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The risk effects of corporate digitalization: exacerbate or mitigate?

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This study elaborates on the risk effects of corporate digital transformation (CDT). Using the ratio of added value of digital assets to total intangible assets as a measure of CDT, this study overall reveals an inverse relationship between CDT and revenue volatility, even after employing a range of technical techniques to address potential endogeneity. Heterogeneity analysis highlights that the firms with small size, high capital intensity, and high agency costs benefit more from CDT. It also reveals that advancing information infrastructure, intellectual property protection, and digital taxation enhances the effectiveness of CDT. Mechanism analysis uncovers that CDT not only enhances financial advantages such as bolstering core business and mitigating non-business risks but also fosters non-financial advantages like improving corporate governance and ESG performance. Further inquiries into the side effects of CDT and the dynamics of revenue volatility indicate that CDT might compromise cash flow availability. Excessive digital investments exacerbate operating risks. Importantly, the reduction in operating risk associated with CDT does not sacrifice the potential for enhanced company performance; rather, it appears to augment the value of real options.

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Introduction

The digital economy has emerged as a cornerstone, comprising a substantial portion of the GDP, particularly in the US where it witnessed marked growth from 2005 to 2019. This economy is defined by its reliance on data and information as fundamental production factors, with digital technology serving as the primary catalyst. It fosters the comprehensive integration of digital technologies with the tangible economy, perpetually augmenting the digitalization, connectivity, and intelligence of both the economy and society. This progression accelerates the transformation of economic development and governance paradigms into a novel economic archetype. Consequently, the digital economy encompasses not only the digital endeavors of conventional industries but also the proliferation of the digital technology sector, the establishment of digital infrastructure, and the regulation of digital markets (Carlsson, 2004).

Enterprises act as pivotal agents in microeconomic dynamics. Corporate digital transformation (CDT) represents the fundamental unit and micro-level impetus behind the development of the digital economy. CDT involves leveraging digital technologies, such as cloud computing, big data, artificial intelligence, and the Internet of Things, to refine and revamp business processes, operational frameworks, organizational structures, products, and services (Du et al., 2024; Jiang et al., 2025a). The burgeoning digital economy engenders a conducive digital ecosystem characterized by robust infrastructure, a wealth of technological resources, and vibrant digital markets, which collectively provide the technical support, market opportunities, and innovation stimuli essential for CDT (Jiang et al., 2025a). Beyond transforming internal operations, CDT influences both the upstream and downstream components of supply chains as well as the broader ecosystem, fostering a digitally collaborative evolution across the entire industrial spectrum. This shift not only elevates the societal digital literacy and overall digitalization level but also cultivates the requisite talent and market infrastructure for the digital economy's expansion. In this context, CDT has become an indispensable strategy for enterprises striving to enhance their efficiency, innovative capacity, and competitive edge, while aligning with the market exigencies and evolutionary trends of the digital era (Annarelli et al., 2021; Du et al., 2024; Liu et al., 2023a).

Existing studies have probed the myriad benefits of CDT, including enhancements in financial performance (e.g., Zhai et al., 2022; Liu et al., 2023a; Liu et al., 2023b; Peng and Tao, 2022; Babina et al., 2024; Chen and Srinivasan, 2024), productivity (e.g., Du and Jiang, 2022; Guo et al., 2023), innovation capabilities (e.g., Zhuo and Chen, 2023; Rubio-Andrés et al., 2024; Wu and Li, 2024), environmental outcomes (e.g., Shang et al., 2023; Bendig et al., 2023; Zhou et al., 2023), and external financing (e.g., Sun et al., 2024; Jiang et al., 2025a), among other economic advantages (e.g., Geng et al., 2024; Dubey et al., 2024; Fedyk et al., 2022; Zhou and Li, 2023). Nonetheless, digital transformation (DT) is not a universal remedy and may not align with the strategic needs of every enterprise. Challenges such as technological fit, business model synchronization, management effectiveness, and liquidity constraints can impede successful DT (Dewan and Ren, 2011; Oludapo et al., 2024), occasionally resulting in failure (Oludapo et al., 2024; Kempeneer and Heylen, 2023; Sun et al., 2024). Moreover, the literature highlights potential drawbacks of DT including diminished innovation efficiency (Usai et al., 2021), profitability (Guo et al., 2023), and external financing capabilities (Sun et al., 2024). The uncertainty in economic outcomes associated with CDT accentuates the necessity to investigate its risk implications. Contemporary studies focus predominantly on the risk dimensions, analyzing aspects such as default risk (Chen et al., 2024a), governance risk (Luo, 2021), equity volatility (Jiang et al., 2024), supply chain fragility (Chen et al., 2025), and the propensity toward proactive risk management (Luo et al., 2024; Wu and Wang, 2024; Feng and Yu, 2025).

Despite these thorough investigations, discourse on the linkage between CDT and passive product risk exposure (operating risk) remains limited. Furthermore, there is a notable scarcity of research incorporating non-financial factors, mechanisms for amplifying risk management efficacy through CDT, potential pitfalls of DT, and revenue fluctuation trends when evaluating the interplay between CDT and corporate risk. Our study seeks to bridge these scholarly voids by focusing primarily on the influence of CDT on firms' operational risks, crucial for sustaining corporate operations and securing competitive advantage. Operational risks not only mirror the competitiveness and market presence of a company's products but also underscore the compliance and effectiveness of its internal management. This research endeavors to provide a multidimensional theoretical analysis, mechanism elucidation, and heterogeneity investigation, furnishing pivotal insights for a comprehensive understanding of CDT's economic benefits, enhancing corporate risk management, boosting market competitiveness, and reinforcing adaptability in the digital age.

There are several compelling reasons for selecting Chinese mainland as the focus of this study on DT. First, Chinese mainland has heavily invested in digital infrastructure and achieved early progress in this domain. It boasts the world's largest fiber optic network and is a global leader in 5G network development. Chinese enterprises have showcased robust innovation during their DT, tailoring technology applications to their unique characteristics and market demands (Huang et al., 2023; Liu et al., 2023a). For example, some traditional manufacturing firms have integrated industrial Internet platforms to enable intelligent production and connectivity of production equipment, significantly enhancing productivity and product quality. This advanced state of DT in Chinese enterprises provides a fertile ground for drawing representative conclusions about the economic impacts of DT.

Second, the DT in Chinese enterprises is rapidly evolving, with notable advancements in big data analytics, the Internet of Things, and smart manufacturing. Yet, the pace and extent of CDT vary significantly across different sectors and company sizes (Li et al., 2018). This contrasts with enterprises in developed countries like the US, where DT commenced earlier and has reached a more stable and mature phase, influencing operational risks differently (Chen and Srinivasan, 2024). Analyzing data from A-listed companies allows us to capture the diverse and dynamic nature of the DT process, offering insights applicable to enterprises at similar developmental stages.

Third, as the largest developing country, China has implemented numerous policies to foster the digital economy and informatization, profoundly influencing CDT strategies and outcomes (Wang et al., 2023a; Wang et al., 2023b). During their DT journeys, Chinese companies have innovatively merged local market demands with technological strengths to develop unique applications and models. These include leveraging advanced smart manufacturing to reduce reliance on low-skilled labor and employing big data technologies for energy efficiency and emissions reduction (Dou et al., 2023; Wang et al., 2024; Yang et al., 2024). These innovations, deeply intertwined with the context of a developing country, significantly affect operational risks. Comprehensive heterogeneity and mechanism analyses of Chinese samples will help pinpoint critical policy levers to amplify the enabling effects of DT, offering pivotal policy recommendations for technological transformation and risk management in the developing world.

Fourth, the strong policy support and public opinion guidance from the Chinese government on developing the digital economy can sometimes lead enterprises toward irrational digital investment scales and speeds (Guo et al., 2023). Overinvestment, frequently spurred by government intervention, is relatively common among Chinese firms (Chen and Jiang, 2024). Focusing on Chinese samples allows us to explore the "excess is as bad as deficiency" dilemma inherent in DT.

Finally, data from A-listed companies are relatively more accessible, including financial data, governance information, ESG ratings, digital intangible assets, and annual report texts. In contrast, data collection from other developing countries or international and developed nations often encounters challenges such as inconsistent statistical standards, high data acquisition costs, and difficulties in accessing specific data. This accessibility further justifies the selection of Chinese mainland as a primary study locale for examining the nuances of DT.

This study makes several significant contributions to the existing literature on the effects of digitalization on corporate risk, enriching the discourse with nuanced insights and methodological advancements. First, the research introduces novel perspectives by focusing on the impact of CDT on passive product market risks, specifically operating risks, diverging from the prevalent focus on proactive risk-taking post-digitalization seen in prior studies (Feng and Yu, 2025; Liu and Liu, 2024; Wu and Wang, 2024; Luo et al., 2024). While revenue volatility is commonly used as a risk metric, our findings challenge this norm by examining the directional volatility of revenue and exploring changes in the firm's real options value, encompassing both potential growth and decline risks.

Second, this paper broadens the analytical framework on how CDT impacts risk by highlighting the costs and uncertainties associated with DT. While much of the literature primarily confirms the benefits of DT (e.g., Jiang et al., 2025a; Feng and Yu, 2025; Babina et al., 2024; Chen and Srinivasan, 2024), this study acknowledges the significant investments and rapid technological updates that complicate cash flow and talent management, which can precipitate failures in DT (Oludapo et al., 2024; Kempeneer and Heylen, 2023; Sun et al., 2024). Here, we extend the theoretical analysis to illustrate how CDT may exacerbate operating risks, empirically demonstrating the potential for a "too much of a good thing" scenario in DT.

Third, whereas existing literature often centers on the impact of digitalization on primary financial variables, our research expands the dialogue to include off-balance-sheet financial conditions and non-financial performance. We enhance the theoretical framework to show how CDT can mitigate operating risks through both financial and non-financial channels, providing empirical evidence to support these claims.

Fourth, the methodological contribution of this study is notable. Unlike previous research that predominantly relies on digitalization indices based on text frequency analysis (e.g., Feng and Yu, 2025; Liu and Liu, 2024; Wu and Wang, 2024; Jiang et al., 2024; Sun et al., 2024), our approach uses indicators based on changes in digital intangible assets. This asset-based metric not only avoids the pitfalls of frequency count noise but also more accurately reflects a firm's investment behavior in DT, aiding in pinpointing specific scenarios where DT may falter.

Finally, the paper constructs a comprehensive heterogeneity analysis considering firm characteristics, intellectual property protection, and local government digitalization policies. This analysis provides crucial empirical evidence on how to effectively synergize DT with real economic development to boost corporate competitiveness and reduce operational risks. Through these multifaceted contributions, the study offers a richer, more detailed understanding of the complex interplay between DT and corporate risk management.

In order to contextualize our research, the "Literature review and development of the theory" section provides a comprehensive literature review and theoretical development. As described in the "Methodology, variables and data" section, we describe the methodology and framework used in our analysis. The purpose of the "Corporate digitalization and operating risk" section is to present our empirical results. The "Mechanism analysis" section is to undertake the mechanism analysis. The "Heterogeneity analysis" section is to undertake the heterogeneity analysis. The "Further analyses" section is to undertake the further analysis. Finally, the "Conclusion" section offers concluding remarks, summarizing key findings and implications drawn from our study.

Literature review and development of the theory

Literature review of corporate digital transformation

Corporate digital transformation and economic outcomes. CDT has become an essential strategy for global enterprises aiming to bolster competitiveness, foster innovation, and enhance operational efficiency. CDT entails a holistic refinement of business processes, operational frameworks, products, and services through the integration of advanced technologies, including cloud computing, big data, artificial intelligence (AI), and the Internet of Things (IoT) (Annarelli et al., 2021; Verhoef et al., 2021; Chen et al., 2023; Babina et al., 2024; Jiang et al., 2025a). As digitalization increasingly becomes the norm for companies navigating the digital economy's landscape, it has also garnered considerable attention in academic circles. A review of existing literature traces the evolution of the concept of DT, shifting from mere 'investment in Information and Communication Technology (ICT)' to broader 'digitization' and ultimately to 'digital transformation' (Verhoef et al., 2021). ICT is defined as systems utilized for transmitting, storing, processing, displaying, creating, and automating the dissemination of information, typically including technology such as television, landline and mobile phones, radio, satellite systems, and computer software and hardware (Du and Jiang, 2022).

Verhoef et al. (2021) delineate three evolutionary stages of DT: the initial stage focuses on converting analog signals into digital formats, essentially the ICT investment phase; the second stage enhances business processes via digital technologies (digitization); and the third stage involves strategic overhauls of business models and organizational cultures (digital transformation), building on the technological foundations established in the earlier stages. Vial (2019) argues that DT represents the convergence of the tangible and technological realms, profoundly altering the functionality of the tangible and enhancing its characteristics. Baskerville et al. (2020) describe digitization as an outcome of the convergence of digital tools such as 5G mobile networks, sensors, 3D printing, and blockchain, technologies that have emerged from advancements in ICT and that integrate the digital and physical worlds.

DT signifies a pivotal process enabled by digital technology, exerting profound impacts on companies. Empirical studies have validated the positive effects of digitization across various domains, including profitability (Oh et al., 2012; Liu et al., 2023a; Liu et al., 2023b; Peng and Tao, 2022; Babina et al., 2024; Chen and Srinivasan, 2024;), cost management (Du et al., 2024; Li et al., 2024), productivity (Du and Jiang, 2022; Guo et al., 2023), technological innovation (Mikalef et al., 2019; Usai et al., 2021; Radicic and Petkovic, 2023; Rubio-Andrés et al., 2024; Wu and Li, 2024), sustainable performance (Zhou et al., 2023; Shang et al., 2023; Bendig et al., 2023; Xiao et al., 2024), external financing (Sun et al., 2024; Jiang et al., 2025a), and supply chain relationships (Geng et al., 2024; Dubey et al., 2024). This body of research underscores the transformative potential of digital technologies in reshaping corporate landscapes and driving forward economic progress.

Numerous studies have affirmed the advantages of DT, yet the relationship between such transformation and economic outcomes is multifaceted. Babina et al. (2024) utilized recruitment data from American companies to demonstrate that firms making substantial investments in AI technology tend to experience enhanced growth, larger employment scales, and increased corporate value. Similarly, Du et al. (2024) found that innovations rooted in digital technology can increase operational flexibility and reduce cost stickiness. Through a textual analysis of digitization in corporate reporting, Chen and Srinivasan (2024) empirically established a positive correlation between the frequency of digital-related keywords and elevated corporate value levels. Zhou et al. (2023) also employed textual analysis but focused on a sample of Chinese firms, finding significant improvements in environmental public sentiment as a result of company digitization. Jiang et al. (2025a) identified an enhancement in external financing capabilities linked to increased corporate digital awareness, reflected by improved bond credit ratings.

However, the narrative of universally positive outcomes from DT is challenged by some researchers. Oludapo et al. (2024) and Kempeneer and Heylen (2023) argue that DT, while fundamentally an investment activity, can lead to significant resource displacement effects if pursued too rapidly or extensively. Sun et al. (2024) suggest that an accelerated pace of digitization could exacerbate a company's financial constraints. Furthermore, Usai et al. (2021) analyzed data from companies within the European Union and observed that commonly implemented digital technologies exert a minimal impact on corporate innovation performance. This minimal impact suggests that innovation stems more from creativity and sustained research and development efforts than from mere technological adoption. Excessive reliance on digital technologies might even erode a firm's long-term innovative capacity, as indicated by Guo et al. (2023), who found that while DT indicators increase a company's TFP, they may concurrently lower performance metrics.

In conclusion, while DT presents significant benefits, it epitomizes a technological investment that can also encounter the paradox of "too much of a good thing." As highlighted by Oludapo et al. (2024) and Kempeneer and Heylen (2023), despite its potential advantages, corporate digitization may culminate in "failure," illustrating the complex dynamics between DT and corporate performance.

Corporate digital transformation and corporate risk. The ambiguous relationship between DT and economic outcomes underscores the necessity of examining the risk effects associated with digitization. Recent studies delve into the complex interplay between corporate digitization and various forms of risk or risk-bearing capacities. Regarding financial risk, research by Chen et al. (2024a) reveals that CDT substantially alleviates firms' default risk, thereby enhancing financial stability and reducing uncertainties associated with external financing. Concerning market risk, empirical analyses indicate that CDT significantly curtails the risk of stock price crashes (Jiang et al., 2022) and systemic risks (Jiang et al., 2024), particularly by bolstering firms' capacity to counteract information asymmetry amid market volatility. In the realm of governance risk, Xu et al. (2024) have discovered that the effectiveness of CDT on enterprise risk management is contingent upon the firm's governance capabilities. Their findings suggest that board-level IT governance exerts a negative moderating influence on the outcomes of CDT, underscoring the necessity of robust governance frameworks to navigate the complexities associated with DT. Luo (2021) examines the governance risks specific to multinational enterprises, highlighting the critical role of geographic diversity and international strategic planning in managing risks related to information security and regulatory challenges, especially in the context of intricate cross-border data flows and global regulatory frameworks. Regarding supply chain risk, Ivanov et al. (2019) developed a framework to analyze how Industry 4.0 technologies mitigate risks associated with supply chain disruptions and their consequent ripple effects. This study accentuates CDT's vital role in the strategic management of supply chain risks. Additionally, research by Chen et al. (2025) focuses on the spillover effects of delayed digitization within supply chains, noting that such delays can escalate financial risks for suppliers and intensify revenue volatility. This body of work collectively emphasizes the transformative impact of CDT across various dimensions of corporate risk, advocating for strategic implementations to harness its full potential while mitigating associated vulnerabilities.

Some research discusses the risk-bearing capacity of companies following digitization (Liu and Liu, 2024; Luo et al., 2024; Wu and Wang, 2024; Feng and Yu, 2025). For instance, Luo et al. (2024) observed in A-share listed companies that CDT correlates with an increase in firms' propensity for risk-taking, potentially due to enhanced capabilities to identify and exploit new market opportunities. This suggests that CDT equips firms to more effectively adapt to market shifts and discover novel business prospects. Other research employing textual indicators of digitization also confirms that CDT raises risk-taking levels.

To summarize, significant advancements have been made in examining the potential linkages between DT and corporate risk, characterized by uncertainties in economic output. However, several areas remain underexplored. First, while there is considerable discussion on firms' increased propensity to assume risk post-digitization, there is limited research addressing operational risks and the valuation of real options following digitalization. Second, while existing studies extensively assess the impact of digitalization on key financial metrics, there is a notable deficiency in the exploration of non-operational financial conditions. Moreover, as sustainable growth achieves global consensus and ESG performance becomes critically important for securing stakeholder trust (Zhou et al., 2023; Singhania and Gupta, 2024), these aspects demand further scholarly attention. Third, although the literature frequently underscores the advantages of corporate digitalization, it is equally important to acknowledge that DT can fail, as noted by Oludapo et al. (2024) and Kempeneer and Heylen (2023). A too-rapid digital transition can necessitate significant investments in new technologies and infrastructures, imposing considerable strains on firms. Fourth, the prevalent use of textual indicators to gauge digitalization levels within firms, while indicative of executive awareness toward a digital economy, fails to capture the actual economic impact. This paper proposes a novel digitalization index based on asset conditions to analyze its influence on operational risks, substantiating the findings via both financial and non-financial channels, and documents instances of digitalization failures.

Determinants of corporate digital transformation. In Chinese mainland, CDT is driven by distinct motivations and contextual factors. Research indicates that the Chinese government has been a pivotal force in promoting CDT through both policy support and the enhancement of infrastructure (Wang et al., 2023a; Wang et al., 2023b; Wu et al., 2023; Zhao et al., 2024; Zhu et al., 2023). For instance, Wu et al. (2023) analyze the impact of "Broadband China" initiative on CDT in Chinese mainland, and Wang et al. (2023b) investigate the influence of governmental digital initiatives on corporate digital innovation. Despite these advancements facilitated by state support, Chinese enterprises continue to encounter unique challenges such as the funding requirements for technological innovation and shortages of skilled talent (Bai et al., 2024).

Moreover, the existing literature has seldom addressed the heterogeneous impacts of CDT across diverse enterprise types. Factors like firm size, capital intensity, and governance structure contribute to varying outcomes in CDT implementation. For example, Jia et al. (2024) observe that small enterprises, constrained by limited resources, often struggle more with DT compared to larger organizations, which typically possess more technological resources and capital for such endeavors. Capital-intensive enterprises, while facing heightened financial pressures and risks during transformation, stand to gain substantial efficiency improvements and reductions in carbon emissions due to their high energy consumption and resource usage. Over time, these benefits can translate into significant cost savings and competitive advantages (Shang et al., 2023). Additionally, enterprises with centralized governance structures, such as state-owned enterprises or those controlled by a few shareholders, may experience slower decision-making processes, particularly when cross-departmental collaboration is required. This can lead to bureaucratic impediments and internal conflicts, thus undermining the efficiency and effectiveness of CDT (Zhang, 2024; Zhu, 2024).

The literature reviewed underscores that factors like intellectual property, market demand, and robust cash flow are critical in determining a company's propensity to undertake DT. In light of these insights, our study will conduct heterogeneous analyses from multiple perspectives to explore protective measures for digitalization initiatives and strategies to enhance digitalization efforts effectively.

Theoretical considerations and research hypotheses

The characteristic of corporate digital transformation. Utilizing advanced technologies, CDT seeks to overhaul production processes, business paradigms, and organizational ethos. This transformative initiative endows firms with four pivotal attributes:

Dataization: Traditional business operations, previously compartmentalized, now generate extensive datasets. Modern intelligent hardware and software systems streamline the aggregation and visualization of this data, thus dismantling intra-organizational information silos.

Intelligence: The integration of digital technologies fosters intelligent operations across manufacturing, decision-making, and management spheres. The deployment of industrial robots, IoT devices, and AI algorithms advances automation and enhances monitoring capabilities, significantly reducing operational errors and optimizing resource allocation. For instance, Tencent leverages big data analytics to fortify internal controls and diminish fraud risks.

Networking: Transforming conventional supply chain frameworks into dynamic, network-based models facilitates direct engagement with consumers and supports the customization of services. Digital platforms foster robust cooperative relationships, amplifying service delivery and enabling value co-creation with customers.

Collaboration: Digital tools streamline inter-firm collaboration, reducing transaction costs and fostering seamless online partnerships. The exchange of real-time data and collaborative innovation across sectors propels the growth of digital ecosystems and enhances supply chain cohesion.

Corporate digital transformation and operating risk: a perspective on negative impacts. Scholarly investigations into the operational risks of firms have deeply explored the influences of corporate governance, business behavior, and adjustments to external environments. Central to these discussions is the role of corporate governance-encompassing board composition, equity structure, and internal controls-in modulating risks through enhanced oversight and strategic decision-making. For instance, research suggests that gender diversity within executive teams bolsters monitoring effectiveness and diminishes risk exposure (Perryman et al., 2016). Similarly, specific business behaviors, such as Corporate Social Responsibility (CSR) (Jo and Na, 2012; Albuquerque et al., 2019), social performance (Bouslah et al., 2013), derivative hedging (Bartram et al., 2011), tax avoidance practices (Guenther et al., 2017), and customer concentration (Kim et al., 2023), significantly impact operational risk profiles. Notably, proactive CSR engagement is linked to reduced risk via improved stakeholder relationships and the acquisition of competitive advantages (Jo and Na, 2012; Albuquerque et al., 2019). Collectively, these elements underscore the pivotal role of both financial and non-financial performance in curtailing operational risks and fostering sustainable corporate growth.

In the context of CDT, emerging literature posits that this paradigm introduces distinct risk dimensions in technology, organizational management, and business processes (Dewan and Ren, 2011; Oludapo et al., 2024). Initially, while CDT fosters efficiency and innovation, it simultaneously escalates technological risks. Firms increasingly reliant on digital infrastructures may face significant disruptions from system failures or cyber threats, severely impacting operations (Martínez-Caro et al., 2020). Moreover, the misalignment of digital technologies with corporate needs can precipitate project failures, squander resources, and diminish operational efficacy. The rapid obsolescence of digital tools further complicates maintenance and escalates costs, thereby amplifying operational uncertainty (Dewan and Ren, 2011).

Second, CDT can catalyze risks associated with organizational management (Xu et al., 2024). The transition often necessitates structural adjustments away from traditional hierarchies to accommodate digital-centric workflows. This shift may result in role ambiguities and misaligned authority distribution, reducing managerial efficiency. The integration of cross-departmental digital initiatives might provoke internal conflicts due to unclear roles and responsibilities, obstructing project execution. Additionally, the heightened demand for digitally proficient personnel, such as data analysts and AI engineers, confronts firms with potential talent deficits, impairing the quality and execution of digital projects (Guerra et al., 2023). This mismatch between technological needs and available expertise heightens the complexity and unpredictability of operational frameworks.

Third, CDT may introduce business process-related operational risks (Ivanov et al., 2019). The reorganization or optimization of business processes necessitated by CDT (Baiyere et al., 2020) can engender complications such as inherent design flaws, resulting in overly complex procedures or inadequate integration between process stages. These deficiencies can extend processing times and elevate error rates, undermining operational efficiency (Wong et al., 2020). For example, a poorly configured Customer Relationship Management (CRM) system might delay the resolution of customer complaints, adversely affecting customer satisfaction and tarnishing the firm's reputation. Additionally, CDT's impact on external partnerships, such as those with suppliers and distributors, introduces further complications. Implementing a digital procurement system, for instance, might lead to compatibility issues with suppliers' systems, causing delays in order processing and subsequently affecting production schedules and delivery capabilities. The varying degrees of digital adaptability among partners can significantly augment operational uncertainty, particularly in highly digitized supply chains (Rauniyar et al., 2023).

Fourth, CDT may precipitate cash flow disruptions. DT demands substantial investments in advanced hardware, such as high-performance servers, data storage devices, and smart terminals, as well as in sophisticated software solutions like Enterprise Resource Planning (ERP) and CRM systems (Kempeneer and Heylen, 2023). These expenditures can immobilize considerable capital, exerting pressure on the firm's cash flows. DT projects are typically intricate and protracted, often requiring years from conceptualization to full operational deployment. The construction of digital factories or the overhaul of digital supply chains in large enterprises is an example, where significant capital is continuously invested over an extended period without immediate financial returns, potentially straining cash flows. Furthermore, DT frequently necessitates investments in technology research and development, the assembly of specialized R&D teams, or collaboration with external research institutes to pioneer new technological applications in business. The uncertainty and prolonged nature of these R&D investments can substantially increase short-term cash outflows, thus exacerbating financial constraints. Given these considerations, CDT may represent a case of "too much of a good thing," where the pursuit of technological advancement intensifies cash flow challenges and elevates operational risks (Oludapo et al., 2024). Based on this analysis, we propose the following research hypothesis (***H1***):

H1: CDT may exacerbate operating risks for enterprises.

Corporate digital transformation and operating risk: a perspective on positive impacts. However, CDT can also bring efficiency improvements, cost reductions, and competitive advantages (Du and Jiang, 2022; Du et al., 2024), which may endow companies with competitive advantages in the product market and mitigate operational risks through both financial and non-financial channels.

The financial channel refers that CDT entails enhancing core business advantages and mitigating non-business operating risks for companies. With CDT, firms are able to collect and analyze vast quantities of data and adjust their strategies to competitive trends promptly (Chen et al., 2012; Mikalef et al., 2020; Babina et al., 2024). This agility enables companies to identify industry risks and opportunities swiftly, gaining incremental competitive edges (Erevelles et al., 2016; Kiron, 2017).

First, intelligent analysis and networked interactions facilitate the creation of products and services aligned with consumer preferences, driving innovation in product, service, and design (Babina et al., 2024; Blichfeldt and Faullant, 2021). Second, emerging digital technologies reduce customer tracking costs, enabling companies to authenticate customers more affordably and implement new forms of price discrimination based on past behaviors (Bhargava and Choudhary, 2008; Goldfarb and Tucker, 2019). Third, by refining customer tracking and behavior analysis, companies can send personalized advertisements to target customers, reducing ineffective advertising expenses and expanding market share (Goldfarb and Tucker, 2019). Lastly, big data and AI-driven cost management streamline business processes, reducing production and management costs (Kusiak, 2017). This cost reduction improves pricing advantages and market share, bolstering resilience against market competition and reducing performance fluctuations. In conclusion, CDT enhances product pricing abilities and market share, providing a shield against market risks and stabilizing performance.

Additionally, CDT may counteract the financialization trend within companies, thereby mitigating non-business operating risks. Financial asset allocation, while potentially boosting short-term performance, can erode long-term competitiveness by diverting funds away from crucial areas like R&D investment. Moreover, the volatility of financial asset prices can exacerbate overall performance fluctuations, amplifying operating risks. However, existing literature highlights the positive impact of CDT on various aspects of firm operations, including internal control quality (Jiang et al., 2022), operating and innovation performance (Chen and Srinivasan, 2024; Peng and Tao, 2022; Wu and Li, 2024; Zhai et al., 2022), cash holdings (Sun et al., 2022), and financing advantages (Liu et al., 2023a; Liu et al., 2023b). In this regard, there is less incentive for investors to allocate financial assets in accordance with motivations such as investment substitution, agency, and preventive measures. Consequently, as firms prioritize DT, the mitigation effect on operating risks is likely to strengthen further, as financialization motivations wane.

Product pricing capabilities enable firms to maintain profit levels amid rising costs by appropriately increasing prices. Should the price of raw materials rise, a company can pass on the increased costs to the product price. Furthermore, in the face of market demand fluctuations, companies can also adjust prices to balance supply and demand, thereby reducing risks associated with inventory backlogs. A larger market share often accompanies economies of scale, allowing firms to reduce unit costs in procurement, production, and sales. Moreover, companies with significant market shares are better equipped to withstand competitive pressures. When new competitors enter the market, established firms, leveraging their substantial customer bases, can retain customers through loyalty programs, thereby maintaining stable sales performance and reducing operational risks. Reducing financialization allows a company to focus more on its core business. By curtailing speculative activities in financial markets, firms lower the risks associated with financial market volatility. Decreasing the use of financial leverage can reduce a company's debt risk. Excessive financial leverage may expose firms to significant debt repayment pressures during economic downturns, potentially leading to bankruptcy. By minimizing financialization, companies can allocate resources to core activities such as product development, production, and market expansion, thereby enhancing the competitiveness of their primary business and strengthening their ability to adapt to market changes and manage operational risks. Thus, it can be inferred that CDT, by bolstering financial performance through enhanced product pricing capabilities, market share, and avoidance of financialization, consequently reduces operational risks.

Non-financial channels of CDT include improvements in corporate governance and environmental, social, and governance (ESG) performance, contributing to lower firm operating risks. First, CDT elevates internal control quality and corporate governance standards by facilitating the presentation of all company operations in data form, thus mitigating information asymmetry among departments. This improvement in information circulation efficiency strengthens internal supervision, aids in the timely detection of control deficiencies, reduces unnecessary costs and facilitates efficient performance appraisal systems. By reducing managerial autonomy, digital technologies also enhance the independence of internal control systems, which in turn curbs irrational executive behavior. Big data analysis and artificial intelligence algorithms, for instance, enable the identification and analysis of potential risks in a timely manner, resulting in proactive risk prevention measures. Moreover, CDT enhances audit quality, augments auditor efficiency, bolsters asset review effectiveness and lowers internal personnel fraud risks (Fedyk et al., 2022).

Second, CDT fosters a stronger focus on social responsibility as internet technology streamlines internal information transmission, enabling more efficient and timely content dissemination and effective external communication. This, coupled with the popularity boost generated by CSR initiatives, amplifies firms' commitment to social responsibility. Furthermore, the cash flow benefits of CDT provide a financial impetus for companies to fulfill their social responsibilities.

Lastly, CDT enhances corporate environmental performance by accelerating the integration of operations with digital technologies, thereby achieving intelligence and digitization in energy and sewage systems (Bendig et al., 2023; Xu et al., 2022; Zhou et al., 2023). It enables firms to integrate internal and external information to guide sustainable development strategies, fostering increased investment in green innovation. Research indicates that CDT reduces carbon emission intensity in manufacturing firms (Shang et al., 2023), electricity consumption, and intensity (Wang et al., 2022), enhances capacity efficiency (Du and Jiang, 2022), and drives green innovation (Tang et al., 2021). By improving corporate ESG performance, CDT mitigates agency, social, and environmental risks.

The mitigating effect of ESG performance on corporate operational risks manifests in several key areas: First, robust ESG performance can enhance the stability of a company's cash flows by improving internal operational efficiency, reducing costs, increasing employee satisfaction, and optimizing governance structures. Stable cash flows help companies maintain routine operations and respond to unforeseen events amid market volatility and uncertainty, thus reducing operational risks associated with cash shortages. Companies with strong ESG performance often attract more analyst attention. Second, this attention can enhance a company's transparency and market recognition, reducing problems associated with information asymmetry. When corporate information is more transparent, investors and other stakeholders can more accurately assess the company's operational status and risk levels, thereby lowering the company's financing costs and operational risks. Third, an improvement in ESG performance can help alleviate internal agency conflicts—discrepancies between the interests of owners and managers, which can lead managers to make decisions detrimental to owners' interests. Good ESG performance can enhance transparency and governance levels, prompting managers to focus more on the long-term development and stakeholders' interests, thus reducing agency conflicts and the associated operational risks. Fourth, companies with strong ESG performance often secure financing at lower costs. On one hand, good ESG performance can improve a company's credit rating and reduce default risks, thus lowering debt financing costs. On the other hand, as investors increasingly value ESG performance, they are more willing to provide financial support to companies demonstrating strong ESG credentials, allowing these companies to obtain more favorable financing terms. Therefore, it is believed that by enhancing non-financial performance (ESG), CDT subsequently reduces operational risks.

Based on this, we propose the following alternative hypothesis:

H2: CDT may reduce operating risks for enterprises.

The theoretical framework of this paper is presented in (Fig. 1).

Methodology, variables and data

Identification strategy. In accordance with existing studies (such as Jiang et al., 2022), we set our empirical specifications in order to examine the impact of CDT on operating risk. The baseline empirical model is designed as follows:

$$OR_{it} = \alpha + \beta CDT_{it} + \gamma \boldsymbol{CX} + Indu_{FE} + Year_{FE} + \varepsilon_{it} \quad (1)$$

where i denotes firm and t denotes year. Firm i's operating risks during year t are represented by the independent variable, OR_{it}; CDT_{it} represents the degree of DT of firm i in year t. $\boldsymbol{CX}$ is a collection of firm-level control variables that may impact the operating risks of a firm. To control for the interference of factors that do not change over time and industry on the regression conclusion, we further add industry dummy variables (industry-fixed effects) and year dummy variables (year-fixed effects) to the regression considering the heterogeneity of CDT in terms of time and industry dimensions. We cluster the standard errors by firm to control the effects of heteroscedasticity. The estimated value $\widehat{\beta}$ represents marginal effect of CDT on its operating risks. Therefore, if the hypothesis that firm going digital reduces operating risks is true, then $\widehat{\beta}$ should be statistically negative. The following section attempts to address the endogenous problems associated with model (1), including missing key variables, reverse causality, sample self-selection, and measurement bias.

Variables definitions

Corporate digitalization. In their innovative approach, Jiang et al. (2022) utilized the RoBERTa-wwm-ext deep learning model, developed by Cui et al. (2021), to construct a sophisticated keyword dictionary from the management discussion and analysis sections of annual reports from listed companies. This methodology overcomes the shortcomings of traditional word frequency-based techniques, which often overlook subtle nuances in digital expenditures essential for assessing the extent of CDT.

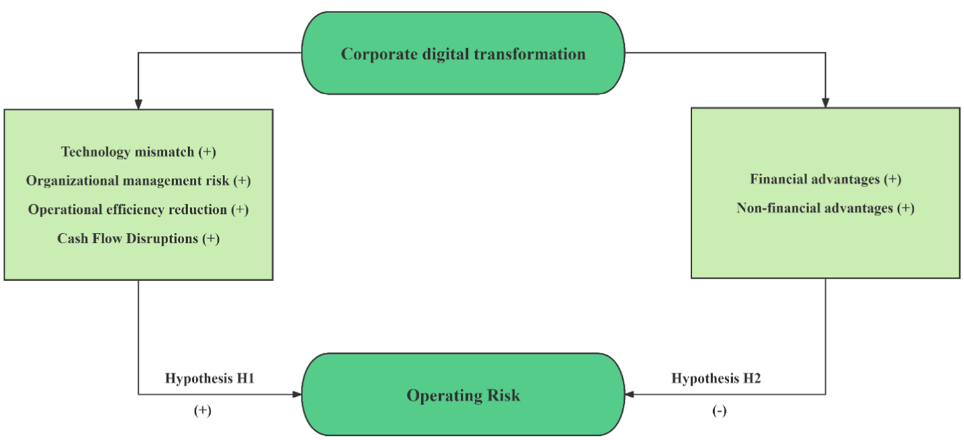

Fig. 1 Theoretical framework diagram.

By employing advanced machine learning techniques, this method significantly enhances the precision in identifying investments related to digital assets.

The process began with the manual creation of an initial keyword dictionary focused on digital technologies, drawing from relevant literature and industry reports. This dictionary encompassed terms such as “cloud computing,” “big data,” “artificial intelligence,” “Internet of Things,” and “blockchain.” Subsequently, the RoBERTa-wwm-ext model was trained on an extensive Chinese corpus to refine and expand this list, ensuring comprehensive coverage of all pertinent technologies associated with digital transformation.

Following the refinement and expansion of the digital technology keywords, these terms were applied to analyze the intangible asset disclosures of listed companies. Assets mentioned in conjunction with keywords like “cloud computing platform development” or “big data analytics software” are classified as “digital assets.” This categorization facilitated the development of a CDT indicator, defined as the ratio of the increase in digital assets to the total intangible assets. This metric effectively quantifies the relative significance of digital assets within the total intangible asset portfolio during the digital transformation process, providing a nuanced and accurate measure of a company’s digital advancement.

To ensure the robustness of our results, we introduced *CDT*2 as an alternative indicator. *CDT*2 is defined as the ratio of the increase in digital intangible assets to total assets, providing additional validation for the economic consequences of CDT. Additionally, we introduced *CDT*3, which is the ratio of the increase in digital fixed assets to the total fixed assets. Digital fixed assets refer to investments made by enterprises in areas such as electronics, computers, communications, information, and networks, which support their DT. Specifically, we identified projects in the fixed asset disclosures containing keywords like “electronics,” “computers,” “communications,” “information,” and “network,” classifying them as digital fixed assets. However, given the presence of many missing values in *CDT*3, we treat it as an alternative indicator rather than the primary one.

Our methodology for constructing indicators of CDT presents several distinct advantages over conventional approaches. Primarily, our focus on digital intangible assets facilitates a more precise quantification of CDT investments. This refinement enhances accuracy by circumventing the prevalent measurement biases associated with traditional word frequency methods, as discussed in recent literature (Bendig et al., 2023; Chen and Srinivasan, 2024). Such biases often arise from the ‘noise’ inherent in corporate disclosures, which our approach effectively mitigates. Second, our indicators are designed to reflect the dynamic valuation of digital assets, thereby controlling for variables such as corporate size and temporal trends. Critically, they are also structured to adapt to potential disruptions or setbacks in digital transformation attributable to business adversities, offering a significant improvement over the static nature of word frequency analysis. Third, the versatility of our indicators extends beyond the confines of Chinese listed companies. They are equally applicable to scholarly investigations into the effects of CDT on capital market dynamics and corporate governance structures. This broader applicability provides a substantial extension of the research scope compared to studies reliant solely on micro-survey data (Mikalef et al., 2019; Mikalef et al., 2020). Furthermore, the diverse composition of our sample, which spans multiple regions and industries, significantly enhances the generalizability and representativeness of our findings. This breadth ensures that our results are not merely reflective of specific sectoral or geographic characteristics but are indicative of broader trends. Fourth, the comprehensiveness of our selected keyword dictionary ensures the thorough identification of digital assets across a vast spectrum. This feature surpasses the capabilities of indicators based solely on capital investments, such as those documented by Chen et al. (2022), by encompassing a wider array of digital asset types. Lastly, our approach of considering total intangible assets as the denominator provides a holistic perspective that more accurately captures the extent to which companies depend on intangible assets for their operational and strategic maneuvers. This comprehensive view is crucial for understanding the full impact of digital transformation within the corporate context.

Corporate operating risk. Corporate operating risk refers to the possibility of losses caused by changes in a company’s operating fundamentals and is generally calculated as earnings volatility (Chen et al., 2020). Accordingly, we utilize the volatility of corporate earnings over a rolling three-year period (from $t-1$ to $t+1$) to measure the operational risks faced by companies. The calculation details are presented as follows:

$$EROA_{it} = \frac{EBIT_{it}}{Asset_{it}} \tag{2}$$

$$Adj\_ROA_{it} = EROA_{it} - \frac{1}{nj}\sum_{t=1}^{nj} EROA_{it} \tag{3}$$

$$OR_{it} = STD(Adj\_ROA_{it-1}, Adj\_ROA_{it}, Adj\_ROA_{it+1}) \tag{4}$$

In order to distinguish between operating risks and debt financing risks, we focus on the volatility in earnings before interest and tax ($EBIT_{it}$). $Asset_{it}$ denotes firm i’s total asset in year t.nj is the number of companies in the industry j where firm i belongs in year t. Adj_ROA_{it} is industry-adjusted ROA which can alleviate the interference of cyclical factors and industry factors. We mainly use two-digit industry codes in this study. *OR* denotes the first indicator for firm operating risks, measured as the standard deviation of the industry-adjusted ROA over the rolling three periods (from $t-1$ to $t+1$). In robustness tests, we intend to change the rolling periods and calculate alternative indicators for firm operating risks.

Control variables. The extensive literature review underscores the influence of various determinants on business operational risks, including fundamental company attributes, financial health, asset characteristics, internal governance mechanisms, and equity performance. Drawing upon the methodologies advanced by Guenther et al. (2017), Jiang et al. (2022), Zhou and Jiang (2025), and Timbate et al. (2024), our study integrates a suite of control variables that represent time-varying firm characteristics potentially impacting operational risks. These variables are elucidated as follows: (1) Firm Size (*Size*): Larger firms generally exhibit enhanced resilience against market fluctuations due to their substantial resources and entrenched market positions, which bolster their risk management capacities. (2) Firm Established Age (*Age*): Firms with a longer history in the market have navigated numerous economic cycles, accumulating valuable experience and potentially developing superior risk management strategies. (3) Capital Structure (*Lev*): The leverage ratio, indicative of a firm’s debt level, correlates with financial stress. Elevated leverage can heighten operational risks, as noted by Bates et al. (2009). (4) Tax Rate (*Tax*): The overall tax rate a firm faces can significantly influence its profitability. Higher tax burdens may intensify operational risks by eroding financial health, whereas lower taxes might mitigate these risks by easing the burden during uncertain market conditions (Langenmayr and Lester, 2018). (5) Capital Intensity (*Density*): Firms with high capital intensity face substantial fixed asset investments, which can lead to escalated fixed costs and, consequently, increased operational risks during economic downturns (Lee and Xiao, 2011). (6) Asset Tangibility (*Tangibility*): A greater proportion of tangible assets enhances a firm's collateral quality, thereby potentially reducing financial risks through improved financing conditions (Almeida and Campello, 2007). (7) Duality (*Duality*): The convergence of the roles of CEO and chairman can lead to a significant concentration of power, potentially impairing governance efficacy and elevating operational risks (Baliga et al., 1996). (8) Proportion of Independent Directors (*Indirector*): A higher proportion of independent directors tends to enhance governance transparency and strengthen monitoring mechanisms, effectively mitigating agency problems and reducing operational risks (Jiraporn and Lee, 2018). (9) Proportion of the Largest Shareholder (*SH*): Elevated ownership concentration may provoke governance challenges due to potential control by minority shareholders, thus increasing operational risks (Faccio et al., 2011). (10) Tobin's Q (*TQ*): This ratio, reflecting market valuation against asset replacement cost, indicates market expectations and growth potential. A higher Tobin's Q is generally associated with reduced operational risks (Yang et al., 2019). By incorporating these variables into our empirical framework, we aim to facilitate a nuanced understanding of the myriad factors that influence the operational risks faced by firms. This comprehensive approach ensures that our analysis captures the interplay between firm-specific characteristics and their operational risk profiles.

Sample and descriptive statistics. We use financial data from the CSMAR and Wind databases in order to compile our sample of Chinese companies listed on the Shanghai and Shenzhen stock exchanges. To calculate firm operating risk (*OR*), we employ a rolling three-period approach, covering the period from 2007 to 2020. For the purpose of mitigating the influence of extreme outliers, financial and real estate companies, as well as *ST or ST companies are excluded from the sample; all continuous variables at the firm level are winsorized at the 1% level.

The descriptive statistics for the variables are presented in Table 1. Firms' operating risks exhibit relative stability, as reflected by a mean value of 0.0516 and a standard deviation of 0.0747. This indicates significant earnings fluctuation disparities among companies. As for *CDT* and *CDT*3, their means are 0.0147 and 0.0084, with standard deviations of 0.1115 and 0.0259, respectively. These figures indicate that A-listed companies are increasingly investing in digital assets; however, there are significant variations in digital investment levels across firms. Negative values for *CDT* and *CDT*3 indicate challenges in DT for some companies. *Size* and *Age* align with existing literature, with mean values of 22.1446 and 2.8375, respectively. In A-share listed companies, the mean debt ratio (*Lev*) is 0.4509, reflecting a general high level of debt burden. Controlling for *Lev* in regression is reasonable given its potential impact on firms' investment and operating risks. According to the mean value of *Tax* (0.0348), the tax burden is moderate, with negative minimum values indicating that some companies are overpaying taxes in their tax returns. Overall, the descriptive statistics underscore the typicality and rationality of our research sample distribution.

Corporate digitalization and operating risk

Correlation analysis. Figure 2 displays the scatter distribution and fitting line of the means of CDT and operating risk. Specifically, the horizontal axis represents the mean value of the CDT for each industry and each year (*Mean_CDT*), and the vertical axis is the mean value of companies' first operating risk indicators

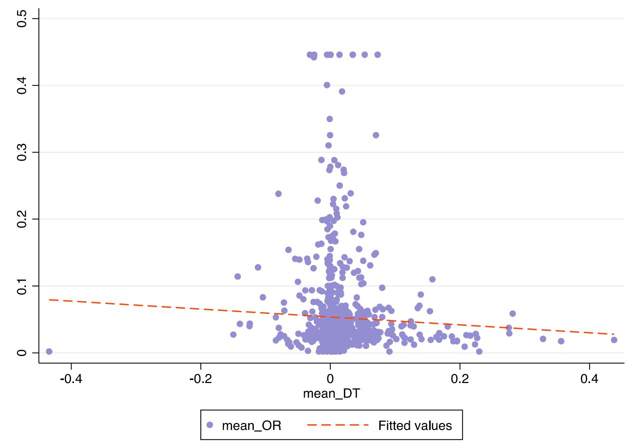

Fig. 2 Scatter distribution of firm digital transformation and business risk. The horizontal axis is the mean value of firms' digital transformation for each industry and each year (*Mean_CDT*), the vertical axis is the mean value of companies' first operating risk indicators for each industry and each year (*Mean_OR*).

Table 1 Descriptive statistics.

Variable	N	Mean	Std.	Min	P25	P50	P75	Max
OR	29,956	0.0516	0.0747	0.0019	0.0122	0.0237	0.0526	0.4459
OR1	26,502	0.0517	0.0748	0.0019	0.012	0.0234	0.0527	0.4379
OR2	29,951	0.0528	0.077	0.002	0.0126	0.0245	0.0541	0.4774
CDT	22,984	0.0147	0.1115	−0.4341	−0.0022	0.0003	0.0094	0.6563
CDT2	22,984	0.0004	0.0016	−0.0031	−0.0001	0.0000	0.0003	0.0109
CDT3	12,237	0.0084	0.0259	−0.0695	0.001	0.0029	0.0076	1.2283
Size	29,956	22.1446	1.2967	19.5514	21.2282	21.9855	22.8839	26.1093
Age	29,956	2.8375	0.3468	1.7918	2.6391	2.8904	3.091	3.4965
Lev	29,956	0.4509	0.2069	0.0593	0.2888	0.4475	0.608	0.9101
Tangibility	29,956	0.9262	0.0893	0.5225	0.9129	0.9562	0.9796	1
Density	29,956	0.0257	0.0233	0.0039	0.0129	0.019	0.0295	0.158
Tax	29,956	0.0348	0.0422	−0.0183	0.0108	0.0216	0.0405	0.2326
Indirector	29,956	0.3736	0.0533	0.3077	0.3333	0.3333	0.4286	0.5714
Duality	29,956	0.2413	0.4279	0	0	0	0	1
SH	29,956	0.3448	0.1495	0.0857	0.2268	0.3227	0.448	0.7465
TQ	29,956	2.0695	1.3957	0.8625	1.2325	1.6137	2.3458	9.2829

Descriptive statistics on variables in Model (1) are displayed. Consult Table A7 in Appendix A3 for precise variable definitions. P25 represents the 25% quantile, and so on.

Table 2 Effects of firm digital transformation on operating risks.

	(1)	(2)
	OR	*OR*
CDT	−0.033***	−0.031***
	(−5.834)	(−5.677)
Size		−0.009***
		(−12.768)
Age		−0.001
		(−0.254)
Lev		0.055***
		(11.761)
Tangibilty		−0.056***
		(−6.374)
Density		0.279***
		(7.167)
Tax		0.027
		(1.120)
Indirector		0.008
		(0.727)
Duality		−0.000
		(−0.054)
SH		−0.027***
		(−6.215)
TQ		0.002***
		(3.104)
Constant	0.051***	0.267***
	(78.179)	(14.277)
Y-FE	√	√
Ind-FE	√	√
R^2	0.283	0.287
N	23,008	23,004

The t-statistics for each coefficient are enclosed in parentheses, with significance levels indicated by *** for 1%. Y-FE indicates year-fixed effect, Firm-FE represents firm-fixed effect, and Ind-FE signifies industry-fixed effect. The symbols √ and × represent "yes" and "no," respectively. Consult Table A7 in Appendix A3 for precise variable definitions.

for each industry and each year (*Mean_OR*). As shown in Fig. 2, the fitting line between *Mean_CDT* and the mean value of firm operating risks (*Mean_OR*) is tilted to the lower right, indicating that CDT is negatively correlated with operating risks, which preliminarily supports the hypothesis that CDT reduces the risks associated with operations.

Baseline results. The outcomes of model (1) are illustrated in Table 2. Column (1) controls for industry- and year-fixed effects without including firm-level controls. In this case, *GDT* has a coefficient of −0.033, which is significant at the 1% level. When firm-level control variables are incorporated into column (2), the coefficient of *GDT* remains statistically significant. Accordingly, GDT is able to reduce the volatility of corporate earnings before interest and taxes, thus mitigating the risk associated with firm operations. The estimated coefficient ($\widehat{\beta}$) in column (2) is −0.031. Accordingly, for every unit increase in the proportion of digital assets to total intangible assets, the volatility of earnings before interest and tax over the rolling three periods decreases by 0.031 units. This reduction represents approximately 60.07% of the mean of *OR*, demonstrating significant economic significance.

Moreover, with the inclusion of control variables, the absolute value of $\widehat{\beta}$ diminishes, indicating that our selection of control variables and fixed effects effectively mitigates the impact of unobservable factors on firms' operating risks. These results robustly demonstrate that CDT effectively reduces operating risks, aligning with our hypothesis.

In terms of control variables, *Size* demonstrates a statistically significant negative coefficient, indicating that larger firms tend to exhibit smaller earnings volatility and lower operating risks. This trend can be attributed to several factors. First, larger companies often possess larger market sizes and more extensive financing channels, enhancing their resilience against risks. Second, these firms, typically in mature stages, tend to pursue non-aggressive investment policies, resulting in slower asset expansion and, consequently, lower earnings volatility. Conversely, the asset-liability ratio (*Lev*) shows a positive correlation with firm operating risks. This relationship arises from heavy borrowing potentially amplifying future yield volatility and increasing financial risk. Additionally, higher debt ratios imply heightened financial risk, reduced loan availability from financial institutions, and elevated downside risks to corporate performance. Asset tangibility (*Tangibility*) significantly impacts operating risks negatively as tangible assets can serve as collateral for loans, bolstering enterprises' financial standing. On the other hand, capital intensity (*Density*), representing a firm's resource adjustment ability, exhibits a positive coefficient. Elevated capital density may elevate adjustment costs, hindering timely responses to external risks or investment opportunities consequently diminishing a company's real option value. Furthermore, ownership concentration (*SH*) yields a negative and statistically significant coefficient at the 1% level. This suggests that major shareholders may intervene to steer management toward conservative business strategies, aiming to reduce future risks and bolster internal control measures.

In the robustness test (Appendix A1), we changed the measurement methods for CDT and operational risk, fixed effects combinations, and sample selection. The research hypothesis still holds true.

Addressing endogeneity concerns. The benchmark results may be influenced by endogeneity issues arising from omitted variables, reverse causality, and self-selection. While our regressions include various controls and fixed effects, some factors affecting firm operating risks may still be missing. Additionally, reduced operational risks can lead to a positive feedback loop, encouraging DT. Moreover, firms with lower risks may be more likely to adopt CDT, resulting in self-selection bias. To address these concerns, we employ several methods: instrumental variable regressions, Heckman two-step model, propensity score matching (PSM), placebo tests, and double machine learning.

Instrument variable regressions. We utilize executives' awareness of DT (*IV*) as an instrument variable for firm DT. This approach is grounded in the belief that corporate executives' strategic understanding of DT incentivizes firms to invest in digital assets, facilitating CDT (Chen and Srinivasan, 2024). However, it is evident that executives' digital awareness does not directly impact business operations; rather, it influences activities through strategic implementation. Consequently, our paper asserts that the *IV* must satisfy both the correlation and exogeneity hypotheses. The management discussion and analysis (MD&A) section of a company's annual report typically contains executive opinions about the company's future prospects (Muslu et al., 2015). Accordingly, the frequency of digital keywords mentioned in the MD&A is applied to gauge managers' awareness of DT.

Table 3 presents the results from the Two-Stage Least Squares (2SLS) method. The first-stage F-value (84.769) confirms the absence of weak IV issues, and the second-stage results show that CDT significantly reduces operating risks. These results remain consistent when switching to firm- and year-fixed effects.

Table 3 IV regressions.

	(1) IV First DT	(2) IV First DT	(3) IV Second OR	(4) IV Second OR
DT			−0.347***	−0.208*
			(−3.864)	(−1.702)
IV	0.007***	0.007***		
	(9.21)	(6.29)		
CX	√	√	√	√
Y-FE	√	√	√	√
Ind-FE	√	×	√	×
Firm-FE	×	√	×	√
R^2			−0.211	−0.072
N			22,509	22,334
KPF	84.769	39.593		
CDF	104.775	58.928		
KPM	82.269	38.632		

Columns (1) and (2) display the results of the first stage of instrumental variable regressions, while columns (3)–(6) report the second stage. The t-statistics for each coefficient are enclosed in parentheses, with significance levels indicated by *, and *** representing 10%, and 1%, respectively. Y-FE indicates year-fixed effect, Firm-FE represents firm-fixed effect, and Ind-FE signifies industry-fixed effect. The symbols √ and × represent "yes" and "no," respectively. KPF denotes Kleibergen-Paap rk Wald F statistic; CDF denotes Cragg-Donald Wald F statistic; KPM denotes Kleibergen-Paap rk LM statistic. Consult Table A7 in Appendix A3 for precise variable definitions.

Table 4 PSM method.

	(1) PSM 1:1	(2)	(3) PSM 1:2	(4)
	OR	*OR*	*OR*	*OR*
CDT	−0.022***	−0.020***	−0.026***	−0.022***
	(−3.425)	(−2.748)	(−4.537)	(−3.643)
CX	√	√	√	√
Y-FE	√	√	√	√
Ind-FE	√	×	√	×
Firm-FE	×	√	×	√
R^2	0.175	0.456	0.184	0.413
N	10,395	9766	14,500	14,094

Columns (1)–(2) present the results of nearest neighbor matching (1:1). Columns (3)–(4) display the results of nearest neighbor matching (1:2). The t-statistics for each coefficient are enclosed in parentheses, with significance levels indicated by *** for 1%. Y-FE indicates year-fixed effect, Firm-FE represents firm-fixed effect, and Ind-FE signifies industry-fixed effect. The symbols √ and × represent "yes" and "no," respectively. Consult Table A7 in Appendix A3 for precise variable definitions.

PSM method. To address potential sample selection bias, we apply PSM. Using a logit model, we create a binary variable (*CDT dummy*1) indicating whether a firm's digital asset value exceeds the 75th percentile. Nearest neighbor matching (1:1 and 1:2) is employed, and balance tests confirm no significant differences between treatment and control groups after matching (see results of Table A8 in Appendix). Re-estimated results in Table 4 show that the coefficient $\widehat{\beta}$ remains significant and negative.

Heckman two-stage method. To further address self-selection bias, we apply the Heckman two-stage method. In the first stage, we use a probit model where the dependent variable is a binary indicator (*CDT_dummy*2) representing whether a firm's digital asset value exceeds the 50th percentile. Executives' digital awareness is also used as the instrumental variable (*IV*), and the Inverse Mills Ratio (IMR) is constructed based on the first stage. Table 5 shows that the IMR is significant, confirming the presence of self-selection bias. Nevertheless, the results remain consistent with our main findings.

Table 5 Heckman two-stage method.

	(1) *OR*	(2) *OR*
CDT	−0.031***	−0.024***
	(−5.543)	(−4.393)
IMR	0.031***	−0.005
	(4.071)	(−0.541)
CX	√	√
Y-FE	√	√
Ind-FE	√	×
Firm-FE	×	√
R^2	0.187	0.382
N	22,507	22,332

The t-statistics for each coefficient are enclosed in parentheses, with significance levels indicated by *** for 1%. Y-FE indicates year-fixed effect, Firm-FE represents firm-fixed effect, and Ind-FE signifies industry-fixed effect. The symbols √ and × represent "yes" and "no," respectively. Consult Table A7 in Appendix A3 for precise variable definitions.

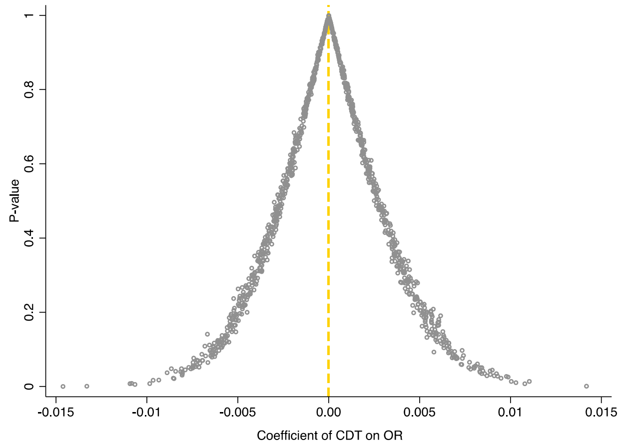

Fig. 3 Placebo test. The horizontal axis is the estimated coefficients of *CDT* on *OR*, and the vertical axis is the corresponding *P*-values of each estimated coefficient.

Placebo test. We conduct a placebo test by randomly assigning CDT values and re-estimating Model (1). As shown in Fig. 3, the estimated coefficients for the randomized *CDT* are close to zero and mostly insignificant, indicating that our results are not driven by unobservable factors.

Double machine learning method. The empirical analysis above primarily relies on OLS estimation, but linear model assumptions often do not align with reality. Conventional econometric models encounter issues such as multicollinearity, confounding factors, and departure from predetermined functions. With technology advancing, machine learning is increasingly used in financial analysis and prediction. Athey (2017) argues that machine learning outperforms traditional econometric models in policy evaluation by better capturing how covariates influence outcome variables. Therefore, to complement predictions where OLS estimation bias cannot be entirely eliminated, this paper proposes employing machine learning methods.

The double machine learning method is adopted to forecast the impact of CDT on operating risks. The Toolbox for Dual machine Learning is derived from Chiang et al. (2022). We also include covariates (***CX***), year dummy variables and industry dummy

Table 6 Double machine learning method.

	(1)	(2)	(3)	(4)
	OR	**OR**	**OR**	**OR**
CDT	−0.027***	−0.027***	−0.031***	−0.031***
	(−5.200)	(−5.409)	(−6.074)	(−6.245)
CX	√	√	√	√
Y-FE	×	√	×	√
Ind-FE	×	×	√	√
N	22,885	22,885	22,885	22,885

The t-statistics for each coefficient are enclosed in parentheses, with significance levels indicated by *** for 1%. Y-FE indicates year-fixed effect, Firm-FE represents firm-fixed effect, and Ind-FE signifies industry-fixed effect. The symbols √ and × represent "yes" and "no," respectively. Consult Table A7 in Appendix A3 for precise variable definitions.

Table 7 Mechanism analysis: financial channel.

	(1)	(2)	(3)	(4)
	Pricing	***Consumer***	***Fin1***	***Fin2***
CDT	0.0369***	−1.9236**	−0.143***	−0.004***
	(3.9714)	(−2.5767)	(−2.722)	(−3.314)
CX	√	√	√	√
Y-FE	√	√	√	√
Ind-FE	√	√	√	√
R^2	0.194	0.531	0.054	0.077
N	19,109	22,921	22,922	22,922

The t-statistics for each coefficient are enclosed in parentheses, with significance levels indicated by ** and *** representing 5% and 1%, respectively. Y-FE indicates year-fixed effect, Firm-FE represents firm-fixed effect, and Ind-FE signifies industry-fixed effect. The symbols √ and × represent "yes" and "no," respectively. Consult Table A7 in Appendix A3 for precise variable definitions.

variables. As shown in Table 6, the estimated $\widehat{\beta}$ in all columns are statistically significant and negative, supporting our benchmark conclusion.

Mechanism analysis

Building on the theoretical framework presented in the "Sample and descriptive statistics" section, this section empirically examines the mechanisms through which CDT mitigates operating risks. The analysis focuses on two main channels: (1) the financial channel, which emphasizes firms' pricing and market expansion abilities and the mitigation of financialization risks, and (2) the non-financial channel, which centers on corporate governance and ESG performance. By constructing and testing mechanism variables, we aim to validate how these channels contribute to risk reduction.

Financial channel. The financial channel of CDT is rooted in the theories of operational efficiency and market dynamics. CDT enhances firms' profitability and resilience by improving cost management, pricing strategies, and market adaptability (Babina et al., 2024).

Pricing is selected to measure firms' pricing power and profitability, a critical aspect of financial resilience. The concept is grounded in the theory of price elasticity and competitive strategy, which emphasizes the role of cost efficiencies in enabling firms to improve their pricing strategies and market positioning. Operating margin, as an indicator of *Pricing*, reflects a firm's ability to sustain profitability amid cost fluctuations and competitive pressures. High operating margins indicate stronger profitability and pricing power, which are key components in mitigating operational risks. This approach is supported by prior research, such as Babina et al. (2024), which highlights the relationship between cost optimization enabled by digital technologies and enhanced firm profitability.

Consumer is chosen to represent changes in customer market structure, capturing the extent to which CDT enables firms to diversify their customer base and reduce reliance on a few key customers. This variable aligns with theories of market dynamics and risk diversification, which argue that a broader customer base can lower a firm's vulnerability to specific client-related risks (Erevelles et al., 2016). The *Consumer* can be calculated as $Consumer_{i,t} = Content_{i,t} - Content_{i,t-1}$. A lower value signifies greater diversification and thus a reduced risk profile. By leveraging digital technologies, firms can access new customer segments, improve targeting strategies, and expand their market share, all of which enhance resilience against revenue volatility (Bhargava and Choudhary, 2008; Goldfarb and Tucker, 2019).

We replace the dependent variable in Model (1) with *Pricing* and *Consumer*, and then re-estimate Model (1) accordingly. The pertinent findings are displayed in columns (1)–(2) of Table 7. The estimated $\widehat{\beta}$ in column (1) is positively significant at the 1% level, suggesting that a one-unit rise in the proportion of added value of digital assets to total intangible assets leads to a 3.69% increase in the company's operating margin. In column (2), the estimated $\widehat{\beta}$ is negative and statistically significant at the 5% level. For each additional unit increase in the ratio of added value of digital assets to total intangible assets, the company's customer concentration decreases by 192.36%. The firm's ability to price products and expand into new markets has greatly increased due to its involvement in CDT.

We delve deeper into whether CDT indeed steers companies away from financial investments, thereby reducing non-business operating risks as anticipated. Financialization refers to the reallocation of corporate resources from core business activities to financial assets, driven by factors such as investment substitution, agency problems, and precautionary motives (Jensen, 1986; Tori and Onaran, 2018). While financial investments may provide short-term gains, they often erode long-term competitiveness by diverting resources from productive investments like R&D. Moreover, the high volatility of financial asset prices exacerbates performance fluctuations and amplifies operating risks (Demir, 2009). CDT mitigates financialization by enhancing firms' core business capabilities, such as operational efficiency, innovation, and internal control quality (Peng and Tao, 2022; Jiang et al., 2022). By reducing over-reliance on financial assets, CDT fosters financial stability and helps firms focus on their core competencies.

We construct two variables, *Fin*1 and *Fin*2, to gauge the extent of corporate financialization behavior. *Fin*1 is the ratio of financial activity profit to total profit, whereas *Fin*2 is the ratio of profit from financial activities to total assets. We then replace the independent variable in Model (1) with *Fin*1 and *Fin*2, and re-evaluate Model (1) accordingly. The data in columns (3)–(4) of Table 7 show that CDT greatly decreases the percentage of income obtained from financial activities.

To succinctly summarize, on one hand, digital transformation facilitates an enhancement in gross margin and a reduction in customer concentration, the latter serving as an indicator of product market competitiveness. The increase in gross margin addresses the pain point associated with the company's limited pricing power. With higher gross margins, the company is able to flexibly set prices based on factors such as cost, market demand, and competitive conditions, thereby maintaining profitability while ensuring a price advantage relative to competitors. A decrease in customer concentration signifies the acquisition of a broader new customer base and an expansion in market share, often accompanied by economies of scale. Businesses can reduce per-unit costs in procurement, production, and sales phases. On the other hand, digital transformation curtails the company's financial activities. Financial markets are characterized by high uncertainty and volatility, such as stock markets which can fluctuate significantly due to macroeconomic policies, international situations, and other factors. If a company excessively invests in the stock market, a market crash could lead to substantial losses. By reducing investments in financial derivatives and reallocating funds toward upgrading production equipment and enhancing product quality, manufacturing enterprises can better navigate market competition and mitigate the risks of operational crises stemming from financial investment errors. Taken together with the findings from Table 7, it becomes evident that through financial channels, CDT can indeed mitigate firms' operating risks by bolstering core business advantages and curbing risks associated with non-business operations.

Non-financial channel. We then delve into the influence of CDT on firms' non-financial advantages, particularly corporate governance and ESG performance. Theoretical insights from agency theory and transaction cost theory suggest that digital technologies play a pivotal role in reducing agency costs and enhancing internal control systems (Jenson and Meckling, 1976; Jiang et al., 2022). By mitigating information asymmetry and increasing operational transparency, CDT not only advances audit capabilities but also streamlines internal audits, strengthens corporate internal governance, and enhances the autonomy of internal control systems.

With this in mind, we construct two variables, internal control (*IC*) and agency cost (*Agency*), to assess the impact of CDT on corporate governance. The natural logarithm of the internal control quality score from the DiBo Internal Control and Risk Management Database measures the internal control quality of listed corporations (*IC*). This index, recognized in academic literature by Li et al. (2021) and Jiang et al. (2022), is utilized to assess the risk management and internal control quality of Chinese listed businesses. The agency cost (*Agency*) is represented by the management expense ratio, which is computed as management expenses divided by operational income, in line with Jiang et al. (2022). A higher *Agency* value corresponds to weaker corporate governance.

Upon substituting the dependent variable in Model (1) with *IC* and *Agency*, and subsequently re-estimating Model (1), the findings in columns (1)–(2) of Table 8 show that CDT improves internal control quality and decreases agency expenses, ultimately strengthening corporate governance. For example, when looking at the data in column (1) of Table 8, the estimated coefficient $\widehat{\beta}$ is 0.042, showing a statistically significant positive relationship at the 1% significance level. For each additional unit increase in the ratio of added value of digital assets to total intangible assets, the company's internal control quality increases by 4.2%.

Table 8 Mechanism analysis: non-financial channel.

	(1)	(2)	(3)	(4)
	IC	*Agency*	*ESG_rating*	*ESG_news*
CDT	0.042***	−0.010**	0.439***	0.079*
	(5.072)	(−2.325)	(6.284)	(1.835)
CX	√	√	√	√
Y-FE	√	√	√	√
Ind-FE	√	√	√	√
R^2	0.194	0.531	0.193	0.039
N	19,109	22,921	20,923	19,387

The t-statistics for each coefficient are enclosed in parentheses, with significance levels indicated by *, **, and *** representing 10%, 5%, and 1%, respectively. Y-FE indicates year-fixed effect, Firm-FE represents firm-fixed effect, and Ind-FE signifies industry-fixed effect. The symbols √ and × represent "yes" and "no," respectively. Consult Table A7 in Appendix A3 for precise variable definitions.

The integration of digital technologies through CDT significantly enhances firms' ESG performance, which serves as a key mechanism in mitigating operating risks. Theoretical insights from sustainable development theory and stakeholder theory suggest that firms with strong ESG performance are better positioned to manage environmental, social, and governance risks (Talan et al., 2024; Zhou et al., 2022). Specifically, ESG performance reflects a firm's ability to meet the expectations of various stakeholders while pursuing sustainable growth, thereby reducing reputational and compliance risks (He et al., 2023; Singhania and Gupta, 2024; Zhou et al., 2024).

We examine how CDT affects ESG performance by using the Huazheng ESG index, which ranges from AAA to C, as a measure of corporate ESG performance. We transform the nine ESG ratings into numerical values, abbreviated as *ESG_rating*, where 9 indicates the highest ESG rating and 1 represents the lowest ESG rating for analysis. We enhance our analysis by including public perceptions of ESG performance, despite debates about using ESG ratings as proxies for companies' ESG performance due to variations in rating systems among agencies (Gibson Brandon et al., 2021; Jiang et al., 2025b). Drawing from the company's ESG news coverage and public sentiment, denoted as *ESG_news*, we leverage the "Quantitative Public Opinion Database of Newspapers and Newspapers" by Digitizer Technology. This database employs advanced machine learning techniques to discern emotional sentiments from news articles and assess their relevance to listed companies, ultimately determining an average score reflecting public perceptions of ESG-related news.

Replacing the independent variable in Model (1) with *ESG_rating* and *ESG_news*, and subsequently re-estimating Model (1), we observe in columns (3)-(4) of Table 8 that CDT positively influences ESG rating and public perceptions of ESG news. For instance, in column (1), the calculated coefficient $\widehat{\beta}$ is positive and statistically significant at the 1% level. This suggests that a one-unit increase in the proportion of added value of digital assets to total intangible assets results in a 0.143-point gain in the ESG rating.

To concisely summarize, digital transformation has elevated the level of internal governance and improved ESG performance, which in turn helps companies establish a solid reputation and mechanisms for risk management. First, as global attention to climate change increases, governments worldwide are implementing stricter environmental regulations. Companies, particularly in their energy use, may face pressures to transition from traditional fossil fuels to cleaner energy sources. Companies that proactively improve their environmental performance are better positioned to adapt to increasingly stringent environmental regulations. Enhanced consumer awareness of environmental issues also shifts preferences toward eco-friendly products. Companies with strong environmental records can meet this market demand by launching green products and services, thereby expanding their market share. Second, companies that focus on product liability and consumer rights are able to build a positive brand image. Third, a robust corporate governance structure ensures the independence of the decision-making process, preventing autocratic management behaviors and decision-making errors. Through rational decision-making processes, companies can avoid risks such as blind investments and overexpansion, ensuring the efficient allocation of resources. A sound internal audit and risk control system can timely detect and assess operational risks. Taken together with the findings from Table 8, it becomes evident that through non-financial channels, CDT can indeed mitigate firms' operating risks by bolstering internal governance and ESG performance.

Heterogeneity analysis

Perspective of firm characteristics. This section explores the heterogeneity in the effect of CDT on operating risks across firms with varying characteristics. We focus on three dimensions: firm size, capital intensity, and agency costs.

First, smaller firms typically face greater obstacles compared to larger firms in securing external financing, expanding their market share, achieving scalability, and maintaining resilience to risks. Resource dependency theory suggests that smaller firms, being more dependent on external resources, are more constrained by these challenges. As a result, they stand to gain disproportionately from CDT, which can enhance their competitiveness by optimizing resource utilization and access to information. Additionally, economies of scale theory highlights that larger firms benefit from spreading fixed costs over a greater output, while smaller firms lack such advantages. Therefore, CDT offers smaller firms a pathway to improve efficiency and mitigate risks associated with resource constraints and market competition.

Second, capital intensity refers to the degree to which a firm relies on physical assets. Firms with higher capital intensity often face challenges in efficiently allocating resources, as noted in asset specificity and resource allocation efficiency theory. CDT, by enhancing operational efficiency through data analytics, process automation, and optimization of resource usage, provides these asset-heavy firms with tools to overcome these inefficiencies. Information asymmetry and transaction cost theory further support this by suggesting that CDT reduces information asymmetries and transaction costs, particularly in firms that have large physical assets and complex operations.

Third, firms with weaker governance structures often face higher agency costs, which result from conflicts between management and shareholders due to misaligned incentives. Agency theory posits that such firms are more prone to inefficient decision-making and resource misuse, which increases operational risks. CDT can mitigate these issues by improving transparency, enhancing corporate governance, and streamlining management processes. Additionally, CDT can strengthen ESG practices, further reducing risks associated with poor governance.

In Appendix A2.1, we establish empirical analysis and validate the above viewpoints.

Perspective of regional attributes. To further explore how regional attributes affect the relationship between CDT and operating risks, we conduct a heterogeneity analysis from three perspectives: government informatization policies, digital tax regulation, and intellectual property protection.

First, we suggest that the suppressive effect of CDT on operating risks is stronger in cities with advanced digital government service infrastructures. This enhanced effect can be attributed to the higher level of digital infrastructure and public service provision in informatization pilot cities. Firms in these cities are better able to access and utilize digital technologies, leading to improved operational efficiency and reduced compliance and market risks. Moreover, government support for digital initiatives and increased transparency further promotes CDT, allowing firms to adapt more effectively to the digital business environment and enhance their risk resilience. Thus, in cities with informatization pilot policies, the impact of DT on reducing operating risks is more pronounced.

Next, we argue that the suppressive effect of CDT on operating risks is stronger in cities with advanced digital tax administration systems. In Golden Tax Phase III pilot cities, the tax system is more digitalized and transparent. Firms in these cities through DT, are better able to adapt to the new regulatory environment, reducing their tax compliance risks and, consequently, their overall operating risks. Additionally, digitalization improves firms' management efficiency, reducing human errors and operational risks, which enhances their overall resilience to risk. In these pilot cities, the benefits of CDT are more fully realized, thus leading to a more significant reduction in operating risks. The enhanced digital tax infrastructure in these cities plays a crucial role in magnifying the risk-reduction effect of CDT.

Finally, we confirm that the suppressive effect of CDT on operating risks is stronger in cities with enhanced IP protection. This result can be explained by the fact that CDT often involves extensive use of new technologies and data, both of which are closely tied to intellectual property. In cities where IP protection is more comprehensive, companies' innovations, trade secrets, technological patents, and other intellectual assets are better safeguarded from infringement or unauthorized use. In such an environment, firms are more motivated to pursue DT, as they can protect their innovations and technologies more effectively, without fear of significant losses due to IP risks. The robust IP protection system in these cities reduces the legal and market risks that firms face during DT, thereby mitigating overall operational risks. As a result, the risk-reducing effect of CDT is more pronounced in IP demonstration cities, where firms can reap the benefits of innovation in a more secure and protected environment.

In Appendix A2.2, we provide detailed information on government policies and validate the above viewpoints through empirical analysis.

Further analyses

Too much of a good thing? In our theoretical analysis, we examine the negative impacts of DT on corporate operational risks through the lenses of technology, organizational management, business models, and cash flow. This analysis leads to the formulation of Research Hypothesis ***H1***, which posits that DT can exacerbate operational risks. Conversely, we also outline the benefits of DT, identified through both financial and non-financial channels, leading to the development of Research Hypothesis ***H2***. This hypothesis suggests that DT, on the whole, reduces the operational risks faced by businesses. Empirical results, based on evidence from Chinese firms, support the assertion that DT generally diminishes operational risks, thus validating Research Hypothesis ***H2***. However, this finding does not negate the burdens that companies bear during the process of DT. The initial challenges posed by DT in terms of technology, organizational management, and business models may diminish or even dissipate as companies gradually adapt to new technologies and adjust their management approaches. Nevertheless, DT inherently represents an investment project that has a significant and ongoing impact on operational cash flows. Specifically, when the scale of digital investments is overly large or rapidly executed, the crowding-out effect on cash flows intensifies, potentially causing the negative impacts on operational risks to outweigh the positive effects.

In summary, while Research Hypothesis ***H2*** holds true in the general sample—indicating that DT significantly mitigates revenue volatility—for companies with excessive digital investments, Hypothesis ***H2*** might not hold, and Hypothesis ***H1*** could be significantly validated in such instances. This nuanced

Table 9 The dilemma of "too much of a good thing".

	(1) *OR*	(2) *Cash1*	(3) *Cash2*
CDT	−0.0475***	−0.056**	−9.471***
	(−5.7668)	(−2.484)	(−2.896)
CDT^2	0.0624***		
	(3.7778)		
CX	√	√	√
Y-FE	√	√	√
Ind-FE	√	√	√
R^2	0.1869	0.303	0.026
N	22,885	22,922	22,101

The t-statistics for each coefficient are enclosed in parentheses, with significance levels indicated by ** and *** representing 5% and 1%, respectively. Y-FE indicates year-fixed effect and Ind-FE signifies industry-fixed effect. The symbols √ and × represent "yes" and "no," respectively. Consult Table A7 in Appendix A3 for precise variable definitions.

Table 10 CDT and real options.

	(1) *Up3*	(2) *Up5*	(3) *Up3*	(4) *Up5*
CDT	0.007**	0.014***	0.005*	0.009**
	(2.425)	(4.062)	(1.661)	(2.382)
CX	√	√	√	√
Y-FE	√	√	√	√
Ind-FE	√	√	×	×
Firm-FE	×	×	√	√
R^2	0.193	0.039	0.201	0.203
N	20,923	19,387	26,976	26,976

The t-statistics for each coefficient are enclosed in parentheses, with significance levels indicated by *, **, and *** representing 10%, 5%, and 1%, respectively. Y-FE indicates year-fixed effect and Ind-FE signifies industry-fixed effect. The symbols √ and × represent "yes" and "no," respectively. Consult Table A7 in Appendix A3 for precise variable definitions.

perspective underscores the complexity of DT and its varying impacts depending on the scale and speed of implementation.

To explore this idea, we construct a nonlinear estimation model following Anwer et al. (2023). The model is specified as follows:

$$OR_{it} = \alpha + \beta_1 CDT_{it} + \beta_2 {CDT_{it}}^2 + \gamma \boldsymbol{CX} + Indu_{FE} + Year_{FE} + \varepsilon_{it} \tag{5}$$

where ${CDT_{it}}^2$ is the squared term of CDT_{it}, capturing a curvilinear relationship if one exists. The other settings in model (5) are consistent with model (1). The coefficients $\widehat{\beta_1}$ and $\widehat{\beta_2}$ are the main focus of our analysis. If the estimated $\widehat{\beta_1}$ and $\widehat{\beta_2}$ are separately negative and positive, and both are statistically significant, this result implies a U-shaped relationship between CDT and operating risks. Conversely, if $\widehat{\beta_1}$ and $\widehat{\beta_2}$ are positive and negative, respectively, and both are statistically significant, this suggests an inverted U-shaped relationship.

Table 9 presents the nonlinear relationship between CDT and firm operating risks. The dependent variable is *OR*. The regression results show that the estimated coefficients $\widehat{\beta_1} = -0.0475$ and $\widehat{\beta_2} = 0.0624$ are statistically significant at the 1% level. This indicates a nonlinear U-shaped relationship between CDT and firm operating risks. Specifically, CDT is expected to reduce operational risks up to a certain threshold, but once the CDT level exceeds a critical point $\left(CDT = 0.3806, \text{calculated as} \frac{0.0475}{2\times 0.0624}\right)$, it starts to have a negative impact on operational risks. Overall, the results support our hypothesis, suggesting that after reaching a certain threshold, CDT starts to introduce risks.

We believe that the dilemma of "too much of a good thing" essentially stems from the crowding-out effect on cash flows caused by DT. To test this hypothesis, we further examine the impact of digital investments on cash flow conditions. We constructed two variables, *Cash1* and *Cash2*, to reflect the adequacy of operational cash flows, whose definitions are provided in Table A7. We replaced the risk variables in the baseline model with these cash flow variables and reran the regression analysis. The results presented in Columns (2) and (3) of Table 9 highlight our conjecture: DT can crowd out the availability of corporate operational cash flows.

In conclusion, our findings demonstrate that even though DT generally reduces income volatility on a broad scale, excessive digital investments can lead to transformation failure, thus exacerbating operational risks. This underscores the critical balance required in DT investments, highlighting the importance of not only pursuing technological advancement but also managing its financial implications to avoid compromising the company's liquidity and increasing its operational risks.

CDT and corporate real option value. In the preceding sections, we extensively explored the influence of CDT on operating risks. However, a pertinent issue arises: does the reduction in earnings volatility come at the expense of sacrificing the upward potential for corporate performance? The relationship between CDT and corporate real option value remains uncertain. We will thoroughly analyze the relationship between CDT and performance improvement to acquire a more comprehensive understanding of their connection.

CDT decreases the expenses associated with customer search and tracking (Goldfarb and Tucker, 2019), as well as fosters product innovation (Blichfeldt and Faullant, 2021). This allows firms to enter new markets and perhaps improve their performance and elevates the value of real options. The upward potential of a company's performance can be quantified using the following equation:

$$IEROA_{i,t} = \frac{1}{nj}\sum_{t=1}^{nj} EROA_{i,t} \tag{6}$$

$$\varnothing_{i,t} = \begin{cases} 0, EROA_{i,t} - IEROA_{i,t-1} < 0 \\ EROA_{i,t} - IEROA_{i,t-1}, EROA_{i,t} - IEROA_{i,t-1} \geq 0 \end{cases} \tag{7}$$

$$Up3 = \sqrt{\frac{1}{3}\sum_{t=0}^{-2} {\varnothing_{i,t}}^2} \tag{8}$$

$$Up5 = \sqrt{\frac{1}{5}\sum_{t=0}^{-4} {\varnothing_{i,t}}^2} \tag{9}$$

where $IEROA_{i,t}$ is the proportion of firm i's profit before interest and tax to total assets in year t. $IEROA_{i,t-1}$ is the average revenue of firm i's industry in year $t-1$ and represents firm i's target return rate in year t. *Up*3 is the upward potential of performance calculated over a 3-year period, while *Up*5 is the upward potential of performance calculated over a 5-year period. We then substitute the dependent variable in Model (1) with *Up*3 and *Up*5, and re-estimate Model (1), respectively. Corresponding results are displayed in Table 10.

Columns (1) and (2) show a positive and statistically significant estimated coefficient $(\widehat{\beta})$ at the 5% level for CDT, suggesting that it effectively enhances upward volatility. For instance, considering the results in column (2), the absolute value of $\widehat{\beta}$ is 0.014. For each incremental rise in the ratio of added value of digital assets to total intangible assets, there is a corresponding 1.4% increase in the potential for corporate performance to improve. Controlling for firm-fixed effects in columns (3) and (4) had no impact on the results.

The results in this section clearly show that CDT's impact on reducing operating risks does not hinder performance potential growth; rather, it improves it.

Conclusion

Findings. This paper delves into the significance of DT for companies, particularly in mitigating operating risks. Using the volatility of corporate earnings over rolling three periods as a metric for operating risk, our benchmark results demonstrate a clear inverse relationship between CDT and earnings volatility. According to our findings, the volatility of earnings before interest and taxes decreases for each increase in the ratio of the added value of digital assets to the total intangible assets. Employing diverse methodological approaches, including instrumental variable methods, Heckman two-step methods, PSM, placebo tests and double machine learning estimation, we ensure the robustness of our findings. Heterogeneity analysis further reveals that small firms, those with high capital intensity, and those with high agency costs stand to benefit the most from CDT, emphasizing the imperative for transformation in these segments. We further substantiated that the enhancement of informational infrastructure, the reinforcement of intellectual property protection, and the advancement of digital taxation infrastructure can amplify the risk mitigation effects of DT. Mechanism analysis uncovers two key channels through which CDT influences operating risks. First, in the financial channel, digitalization enhances core business benefits while reducing non-business operation risks. Second, in the non-financial channel, DT improves corporate governance and ESG performance. We have further expanded our analysis to explore the side effects of DT and the direction of revenue volatility. We discovered that DT can encroach upon the availability of cash flows. Excessive digital investments may exacerbate operational risks. Furthermore, our analysis indicates that CDT enhances the value of real options, indicating that the reduction in operating risks does not compromise a company's upside potential for performance.

Discussions. To summarize, this article continues to affirm the advantages of DT. Although companies may face challenges in technology alignment, internal management, business model adaptation, and cash flow management during the digitalization process, digital empowerment has emerged as a dominant factor. CDT enhances both financial and non-financial performance, reducing passive product market risks. Furthermore, the reduction in revenue volatility driven by digitalization does not compromise a company's potential for growth, primarily due to diminished downside risks. These observations indicate that DT bolsters corporate risk management and operational resilience, enhancing overall defensiveness, which directly contradicts existing literature on digitalization and corporate risk appetite. However, our findings also highlight several cautionary insights specific to Chinese mainland. Excessive investment behavior is prevalent among Chinese enterprises. Similarly, the tendency toward excessive digital investment, which encroaches on operational cash flows and intensifies business risks, serves as a warning, particularly for countries that have historically relied on robust input-driven models for economic growth, such as most emerging market nations. Additionally, Chinese mainland's policies on enhancing digital infrastructure and protecting digital tax property rights significantly contribute to the efficacy of CDT, underscoring the importance of proactive government involvement in facilitating digital progress.

This article inspires the following policy recommendations. First, local governments should promote the importance of DT in mitigating operational risks to enterprises, enhance enterprises' recognition of the value of DT, and encourage them to actively undertake DT initiatives. Second, local governments should establish specialized funds or subsidy policies for DT support to assist enterprises, especially small businesses, high capital-intensive firms, and those with high agency costs, in overcoming financial challenges encountered during DT, enabling them to better upgrade digitally and fully enjoy the benefits of reduced operational risks brought by DT. Third, governments should increase investment in information infrastructure, such as expanding and optimizing high-speed broadband and 5G networks, to provide a solid hardware foundation for CDT. Fourth, governments should improve intellectual property-related laws and regulations, strengthen enforcement efforts, and establish a comprehensive intellectual property protection regulatory system. Fifth, actively advance the construction of a digital taxation system. On one hand, use digital means to simplify tax processes and improve the efficiency of tax handling for enterprises; on the other hand, utilize big data and other technologies for precise tax revenue supervision to create a fair and regulated tax environment for enterprises, helping DT more effectively mitigate operational risks. Sixth, governments should issue relevant guidance or norms to guide enterprises in making reasonable digital asset investments, avoiding excessive investment in digital assets that encroach upon the availability of cash flows and exacerbate operational risks. This can be achieved through organizing regular expert lectures, publishing industry investment reference guides, and other means to help enterprises scientifically plan the scale and pace of investment in DT.

Despite significant efforts in theory, data, and technology, this paper still confronts several unresolved deficiencies. First, although a detailed theoretical analysis is provided, the paper currently lacks a rigorous mathematical model to deduce the marginal effects of digital transformation on operational risks. Second, despite the application of various methods to address endogeneity, the paper inevitably suffers from endogeneity bias. Third, due to data limitations, we have only identified digital intangible assets as the company's investment in digital transformation. Further exploration is warranted to examine other heterogeneous digital investments.

In response to both the academic shortcomings and the developmental needs of the industry, our research team plans to expand our study of digitalization in the following areas. First, we will focus on the innovative outputs of digital transformation—digital innovation. Digital technology innovation refers to the process of creating, improving, or integrating new digital technologies, thereby generating new products, services, business models, or business processes. Thus, digital innovation represents an advanced stage of digital transformation, exemplifying the deep integration of digitalization with innovative activities. Our attention will be directed toward the positive outcomes, costs, and driving mechanisms of digital innovation. Second, we aim to employ cutting-edge machine learning algorithms to assist in our research on digitalization. For instance, we plan to extensively collect big data from patent texts and apply the Chinese-Roberta-wwm-ext model along with LSTM text classification models to identify corporate digital technology patents. We intend to utilize ensemble learning algorithms, such as Random Forest, GBDT, and Xgboost, to portray the nonlinear performance of corporate digital investment. These methodologies will enable a more nuanced analysis of the impacts and efficiencies of digital transformation initiatives within the corporate sector.

Data availability

The datasets generated during and/or analyzed during the current study are available in the Harvard Dataverse repository, https://doi.org/10.7910/DVN/ZKXZDT.

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Additional information

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