

THE EFFECT OF CARBON TRADING ON CORPORATE DIGITAL TRANSFORMATION

Guanqiuyue Chen¹, Edmund H.N Loi^{1*}, Ka Ip Chan¹

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¹ Faculty of Humanities and Social Sciences, Macao Polytechnic University, Macau, China

*Corresponding Author:
Edmund H.N Loi

Email:
hnloi@mpu.edu.mo

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ABSTRACT

This study examines the impact of market-based environmental regulation on corporate digital transformation, using China's carbon emission trading pilot policy as a representative initiative. Analyzing data from Shanghai and Shenzhen A-share listed companies between 2009 and 2020 through a multi-period difference-in-differences (DID) approach with two-way fixed effects, we investigate the underlying mechanisms. By developing a comprehensive evaluation framework encompassing five technological dimensions—artificial intelligence, big data, cloud computing, blockchain, and digital technology applications—we find that market-based environmental regulation significantly promotes corporate digital transformation, demonstrating a robust positive causal relationship. To ensure reliability, our findings withstand a series of robustness checks, including parallel trend tests, placebo tests, PSM-DID estimations, and variable replacement tests. Heterogeneity analysis reveals substantial variations in policy effects: the promoting effect on state-owned enterprises is approximately twice as strong as that on non-state-owned enterprises. Furthermore, while the policy significantly enhances digital transformation among small and medium-sized enterprises, its impact on large enterprises remains statistically insignificant. This research highlights the crucial role of market-based environmental regulation in driving corporate digital advancement, providing empirical evidence for policymakers to refine environmental regulation systems and implement differentiated strategies for corporate green transformation. It also offers practical insights for enterprises of varying ownership structures and sizes in pursuing digital transformation within sustainable development frameworks.

Keywords: Market-Based Environmental Regulation, Corporate Digital Transformation, Difference-in-Differences, State-Owned Enterprises, Large Enterprises

1. INTRODUCTION

In recent years, the world has faced intensifying environmental crises, including accelerated glacial melt, rising sea levels, and increasing natural disasters, which have profoundly impacted societies, economies, and ecosystems worldwide (Huang et al., 2022; Guo et al., 2023a). A primary driver of these challenges is the continued overreliance on fossil fuels, which has significantly elevated greenhouse gas emissions, especially carbon dioxide, thereby exacerbat-

ing global warming. Addressing this issue demands coordinated global efforts to reduce carbon emissions, leading many countries to prioritize decarbonization initiatives. As the world's largest carbon emitter, China has committed to achieving peak carbon emissions by 2030 and carbon neutrality by 2060, demonstrating its ambition to pursue stringent climate targets.

China employs two main types of environmental governance: command-and-control and market-based environmental regulation. While both aim to mitigate environmental degradation, market-based instruments have been shown to be particularly effective in enhancing carbon productivity (Song & Han, 2022). Command-and-control policies impose uniform emission standards and technical requirements, forcing polluters to reduce output or adopt new technologies. In contrast, market-based regulations utilize economic tools such as environmental taxes and emissions trading systems to transmit policy signals through price mechanisms. This allows firms to choose between purchasing emission permits or investing in abatement technologies, thereby aligning environmental goals with economic incentives (Guo et al., 2021).

As China's regulatory system has evolved, market-based policies, especially the carbon emissions trading system, have become central to its sustainable development strategy. This study examines how such policies shape corporate behavior, with a particular focus on their role in driving digital transformation among publicly listed companies. Carbon trading, a key form of market-based regulation, has gained global prominence for its effectiveness in reducing greenhouse gas emissions. The concept, first proposed by John Dales in 1968, involves creating tradable rights to pollute, transforming environmental compliance into a market activity (Felli, 2025). Initially implemented in the United States to control air and water pollution, emissions trading was later adopted by countries such as Germany, Australia, and the United Kingdom. A major milestone came with the Kyoto Protocol in 1997, which established an international framework for carbon trading and set binding emission reduction targets for developed countries. Since its enforcement in 2005, carbon emission rights have become a globally traded commodity, attracting interest from financial institutions and other stakeholders.

In line with its emission reduction goals, China's National Development and Reform Commission issued the "Notice on Carbon Emission Trading Pilot Work" in October 2011, designating seven pilot regions: Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Shenzhen. These pilots aimed to generate practical experience to support the national rollout of carbon trading. Trading began in Shenzhen in June 2013, with Fujian Province launching the last pilot market in December 2016. By 2021, China officially launched its nationwide carbon emissions trading system, marking a major advancement toward its carbon neutrality goal. During the initial compliance period in 2021, covered enterprises reported 4.5 billion tons of annual emissions, with a cumulative trading volume of 167 million tons. From 2022 to 2023, trading volume rose to 263 million tons, indicating the system's growing role in helping firms reduce compliance costs through market mechanisms.

Existing research on market-based environmental regulation has focused mainly on three areas: environmental performance, economic outcomes, and technological innovation. For example, Zhou et al. (2023b) found that local fiscal pressures can weaken corporate environmental performance, but this effect can be mitigated through well-designed regulations and incentives. Market-based policies have been shown to improve environmental performance by spurring environmental innovation (Wu et al., 2020) and can also enhance firms' financial results (Clarkson et al., 2011). Compared to command-and-control approaches, market-based mechanisms are more effective in stimulating technological progress and operational efficiency, particularly in manufacturing (Chen et al., 2022b).

In terms of technological innovation, numerous studies highlight the positive role of market-based environmental policies. Such regulations strengthen innovation capacity and produc-

tivity (Chakraborty & Chatterjee, 2017; Xu et al., 2022; Chen et al., 2022a), promote high-quality green innovation, and facilitate a shift from resource-dependent to technology-driven, smart production models. Stricter environmental standards also support regional economic development and the adoption of digital technologies (Jia et al., 2022). In the context of the digital economy, firms are increasingly using digital tools to address environmental issues, mitigate ecological pressures, and support carbon peak and neutrality goals.

As digitalization advances, companies are transforming their production and management models, increasing output while reducing energy consumption (Zhao & Yan, 2023). Carbon trading policies, combined with a higher degree of digitalization, are identified as key drivers of green innovation, especially in high-carbon firms (Wang & Dou, 2024). A stronger digital orientation not only improves environmental performance but also enhances market competitiveness (Bendig et al., 2023). Moreover, digital transformation helps attract external investors by strengthening environmental responsibility and building a positive social reputation (Shen et al., 2023). For small and medium-sized enterprises (SMEs), digitalization improves agility, customer relations, cost management, and regulatory compliance (Skare et al., 2023). Environmental regulations also raise public awareness, which drives digital adoption in polluting industries and facilitates their transformation (Wu et al., 2023; Wu et al., 2024a; Chen et al., 2025).

Although carbon emissions trading policies push firms to balance economic and sustainability objectives, fostering both environmental performance and digital transformation, existing research has paid limited attention to the link between market-based environmental regulation and corporate digitalization. To address this gap, this study uses China's carbon emissions trading pilot as a quasi-natural experiment representing market-based regulation. It employs keyword analysis from corporate annual reports to measure digital transformation and applies a multi-period Difference-in-Differences (DID) model to assess the causal effect of market-based environmental policy on the digital transformation of listed companies.

This research contributes by empirically examining the connection between carbon trading policy and corporate digital transformation across five core dimensions: artificial intelligence, big data, cloud computing, blockchain technology, and digital tool utilization. The findings not only enrich the literature on corporate digitalization but also offer actionable insights for policymakers and firms seeking to achieve both carbon reduction and digital transformation goals.

2. THEORETICAL ANALYSIS AND RESEARCH HYPOTHESIS

The complex interrelationships between economic growth, energy consumption, and environmental outcomes establish the broader context for examining corporate environmental behavior. Research demonstrates that energy market dynamics significantly influence financial markets, with oil price fluctuations positively affecting stock returns in China's financial sector (Caporale et al., 2022). Furthermore, the economic development-environmental pollution nexus follows an inverted U-shaped pattern, where economic growth initially exacerbates environmental degradation until per capita GDP reaches approximately \$23,442, after which further development correlates with environmental improvement (Çatik et al., 2024).

Within this framework, market-based environmental instruments, particularly carbon emissions trading schemes, have emerged as prominent mechanisms for driving corporate green transformation. The theoretical foundation presents two contrasting perspectives. Neoclassical economic theory posits that environmental regulations primarily represent cost burdens that may inhibit innovation (Kneller & Manderson, 2012). Conversely, the Porter Hypothesis suggests that properly designed environmental regulations can stimulate innovation by revealing resource inefficiencies and creating compensatory effects (Porter, 1991). Empirical evidence

increasingly supports the latter view in the context of market-based mechanisms, demonstrating their effectiveness in fostering innovation (Chen et al., 2021; Hu et al., 2020).

The distinctive nature of green innovation, characterized by dual externalities including both technology spillovers and pollution externalities (Xu et al., 2023; Zhu & Tan, 2022), necessitates robust institutional support. Carbon trading policies serve as crucial mechanisms for internalizing these externalities and promoting sustainable technological advancement (Ge et al., 2023; Han et al., 2022). These market-based approaches provide greater flexibility than command-and-control regulations, enabling more efficient resource allocation, stimulating R&D investment, and facilitating capital reallocation toward sustainable enterprises (Yu et al., 2022; Zhang et al., 2023; Li et al., 2023).

Parallel to these developments, digital transformation has emerged as a significant corporate strategy that enhances innovation quality, alleviates financing constraints, and improves overall performance (Zhao et al., 2024). The integration of digital technologies enables more effective resource management, pollution reduction, and positive signaling to investors, thereby facilitating access to venture capital and strengthening innovation capabilities (He et al., 2024). Given that public environmental concern serves as a key driver of corporate digital transformation (Wu et al., 2023), we propose that H_1 : *Market-based environmental regulations have a facilitating effect on corporate digital transformation.*

The effectiveness of these regulations is likely moderated by firm-specific characteristics. State-owned enterprises (SOEs), owing to their strategic alignment with national objectives and superior access to governmental resources, demonstrate greater policy compliance and stronger inclination toward long-term digital investments (Zhan & Zhu, 2021). This strategic positioning provides SOEs with comparative advantages in leveraging regulatory frameworks to accelerate digital initiatives. Therefore, we hypothesize that H_2 : *Market-based environmental regulations are more effective in facilitating digital transformation in SOEs compared to non-SOEs, due to their unique operational contexts and strategic priorities.*

Organizational size constitutes another significant moderating factor. Large enterprises frequently encounter structural complexities that impede transformation objectives and slow innovation implementation (Brink & Packmohr, 2023). In contrast, micro, small, and medium-sized enterprises (MSMEs) benefit from inherent structural flexibility that enables more responsive adaptation to regulatory changes and market dynamics (Teoh et al., 2022). This organizational agility allows MSMEs to leverage digital technologies more effectively in enhancing green competitiveness (Wu et al., 2024b) and strengthening overall resilience (Skare et al., 2023). Consequently, we propose that H_3 : *Market-based environmental regulations are more effective in facilitating digital transformation in micro, small, and medium-sized enterprises compared to large enterprises, due to their inherent flexibility and agility in adapting to regulatory changes and market dynamics.*

3. RESEARCH DESIGN

3.1. DATA AND SAMPLE

This research utilizes data from Chinese A-share companies listed on the Shanghai and Shenzhen stock exchanges, covering the period from 2009 to 2020. The study deliberately excludes the influence of two significant events: the nationwide introduction of the carbon emissions trading market in 2021 and the outbreak of the COVID-19 pandemic. To guarantee the reliability and precision of the analysis, the dataset undergoes rigorous processing.

As a preliminary step, the financial services sector is excluded from the sample. This decision is based on the sector's heavy reliance on data analytics and risk management, where digital

transformation primarily targets compliance and risk control rather than improving operational efficiency. Similarly, the real estate industry is excluded because of its long project development cycles and rapid market fluctuations, which complicate the assessment of short-term returns on digital investments. Both sectors are also heavily influenced by government policies; for example, restrictions such as purchase limits and loan controls can affect liquidity and price volatility in the real estate market, thereby impacting firms' digital transformation decisions. As a result, removing financial and real estate companies from the dataset helps reduce the impact of industry-specific characteristics, ensuring a more accurate analysis of overall market trends.

Firms classified as ST (Special Treatment), PT (Provisional Transfer), and *ST (Special Treatment with higher risk) are excluded from this analysis, as these companies are subject to specific regulatory constraints that could skew their representation of broader market trends. To enhance the reliability of the dataset, a winsorization process is applied to all micro-level continuous variables. This technique mitigates the effect of outliers by capping extreme values: those above the 99th percentile are replaced with the 99th percentile value, while those below the 1st percentile are substituted with the 1st percentile value.

The dataset is constructed from authoritative sources, including the Chinese Research Data Services Platform (CNRDS), the China Stock Market & Accounting Research Database (CSMAR), and the Wind Database. Furthermore, annual report data for the sampled firms are directly obtained from the official websites of the Shanghai and Shenzhen Stock Exchanges, ensuring data accuracy and integrity.

3. 2. RESEARCH MODEL

In this study, the carbon emissions trading pilot policy is utilized as a quasi-natural experiment, and the analysis is conducted following a structured approach. If a firm is located in a city covered by the policy implementation, it is assigned to the treatment group ($Treat_i = 1$); otherwise, it is classified into the control group ($Treat_i = 0$). Furthermore, within the treatment group, the time when a firm's city is first included in the CETR (Carbon Emission Trading Rights) is defined as the policy shock start date ($Time_t$). From that point onward, the policy shock variable for the corresponding firm takes a value of 1, as specified in equation (1).

Second, the timing of policy implementation is determined. Since the official launch dates of carbon trading markets vary across pilot cities, the policy implementation years are set as 2013, 2014, and 2017, respectively. The average variations in outcomes before and after the policy implementation are subsequently measured for both the treatment and control groups.

Finally, the DID approach is applied to calculate the average treatment effect of the carbon emissions trading pilot policy. Considering the staggered implementation of the policy across different time periods, a multi-period DID model is utilized to provide a more precise evaluation of how market-based environmental regulations influence firms' digital transformation.

$$CETR_{i,t} = Treat_i \times Time_t \quad (1)$$

$$CDT_{i,t} = \alpha_0 + \alpha_1 CETR_{i,t} + \alpha_2 Control_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (2)$$

In model (2), the dependent variable $CDT_{i,t}$ represents the level of digital transformation achieved by firm i in year t . The independent variable, $CETR_{i,t}$, reflects whether the carbon trading rights pilot policy has been implemented. $Control_{i,t}$ includes all control variables used in this study, while μ_i captures firm-specific fixed effects, γ_t accounts for time-specific fixed effects, and $\varepsilon_{i,t}$ denotes the random error term.

3. 3. VARIABLE DEFINITION

3. 3. 1. DEPENDENT VARIABLE

Corporate Digital Transformation (CDT) involves leveraging internet technologies to optimize and improve different facets of business activities, such as production workflows, sales strategies, and management systems. Accurately defining the “digital transformation” variable is critical for empirically assessing its economic impact. While some researchers create a binary variable based on aggregated data from corporate annual reports to indicate whether a company has undergone digital transformation (Peng & Tao, 2022), this method fails to capture the depth and intensity of the transformation.

Annual corporate reports serve as a vital medium for showcasing a company’s strategic direction and operational principles. Therefore, the extent of digital transformation should be observable in the summarizing and directive language used in these reports. The lexicon employed in annual reports mirrors a company’s strategic direction and outlook, outlining its endorsed management principles and development trajectory. Analyzing the presence of keywords related to “corporate digital transformation” in annual reports offers a practical and dependable method for evaluating the degree of digital transformation. In this research, the frequency of these specific terms appearing in the annual reports of publicly listed companies serves as a proxy metric to quantify the extent of their digital transformation efforts.

This paper builds upon the research conducted by Wu et al. (2021), who classify digital transformation-related keywords into two categories: “bottom-up technological applications” and “technological practice applications.” The former identifies four major technological trends and highlights specific digital business scenarios. This study utilizes Python web scraping techniques to gather annual reports from all A-share listed companies on the Shanghai and Shenzhen Stock Exchanges for data collection and analysis. Subsequently, the Java PDFBox library is employed to extract text from the collected reports, facilitating the identification and selection of relevant keywords.

To refine the analysis, the study filters out key phrases that begin with negations (e.g., “no,” “not,” or “non”) and excludes digital transformation keywords that are irrelevant to the company itself, such as references to shareholders, customers, suppliers, or executives. Using Python, the study searches, matches, and calculates the frequency of relevant keywords, categorizing and aggregating these frequencies based on key technological trends. As a result, an overall frequency analysis is conducted to develop an index system that evaluates corporate digital transformation. This system assesses transformation across five key dimensions: big data technologies, artificial intelligence, cloud computing, blockchain, and the application of digital technologies. Given the right-skewed distribution of the data, a logarithmic transformation is applied, providing a more comprehensive representation of the composite index for corporate digital transformation.

3. 3. 2. INDEPENDENT VARIABLE

In October 2011, China’s National Development and Reform Commission issued the “Notice on Launching Pilot Programs for Carbon Emission Trading,” which initiated pilot carbon trading programs in seven regions: Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Shenzhen. Between 2013 and 2014, these regions successively established their carbon trading markets. Later, in late 2016, Fujian province officially launched its own carbon trading market. Details of the specific launch dates and locations are provided in Table 1.

Taking into account the lagged effects of policy implementation, this study designates 2013 as the starting year for Shenzhen’s carbon trading policy, 2014 for the regions of Beijing, Shang-

hai, Tianjin, Chongqing, Hubei, and Guangdong, and 2017 for Fujian province. To assess the specific influence of the pilot carbon trading policy, the CETR is used as a proxy variable. CETR is assigned a value of 1 if a firm is located in a pilot region and the year is either the policy's implementation year or any year thereafter; otherwise, it is assigned a value of 0.

Table 1. List of pilot cities

Time	City
June 18, 2013	Shenzhen
November 26, 2013	Shanghai
November 28, 2013	Beijing
December 19, 2013	Guangzhou, Zhuhai, Dongguan, Foshan, Zhongshan, Huizhou, Shantou, Jiangmen, Zhanjiang, Zhaoqing, Meizhou, Maoming, Yangjiang, Qingyuan, Shaoguan, Jieyang, Shanwei, Chaozhou, Heyuan, Yunfu
December 26, 2013	Tianjin
April 2, 2014	Wuhan, Huangshi, Shiyan, Yichang, Xiangyang, Ezhou, Jingmen, Xiaogan, Jingzhou, Huanggang, Xianning, Suizhou
June 19, 2014	Chongqing
December 22, 2016	Fuzhou, Xiamen, Putian, Longyan, Zhangzhou, Sanming, Quanzhou, Ningde, Nanping

Source: China's National Development and Reform Commission

3. 3. 3. CONTROL VARIABLES

To address the potential impact of omitted variables and drawing on prior studies related to corporate digital transformation (Zhao et al., 2024; Guo et al., 2023b), this study includes the following control variables: (1) Firm size (Size): measured as the natural logarithm of total assets; (2) Firm value (TobinQ): represented by Tobin's Q ratio; (3) Firm leverage (Lev): calculated as the ratio of total liabilities to total assets; (4) Cash ratio (Cash): defined as the proportion of cash and cash equivalents at year-end to total assets; (5) Firm growth (Growth): expressed by the growth rate of total operating revenue; (6) Firm age (Age): calculated as the natural logarithm of the number of years since the company's listing, plus one; (7) Dual leadership roles (Dua): a dummy variable indicating whether the Chairman and CEO roles are held by the same person (1 for yes, 0 for no); (8) Ownership concentration (Top1): measured as the percentage of shares owned by the largest shareholder; (9) Ownership type (Soe): distinguishing between state-owned enterprises (SOEs) and non-state-owned enterprises, where SOEs are assigned a value of 1, and non-SOEs are assigned a value of 0.

Table 2. Variables definition

Type of variables	Variables	Variable symbols	Variables definition
Dependent variables	Corporate digital transformation	<i>CDT</i>	The corporate digital transformation index comprises five mainstream directional indicators
	Corporate artificial intelligence technology	<i>CAIT</i>	
	Corporate big data technology	<i>CBDT</i>	
	Corporate cloud computing technology	<i>CCCT</i>	
	Corporate blockchain technology	<i>CBCT</i>	
	Corporate digital technology applications	<i>CDTA</i>	
Independent variable	Carbon Emission Trading Rights	<i>CETR</i>	The interaction between the pilot cities and the pilot time
Control variables	Firm size	<i>Size</i>	Natural logarithm of total assets at the end of the year
	Firm value	<i>TobinQ</i>	Market value/Total assets
	Firm leverage	<i>Lev</i>	Total liabilities/Total assets
	Cash ratio	<i>Cash</i>	Cash and equivalents/total assets at end of period
	Firm growth	<i>Growth</i>	The growth rate of total operating revenue
	Firm age	<i>Age</i>	Natural logarithm after adding 1 to the number of years listed
	Dual roles of the Chairman	<i>Dua</i>	A value of 1 is assigned when the Chairman and CEO are the same person, and a value of 0 is assigned otherwise.
	Ownership concentration	<i>Top1</i>	The shareholding ratio of the largest shareholder
	Ownership nature	<i>Soe</i>	State-controlled enterprises denote as 1, otherwise 0

Source: Authors' own elaboration

4. EMPIRICAL RESULTS AND ANALYSIS

4. 1. DESCRIPTIVE STATISTICS

Table 3 presents the descriptive statistics for all variables. The mean value of CDT is 1.334, with a median of 1.099 and a standard deviation of 1.427. The values range from 0 to a maximum of 5.165, indicating significant variation in the degree of digital transformation across firms. Figure 1 depicts the trend of average CDT values over time. Beginning in 2009, the average CDT has shown a consistent upward trajectory, increasing from 0.306 to 1.916, which highlights the increasing importance companies place on digital transformation.

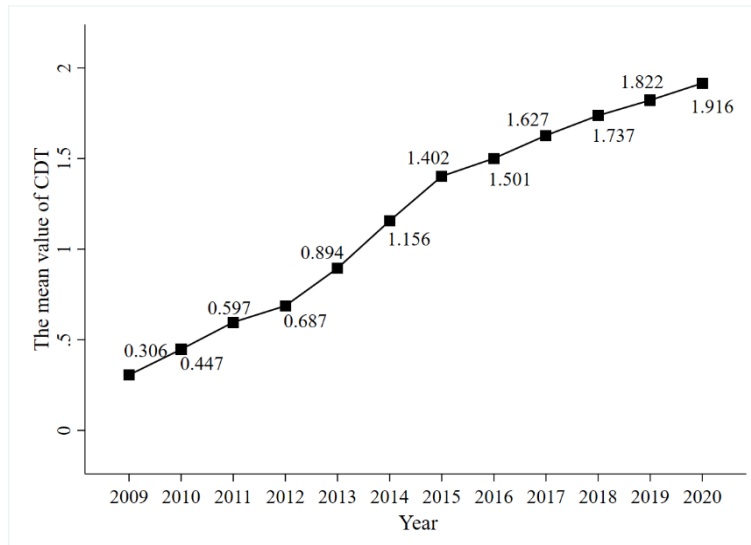
Among the five indicators of corporate digital transformation, the average value of CBCT (blockchain technology) is the lowest, suggesting that companies place comparatively less emphasis on blockchain technology. Moreover, the control variables exhibit median values that are close to their corresponding means, suggesting that the data is distributed relatively evenly.

Table 3. Descriptive statistics

Variables	Obs	Mean	Med	SD	Min	Max
<i>CDT</i>	20,922	1.334	1.099	1.427	0	5.165
<i>CAIT</i>	20,922	0.274	0	0.657	0	3.219
<i>CBDT</i>	20,922	0.483	0	0.89	0	3.892
<i>CCCT</i>	20,922	0.489	0	0.921	0	3.892
<i>CBCT</i>	20,922	0.049	0	0.238	0	1.609
<i>CDTA</i>	20,922	0.935	0.693	1.159	0	4.29
<i>CETR</i>	20,922	0.315	0	0.464	0	1
<i>Size</i>	20,921	21.992	21.822	1.269	19.629	26.974
<i>TobinQ</i>	20,491	2.15	1.706	1.394	0.861	9.207
<i>Lev</i>	20,921	0.407	0.395	0.209	0.053	1.067
<i>Cash</i>	20,921	0.174	0.133	0.138	0.009	0.661
<i>Growth</i>	20,904	0.178	0.114	0.413	-0.591	2.821
<i>Age</i>	20,922	1.975	2.079	0.886	0	3.401
<i>Dua</i>	20,673	0.295	0	0.456	0	1
<i>Top1</i>	20,922	34.034	31.92	14.723	8.48	74.66
<i>Soe</i>	20,794	0.117	0	0.321	0	1

Source: Compiled by authors

Figure 1. The mean value of CDT in each year



Source: Compiled by authors

4. 2. PARALLEL TREND TEST

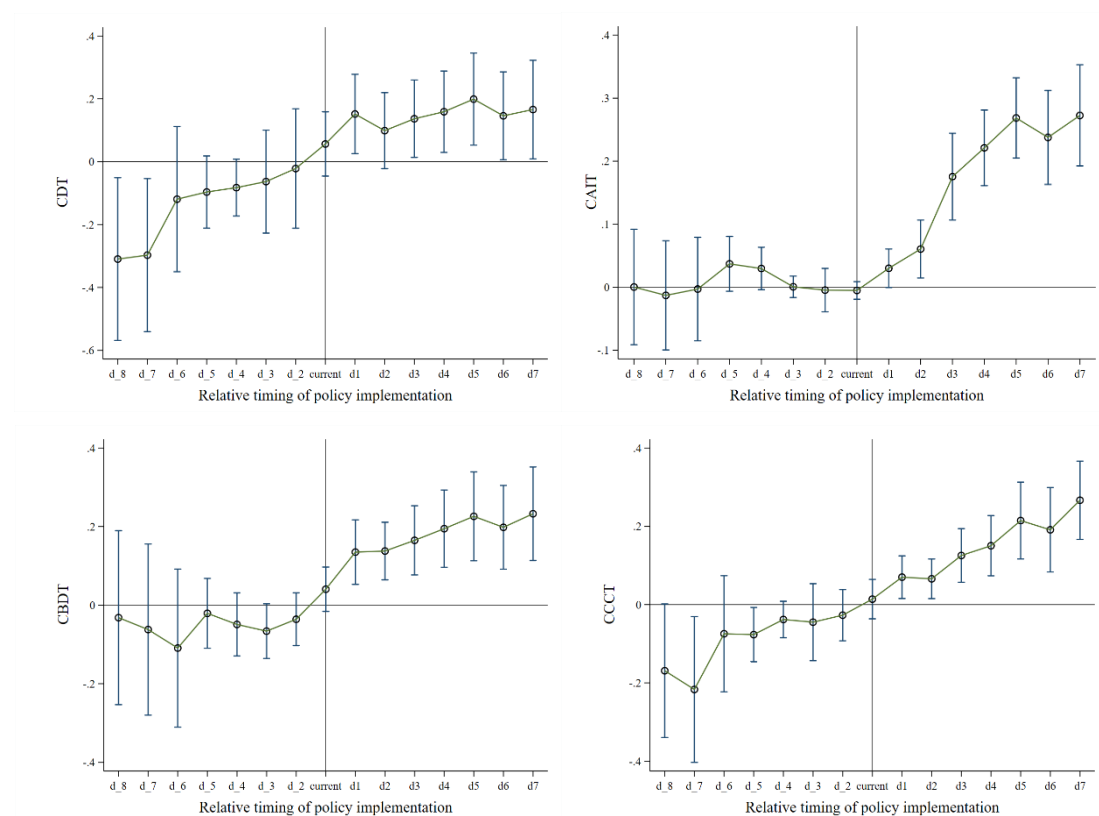
The parallel trends assumption is a critical prerequisite for ensuring the validity of the DID model in empirical studies, as it requires that treatment and control groups exhibit similar trends prior to the policy's implementation. Specifically, firms located in cities participating in the carbon emissions trading pilot program should demonstrate pre-policy digital transformation trends consistent with those of firms in non-participating cities. To verify this assumption, the study conducts a parallel trends test by visualizing and analyzing the changes in digital transformation for both groups before and after the introduction of market-based regulatory policies. The years 2013, 2014, and 2017 are designated as the policy implementation points. To minimize the risk of multicollinearity, the analysis excludes the earliest pre-policy period that predates the

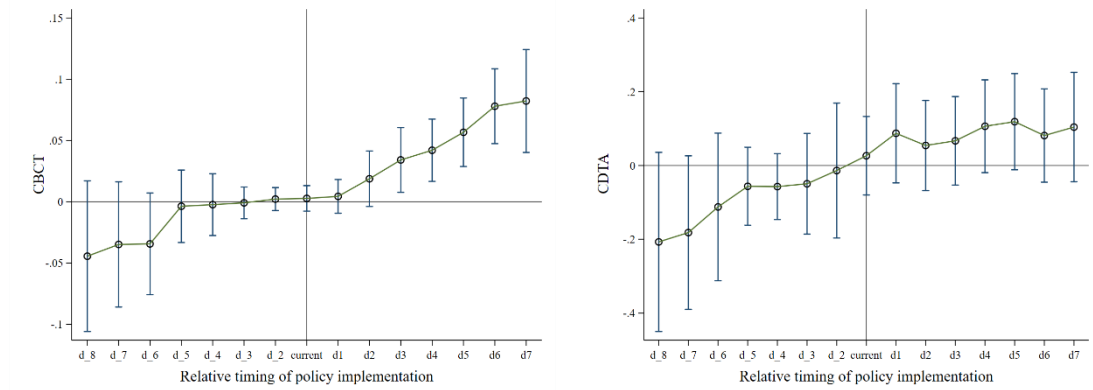
launch of the carbon emissions trading pilot program. Parallel trend graphs are generated for the overall indicator (CDT) and five dimension-specific indicators: CAIT, CBDT, CCCT, CBCT, and CDTA. In these graphs, d_i denotes the interaction term between the policy and the i -th year prior to its implementation, while d_j represents the interaction term between the policy and the j -th year after implementation. The term “current” corresponds to the interaction term for the policy implementation year. The graphs display the coefficients for eight pre-policy periods and seven post-policy periods, along with their 90% confidence intervals. Due to the time lag in firms’ responses to policy changes, the coefficient for the implementation year may lack statistical significance.

Before the policy was implemented, there were no significant differences in corporate digital transformation trends between the treatment and control groups. However, after the policy went into effect, firms began to exhibit a noticeable upward trend in digital transformation, as well as in the five dimensions: CAIT, CBDT, CCCT, CBCT, and CDTA. The coefficients demonstrate a general shift from negative to positive over time. These results confirm that the pre-policy trends in corporate digital transformation and its five dimensions are consistent between the two groups, regardless of the presence of market-based regulatory policies. This finding validates the parallel trends assumption and supports the application of the DID model in this study.

In summary, holding other conditions constant, market-based regulatory policies significantly promote corporate digital transformation, with the effects strengthening over time, providing robust support for Hypothesis H_1 .

Figure 2. Parallel trend test results





Source: Compiled by authors

4.3. BASELINE REGRESSION

This study examines how market-based environmental regulations facilitate corporate digital transformation by incentivizing green innovation, grounded in the Porter Hypothesis. According to this theory, properly designed environmental policies can stimulate innovation compensation effects, and digital transformation represents a critical pathway for firms to pursue technological innovation and efficiency improvements under carbon constraints.

The baseline regression results in Table 4 support this mechanism. After controlling for firm and year two-way fixed effects, the CETR consistently demonstrates a significant positive impact on the CDT. Without control variables, the coefficient is 0.195, significant at the 1% level. After incorporating control variables, the policy raises the digitalization level of pilot firms by an average of 16.7%, significant at the 5% level. This indicates that market-based environmental regulations effectively trigger the transmission mechanism of “innovation incentive-digital transformation.”

Among the control variables, factors including firm size, enterprise value, and firm age show positive correlations with digital transformation, whereas leverage ratio, cash holdings, and ownership concentration exhibit inhibitory effects. Only ownership concentration (Top1) passes the significance test, highlighting the important influence of corporate governance structure on technological responsiveness.

Further analysis across five technological dimensions reveals that the policy exerts the strongest promoting effect on big data technology (CBDT), with a coefficient of 0.175 significant at the 1% level, underscoring its core role in carbon data monitoring, emission management, and energy efficiency optimization. Although blockchain technology (CBCT) shows a coefficient of 0.029, it is only significant at the 10% level, reflecting its current status as an auxiliary technological application. This differential pattern indicates that firms’ chosen digital pathways in response to environmental regulations demonstrate clear problem-oriented characteristics and technology-scenario adaptation.

Our empirical results substantiate the applicability of the Porter Hypothesis in the digital context: market-based environmental regulations not only stimulate green innovation but also systematically guide firms to advance digital transformation along different technological trajectories, establishing a virtuous cycle that synergistically enhances both environmental performance and digital capabilities.

Table 4. Baseline regression results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDT	CDT	CAIT	CBDT	CCCT	CBCT	CDTA
<i>CETR</i>	0.195*** (0.062)	0.167** (0.056)	0.110** (0.042)	0.175*** (0.046)	0.133*** (0.040)	0.029* (0.013)	0.099* (0.051)
<i>Size</i>		0.280*** (0.029)	0.146*** (0.024)	0.217*** (0.032)	0.166*** (0.020)	0.030** (0.010)	0.189*** (0.025)
<i>TobinQ</i>		0.039*** (0.012)	0.011 (0.011)	0.031** (0.013)	0.023** (0.007)	-0.003 (0.005)	0.035*** (0.009)
<i>Lev</i>		-0.079 (0.088)	0.008 (0.060)	0.034 (0.074)	-0.065 (0.057)	-0.012 (0.025)	-0.017 (0.073)
<i>Cash</i>		-0.016 (0.088)	-0.271*** (0.068)	-0.276*** (0.072)	-0.163** (0.061)	-0.078** (0.030)	0.066 (0.075)
<i>Growth</i>		0.019 (0.017)	-0.039*** (0.010)	-0.012 (0.015)	-0.020 (0.011)	-0.015*** (0.004)	0.025 (0.015)
<i>Age</i>		0.142*** (0.034)	0.042* (0.021)	0.059* (0.030)	0.064** (0.023)	0.005 (0.009)	0.104*** (0.033)
<i>Dua</i>		0.034 (0.026)	0.025 (0.018)	0.026 (0.025)	0.016 (0.016)	0.018* (0.010)	0.020 (0.024)
<i>Top1</i>		-0.005** (0.002)	-0.003** (0.001)	-0.005*** (0.002)	-0.003** (0.001)	-0.001 (0.000)	-0.002 (0.001)
<i>Soe</i>		0.048 (0.034)	-0.002 (0.014)	-0.003 (0.023)	0.026 (0.019)	-0.005 (0.008)	0.040 (0.030)
<i>Constant</i>	1.273*** (0.019)	-5.046*** (0.642)	-2.932*** (0.521)	-4.317*** (0.676)	-3.227*** (0.431)	-0.573** (0.206)	-3.480*** (0.550)
<i>Year</i>	YES	YES	YES	YES	YES	YES	YES
<i>Firm</i>	YES	YES	YES	YES	YES	YES	YES
<i>Observations</i>	20,887	20,074	20,074	20,074	20,074	20,074	20,074
<i>R-squared</i>	0.800	0.811	0.642	0.705	0.776	0.457	0.751
The values in parentheses indicate robust standard errors clustered at the year and firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Same below.							

Source: Compiled by authors

4. 4. ROBUSTNESS TESTS

4. 4. 1. PLACEBO TEST

To evaluate the potential influence of unobservable factors on the relationship between market-based environmental regulations and corporate digital transformation, this paper employs two methods: conducting 500 regressions using randomly selected treatment groups and performing 1,000 random samplings with a fictional treatment group. The objective is to compare the interaction coefficients with the baseline regression estimates and determine if any significant differences arise.

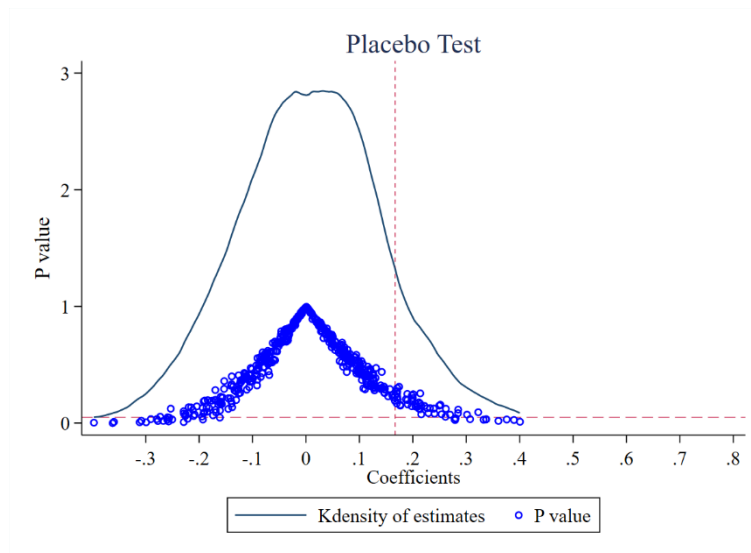
To ensure that the observed impact of market-based environmental regulations on corporate digital transformation is not a result of random chance, a placebo test was performed. In this test, 46 cities were randomly selected from the full sample to form a hypothetical “pilot” treatment group, while the remaining cities were treated as the control group. A placebo interaction

term was then created to serve as the core variable and replaced the original interaction term in Equation (1) for regression analysis. This randomization process was repeated 500 times. The results, displayed in Figure 3, reveal that in 471 out of the 500 iterations, the estimated interaction coefficients failed to reach statistical significance at the 5% level. These findings confirm the robustness of the original results.

Furthermore, a second placebo test was carried out by randomly creating treatment groups based on various combinations of cities and years, with this procedure repeated 1,000 times. Figure 4 presents the results of the 1,000 random samplings with fictitious treatment groups, indicating that only 33 out of the 1,000 estimated coefficients exceeded the baseline regression coefficient.

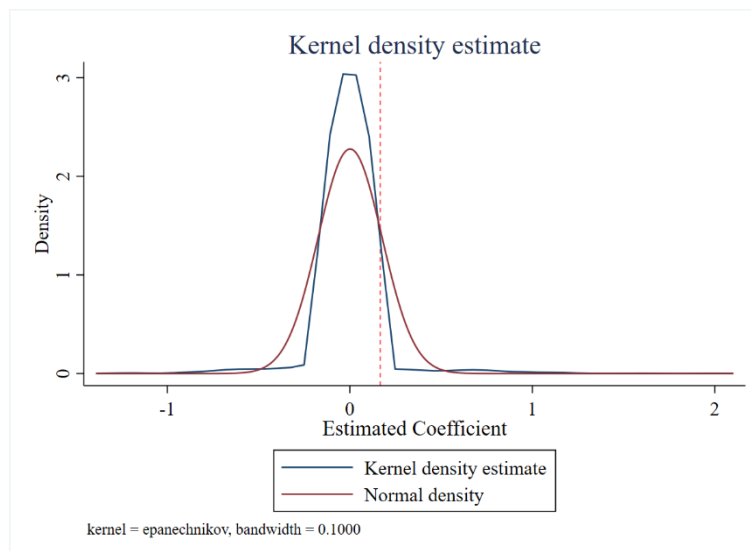
Both approaches provide evidence that the results are neither coincidental nor influenced by unrelated policies or random factors. Thus, the placebo test results affirm the validity and robustness of the baseline regression's conclusion that market-based environmental regulations effectively promote corporate digital transformation.

Figure 3. Randomly selected treatment groups



Source: Compiled by authors

Figure 4. Fictitious treatment groups



Source: Compiled by authors

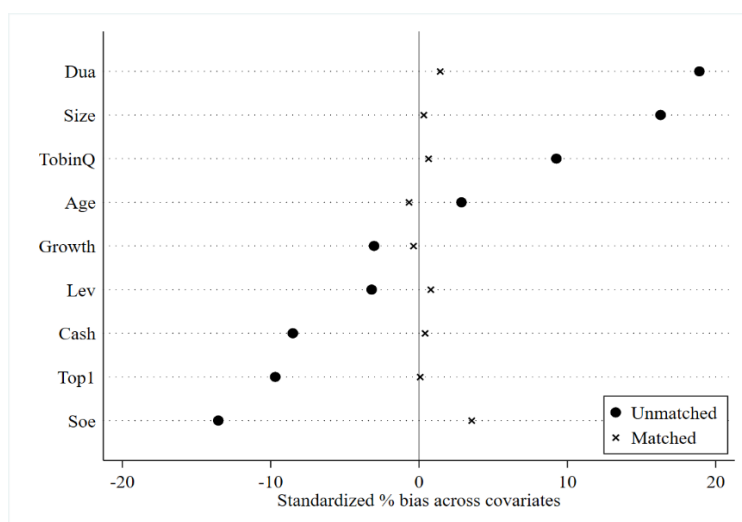
4. 4. 2. PSM-DID TEST

To address potential bias stemming from the non-random selection of cities for the carbon emissions trading pilot program, which was based on government evaluations, this study employs the Propensity Score Matching (PSM) method to verify the robustness of the findings. Specifically, a 1:2 nearest-neighbor matching approach is applied, with propensity scores estimated through a Logit model. Following the matching process, a DID regression is performed on the matched sample to reexamine the results.

As illustrated in Figure 5, the absolute values of the standard deviations for all matching variables are significantly below 10, demonstrating a high-quality match. The results of the PSM-DID analysis are summarized in Table 5. Specifically, Column (1) displays the regression results based on pooled OLS, Column (2) shows the outcomes derived from the two-way fixed effects model, and Column (3) presents the findings for the sample that meets the common support assumption.

Although the estimated coefficients show slight variations before and after applying PSM, they remain consistently and significantly positive. This demonstrates that the bias caused by sample selection is minimal, confirming the robustness and reliability of the study's conclusions.

Figure 5. Change in standard deviation of variables



Source: Compiled by authors

Table 5. PSM-DID test results

	(1)	(2)	(3)
<i>CETR</i>	0.875*** (42.888)	0.167** (0.056)	0.167** (0.056)
<i>Constant</i>	-3.201*** (0.204)	-5.046*** (0.642)	-5.048*** (0.635)
<i>Control</i>	YES	YES	YES
<i>Year</i>	YES	YES	YES
<i>Firm</i>	YES	YES	YES
<i>Observation</i>	20109	20074	20059
<i>R-squared</i>	0.146	0.811	0.811

Source: Compiled by authors

4. 4. 3. REPLACEMENT OF THE DEPENDENT VARIABLE TEST

To mitigate potential estimation biases arising from inherent differences in digital transformation levels among firms, this study conducted robustness checks by replacing the dependent variable. Specifically, we employed two alternative measures for regression analysis: first, the average value of the digital transformation index of all firms within the same city (denoted as CDT_mean), and second, the natural logarithm of one plus the number of digital technology invention patents granted to the firm (denoted as Digpat). All regressions controlled for both year and firm two-way fixed effects, with standard errors clustered at the firm level. The results are reported in Table 6.

Columns (1) and (3) present the baseline specifications without control variables. The results show that the coefficients of the core explanatory variables are significantly positive. After incorporating a set of control variables, as shown in Column (2), the coefficient for CDT_mean is 0.244 and statistically significant at the 1% level, indicating that the implementation of carbon emission trading pilot policy significantly enhanced the overall level of digital transformation in the cities where the treatment group is located. Column (4) further shows that the coefficient for Digpat is 0.021, also significant at the 1% level, suggesting that the policy effectively incentivized firms' digital technology innovation capacity.

These findings demonstrate that the promoting effect of the carbon emissions trading policy on corporate digital transformation remains highly significant even when alternative measures of the dependent variable are used. This further reinforces the core conclusion of this paper: market-based environmental regulations have a robust and substantial driving effect on corporate digital transformation.

Table 6. Replacement of dependent variable regression results

Variables	(1)	(2)	(3)	(4)
	CDT_mean	CDT_mean	Digpat	Digpat
<i>CETR</i>	0.248*** (0.014)	0.244*** (0.014)	0.023*** (0.008)	0.021*** (0.008)
<i>Constant</i>	1.256*** (0.005)	0.499** (0.222)	0.033*** (0.002)	-0.293*** (0.091)
<i>Control</i>	NO	YES	YES	YES
<i>Year</i>	YES	YES	YES	YES
<i>Firm</i>	YES	YES	YES	YES
<i>Observations</i>	20,887	20,074	18991	18276
<i>R-squared</i>	0.906	0.909	0.534	0.536

Source: Compiled by authors

4. 5. HETEROGENEITY TEST

4. 5. 1. HETEROGENEITY TEST OF ENTERPRISE OWNERSHIP

SOEs and non-SOEs demonstrate markedly different patterns of digital transformation under market-based environmental regulations, a divergence deeply rooted in their distinct ownership structures, policy roles, and resource allocation mechanisms.

SOEs, being under direct or indirect government control, generally align their strategic decisions with policy objectives. This alignment not only enhances their political motivation to respond to carbon trading policies but also grants them preferential access to critical resources such as government credit and R&D subsidies. Consequently, SOEs possess significant advantages in pursuing digital transformation, particularly in resource-intensive technological domains like big data and cloud computing. This explains why the policy-induced boost in the

CDT for SOEs is approximately twice that for non-SOEs, with both groups showing the most substantial improvements in big data technologies.

In contrast, although non-SOEs exhibit greater operational flexibility, their responses rely more heavily on market incentives and cost-benefit calculations, resulting in a more indirect policy transmission mechanism. This structural characteristic enables them to develop distinctive strengths in certain frontier and high-risk technological fields. For instance, as shown in Column (5) of Table 7, market-based environmental regulations did not significantly affect blockchain technology upgrades in SOEs but generated a positive impact on non-SOEs at the 10 percent significance level. This suggests that non-SOEs may be more adaptable in exploring technologies that require greater flexibility and tolerance for experimentation.

Thus, the carbon emissions trading policy drives digital transformation in SOEs through what is essentially a dual track mechanism combining administrative and market forces, integrating both the binding force of institutional targets and the enabling effects of resource allocation. For non-SOEs, however, the impact operates primarily through price signals and market competition. This fundamental difference not only shapes the extent of digital transformation across ownership types but also influences their respective focuses in selecting technological pathways.

Table 7. Results of the heterogeneity test for state-owned enterprises

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	CDT	CAIT	CBDT	CCCT	CBCT	CDTA
<i>CETR</i>	0.334**	0.148*	0.260**	0.202**	0.000	0.188*
	(0.111)	(0.073)	(0.096)	(0.075)	(0.015)	(0.100)
<i>Constant</i>	-3.362*	-1.301	-4.088***	-1.837	0.084	-1.192
	(1.770)	(0.894)	(1.251)	(1.076)	(0.417)	(1.700)
<i>Control</i>	YES	YES	YES	YES	YES	YES
<i>Year</i>	YES	YES	YES	YES	YES	YES
<i>Firm</i>	YES	YES	YES	YES	YES	YES
<i>Observation</i>	2,233	2,233	2,233	2,233	2,233	2,233
<i>R-squared</i>	0.850	0.677	0.741	0.818	0.478	0.825

Source: Compiled by authors

Table 8. Results of the heterogeneity test for non-state-owned enterprises

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	CDT	CAIT	CBDT	CCCT	CBCT	CDTA
<i>CETR</i>	0.147**	0.109**	0.159***	0.134**	0.031*	0.090
	(0.058)	(0.043)	(0.049)	(0.045)	(0.014)	(0.054)
<i>Constant</i>	-5.342***	-3.126***	-4.325***	-3.355***	-0.581***	-3.917***
	(0.729)	(0.562)	(0.744)	(0.487)	(0.187)	(0.594)
<i>Control</i>	YES	YES	YES	YES	YES	YES
<i>Year</i>	YES	YES	YES	YES	YES	YES
<i>Firm</i>	YES	YES	YES	YES	YES	YES
<i>Observation</i>	17,700	17,700	17,700	17,700	17,700	17,700
<i>R-squared</i>	0.815	0.649	0.712	0.779	0.475	0.754

Source: Compiled by authors

4. 5. 2. HETEROGENEITY TEST OF ENTERPRISE SIZE

Firms of varying sizes encounter distinct challenges in digital transformation due to differences in financial resources, technological expertise, and human capital. These disparities influence their responsiveness to regulatory policies in market-based environments. Drawing on the approach of [Liu et al. \(2024\)](#), this study divides the sample firms into two categories based on the median of the logarithmic values of their total assets: large enterprises and MSMEs. Separate regressions are conducted for each category, with the results for large enterprises and MSMEs presented in Tables 9 and 10, respectively.

The results reveal that market-based environmental regulations do not exert a significant influence on the digital transformation of large enterprises. However, these policies have a markedly positive impact on the digital transformation of MSMEs, with the effect being statistically significant at the 1% level. A closer examination of the five dimensions of digital transformation shows that the policies significantly boost large enterprises' technological capabilities in areas such as artificial intelligence, big data, and blockchain. For MSMEs, the regulations promote digital transformation by approximately 27.1%, though the impact on blockchain technology development is not statistically significant.

These results highlight that market-based environmental regulations play a critical role in advancing the digital transformation of MSMEs, while their influence on large enterprises remains limited. Due to their smaller scale and greater operational agility, MSMEs are better equipped to adapt to and implement digital transformation initiatives more effectively than their larger counterparts.

Table 9. Results of the heterogeneity test for large enterprises

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	CDT	CAIT	CBDT	CCCT	CBCT	CDTA
<i>CETR</i>	-0.016 (0.054)	0.088* (0.042)	0.118** (0.048)	0.039 (0.041)	0.028* (0.015)	-0.060 (0.048)
<i>Constant</i>	-5.384*** (0.842)	-3.173*** (0.732)	-4.138*** (0.760)	-3.458*** (0.696)	-0.393 (0.299)	-3.504*** (0.845)
<i>Control</i>	YES	YES	YES	YES	YES	YES
<i>Year</i>	YES	YES	YES	YES	YES	YES
<i>Firm</i>	YES	YES	YES	YES	YES	YES
<i>Observation</i>	9,951	9,951	9,951	9,951	9,951	9,951
<i>R-squared</i>	0.842	0.720	0.784	0.826	0.530	0.795

Source: Compiled by authors

Table 10. Results of the heterogeneity test for micro, small and medium-sized enterprises

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	CDT	CAIT	CBDT	CCCT	CBCT	CDTA
<i>CETR</i>	0.271*** (0.076)	0.083* (0.044)	0.181** (0.060)	0.176*** (0.049)	0.017 (0.015)	0.181** (0.073)
<i>Constant</i>	-5.554*** (1.081)	-2.860*** (0.804)	-5.693*** (1.019)	-2.602*** (0.633)	-0.856** (0.291)	-4.206*** (1.023)
<i>Control</i>	YES	YES	YES	YES	YES	YES
<i>Year</i>	YES	YES	YES	YES	YES	YES
<i>Firm</i>	YES	YES	YES	YES	YES	YES
<i>Observation</i>	9,805	9,805	9,805	9,805	9,805	9,805
<i>R-squared</i>	0.842	0.693	0.742	0.812	0.555	0.787

Source: Compiled by authors

5. CONCLUSIONS

Drawing on a sample of A-share listed companies in Shanghai and Shenzhen from 2009 to 2020, this study employs China's carbon emission trading pilot policy as a quasi-natural experiment to examine the driving effect of market-based environmental regulation on corporate digital transformation using a multi-period DID model. Robustness tests reveal that the carbon trading policy significantly promotes corporate digital transformation, with pilot enterprises experiencing an average increase of 16.7% in digitalization level, confirming the innovation compensation mechanism underlying the Porter Hypothesis. Heterogeneity analysis demonstrates that the policy's promoting effect on state-owned enterprises is more than double that on non-state-owned enterprises, while its impact on micro, small, and medium-sized enterprises significantly surpasses that on large enterprises, highlighting the critical roles of ownership attributes and organizational flexibility in green innovation responses.

Compared to price-driven carbon market mechanisms in developed economies like the EU, China's carbon trading system exhibits a distinctive policy-embedded nature. While the EU system relies more on mature market mechanisms to drive corporate low-carbon transition, China's practice reflects an organic integration of government guidance and market mechanisms, particularly in stimulating demonstration effects in state-owned enterprises and dynamic responses in small and medium-sized enterprises, offering a novel institutional paradigm. This pathway provides important references for emerging economies balancing environmental goals and digital transformation.

Based on empirical findings, this paper proposes a graded policy framework: governments should improve carbon pricing mechanisms and strengthen guidance for digital emission reduction; state-owned enterprises need to leverage their institutional advantages to deepen digital transformation; large enterprises should focus on restructuring business processes through digitalization to enhance sustainable performance; while small and medium-sized enterprises can utilize their flexibility to rapidly build digital competitiveness.

The study identifies two main limitations: the measurement of digital transformation still faces standardization challenges, and the sample is limited to A-share markets. Future research could expand to cross-economy comparative analysis and explore the establishment of more internationally comparable digital measurement systems, thereby deepening the understanding of the integration mechanism between market-based environmental policies and the digital economy.

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