{i,t}$	6.6209	6.2010	-0.4200	0.000	6.5864	6.5072	-0.0790	0.0540
$LNFIRMAGE_{i,t}$	2.7280	2.8249	0.0970	0.000	2.7421	2.7468	0.0050	0.7820
$ROA_{i,t}$	0.0682	0.0898	0.0220	0.000	0.0701	0.0683	-0.0020	0.5770
$PPE_{i,t}$	0.1407	0.2481	0.1070	0.000	0.1415	0.1380	-0.0040	0.2170
$LEV_{i,t}$	0.1469	0.2020	0.0550	0.000	0.1483	0.1468	-0.0020	0.6770
$CAPEX_{i,t}$	0.0365	0.0474	0.0110	0.000	0.0356	0.0351	-0.0010	0.4030
$RDEXP_{i,t}$	0.0917	0.0439	-0.0480	0.000	0.0874	0.0872	0.0000	0.9240
$TOBINQ_{i,t}$	2.4117	1.9721	-0.4400	0.000	2.3642	2.3285	-0.0360	0.2640
$KZINDEX_{i,t}$	-9.9833	-7.7026	2.2800	0.000	-9.6832	-9.4329	0.2510	0.4640
$HHI_{i,t}$	0.3420	0.3723	0.0300	0.000	0.3432	0.3339	-0.0090	0.0540
$HHI2_{i,t}$	0.1671	0.1927	0.0260	0.000	0.1681	0.1585	-0.0090	0.0480
$INSTOWN_{i,t}$	0.7424	0.6652	-0.0770	0.000	0.7433	0.7394	-0.0040	0.5470
$LNEMP_{i,t}$	1.4383	1.3435	-0.0950	0.000	1.4291	1.4006	-0.0290	0.2930
$LNCEOAGE_{i,t}$	4.0009	4.0323	0.0320	0.000	4.0023	4.0027	0.0010	0.8940
$LNCEOTENURE_{i,t}$	1.2577	1.3934	0.1360	0.000	1.2684	1.2883	0.0200	0.2670
$DUALITY_{i,t}$	0.5075	0.5202	0.0130	0.120	0.5061	0.5059	0.0000	0.9870
$ICMW_{i,t}$	0.0376	0.0340	-0.0040	0.225	0.0385	0.0417	0.0030	0.4590

Panel B The effect of Corporate Technology Officer on corporate innovation efficiency using propensity score matching

	(1)	(2)	(3)
Dep. variable	$IEPAT_{i\ t+3}$	$IECIT_{i\ t+3}$	$IEMVE_{i\ t+3}$
$CTO_{i,t}$	0.0139***	0.0122*	0.1075**
	(3.43)	(1.79)	(2.31)
$LNAT_{i,t}$	0.0124*	0.0145**	0.1940***
	(1.81)	(2.21)	(4.65)
$LNFIRMAGE_{i,t}$	0.0004	0.0003	0.0421*
	(0.14)	(0.07)	(1.87)
$ROA_{i,t}$	0.0105	-0.0018	0.0746
	(0.83)	(-0.13)	(0.84)
$PPE_{i,t}$	0.0121	0.0087	-0.1296
	(0.20)	(0.14)	(-0.62)
$LEV_{i,t}$	-0.0427***	-0.0417***	-0.2426***
	(-4.24)	(-6.48)	(-2.79)
$CAPEX_{i,t}$	0.1752***	0.1786**	1.1660**
	(3.18)	(2.14)	(2.12)
$RDEXP_{i,t}$	0.0077	0.1280***	0.4093***
	(0.45)	(4.70)	(3.38)
$TOBINQ_{i,t}$	0.0093***	0.0068***	0.1242***
	(7.79)	(4.69)	(12.55)
$KZINDEX_{i,t}$	0.0000	0.0001	-0.0001
	(0.12)	(1.26)	(-0.10)
$HHI_{i,t}$	-0.0801	-0.0817	-0.1159
	(-1.60)	(-1.09)	(-0.95)
$HHI2_{i,t}$	0.0993**	0.0877	0.3437***
	(1.99)	(1.18)	(2.74)
$INSTOWN_{i,t}$	-0.0223*	0.0017	-0.2532***
	(-1.87)	(0.11)	(-3.84)
$LNEMP_{i,t}$	-0.0080	-0.0122*	-0.0366
	(-1.06)	(-1.74)	(-0.58)
$LNCEOAGE_{i,t}$	-0.0006	0.0277*	-0.0610
	(-0.06)	(1.81)	(-0.56)
$LNCEOTENURE_{i,t}$	0.0038	0.0045**	0.0215
	(1.50)	(2.52)	(1.04)
$DUALITY_{i,t}$	0.0038**	-0.0012	0.0348
	(2.27)	(-0.39)	(0.77)
$ICMW_{i,t}$	-0.0126***	-0.0021	-0.0919***
	(-6.03)	(-0.99)	(-5.89)
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Obs.	8,455	8,455	8,455
Adj. R^2	0.0961	0.145	0.242

This table presents the results of testing the association between Corporate Technology Officer and corporate innovation efficiency using propensity score matching. We use three proxies for corporate innovation efficiency as dependent variables in the analyses, that is, $IEPAT_{i\ t+3}$, $IECIT_{i\ t+3}$, and $IEMVE_{i\ t+3}$. *t*-statistics are reported in parentheses, based on standard errors clustered by year and industry. The sample comprises 4,207 firm-year observations for CTO firms and 4,248 firm-year observations for non-CTO firms as the final sample during the period from 2001 to 2016. Variable definitions are provided in Appendix A. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Table 11 The effect of Corporate Technology Officer on corporate innovation efficiency using entropy balancing

	(1)	(2)	(3)
Dep. variable	$IEPAT_{i\ t+3}$	$IECIT_{i\ t+3}$	$IEMVE_{i\ t+3}$
$CTO_{i,t}$	0.0170***	0.0191**	0.1381*
	(4.38)	(2.45)	(2.21)
$LNAT_{i,t}$	0.0087	0.0097	0.1721***
	(1.15)	(1.45)	(3.65)
$LNFIRMAGE_{i,t}$	0.0000	0.0014	0.0379*
	(0.01)	(0.33)	(1.93)
$ROA_{i,t}$	0.0057	0.0045	0.0457
	(0.47)	(0.47)	(0.61)
$PPE_{i,t}$	-0.0188	-0.0357	-0.2785
	(-0.39)	(-0.71)	(-1.39)
$LEV_{i,t}$	-0.0357***	-0.0428***	-0.1725**
	(-5.89)	(-4.21)	(-2.44)
$CAPEX_{i,t}$	0.1487**	0.1712***	0.9724*
	(3.35)	(3.67)	(2.10)
$RDEXP_{i,t}$	0.0081	0.0937*	0.2827*
	(0.33)	(2.11)	(1.92)
$TOBINQ_{i,t}$	0.0087***	0.0055***	0.1286***
	(4.30)	(3.42)	(7.63)
$KZINDEX_{i,t}$	0.0000	0.0002	0.0006
	(0.57)	(1.66)	(1.64)
$HHI_{i,t}$	-0.0295	-0.0445	0.1150
	(-0.40)	(-0.53)	(0.53)
$HHI2_{i,t}$	0.0478	0.0514	0.1202
	(0.69)	(0.65)	(0.53)
$INSTOWN_{i,t}$	-0.0183	0.0043	-0.2142**
	(-1.33)	(0.32)	(-2.58)
$LNEMP_{i,t}$	-0.0045	-0.0078	-0.0260
	(-0.58)	(-1.04)	(-0.41)
$LNCEOAGE_{i,t}$	-0.0039	0.0158	-0.0927
	(-0.32)	(0.92)	(-0.80)
$LNCEOTENURE_{i,t}$	0.0026	0.0010	0.0192
	(1.26)	(0.77)	(1.20)
$DUALITY_{i,t}$	0.0023	0.0007	0.0278
	(1.04)	(0.22)	(0.70)
$ICMW_{i,t}$	-0.0141***	0.0017	-0.0988***
	(-3.61)	(0.38)	(-4.62)
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Obs.	30,604	30,604	30,604
Adj. R^2	0.102	0.142	0.237

This table presents the results of testing the association between Corporate Technology Officer and corporate innovation efficiency using entropy balanced matching. We use three proxies for corporate innovation efficiency as dependent variables in the analyses, that is, $IEPAT_{i\ t+3}$, $IECIT_{i\ t+3}$, and $IEMVE_{i\ t+3}$. *t*-statistics are reported in parentheses, based on standard errors clustered by year and industry. The sample comprises 4,384 firm-year observations for CTO firms and 26,220 firm-year observations for non-CTO firms as the final sample during the period from 2001 to 2016. Variable definitions are provided in Appendix A. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Table 12 The effect of Corporate Technology Officer on corporate innovation efficiency using Heckman Models

	State Level			Industry Level		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable	$IEPAT_{i\ t+3}$	$IECIT_{i\ t+3}$	$IEMVE_{i\ t+3}$	$IEPAT_{i\ t+3}$	$IECIT_{i\ t+3}$	$IEMVE_{i\ t+3}$
$CTO_{i,t}$	0.0160***	0.0159*	0.1498**	0.0167***	0.0168*	0.1545**
	(4.01)	(1.93)	(2.61)	(4.44)	(2.08)	(2.73)
$LNAT_{i,t}$	0.0021	0.0021	0.0802**	0.0045	0.0055	0.0962***
	(0.74)	(0.77)	(3.14)	(1.27)	(1.47)	(3.41)
$LNFIRMAGE_{i,t}$	0.0033**	0.0022	0.0414***	0.0027	0.0013	0.0369***
	(2.37)	(1.17)	(3.88)	(1.69)	(0.71)	(3.61)
$ROA_{i,t}$	0.0182**	0.0022	0.0836**	0.0149	-0.0023	0.0607
	(2.65)	(0.23)	(2.70)	(1.82)	(-0.20)	(1.79)
$PPE_{i,t}$	0.0008	0.0165	-0.0604	-0.0139	-0.0037	-0.1612**
	(0.03)	(0.73)	(-0.66)	(-1.03)	(-0.27)	(-2.81)
$LEV_{i,t}$	-0.0266**	-0.0227***	-0.0782*	-0.0322***	-0.0306***	-0.1161**
	(-3.04)	(-3.61)	(-2.27)	(-3.48)	(-3.45)	(-2.88)
$CAPEX_{i,t}$	0.0453	0.0092	0.1425	0.0716	0.0462	0.3208
	(1.07)	(0.28)	(0.47)	(1.60)	(1.16)	(1.11)
$RDEXP_{i,t}$	0.0039	0.0447	0.0873	0.0306	0.0820	0.2686*
	(0.09)	(0.77)	(0.40)	(1.04)	(1.61)	(2.22)
$TOBINQ_{i,t}$	0.0053**	0.0031*	0.0814***	0.0059**	0.0041**	0.0859***
	(2.88)	(2.16)	(5.62)	(3.29)	(2.60)	(5.68)
$KZINDEX_{i,t}$	0.0001	0.0001	0.0005	0.0001*	0.0001**	0.0007**
	(1.36)	(1.55)	(1.54)	(2.22)	(2.71)	(2.35)
$HHI_{i,t}$	0.0011	-0.0227	0.0504	0.0090	-0.0118	0.1048
	(0.02)	(-0.42)	(0.34)	(0.20)	(-0.23)	(0.69)
$HHI2_{i,t}$	0.0066	0.0175	0.0609	0.0011	0.0100	0.0228
	(0.16)	(0.37)	(0.43)	(0.03)	(0.22)	(0.16)
$INSTOWN_{i,t}$	-0.0059	0.0055	-0.1396**	-0.0049	0.0069	-0.1331**
	(-0.90)	(1.35)	(-2.97)	(-0.83)	(1.81)	(-2.98)
$LNEMP_{i,t}$	-0.0023	-0.0041	0.0157	-0.0028	-0.0049	0.0127
	(-0.68)	(-1.12)	(0.40)	(-0.76)	(-1.23)	(0.32)
$LNCEOAGE_{i,t}$	0.0066	0.0119	-0.0464	0.0047	0.0094	-0.0594
	(0.66)	(0.99)	(-0.72)	(0.52)	(0.85)	(-1.01)
$LNCEOTENURE_{i,t}$	0.0024	0.0027	0.0179	0.0015	0.0015	0.0116
	(1.23)	(1.32)	(1.46)	(1.08)	(0.97)	(1.22)
$DUALITY_{i,t}$	0.0031	0.0002	0.0253	0.0039	0.0013	0.0311
	(1.18)	(0.06)	(0.99)	(1.66)	(0.51)	(1.31)
$ICMW_{i,t}$	-0.0043*	0.0044	-0.0533***	-0.0039	0.0049	-0.0507***
	(-1.90)	(1.48)	(-3.53)	(-1.76)	(1.53)	(-3.60)
imr_state	-0.0155	-0.0225	-0.1042			
	(-1.16)	(-1.66)	(-1.37)			
imr_ffi				-0.0015	-0.0028	-0.0087
				(-0.95)	(-1.57)	(-0.98)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Obs.	30,604	30,604	30,604	30,604	30,604	30,604
Adj. R^2	0.0956	0.114	0.180	0.0951	0.113	0.180

Table 13 The effect of Corporate Technology Officer on corporate innovation efficiency using Granger Causality Test

$$IE_t = \sum_{i=1}^{n} \alpha_i IE_{t-i} + \sum_{i=1}^{m} \beta_i CTO_{t-i}$$

Panel A: IE = *IEPAT, n=m=3*					
	$\beta_j = 0 \ \forall j$			$\sum \beta_j = 0$	
Variables	Chi-square	p-value	$\sum \beta_j$	Chi-square	p-value
CTO	7.32	0.0001	0.042	21.9	0.0000
Panel B: IE = *IECIT, n=m=3*					
	$\beta_j = 0 \ \forall j$			$\sum \beta_j = 0$	
Variables	Chi-square	p-value	$\sum \beta_j$	Chi-square	p-value
CTO	5.59	0.008	0.134	16.23	0.0001
Panel C: IE = *IEMKV, n=m=3*					
	$\beta_j = 0 \ \forall j$			$\sum \beta_j = 0$	
Variables	Chi-square	p-value	$\sum \beta_j$	Chi-square	p-value
CTO	11.73	0.0000	0.316	33.22	0.0000