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Reducing Uncertainty and Enabling Digital Transformation in Emerging Economies

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Article

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Abstract

This study examines how institutional design in R&D tax incentives influences firms' digital transformation. Exploiting a quasi-natural experiment created by China's pre-assessment reform of the R&D tax deduction, we employ a progressive difference-in-differences design using panel data on Chinese A-share listed firms from 2009 to 2023. We find that the introduction of the pre-assessment mechanism significantly accelerates firms' digital transformation. Mechanism analyses show that the reform operates primarily by reducing policy-related uncertainty and operational risk, thereby encouraging firms to undertake digital innovation and generate more digital-related patents. Cross-sectional tests further reveal that the effect is stronger for firms with greater managerial attention to innovation, higher risk-taking capacity, and those operating in regions with less developed digital infrastructure.

Our findings contribute to the literature on tax incentives and corporate innovation by highlighting the role of institutional mechanisms—beyond direct fiscal subsidies—in shaping firms' strategic responses to R&D tax policy. More broadly, the study provides causal evidence on how reducing policy uncertainty can facilitate firms' digital transformation, offering important implications for the design of innovation-oriented tax policies in emerging economies.

1. Introduction

In recent years, the R&D tax deduction is widely regarded as a key institutional arrangement for promoting corporate digital innovation and facilitating firms' digital transformation (Ding et al., 2025). Digital transformation has become a core strategic priority for firms to maintain competitive advantage in a technology-driven economy (Fernandez-Vidal et al., 2022; Weritz et al., 2025). By reducing the effective after-tax cost of R&D activities, the R&D tax deduction increases the expected net returns to innovation investment, thereby strengthening firms' internal cash flow positions and alleviating financing constraints (Wan et al., 2022; Xiang et al., 2025). Enterprises can reshape resource allocation mechanisms and improve operational efficiency through digital transformation (Wenjuan, 2025). In this context, the relative returns to innovation projects rise, providing firms with stronger incentives to allocate resources toward long-term projects such as digital innovation, which in turn promotes digital transformation and supports high-quality development (Du & Wang, 2024).

However, the R&D projects have highly specialized and technically complicated recognition standards (Vrontis & Christofi, 2021). Under China's post-filing system, firms face difficulties in ex ante assessing whether their R&D activities will be recognized as compliant in subsequent ex post audits (Kani & Nishimura, 2025). Ex post penalties arising from non-compliance may reduce managers' confidence and willingness to apply for R&D-related innovation activities though intensifying managerial risk aversion (Li et al., 2021). Especially, compared with other forms of innovation, digital transformation constitutes a long-term, organization-wide complex innovation process (Plekhanov et al., 2023). To address this, the Chinese government has gradually implemented the pre-assessment reform[1] in multiple regions since 2016. The pre-assessment policy encourages firms to apply for a pre-assessment from the science and technology regulators prior to submission to ensure that their R&D projects comply with the R&D tax deduction's requirements. Unlike traditional R&D tax instruments such as R&D tax credits, R&D tax subsidies and super-deductions, which primarily provide direct financial incentives, the pre-assessment mechanism functions as an institutional and informational tool (Ivus et al., 2021; Chang et al., 2022; Ni, 2025). This mechanism helps firms accurately assess the compliance of their R&D activities and their own eligibility for claiming the deduction, and thus, reduce the operational risks arising from policy uncertainty (Xu, 2020). Meanwhile, the pre-assessment policy mitigates information asymmetry between taxpayers and tax authorities, helping to alleviate disputes regarding the authenticity of R&D activities, and thus facilitates the smooth implementation of the R&D tax deduction policy (Friesen, 2003; Lei & Luo, 2023).

Although existing literature has extensively examined corporate digital transformation, research on how the internal institutional design of tax incentive policies influences firms' digital transformation decisions remains relatively limited. Prior studies have primarily focused on internal capability factors, such as leadership, digital infrastructure, and organizational agility, or macro-level external drivers, including industrial policies, innovation subsidies, and financial support programs (Sousa & Rocha, 2019; AlNuaimi et al., 2022; Li & Wang, 2023; Liu et al., 2024; Zhu et al., 2023). While some studies suggest that R&D tax incentives can promote corporate innovation and digital transformation (Verhoef et al., 2021; Zhai et al., 2022; Ding et al., 2025; Weritz et al., 2025), these analyses typically treat tax policies as homogeneous tools, overlooking differences in policy implementation mechanisms. In particular, research on whether procedural reforms, such as the pre-assessment mechanism, reduce institutional uncertainty and thereby further facilitate digital transformation remains scarce. This gap highlights a critical avenue for the present study to explore.

This study adopts a progressive difference-in-differences (DID) technique and uses data from Chinese A-share listed companies from 2009 to 2023, evaluating whether firms' digital transformation is influenced by the pre-assessment reform. According to the empirical result, firm's overall digital transformation is significantly improved through the policy's implementation. Meanwhile, the pre-assessment policy indicates that enhancing digital transformation occurs through two primary channels: mitigating operational risks, facilitating digital innovative patents. These channels collectively strengthen firms' ability to implement complex innovation projects, thereby promoting effective and sustained digital transformation.

This study contributes in the following three ways. First, while prior research has primarily examined the effects of traditional R&D tax instruments—such as R&D tax credits, R&D subsidies, and super-deductions—which mainly provide direct financial incentives on firms' innovation investment and R&D intensity (Ivus et al., 2021; Chang et al., 2022; Ni, 2025), these studies largely overlook the role of institutional mechanisms in shaping policy outcomes. In contrast, the pre-assessment mechanism functions as an *ex-ante* compliance-oriented and informational tool, helping firms identify eligible R&D activities, reduce information asymmetry with tax authorities, and lower operational and compliance risks. By enhancing procedural transparency and strengthening internal compliance systems, the pre-assessment mechanism not only reduces implementation uncertainty but also stimulates firms' innovation capabilities, thereby providing a novel channel through which R&D tax policies affect corporate behaviour. This distinction highlights both the theoretical contribution of understanding institutional mechanisms beyond financial incentives and the practical relevance for policymakers aiming to improve the effectiveness of R&D tax policies.

Second, this study identifies two primary channels through which the pre-assessment policy promotes corporate digital transformation: reduction of operational risks and facilitation of digital innovative patents. The findings suggest that the pre-assessment not only lowers operational uncertainties but also transforms the tax benefit from a "potential possibility" into a "deterministic contract," providing firms with certain resource allocation for digital innovation. Overall, this study highlights the differentiated effects of the policy across these two channels, particularly emphasizing its prominent role in enhancing firms' capacity for digital innovation, and systematically clarifies the mechanism through which the pre-assessment policy influences corporate digital transformation.

Third, this study examines the heterogeneous effects of the pre-assessment policy along three dimensions: managerial innovation attention, corporate risk-taking, and regional digital infrastructure. The results indicate that firms with higher managerial innovation attention and stronger risk-taking propensity respond more positively to the policy, while firms in regions with weaker digital infrastructure are more sensitive to policy incentives. This analysis reveals the boundary conditions and applicability of the pre-assessment mechanism under different firm-specific and regional contexts, offering insights into the differentiated incentive paths of policy tools and providing evidence-based guidance for precise policy implementation across diverse types of firms.

The rest of this study is organized as follows: the institutional background and literature review are introduced in Section 2. Research hypotheses are presented in Section 3. Section 4 and 5 discuss the research design and empirical results. Section 6 summarizes key insights and study's limitations.

2. Institutional Background and digital transformation

2.1 Institutional Background

Since 2008, The R&D tax deduction policy in China has evolved from a tightly controlled audit-based system to a more flexible filing- and archival-based system.[2] Initially, enterprises submitted verified documentation to apply for R&D tax deductions and underwent multifaceted mid-process reviews. Such cumbersome filing procedure resulted in excessive compliance costs for enterprises, undermining the original purpose of obtaining tax incentives. Consequently, the 2016 filing-based reform marks a major shift: enterprises could "file first and verify later" enjoying immediate access to tax benefits while authorities audited a sample of projects afterward[3]. This reform significantly boosted tax incentives uptake though lowering the application threshold and cost. However, it introduced uncertainty, as post-application audits prevented enterprises from ascertaining ex-ante whether their R&D activities met the eligibility criteria due to post-application audits. Such uncertainty that further increasing corporate operational risk.

To mitigate the compliance risks for enterprises, certain regions in China began piloting the pre-assessment reform starting in 2016, allowing enterprises to apply for a pre-assessment from the science and technology departments before submission to help clarify whether their R&D projects complied with the policy's stipulations. In 2022, the autonomous pre-assessment mechanism in Foshan, Guangdong, helped 773 firms complete the compliance confirmation of 2,597 R&D projects in advance, effectively helping firms avoid the compliance risks and tax uncertainties caused by assessment discrepancies.[4] In the Pudong New Area of Shanghai, the implementation of detailed pre-assessment management regulations further standardized the R&D project approval and cost accounting processes, improving the transparency and consistency of policy execution. These reforms benefited 42,000 firms by obtaining a tax reduction of 89.96 billion RMB in 2024.[5]

The pre-assessment for tax deductions originated from the increased uncertainty brought about by the filing-based reform, particularly the disputes between tax authorities and enterprises regarding the authenticity of R&D activities. This reform is voluntary. That is, enterprises can choose whether to apply for the assessment, with the choice not affecting their eligibility for the final tax benefits. Subsequently, similar regulations were gradually introduced in various regions. The pilot development process is outlined in Table 1. Figure 1 presents the detailed progression of the R&D Tax Deduction policy.

Table 1
The pilot implementation of the pre-assessment policy

Year	***Pilot***
2016	Anshan, Liaoning; Guang Yuan, Sichuan; Shaanxi
2017	Inner Mongolia; Yueyang, Hunan; Qingyuan, Guangdong; Dongguan, Guangdong
2018	Zhaoqing, Guangdong; Ningxia
2019	Jiading, Shanghai; Zhangzhou, Fujian; Guizhou
2020	Pudong, Shanghai; Foshan, Guangdong; Tibet
2021	Zhongshan, Guangdong
2022	Xiamen, Fujian; Luoyang, Henan; Guangzhou, Guangdong; Yangjiang, Guangdong; Beihai, Guangxi; Chengdu, Sichuan; Yibin, Sichuan
2023	Hebei; Huizhou City, Guangdong

Data source: manually compiled by the authors from municipal policy documents.

2.2 digital transformation

Compared with traditional innovation, which focuses on single technological breakthroughs or product iterations, digital transformation represents a long-term and highly uncertain organizational-level complex innovation (Gong & Ribiere, 2021; Jiang et al., 2025). It not only involves upgrades of IT systems but

also encompasses how firms utilize technologies (such as big data, cloud computing, artificial intelligence, and blockchain) to reshape resource allocation mechanisms (Feliciano-Cestero et al., 2023; Weritz et al., 2025). Actively promoting digital transformation, firms can enhance operational efficiency though optimizing internal processes (Xue et al., 2025). Furthermore, their competitive advantage in the technology-driven markets can be enhanced by digital innovation management (Zhai et al., 2022). Thus, it can significantly improve overall firm performance by enhancing operational efficiency and reinforcing competitive advantage (Appio et al., 2021). Moreover, digital transformation can also reshape labour structures and foster industry-wide innovation ecosystems by facilitating knowledge flows (Dou et al., 2023; Han & Li, 2026). In addition, greener production and stronger positioning in global value chains can be facilitated though digital transformation to enhance the international competitiveness of manufacturing sectors (Jin et al., 2024).

Given its systemic and technology-driven nature, digital transformation inherently demands extensive organizational restructuring and deep process reengineering (Liu et al., 2025). Consequently, it typically involves considerable organizational adjustment expenditures and pronounced risks associated with rapid technological iteration (Rani et al., 2025; Xue et al., 2025). Bagheri et al. (2019) points out that maintaining a sustained technological lead through exploring collaborative opportunities in foreign markets can mitigate corporate risks encountered during digital transformation. Moreover, digital communication infrastructure and digital servitization are beneficial for reinforcing the strategic benefits of sustaining technological leadership through enabling firms to engage in cross-boundary collaboration and create value (Kohtamäki et al., 2019; Verhoef et al., 2021). Beyond technological capabilities and digital infrastructure, leadership dimensions—including the capacity for innovation, change management, and transformation execution—are critical in augmenting digital transformation by promoting organizational agility and strategic decision-making (Sousa & Rocha, 2019; AlNuaimi et al., 2022). Digital transformation is also significantly influenced by external factors, government intervention plays a critical role in facilitating digital transformation by leveraging its regulatory functions in manufacturing enterprises, particularly when these firms exhibit risk-averse behaviour (Zhu et al., 2023). Moreover, the government supports digital transformation through institutional and financial resources by implementing urban innovation policies and green finance policies (Li & Wang, 2023; Liu et al., 2024). Especially, in China, tax policies that offer fiscal incentives play a crucial role in promoting and accelerating enterprise digital transformation (Ding et al., 2025).

In summary, prior studies show that digital transformation is shaped by both firms' internal capabilities and external policy environments, while research on R&D reduction can promote digital transformation though tax incentives (Verhoef et al., 2021; Zhai et al., 2022; Ding et al., 2025; Weritz et al., 2025). However, few studies examine whether the pre-assessment reform of the R&D tax deduction—which streamlines the approval process—reduces the institutional uncertainty associated with claiming the deduction, thereby further facilitating firms' digital transformation. This omission reveals a clear gap that the present study aims to address.

3. Hypotheses development

3.1 The R&D tax deduction pre-assessment policy and digital transformation

Digital transformation signifies a protracted and significantly uncertain complex innovation at the organizational level (Jiang et al., 2025). Its success depends on the support of the stable institutional environment (Li & Wang, 2023; Zhu et al., 2023). Against this backdrop, the pre-assessment policy for R&D tax deductions provides firms stable innovation environment though requiring them to accurately identify R&D activities at an early stage of these activities through the technical assessment (Li et al., 2021). Such enhanced certainty is beneficial for reducing firms' compliance-related concerns regarding innovative issues during the process of digital transformation (Kong et al.,2025). Consequently, firms are more likely to be confident in undertaking and advancing their digital transformation initiatives. Furthermore, the pre-assessment policy can alleviate agency problems by clarifying eligible R&D activities at the early stage (Munari et al., 2010). By aligning managerial decisions with shareholders' interests, the likelihood of underinvesting in or misallocating R&D resources due to risk aversion and incentive misalignment can be reduced from the outset (Jensen & Meckling, 1976; Sirmon et al., 2012). Moreover, the reduced compliance risk can lead tax compensation from the deduction by the firms in a legitimate and predictable manner (Zhao & Qi, 2020). Such tax incentives can mitigate financing constraints associated with long-term innovative activities of firms (Busom et al., 2014). Thus, with a more stable and reliable flow of tax-induced financial resources, firms possess greater internal funding capacity to support and advance their digital transformation initiatives (He et al., 2025).

In addition, the pre-assessment policy requires the science and technology authorities perform a pre-assessment on the team configuration and management processes of innovative projects. This facilitates firms in establishing standardized R&D management systems and strengthening the regulation of R&D management procedures (Appio et al., 2021; Vakili & Kaplan, 2021). Such a standardized management framework can be beneficial for reshaping resource allocation and management mechanisms (Nsaibi et al., 2020). As a result, the improvement of management mechanism can provide a solid foundation for the efficient allocation and coordinated management of complex resources during the process of digital transformation (Klingebiel & Rammer, 2014). Overall, the pre-assessment policy not only provides firms with clearer guidance to identify eligible R&D activities and enjoy related tax incentives but also helps reduce compliance and agency-related risks at an early stage (Li et al., 2021; Zhao & Qi, 2020). By enhancing the certainty of policy implementation, it strengthens firms' confidence in undertaking digital transformation initiatives and promotes the establishment of standardized R&D management mechanisms (Appio et al., 2021; Vakili & Kaplan, 2021). As a result, firms are better able to mobilize internal financial and managerial resources to support innovation, thereby fostering more effective and sustainable digital transformation. Accordingly, based on this discussion, the first hypothesis is proposed:

H1. The pre-assessment policy for the R&D tax deduction promotes digital transformation.

3.2 The pre-assessment policy, operational risk, and digital transformation

Project failures, R&D resource waste, and internal management imbalances constitute the primary operational risks that firms face during digital transformation (Huang et al., 2023; Uddin et al., 2023). Such risks increase the "hidden costs" of innovation activities through potential losses and additional

expenditures (Latham & Braun, 2009). The pre-assessment policy may alleviate these risks at their source by clarifying the standards for project identification, initiation, execution, and accounting before R&D activities formally begin (Wang et al., 2010). Early standard-setting enables firms to screen out low-quality or misaligned projects in advance, thereby reducing the likelihood of project failure and preventing unnecessary resource waste arising from misinformed decisions or execution errors (Altuntas, 2024). Furthermore, the policy institutionalizes internal audits and information-flow mechanisms, which strengthen the transparency, traceability, and reliability of project management throughout the implementation process (Kivilä et al., 2017; Liew, 2019). By embedding these governance routines into daily operations, firms can detect deviations, rectify management imbalances, and prevent inefficient resource allocation at an early stage (Kivilä et al., 2017). As a result, the overall robustness of internal controls is improved, reducing the probability of losses caused by managerial oversight or organizational frictions (Huang et al., 2023).

In addition, by clarifying responsibility boundaries and accountability requirements, the pre-assessment policy reduces the likelihood of governance failures that could lead to legal penalties or reputational damage (Slemrod, 2019). This forms a full-process regulatory loop that continuously monitors operational risks throughout the entire digital transformation lifecycle (Xi & Ling, 2025). By systematically reducing the hidden costs associated with operational risks, the policy is more likely to increase the relative payoff of digital transformation (Hashai et al., 2015; Sun et al., 2024). Lower perceived risks and higher expected benefits enhance firms' willingness to invest in digital initiatives and improve the efficiency of their resource allocation decisions (Ding et al., 2025). Consequently, the pre-assessment policy may not only promote the smooth implementation of digital transformation projects but also support their sustained and long-term advancement. Building on the above discussion, we propose the following hypothesis:

H2. The pre-assessment policy for the R&D tax deduction promotes corporate digital transformation by reducing operational risks.

3. 3 The pre-assessment policy, digital innovative patent, and digital transformation

The essence of digital transformation lies in firms' continuous innovation in digital technologies and their application (Jiang et al., 2025). Digital innovation patents serve as an important indicator of firms' outputs in digital technology innovation (Boudreau et al., 2022; Huang et al., 2023; Han & Li, 2025). The creation of digital innovation patents depends on adequate financial support, which enables firms to carry out high-quality digital R&D activities (Wenjuan, 2025). However, the information asymmetry and risk exposure that external investors and financial institutions face make them more cautious in providing funds for firms' innovation projects (Ascioglu et al., 2008; Li et al., 2023). In this context, the pre-assessment policy for R&D tax deductions can reduce uncertainty regarding the returns and legitimacy of innovation investments by providing a stable and pre-assessed framework. This increased policy certainty is more likely to facilitate greater capital inflows and ease firms' financing constraints through lowering perceived risks for both internal and external financiers (Wang et al., 2021). Such improvements, in turn supports more sustained and effective digital transformation (Dechezleprêtre et al., 2023).

In addition, the predictability of the policy increases the availability of internal funds by obtaining stable tax incentives. This financial support allows firms to allocate R&D resources more efficiently, such as optimally organizing R&D teams, procuring critical technological equipment, and streamlining project management processes, which enables the execution of high-quality digital innovation projects (Hadjielias et al., 2021; Ding et al., 2025; He et al., 2025). Moreover, the high-quality digital innovation not only generates direct technological benefits but also accumulates intellectual property assets through the creation of digital innovation patents (Blichfeldt & Faullant, 2021). These assets provide a foundation and support for the firm's long-term digital transformation (Fernandez-Vidal et al., 2022; Plekhanov et al., 2023). Building on the above discussion, we propose the following hypothesis:

H3. The pre-assessment policy for the R&D tax deduction promotes corporate digital transformation by facilitating digital innovative patents.

4. Research design

4.1 Data

The starting sample for this study consists of Chinese A-shares listed between 2009 and 2023. Data on firm-level variables are obtained from the CSMAR database. The final sample is constructed by (1) retaining only listed companies; (2) excluding firms providing financial services;(3) excluding firms with data available for only a single year; (4) excluding special treatment (S.T.) firm observations in a given year; and (5) excluding firm years with insufficient data. The final sample consists of 43,759 firm-year observations. All continuous variables are winsorized at 1 percent at both tails in order to reduce the impact of extreme values.

4.2 Variables definition

4.2.1 Dependent variable

Following Xiao et al. (2024) and Ding et al. (2025), this study utilises text analysis approaches to evaluate the degree of digital transformation in firms. This study quantifies the occurrence of phrases (including artificial intelligence technology, digital technology application, and big data technology) in company annual reports. Their combined logarithmic numbers indicate the extent of digital change.

4.2.2 Independent variable

Exploiting the quasi-natural experiment arising from the rollout of the pre-assessment policy for R&D project evaluation, this study constructs a time dummy variable (*post*) that equals 1 for observations during the post-implementation period and 0 otherwise. A treatment dummy variable (*treat*) is defined, with companies located in the pre-assessment pilot program cities assigned to the treatment group and 0 to the control group. The key explanatory variable (*DiD*) is defined as the interaction term between *post* and *treat*. The detailed distribution of pilot cities is provided in Table 2.

4.2.3 Control variable

Following Atsu & Adams (2023), Dou et al. (2023) and Ding et al. (2025) and this study introduces a set of control variables, including: Size (the natural logarithm of total assets); Leverage (the ratio of total liabilities to total assets); ROA (the net income divided by total assets); Growth (the rate of sales revenues growth); Independence (the proportion of independent directors to the total number of board members); Duality (a dummy variable equal to 1 if the CEO and chairman positions are held by the same individual, and 0 otherwise); TobinQ (the firm's market value); Firm Age (the natural logarithm of years of establishment); PGDP (the natural logarithm of per capita GDP in the firm's registered region); Finance (the ratio of financial institutions' total loans and deposits to regional GDP); and RD (the ratio of government expenditure on science and technology to regional GDP). Detailed definitions of all variables are provided Table 2.

Table 2
Definition of Variables

Variables	Definition
ESG	Measured by the frequency of digital-related phrases in annual reports, with logarithmic counts indicating the degree of digital adoption.
TREAT	It equals 1 for firm firms located in regions subject to the pre-assessment policy, and 0 otherwise.
POST	It equals 1 for the years following the policy implementation year, and 0 otherwise.
Size	The natural logarithm of total assets.
Leverage	Asset liability ratio.
ROA	Net income is divided by total assets.
Growth	Change in total revenue in the year.
Independence	The ratio of independent directors to total board members.
Duality	It equals 1 if the CEO is also the chairman, and 0 otherwise.
Tobin Q	The market value.
Firm Age	The natural logarithm of the number of years (plus one) since incorporation.
PGDP	The natural logarithm of per capital GDP in the registered region of firms.
Finance	The ratio of financial institutions' total loans and deposits to regional GDP.
RD	The ratio of government expenditure on science and technology to regional GDP.

4.3 Model

This study constructs the following model to examine the relationship between the pre-assessment policy and corporate digital transformation:

$$\varvecD\varvecT_{\varvecit,\varvectt} = \varvec\alpha_0 + \varvec\alpha_1 * \varvecT\varvecR\varvecE\varvecA\varvecT_{\varvecit} \times \varvecP\varvecO\varvecS\varvecT_{\varvectt} + \varvec\alpha_2 \varvecC\varvecO\varvecN\varvecT\varvecR\varvecO\varvecL + \varvecF\varvecI\varvecR\varvecM + \varvecY\varvecE\varvecA\varvecR + \varvecI\varvecN\varvecD\varvecU\varvecS\varvecT\varvecR\varvecY + \varvecC\varvecI\varvecT\varvecY + \varvec\varepsilon$$

Where $\varvecD\varvecT_{\varvecit,\varvectt}$ is the proxy variable for corporate digital transformation. When the firm's location falls inside a pilot region for the pre-assessment policy of the R&D tax deduction, the binary variable $\varvecT\varvecR\varvecE\varvecA\varvecT_{\varvecit}$ = 1; otherwise, it equals 0. Another binary variable is $\varvecP\varvecO\varvecS\varvecT_{\varvectt}$, which has a value of 0 otherwise and 1 for the post-implementation period. Hence, $\varvecT\varvecR\varvecE\varvecA\varvecT_{\varvecit} \times \varvecP\varvecO\varvecS\varvecT_{\varvectt}$ ($\varvecD\varveci\varvecD$) captures the exogenous change from the pre-assessment policy for R&D additional deductions; $\varvecC\varvecO\varvecN\varvecT\varvecR\varvecO\varvecL$ represent the control variables included in the regression analysis. $\varvecF\varvecI\varvecR\varvecM$ controls for the firm; $\varvecY\varvecE\varvecA\varvecR$ controls for the time trend; $\varvecI\varvecN\varvecD\varvecU\varvecS\varvecT\varvecR\varvecY$ controls for industry-specific effects while $\varvecC\varvecI\varvecT\varvecY$ controls for city-level factors that do not vary over time. Additionally, the data is clustered at the firm level to mitigate heteroscedasticity.

5. Results and discussion

5.1 Descriptive statistics

Table 3 presents the descriptive statistics of the observations. The average DT for businesses is 2.792, indicating that most businesses perform moderately well in terms of digital transformation. The key difference-difference variable $\varvecT\varvecR\varvecE\varvecA\varvecT_{\varvecit} \times \varvecP\varvecO\varvecS\varvecT_{\varvectt}$ ($\varvecD\varveci\varvecD$), has a mean of 0.086, suggesting that around 8.6% of firm-year observations correspond to firms located in pilot regions during the post-implementation period. The majority of businesses are typically large in size, as indicated by the SIZE mean of 22.153. The mean of Duality is 0.297, meaning that approximately 30%

of the firms in the sample have the same person serving as both the chairman and the CEO. The findings for the remaining factors are mostly in line with previous research.

Table 3
Descriptive statistics

DT	Count	Mean	STD	Min	P50	Max
	43759	**2.792**	**1.195**	**0.000**	**3.014**	**6.907**
DiD	43759	0.086	0.280	0.000	0.000	1.000
Size	43759	22.153	1.175	20.069	21.973	24.827
Leverage	43759	0.414	0.199	0.068	0.407	0.804
ROA	43759	0.042	0.052	-0.106	0.040	0.157
Growth	43759	0.131	0.259	-0.406	0.099	0.983
Independence	43759	0.374	0.047	0.333	0.364	0.500
Dual	43759	0.297	0.457	0.000	0.000	1.000
Tobin Q	43759	1.938	1.004	0.915	1.606	7.654
Firm Age	43759	2.911	0.338	1.386	2.944	3.466
PGDP	43759	11.475	0.515	9.641	11.545	12.223
Finance	43759	4.112	1.666	1.292	3.816	7.976
RD	43759	0.007	0.004	0.001	0.005	0.023

5.2 Regression results

The results pertaining to the impact of the pre-assessment policy on digital transformation are presented in Table 4. The pre-assessment strategy has had a considerable positive impact on corporate digital transformation, according to the regression results in Table 4 in column (5). The coefficient suggests that a significant association between $\varvecT\varvecR\varvecE\varvecA\varvecT_{\varvec{i}} \times \varvecP\varvecO\varvecS\varvecT_{\varvec{t}} (\varvecD\varvec{i}\varvecD)$ and corporate digital transformation at the 5% statistical level. In particular, the corresponding increase in digital transformation is 0.0014(0.014×0.280/2.792) when the independent variable increases by one standard deviation. The results suggest that enhanced certainty in policy implementation reduces firms' institutional concerns regarding R&D activities, improves resource allocation efficiency, and strengthens their willingness to invest in corporate ESG activities. To further verify the results, we utilize other simplified specifications excluding control variables in column (1) and excluding industry and city fixed effects in column (2). The findings show the same significant result in the simplified specification. Meanwhile, we adjust different combinations of fixed effects, there are still significantly positive results.

Table 4
Regression results

VARIABLES	(1)	(2)	(3)	(4)	(5)
	DT	DT	DT	DT	DT
DiD	0.040***	0.010***	0.013***	0.014***	0.014**
	(12.23)	(3.03)	(4.35)	(4.59)	(2.16)
Size		-0.012***	-0.007***	-0.009***	-0.009**
		(-11.98)	(-4.50)	(-5.70)	(-2.51)
Leverage		0.031***	0.031***	0.034***	0.034**
		(5.14)	(4.86)	(5.28)	(2.51)
ROA		-0.163***	-0.033*	-0.025	-0.025
		(-7.76)	(-1.93)	(-1.48)	(-0.94)
Growth		0.009**	-0.003	-0.004	-0.004
		(2.44)	(-1.21)	(-1.54)	(-1.25)
Independence		0.089***	0.015	0.020	0.020
		(4.61)	(0.77)	(1.05)	(0.65)
Dual		0.005**	0.004**	0.004**	0.004
		(2.37)	(2.15)	(2.24)	(1.34)
Tobin Q		0.009***	-0.002***	-0.003***	-0.003*
		(9.19)	(-2.69)	(-3.03)	(-1.89)
Firm Age		0.005	-0.041***	-0.037***	-0.037*
		(1.58)	(-4.65)	(-4.17)	(-1.84)
PGDP		0.038***	0.030***	0.033***	0.033***
		(15.91)	(4.77)	(5.27)	(2.96)
Finance		0.019***	0.009***	0.010***	0.010***
		(26.86)	(5.04)	(5.58)	(3.26)
RD		1.117***	0.170	0.180	0.180
		(3.82)	(0.52)	(0.55)	(0.29)
Constant	0.088***	-0.236***	-0.028	-0.037	-0.037
	(91.08)	(-7.34)	(-0.33)	(-0.43)	(-0.24)
Observations	43,759	43,759	43,759	43,759	43,759
Adjusted R-squared	0.003	0.072	0.660	0.666	0.664
Firm FE	NO	NO	YES	YES	YES
Year FE	NO	NO	YES	YES	YES
Industry FE	NO	NO	NO	YES	YES
City FE	NO	NO	NO	YES	YES
Cluster Firm	NO	NO	NO	NO	YES

Table 4 shows the baseline regression results of the impact of the policy on digital transformation. In column (1) we do not add any control variables. In column (2) we add all control variables. Columns (3) to (5) gradually incorporate fixed effects to control for unobserved heterogeneity. ***, **, and*indicate significance atthe1%,5%, and 10%levels, respectively.

5.3 Robustness tests

5.3.1 Propensity score matching test

To mitigate self-selection bias, we perform a robustness check on the policy effect using the propensity score matching (PSM-DID) method: nearest neighbor matching. Specifically, we use company size, financial leverage, ROA, Growth, Independence, Duality, Top5, Tobin Q and firm Age as covariates for PSM. The logit model is used to get the propensity score. We compute and match the control group with the comparable treatment group. The DID regression is then

performed again on the matched sample. According to the regression results, there is a positive relationship between $\varvecT\varvecR\varvecE\varvecA\varvecT_{\varvec{i}} \times \varvecP\varvecO\varvecS\varvecT_{\varvec{t}}\ (DiD)$ and digital transformation, which supports the validity of the main regression findings.

Further, the study extends the model by introducing a set of time dummy variables to verify whether the parallel trend assumption underlying the DID model holds. Specifically, **Prior1** to **Prior5** captures the period spanning from one to five prior to the policy's introduction, **adoption** represents the implementation of current year, and **After1** to **After5** represents the years from one to five years after the policy implementation. As illustrated in Fig. 2, the result shows that there are opposite results between pre-implementation period and ex-implementation period: the impact remain insignificant during the pre-implementation period and significant after the policy implementation year, further supporting the robustness of the regression findings.

5.3.2 Placebo test

Whether hidden factors affect the impact of the findings can be investigated through employing the placebo test. The test is primarily conducted by setting up a fictitious treatment group or fictitious policy implementation time. Specifically, we randomly perturb the **TREAT** variable and repeat the regression 1000 times. Figure 3 reports the estimated results; the majority of estimated coefficients lie close to 0. Therefore, the results pass the placebo test and are not influenced by random factors.

5.3.3 Replacing the dependent variable

Following Verhoef et al. (2021) and Xiao et al. (2024), this study uses alternative measure of digital transformation in the robustness tests: the frequency of digital transformation-related keywords in the Management Discussion and Analysis section (MD&A). The results are shown in Column (1) of Table 5, suggesting the corporate digital transformation is enhanced under the influence of the pre-assessment. The relationship between the pre-assessment policy and digital transformation remains significant at the 10% level.

5.5.4 The clustering level of standard errors

Next, we adjust the clustering standard in Eq. (1) by replacing the firm- with industry-level clustering to control for potential homogeneity disturbances and spatial correlations at the city level. This approach helps reduce the risk of underestimating the standard errors and enhances the estimate reliability. The results are still robust after controlling for industry clustering effects in Column (2) of Table 5. The relationship between $\varvecT\varvecR\varvecE\varvecA\varvecT_{\varvec{i}} \times \varvecP\varvecO\varvecS\varvecT_{\varvec{t}}\ (DiD)$ and corporate digital transformation remains positive at the 5% significance level.

5.5.5 Excluding COVID-19 Effects

Following the approach of Ding et al. (2025), we exclude the potential confounding effects of the COVID-19 pandemic by focusing on the period from 2020 to 2022. By limiting the analysis to this post-outbreak period and controlling for pandemic-related disturbances, we aim to isolate the policy's impact on firms' digital transformation more accurately, ensuring that the observed effects reflect firms' responses to the policy rather than exogenous shocks induced by COVID-19.5.5.6 Removing the interference of other policy. The result is shown in Column (3) of Table 5, after excluding the potential influence of the COVID-19 pandemic, with the DiD coefficient of 0.015 being significant at the 5% level (t = 2.19).

5.5.6 Removing the interference of other policy

This study further considers potential interference from other policy shocks, particularly the implementation of R&D additional deduction policy that began in 2016. The policy may have been in effect simultaneously with the pre-assessment policy, and thus, could have potential interference effects that influence corporate financial performance and digital transformation level. To eliminate the interference of these policies, related control variables are introduced in this regression model. The results are shown in Column (4) of Table 5 that after removing the interference from the 2016 policy shock, the coefficient of $\varvecT\varvecR\varvecE\varvecA\varvecT_{\varvec{i}} \times \varvecP\varvecO\varvecS\varvecT_{\varvec{t}}\ (DiD)$ remains significant and positive. This further suggests that the pre-assessment policy enhances enterprises' digital transformation.

Table 5
Other robustness test results

VARIABLES	(1)	(2)	(3)	(4)
	Alternative variable	Changing Cluster Level	Excluding Covid-19 influence	Excluding other policy
	DT	DT	DT	DT
DID	0.050*	0.014**	0.015**	0.013**
	(1.75)	(1.99)	(2.19)	(2.10)
DID_{2006}				-0.021***
				(-4.20)
Size	0.292***	-0.009**	-0.006	-0.009**
	(14.82)	(-2.21)	(-1.60)	(-2.39)
Leverage	-0.118*	0.034**	0.019	0.035**
	(-1.68)	(2.49)	(1.39)	(2.57)
ROA	-0.595***	-0.025	-0.026	-0.022
	(-4.11)	(-0.76)	(-0.81)	(-0.82)
Growth	0.041**	-0.004	-0.001	-0.004
	(2.42)	(-1.06)	(-0.23)	(-1.14)
Independence	-0.674***	0.020	0.017	0.020
	(-3.88)	(0.49)	(0.55)	(0.64)
Dual	0.004	0.004	0.004	0.004
	(0.23)	(0.96)	(1.03)	(1.32)
Tobin Q	0.049***	-0.003	-0.003	-0.002
	(6.22)	(-1.13)	(-1.54)	(-1.46)
Firm Age	0.143	-0.037**	-0.044**	-0.031
	(1.21)	(-2.10)	(-2.28)	(-1.53)
PGDP	-0.063	0.033***	0.031***	0.032***
	(-0.96)	(2.83)	(2.86)	(2.90)
Finance	0.007	0.010***	0.007**	0.009***
	(0.39)	(2.77)	(2.44)	(2.92)
RD	15.494***	0.180	0.847	0.215
	(4.70)	(0.26)	(1.31)	(0.35)
Constant	-4.613***	-0.037	-0.057	-0.043
	(-5.00)	(-0.21)	(-0.37)	(-0.28)
Observations	43,759	43,759	29,977	43,759
Adjusted R-squared	0.780	0.666	0.602	0.664
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Cluster Level	Firm	Industry	Firm	Firm

This table reports the results of a series of robustness tests. Specifically, Column (1) employs an alternative measure of digital transformation (DT); Column (2) adjusts the clustering level by changing firm-level clustering to city-level clustering; Column (3) excludes observations potentially affected by the COVID-19 shock; and Column (4) further excludes the influence of other contemporaneous policies. The coefficient on DID2006 is included to account for pre-existing policy effects. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.4 Mechanism analysis

This study posits that the pre-assessment policy improves the digital transformation by reducing operational risks and facilitating digital innovative patents. To verify this logic, we construct a variable $\varvec{I}\varvec{N}\varvec{T}\varvec{E}\varvec{R}$, representing operational risks and digital innovative patents separately, while the other variables and model specifications remain consistent with model (1).

$$\varvec{I}\varvec{N}\varvec{T}\varvec{E}\varvec{R}_{\varvec{i},\varvec{t}} = \varvec{\alpha}_0 + \varvec{\alpha}_1 * \varvec{D}\varvec{i}\varvec{D} + \varvec{C}\varvec{}$$

According to John et al. (2008), this study measures risk-taking in relation to firms' operational risk by evaluating the volatility of industry-adjusted return on assets before interest and taxes (EBIT/Total Assets).In particular, the three-year rolling standard deviation of the company's total asset return (determined by dividing EBIT by total assets) from year t − 2 to year t, adjusted for yearly and industry norms, serves as a stand-in for operational risk.

Following Li et al. (2024), we identify a firm's digital innovative patents using a hybrid approach that combines patent classification codes and textual keyword matching. Specifically, we first identify patents related to digital technologies based on the International Patent Classification (IPC) codes associated with digital technology domains. To further enhance identification accuracy and capture emerging digital innovations, we complement the IPC-based classification with a keyword-matching method applied to the textual descriptions of patent documents, including the patent name, abstract, and description (Yang, 2022; Liu et al., 2023). A patent is classified as a digital innovative patent if it falls within the relevant IPC digital technology categories and/or contains at least one digital-technology-related keyword in its textual description. Finally, the firm's digital innovation (DI) is measured as the natural logarithm of one plus the number of digital patent applications.

Table 6 presents the mechanism analysis results. In Columns (1) and (2), this study examines whether digital transformation can be improved by the impact of operational risk reduction and digital innovative patents respectively. In Column (1), the coefficient suggests that a statistically negative correlation between $\varvec{T}\varvec{R}\varvec{E}\varvec{A}\varvec{T}_{\varvec{i}} \times \varvec{P}\varvec{O}\varvec{S}\varvec{T}_{\varvec{t}}\ (\varvec{D}\varvec{i}\varvec{D})$ and digital transformation with significance level of 5%. This empirical result suggests that the policy, by embedding institutional credibility and policy precision, enhances firms' ability to evaluate R&D projects. This reduces application errors caused by policy misinterpretations or insufficient information disclosure and consequently lowers compliance costs and operational risks (Wang et al., 2010). In Column (2), the results indicate that the pre-assessment reduces ambiguity regarding policy applicability. This transforms the tax benefit's incentive from a "potential possibility" to a "deterministic contract," thereby providing certain resource allocation for digital innovation. With a p-value below 5%, the research validates a statistically significant positive relationship between the pre-assessment and digital transformation (Hadjielias et al., 2021).

Table 6
Mechanism Analysis

VARIABLES	(1)	(2)
	Operational Risk	Digital Innovative Patents
DiD	-0.012**	0.061**
	(-2.52)	(2.03)
Size	-0.002	0.332***
	(-0.54)	(15.74)
Leverage	-0.000	-0.133*
	(-0.02)	(-1.86)
ROA	-0.046**	-0.042
	(-2.09)	(-0.26)
Growth	-0.000	-0.028
	(-0.12)	(-1.28)
Independence	0.031	-0.063
	(1.05)	(-0.35)
Dual	-0.001	0.014
	(-0.44)	(0.73)
Tobin Q	0.002	0.005
	(1.29)	(0.61)
Firm Age	-0.022	-0.030
	(-1.19)	(-0.24)
PGDP	0.003	0.112
	(0.25)	(1.53)
Finance	0.002	0.014
	(0.75)	(0.71)
RD	0.499	0.738
	(1.17)	(0.24)
Constant	0.108	-6.813***
	(0.81)	(-6.46)
Observations	33,206	27,756
Adjusted R-squared	0.076	0.634
Firm FE	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
City FE	YES	YES

Table 6 reports the mechanism results. Column (1) presents the effect of operational risk, and column (2) reports the effect of digital innovative patents. t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.5 Heterogeneity analysis

5.5.1 Managerial attention to innovation

Managerial attention to innovation reflects the extent to which managers emphasize R&D investments related to technological development and product innovation in strategic decision-making (Nadkarni et al., 2016). Managers with higher innovation attention not only tend to support innovation in the allocation of tangible resources but also integrate innovation into the firm's long-term strategy (Chen et al., 2015). Moreover, management teams with high innovation attention can focus on the long-term accumulation of technological and innovative elements, avoiding interruptions in the innovation process caused by short-term incentives (Ocasio & Joseph, 2018). In this context, during the implementation of the pre-assessment policy, management teams with

high innovation attention are more likely to identify, allocate, and utilize tax incentive resources to accelerate R&D investment and technological innovation related to the firm's digital transformation. To validate this argument, this study constructs an indicator of managerial innovation attention using text analysis method (Chen et al., 2015; Nadkarni et al., 2016). The frequency of these keywords in the MD&A section of the firm's annual report for a given year is then calculated, and the proportion of keyword frequency to the total number of words in the section is computed.

Based on the median of this frequency, the sample is divided into two groups: High MIA (High Managerial Innovation Attention) and Low MIA (Low Managerial Innovation Attention). The results are presented in Columns (1) and (2) of Table 7. For the High MIA group, the coefficient of the DiD on digital transformation is 0.014 and statistically significant at the 5% level (t = 2.04), indicating a positive effect of the pre-assessment policy on firms' digital transformation when managerial innovation attention is high. In contrast, for the Low MIA group, the DiD coefficient is 0.003 and not statistically significant (t = 0.26), suggesting that the policy has little impact on firms with low managerial innovation attention. These findings support that managerial innovation attention moderates the effectiveness of the pre-assessment policy on digital transformation outcomes.

5.5.2 Corporate risk-taking

Corporate risk-taking reflects a firm's proactiveness when facing uncertainty and potential returns (Chen & Ma, 2011). Firms with higher risk-taking propensity are more inclined to allocate resources to technological development, product innovation, and strategic investments (Akbar et al., 2017). In contrast, firms with lower risk-taking propensity may act more cautiously when confronted with policy incentives, exhibiting more conservative resource allocation and innovation decisions, which may result in weaker progress in digital transformation (Yan et al., 2021). To examine whether the pre-assessment policy has differential effects on firms' digital transformation under varying levels of corporate risk-taking. Following Li et al. (2013), we use the average ratio of R&D expenditures to total assets as a measure of corporate risk-taking, reflecting the firm's risk-taking level in long-term investments. Based on the median of the risk-taking measure, the sample is divided into two groups: High CRT (High Corporate risk-taking) and Low CRT (Low Corporate risk-taking). The results are presented in Columns (3) and (4) of Table 7, the DiD coefficient is 0.019 and significant at the 1% level for the High CRT group (t = 2.72), whereas it is 0.008 and not significant for the Low CRT group (t = 0.86). These findings indicate that both managerial innovation attention and corporate risk-taking positively moderate the effect of the pre-assessment policy on firms' digital transformation.

5.5.3 Regional new digital infrastructure

Regional new digital infrastructure reflects the level of local development in digital technologies, communication networks, and information services (Tian & Lu, 2023). Well-developed digital infrastructure can lower the barriers for firms to undertake digital transformation, providing the necessary technological support and network environment (Yang et al., 2023). In regions with high levels of infrastructure, firms are already able to access digital technologies and innovation resources relatively easily in their daily operations, and their digital transformation is not entirely dependent on tax policy incentives; therefore, the marginal effect of the policy is relatively small (Yao et al., 2025). In contrast, in regions with weaker infrastructure, firms are more likely to be sensitive to policy incentives, and tax support may serve as an important driving force for their digital transformation, resulting in a more pronounced policy effect. To examine whether the pre-assessment policy has differential effects on firms' digital transformation under varying levels of regional new digital infrastructure, we follow Tian & Lu (2023) and classify firms into two groups based on whether they are located in pilot areas for regional new digital infrastructure. The results are presented in Columns (5) and (6) of Table 7. For firms located in regional new digital infrastructure (RNDI), the DiD coefficient on digital transformation (DT) is -0.001 and not significant (t = -0.11), whereas for firms not located in regional new digital infrastructure (Non-RNDI), the coefficient is 0.014 and significant at the 10% level (t = 1.78). These findings suggest that the policy effect is more pronounced in firms not located in regional new digital infrastructure and less significant in regions with well-developed digital infrastructure, indicating that the marginal impact of the policy is weaker where infrastructure is already strong.

Table 7
Heterogeneity analysis

	High MIA	Low MIA	High CRT	Low CRT	RNDI Firms	Non-RNDI Firms
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	DT	DT	DT	DT	DT	DT
DiD	0.014**	0.003	0.019***	0.008	-0.001	0.014*
	(2.04)	(0.26)	(2.72)	(0.86)	(-0.11)	(1.78)
Size	-0.004	-0.038***	-0.002	-0.015***	0.000	-0.017***
	(-1.06)	(-3.96)	(-0.54)	(-3.45)	(0.08)	(-2.98)
Leverage	0.029**	0.039	0.046***	0.021	0.003	0.038*
	(2.20)	(1.10)	(2.74)	(1.26)	(0.21)	(1.80)
ROA	0.006	-0.020	-0.014	-0.034	-0.063*	0.014
	(0.19)	(-0.36)	(-0.37)	(-0.97)	(-1.68)	(0.38)
Growth	-0.001	0.001	0.004	-0.006	0.001	-0.006
	(-0.26)	(0.09)	(0.97)	(-1.29)	(0.33)	(-1.50)
Independence	-0.010	0.057	0.001	0.026	0.035	-0.000
	(-0.29)	(0.87)	(0.02)	(0.60)	(0.85)	(-0.00)
Dual	0.003	0.001	0.005	0.005	0.002	0.003
	(0.90)	(0.12)	(1.41)	(1.10)	(0.46)	(0.67)
Tobin Q	-0.001	-0.008**	0.001	-0.004**	0.000	-0.006***
	(-0.75)	(-2.41)	(0.24)	(-2.25)	(0.02)	(-2.92)
Firm Age	-0.045**	-0.057	-0.056***	-0.023	-0.032	-0.034
	(-2.46)	(-0.91)	(-2.64)	(-0.92)	(-1.46)	(-0.86)
PGDP	0.028**	0.039	0.038***	0.029**	0.009	0.021
	(2.57)	(1.07)	(2.93)	(2.01)	(0.77)	(1.07)
Finance	0.005	0.017**	0.009**	0.011***	0.001	0.006
	(1.46)	(2.13)	(2.54)	(2.76)	(0.18)	(1.51)
RD	0.859	-1.922	0.566	-0.398	2.827***	-0.990
	(1.23)	(-1.61)	(0.77)	(-0.49)	(2.86)	(-1.38)
Constant	-0.068	0.645	-0.206	0.118	0.018	0.329
	(-0.46)	(1.26)	(-1.11)	(0.59)	(0.11)	(1.15)
Observations	12,772	28,916	20,923	21,499	16,962	25,881
Adjusted R-squared	0.594	0.733	0.650	0.656	0.574	0.705
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES

Table 7 presents the heterogeneity analysis results for the impact of the pre-assessment policy on firms' digital transformation (DT). Columns (1) and (2) report the results for firms with high and low managerial innovation attention (High MIA and Low MIA), respectively; Columns (3) and (4) report the results for firms with high and low corporate risk-taking (High CRT and Low CRT), respectively; and Columns (5) and (6) report the results for firms located in regional new digital infrastructure pilot areas (RNDI Firms) and those not located in pilot areas (Non-RNDI Firms), respectively. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

6. Conclusions

Focusing on Chinese listed companies, this study systematically investigates the influence of the pre-assessment reform for the R&D tax deduction on corporate digital transformation. The findings reveal that the pre-assessment policy significantly promotes firms' overall digital transformation by

streamlining the evaluation of R&D projects, reducing operational risks, and facilitating the generation of digital innovative patents. Specifically, the results show that the policy effect operates through two main channels: mitigating operational risks and providing certainty in resource allocation for digital innovation. Among these channels, the facilitation of digital innovative patents exhibits the most prominent effect. This study contributes to the literature by highlighting the role of institutional mechanisms—beyond traditional financial incentives—in shaping firms' innovation behaviors and enhancing high-quality digital transformation. "Beyond the specific context of China, our findings offer a vital blueprint for policymakers in other emerging economies (e.g., Brazil, India, or Vietnam) grappling with the 'incentive-compliance' trade-off.

Furthermore, the heterogeneity analysis indicates that the effectiveness of the pre-assessment policy varies across firms with different characteristics and regional contexts. Firms with higher managerial innovation attention and stronger risk-taking propensity respond more positively to the policy, while firms located in regions with well-developed digital infrastructure exhibit relatively smaller marginal effects. These findings not only reveal the boundary conditions of the policy's effectiveness but also provide empirical guidance for the targeted application of institutional tax instruments to promote digital innovation.

This paper has several limitations. First, the results are derived from the unique policy and economic context of China; future research could conduct cross-country comparisons to assess the generalizability of these findings. Second, the study does not fully explore industry-specific heterogeneity, such as differences in technological intensity or reliance on government support, which may influence the transmission mechanism and effectiveness of the policy. Third, while the pre-assessment policy plays a positive guiding role, excessive reliance on ex-ante governmental intervention may constrain firms' autonomous decision-making and market-based resource allocation, potentially leading to compliance-oriented behavior rather than genuinely transformative innovation.

Declarations

Ethics declarations

Competing interests:

The author(s) declare no competing interests.

Ethical approval:

This article does not contain any studies with human participants performed by any authors.

Informed consent:

This article does not contain any studies with human participants performed by any authors.

Author Contribution

F wrote the main manuscript text ,and R and L conducted the empirical analysis. All authors reviewed the manuscript.

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Data Availability

The study examines how institutional design in R&D tax incentives influences firms' digital transformation. Data on firm-level variables are obtained from the CSMAR database. The data supporting the findings of this study are provided in the supplementary materials. These materials include the processed firm-level dataset derived from the CSMAR database, variable definitions and coding schemes, as well as the statistical scripts used for data processing and empirical analysis, enabling full replication of the reported results. The original firm-level data are obtained from the CSMAR database, which is accessible to researchers through institutional subscription.

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Footnotes

1. Notice on Strengthening the Pre-tax R&D Expense Deduction Policy, issued by China's Ministry of Finance and the State Council on May 25, 2016 (available online)https://www.gov.cn/zhengce/2016-05/25/content_5076591.htm.
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Figures

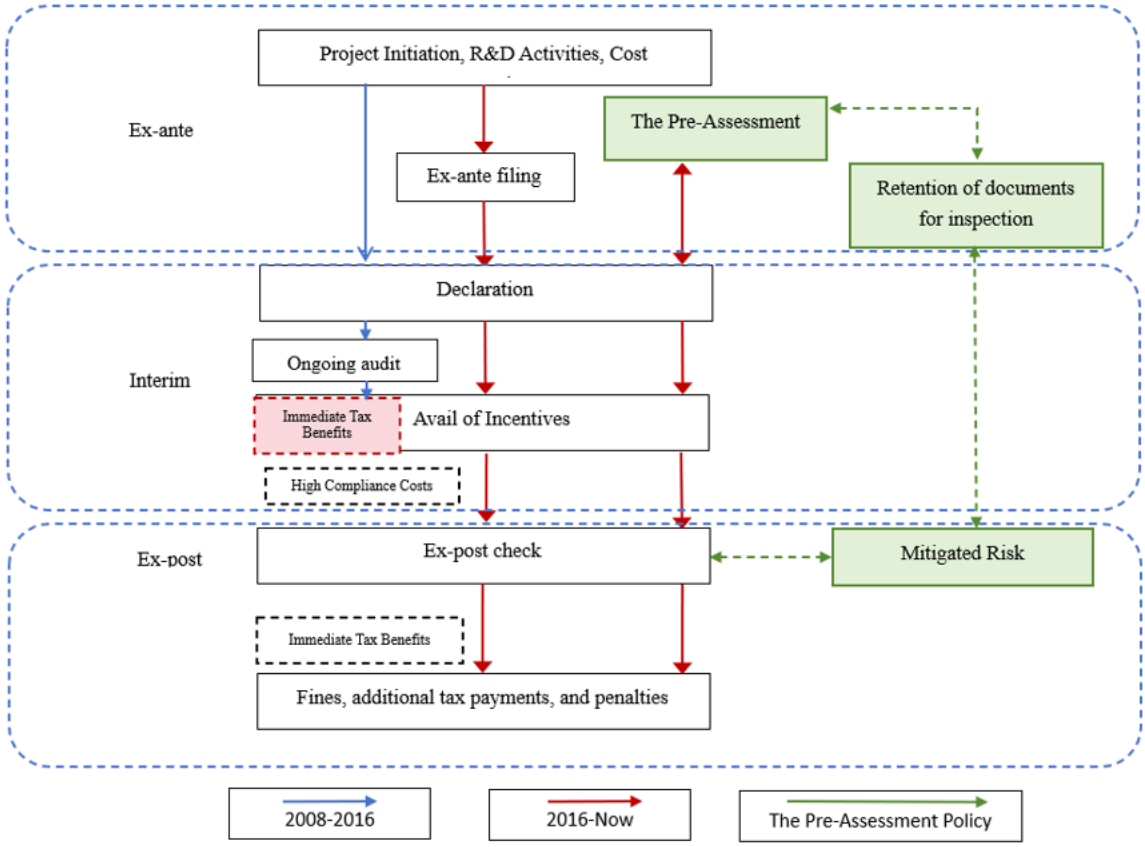


Figure 1

Process of the R&D Tax Deduction

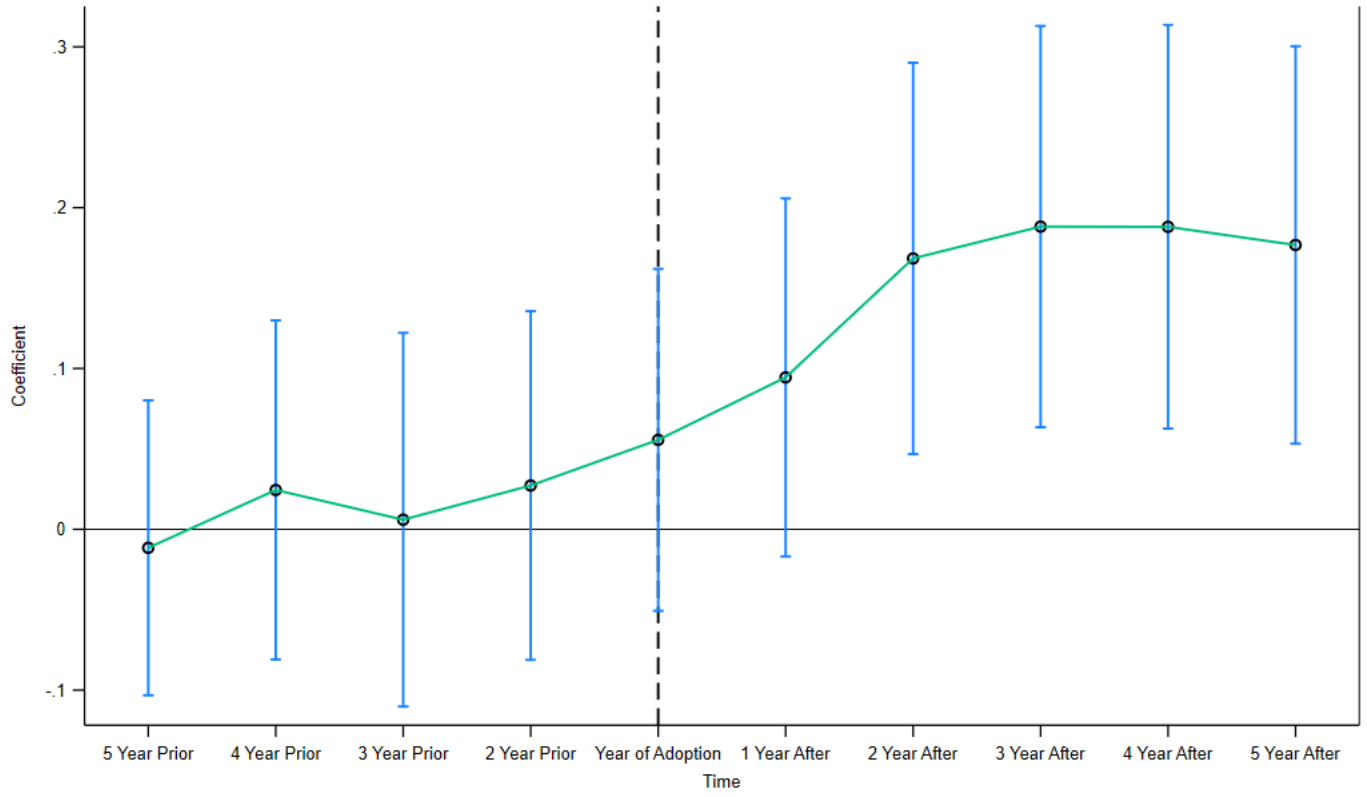


Figure 2

Parallel trend test results

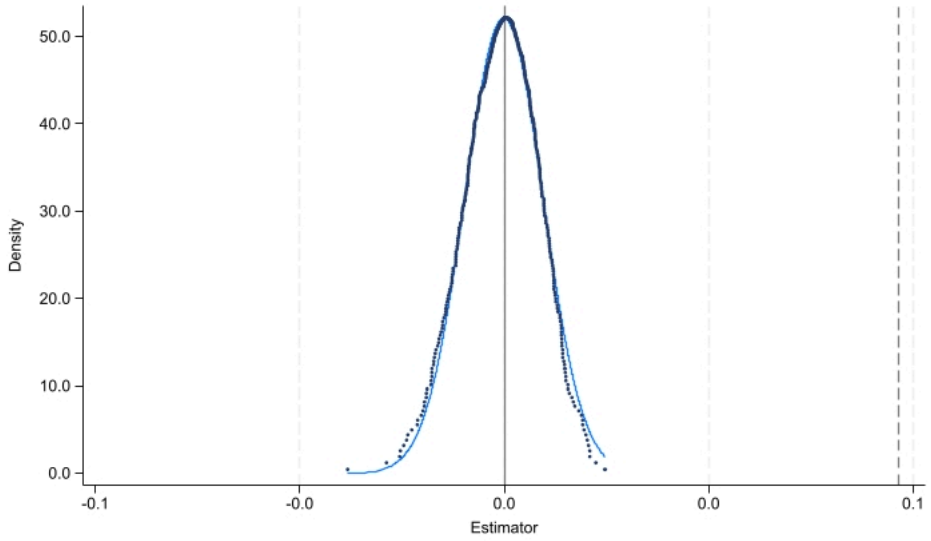


Figure 3

Placebo testresults

Supplementary Files

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- Data.xlsx