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Driving Digital Shift: Carbon Emissions Trading as a Catalyst for Corporate Transformation in China–A Dual Machine Learning and DID Approach

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SUMMARY: *In response to the insufficient research on the collaborative mechanism between environmental regulation and enterprise digital transformation, this article proposes three hypotheses based on Porter's theory of competitive advantage: direct driving of carbon trading policies, alleviation of financing constraints, and green technology innovation; Then, using panel data from Chinese A-share listed companies from 2010 to 2021, and combining dual machine learning and double difference method, a quasi-experimental study was conducted to systematically identify the net effect of policies. The empirical verification results show that the carbon trading pilot policy significantly promotes the digital transformation of enterprises, and the core coefficient remains stable under multiple algorithms and passes the 1% significance test. This indicates that the policy can empower digital transformation through two paths: reducing debt financing costs and enhancing green innovation output, thereby providing empirical evidence for the coordinated promotion of the "dual carbon" strategy and the development of the digital economy.*

KEYWORDS: *Financing constraints; Carbon emissions trading; Dual machine learning; Porter hypothesis; Digital transformation; green innovation*

1 Introduction

The digital economy marks a new stage of global technological change, reshaping the global resource allocation model and economic operation system from the bottom logic. Therefore, digital transformation has become the core support for maintaining stable economic growth and enhancing development resilience [1]. As the core micro entity of the market economy, enterprises need to balance the development scale and high-quality transformation from a strategic perspective, and fully unleash the endogenous driving force of digital transformation [2]. However, at present, the digitalization process of enterprises still faces core bottlenecks concentrated in core technology shortcomings, transformation cost pressures, and internal organizational change inertia. It is urgent to establish a sound policy and institutional system to guide and alleviate difficulties, in order to clear the transformation path and weaken landing risks [3].

The pilot policy of carbon emissions trading is a market-oriented regulatory system built in China with carbon emission quotas as the core. It transforms the externalities of carbon

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emissions into quantifiable cost-benefit indicators in enterprise production decisions, forming differentiated constraints and incentive mechanisms for enterprises [4]. High energy consuming and high emission enterprises actively carry out green technology transformation and production process upgrading to reduce compliance costs; Low carbon emission enterprises can rely on quota trading to activate the remaining emission quotas and realize the market-oriented realization of environmental rights and interests [5]. In addition, the deep application of digital technologies such as big data, artificial intelligence, and cloud computing promotes the deep coupling between digital technology and carbon trading policies, thereby driving enterprises to transform passive compliance requirements into active value creation behaviors, forcing them to optimize production and operation models, and actively tap into the dividends of the carbon trading market. This is a key policy engine driving the digital transformation of enterprises [6].

This study selected panel data from 1416 A-share listed companies from 2010 to 2021 as the research sample, and combined dual machine learning methods with double difference methods to systematically identify the causal relationship between carbon trading policy implementation and corporate digital transformation. By accurately quantifying the transmission path of the causal relationship between carbon trading policy implementation and enterprise digital transformation, this study constructs a comprehensive theoretical analysis framework and clearly explains the interactive mechanism between environmental regulatory policies and enterprise digital transformation.

2 Literature review

2.1 Carbon Emissions Trading Pilot Policy

As a market-oriented environmental governance tool, the carbon emission trading pilot policy has established a total control and quota trading mechanism, guiding enterprises to adjust their emission behavior and regulate emission patterns through market price signals, fully leveraging the decisive role of the market in resource allocation [7]. Empirical studies have shown that compared with command-and-control regulatory measures, this market-oriented governance mechanism has higher operational efficiency, especially in achieving low-cost and high-efficiency emission reduction targets [8]. The carbon trading framework provides incentive mechanisms for enterprises to independently carry out emission reduction through the following five interrelated channels:

(1) Price Signaling Effects. The carbon pricing mechanism establishes a direct economic incentive system, and higher carbon costs will force enterprises to actively adopt green technologies and promote low-carbon production models, which not only improves regional production efficiency [9], but also transforms pollution reduction behavior into economically reasonable enterprise decisions [10], effectively driving enterprises to carry out ecological innovation activities [11].

(2) Compliance Enforcement Mechanisms. Regulatory constraints cover measures such as economic penalties for violations and market access restrictions, which can force companies to focus on emission reduction and low-carbon operations, and promote the inclusion of emission reduction targets in the core business decision-making system [12].

(3) Innovation-Inducing Subsidies. The policy tools supporting the carbon market, such as special subsidies for green technology and tax incentives, can effectively reduce the threshold and cost of green innovation for enterprises by reducing research and development investment costs, improving the feasibility and return rate of green innovation, and helping to accelerate the industrial application of green technology and enhance the emission control capabilities of enterprises [13]. When the marginal emission reduction cost of a company drops below the

marginal revenue, it will trigger a dynamic optimization process of production and operation, which is also a significant advantage of the carbon pricing related institutional system compared to traditional regulatory measures [14].

(4) Market-Driven Efficiency. Entities with lower marginal emission reduction costs can obtain additional income by selling surplus carbon emission quotas, while enterprises with higher emission reduction costs can purchase quotas to meet compliance requirements and enhance operational flexibility. This operating model can strengthen healthy competition among industry entities and promote the implementation of technology driven emission reduction behaviors [15].

(5) Societal Expectation Pressures. The improvement of environmental awareness among the general public has significantly amplified the market competition pressure, consumer choice pressure, and investor preference pressure faced by enterprises, thereby forcing them to increase their investment in green innovation. This not only optimizes the market competition positioning of enterprises, but also indirectly achieves an effective reduction in carbon emission intensity [16].

2.2 Carbon Emissions Trading Policy and Digital Transformation

The carbon emissions trading system can drive the digital transformation of enterprises through multidimensional paths, and existing empirical research has confirmed that digital development can effectively curb the carbon footprint of enterprises [17]. In addition, digital applications can improve the efficiency of enterprise resource utilization and operational adjustment flexibility, thereby accelerating the low-carbon transformation process.

The market-oriented carbon regulation policy guides the reconfiguration of production factors and systematic optimization of production processes by constructing a carbon asset valuation system, improving overall production efficiency while meeting environmental compliance requirements [18]. The above differentiated results indicate that the carbon trading system can serve as a strategic incentive under carbon emission constraints, effectively promoting the digital structural upgrading of enterprises.

There is a bidirectional strengthening coupling mechanism between policy and digitization as follows:

(1)Emission-Driven Digital Adoption. Carbon environmental regulations force enterprises to carry out technological upgrades and transformations. Studies have shown that carbon trading control areas can rely on digital transformation to achieve significant reductions in carbon emission intensity with marginal advantages [19]. In addition, digital technology can achieve precise monitoring of energy consumption and adaptive control of production processes, providing direct technical support for the implementation of low-carbon development goals.

(2)Governance Enhancement Effects. Digital transformation can enhance the efficiency of enterprise environmental governance, and through the improvement of data transparency and algorithmic resource allocation models, it can provide quantitative basis and scientific support for decarbonization strategy formulation, forming a carbon trading market system with diverse collaborative values [20].

(3)Abatement Capacity Amplification. Digital transformation can effectively enhance the emission reduction capability of enterprises, and the implementation path is as follows [21]: 1) improve the financial performance of enterprises through the automation of compliance processes; 2) Improve production management mode based on predictive analysis technology; 3) Relying on the IoT monitoring system to optimize energy utilization efficiency; 4) Relying on digital R&D platforms to accelerate the iteration of green technology innovation [22].

Digitization can effectively reduce market transaction frictions covering dimensions such as industrial symbiosis system applications and advanced end of pipe treatment technology iterations, thereby promoting the implementation of clean production models [23], significantly reducing decision-making cycles, and improving the efficiency of enterprise decision-making operations [24].

(4)Market Infrastructure Development. The digitization of the entire process, relying on automatic reporting and intelligent verification mechanisms, can effectively reduce the threshold for carbon market participation and institutional transaction costs [25]. In addition, the information disclosure system empowered by blockchain further enhances the transparency of the carbon trading market and strengthens the endogenous incentives for enterprises to participate in carbon control and trading [26].

Green supporting policy tools covering special subsidies, tax exemptions, and environmental special subsidies can help mitigate innovation investment risks, continuously empower the digital upgrading process of enterprises [27], and promote the synergistic improvement of environmental performance and long-term value [28].

Although existing research has achieved phased results, the current literature has not yet systematically clarified the heterogeneity characteristics of policy effects at the levels of enterprise size, industry type, and regional endowment [29]. There is insufficient exploration of the interaction mechanism between carbon trading markets and low-carbon city pilot projects, as well as the cross departmental policy synergy path to maximize digital synergy benefits. Therefore, it is urgent to carry out systematic theoretical deduction and quantitative empirical testing.

3 Research Hypotheses

Assumption 1: Carbon emissions trading policies can significantly promote the digital transformation of enterprises.

With the help of Porter's theory of competitive advantage, this study points out that reasonable environmental regulations can drive innovation and upgrading through technological innovation, thereby cultivating long-term competitive advantages for enterprises [30]. In this process, enterprises actively adjust their digital strategic layout by increasing digital capital investment, thereby achieving a comprehensive consideration of multiple development goals such as environmental compliance, operational efficiency improvement, carbon reduction tasks, and quota optimization [31]. The regulatory model combining total quantity control and quota trading continues to force enterprises to carry out technological transformation and business upgrading, while digital technology can achieve precise allocation of production factors and improve total factor productivity [32].

Relying on artificial intelligence and digital management systems to reconstruct traditional production organizational forms, policy compliance adaptation requires enterprises to simultaneously complete technological upgrades and management mode changes [33], which can effectively strengthen the endogenous driving force of enterprise application of emission control digital technologies, promote the landing and popularization of big data analysis, blockchain technology, and machine learning algorithms, thereby reducing compliance costs and alleviating emission reduction pressure. Empirical results have shown that environmental regulations can accelerate the integration and application of digital technology, continuously strengthen enterprise innovation capabilities, and accelerate the transformation process, synchronously driving low-carbon technology innovation and enterprise digital transformation.

Assumption 2: The pilot policy of carbon emissions trading can effectively alleviate the financing constraints of enterprises and empower the process of digital transformation.

Carbon regulation policies can improve the level of corporate environmental information disclosure, shape sustainable development reputation, and enhance capital acquisition conditions [34]. Although the digital adaptation requirements of policies may impose short-term financing constraints on high polluting emission enterprises, the carbon trading mechanism as a whole can reduce external financing costs for enterprises, simultaneously improve information transparency and governance level [35], and is influenced by factors such as property rights, financial status, and regional characteristics.

Digital transformation has strategic attributes such as long investment cycles, high uncertainty, and intensive capital consumption, which can easily weaken the willingness of financial institutions to invest in digital projects. In addition, the large scale of investment in supporting infrastructure for digital transformation and the long investment payback period continue to exacerbate the financial constraints of enterprise digital upgrading. Industrial policies can play a role in information transmission and signal guidance, guiding social capital to flow into key support areas in a targeted manner [36], and alleviating compliance cost pressures for enterprises through differentiated quota allocation rules. At the same time, government subsidies and institutional support can release positive market signals, stabilize capital market expectations, and enhance investor confidence.

Enterprises with ample cash reserves have stronger digital transformation investment capabilities, while financing constrained enterprises often prioritize maintaining precautionary liquidity and reducing long-term strategic investment scale. The carbon trading policy can improve the credit qualifications of enterprises through a dual path of market-oriented realization of carbon quota assets and appreciation of green reputation value. Based on the two-way mechanism of regulatory signal transmission and capital market value feedback, it continuously optimizes the financing environment of enterprises and provides stable financial support for digital transformation.

Assumption 3: Carbon emissions trading policies can promote digital transformation of enterprises by strengthening green technology innovation.

The carbon trading pilot relies on carbon price signals to internalize the external costs of carbon emissions, effectively activating the green innovation driving path of enterprises. The weak Porter hypothesis explains the dual effects of environmental regulation. Although regulatory constraints increase compliance expenditures for businesses, they rely on technological innovation and efficiency improvement to offset emission reduction costs, forming an innovative compensation effect, which in turn releases cash flow to support digital layout.

To reduce the cost of carbon emissions compliance, enterprises actively develop and implement low-carbon technology systems, promoting the construction of a dual dimensional environmental strategy, that is, adaptive adjustments to policy foresight and responsive optimization of current regulatory pressures. Both types of strategies need to rely on green technology innovation to achieve emission reduction targets. Empirical studies have shown that carbon trading systems can significantly incentivize corporate innovation behavior, but there is a certain time lag characteristic [37].

The digital transformation of carbon regulation policies forms a deep synergy with green innovation from three aspects: digital carbon emission monitoring system, intelligent emission reduction regulation optimization platform, and energy management system empowered by artificial intelligence. Among them, digital technologies centered on the Internet of Things and big data analysis can achieve precise identification of emission sources and dynamic optimization of production processes. The integration mode not only meets the requirements of phased environmental compliance, but also helps enterprises cultivate long-term digital core competitive advantages.

4 Model construction and variable description

4.1 Data description

Considering that the national unified carbon emissions trading market will only officially operate in 2021, this study selects panel data of Chinese A-share listed companies from 2010 to 2021 from the CSMAR database as the research sample [38]. To avoid interference from abnormal samples, research subjects in financial distress, including ST, * ST, and PT listed companies, were excluded, and sample observations with asset liability ratios greater than 1 were excluded. To weaken the bias effect of extreme values on regression results, all continuous variables were truncated at the 1% and 99% quantiles, and missing data were filled in using linear interpolation. After a series of screening and data cleaning, 16992 annual balanced observation samples of enterprises were finally obtained.

4.2 Variable selection

4.2.1 Dependent variable selection

Quantitative measurement was conducted using text mining and word frequency statistics of annual reports of listed companies, with enterprise digital transformation (DT) as the core dependent variable. By collecting keyword word frequencies from the five major digital technology fields, the intensity of enterprise digital development can be comprehensively characterized. Specifically, the system compiles 76 feature words covering artificial intelligence, big data, cloud computing, blockchain, and general digital technology application dimensions [39]. After text retrieval and word frequency aggregation, the natural logarithm of the total word frequency is taken to construct a digital transformation index (DT), which objectively reflects the depth and coverage of enterprise digital construction implementation.

4.2.2 Independent variable selection

In 2013, China took the lead in launching carbon trading pilot markets in seven provincial-level administrative regions including Beijing, Shanghai, and Guangdong. This study accurately defines the timing of exogenous policy shocks based on the official implementation of policies in each pilot region. Enterprises registered within the carbon pilot jurisdiction will be designated as the treatment group, while non pilot area enterprises will be included in the control group. The interaction term $did = treat \times time$ will be constructed as the core variable for identifying policy effects. If the enterprise is within the policy implementation cycle, it will be assigned a value of 1, otherwise it will be assigned a value of 0.

4.2.3 Control variables selection

This article follows the mainstream empirical research paradigm and includes nine enterprise level control variables: enterprise size (Size), return on assets (ROA), leverage level (Lev), listing age (ListAge), revenue growth rate (Growth), equity concentration (Top1), per capita net fixed asset value (PFixA) and per capita operating income (PSales), Tobin Q value (TobinQ). The detailed definitions of each variable are shown in Table 1.

Table 1: Variable definition

Type	Name	Symbol	Description
dependent	Digital Transformation	*DT*	Ln (frequency of keywords in digital synonym library)
independent	carbon emissions trading	*did*	The policy pilot area is 1, while other areas are 0
control	size	*Size*	Ln (total assets)
	return on assets	*ROA*	net profit / total assets
	leverage ratio	*Lev*	total liabilities / total assets
	Listing age	*ListAge*	Ln (current year - IPO year + 1)
	revenue growth	*Growth*	(operating income$_t$ - operating income$_{t-1}$) / operating income$_{t-1}$
	ownership concentration	*Top1*	sercentage shareholding of largest shareholder
	Net fixed assets per capita	*PFixA*	Ln (net fixed asset value/total number of employees)
	sales per capita	*PSales*	Ln (revenue/total number of employees)
	Tobin's Q	*TobinQ*	Asset market value/asset replacement cost

4.3 Econometric Specification

This study relies on a quasi-experimental research design to identify causal effects. The carbon trading pilot policy is regarded as an exogenous environmental regulatory shock, and a difference in differences (DID) model is used to test the net effect of the carbon trading pilot policy on the digital transformation of enterprises [40]:

$$\mathrm{DT_{cit}} = \alpha_1 + \beta_1 \times \mathrm{did_{cit}} + \theta_1 \times \mathrm{Control_{it}} + \omega_i + \varphi_t + \varepsilon_{cit} \quad (1)$$

where, *c* represents a prefecture level city, *i* represents a single listed company, and *t* represents the year. DT_{cit} is used to measure the level of digital transformation of the *i*-th enterprise within the c city in the t-th year. DT_{cit} is generated by the interaction between grouping dummy variables and time dummy variables, i.e. $did_{cit} = treat_{ci} \times time_t$, used to identify whether enterprise *i* has been impacted by carbon trading pilot policies during the *t* fiscal year. $treat_{ci}$ is a virtual variable for regional grouping. If the registered location of the enterprise belongs to a pilot region, it is assigned a value of 1, and if it belongs to a non-pilot region, it is assigned a value of 0; $time_t$ is a policy time dummy variable, with a value of 1 for the year after policy implementation and 0 for the year before implementation. $\alpha_1, \beta_1, and\ \theta_1$ are the parameters to be estimated, and β_1 is used to characterize the net processing effect of carbon trading pilot policies on the digital transformation of enterprises. If β_1 is significantly positive, it indicates that the carbon trading pilot policy can effectively promote the digital transformation of enterprises. $Controlit$ is the set of control variables. Further incorporating the fixed effect ω_i of enterprises to absorb the individual heterogeneity of enterprises that does not change over time, and introducing the fixed effect φ_t of years to control time level interference factors such as macro cyclical fluctuations and annual systemic shocks. ε_{cit} is a random perturbation term that satisfies the error distribution assumption of classical econometric regression.

5 Analysis of empirical results

5.1 Distribution properties of variables

Table 2 shows the statistical results of the core research variables. According to the results in Table 1, the digital transformation index (DT), after logarithmic processing, has a mean of 1.100, a standard deviation of 1.400, and a variable range of 6.090. This indicates that there are significant individual differences in the level of digital development among the sample enterprises, and the digital process presents an unbalanced characteristic.

Table 2: Distribution characteristics of empirical variables

variable	N	Mean value	sd value	min value	max value
DT	16992	1.100	1.400	0	6.090
did	16992	0.300	0.460	0	1
Size	16992	22.53	1.410	15.65	52.15
ROA	16992	0.0400	0.0700	-0.910	0.650
Lev	16992	0.450	0.220	-1.110	4.450
ListAge	16992	2.470	0.660	0.290	3.490
Growth	16992	0.150	0.520	-5.990	7.330
Top1	16992	0.350	0.150	0.023	1.150
PFixA	16992	12.61	1.260	1.530	25.34
PSales	16992	13.90	1	-0.380	27.66
TobinQ	16992	2	2.080	-22.37	90.21

5.2 Benchmark regression

We used a dual machine learning estimation framework for benchmark regression, with a fixed random seed of 42. Table 3 shows the regression results of five algorithm models: random forest (column 1), Lasso regression (column 2), gradient boosting (column 3), neural network (column 4), and support vector machine (column 5). According to the results in Table 3, the range of β_1 remains stable between 0.359 and 0.376 under various algorithm settings, and all pass the 1% level significance test. This machine learning empirical conclusion effectively supports research hypothesis 1 and confirms that the carbon emission trading pilot policy can significantly accelerate the digital transformation process of enterprises.

Table 3: Dual machine learning estimation results

	(1) rf	(2) lasso	(3) gradboost	(4) nnet	(5) svm
	ln_DT	ln_DT	ln_DT	ln_DT	ln_DT
did	0.366 ***	0.376 ***	0.359 ***	0.371 ***	0.369 ***
	(14.686)	(15.069)	(14.430)	(14.763)	(14.775)
_cons	-0.029 ***	-0.029 ***	-0.029 ***	-0.029 ***	-0.028 ***
	(-3.612)	(-3.607)	(-3.582)	(-3.542)	(-3.486)
Control Variables	Yes	Yes	Yes	Yes	Yes
N	16992	16992	16992	16992	16992

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The regression results of the supplementary double difference DID test are shown in Table 4. According to the data in Table 4, the core policy coefficient of the complete model with all variables included in the fourth column is 0.188, which is significant at the 1% statistical level. In addition, the first and third columns show the DID test regression results of the benchmark regression framework without introducing fixed effects; The second and fourth columns show the DID test regression results of the regression framework using the enterprise year two-way fixed effects setting. The data in the table shows that there is no significant fluctuation in the coefficient amplitude of the core explanatory variables mentioned above, and the significance remains stable at the 1% level.

Table 4: DID estimation results

	(1)	(2)	(3)	(4)
	DT	DT	DT	DT
did	0.681 ***	0.220 ***	0.490 ***	0.188 ***
	(11.325)	(4.266)	(8.214)	(3.856)
Size			0.244 ***	0.201 ***
			(7.941)	(3.369)
ROA			-1.770 ***	-0.121
			(-4.931)	(-0.684)
Lev			-1.146 ***	-0.109
			(-7.221)	(-0.731)
ListAge			0.085**	0.249 ***
			(2.170)	(3.670)
Growth			0.079**	0.006
			(2.336)	(0.231)
Top1			-1.379 ***	-0.562***
			(-7.819)	(-2.726)
PFixA			-0.324 ***	-0.116 ***
			(-12.437)	(-5.499)
PSales			0.092 ***	0.116 ***
			(3.130)	(4.008)
TobinQ			0.046*	0.008
			(1.852)	(0.769)
_cons	0.890 ***	0.470 ***	-1.003	-5.468 ***
	(28.793)	(13.801)	(-1.632)	(-3.731)
Year FE	No	Yes	No	Yes
Id FE	No	Yes	No	Yes
N	16992	16992	16992	16992
Adjusted R^2	0.050	0.725	0.167	0.735

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3 Parallel trends validation

The effective application of the DID model requires consistency between the digital transformation evolution trends of the treatment group and the control group before policy shocks [41-43]. This article refers to the method proposed by Beck et al. (2010) [44] to conduct parallel trend testing, and uses the policy pre period (t=-1) as the benchmark reference group. Figure 1 shows the estimated coefficient values and 95% confidence interval verification results for each time node.

According to the experimental data in Figure 1, the coefficients of each period before policy implementation did not pass the statistical significance test with p>0.10, and the economic values approached zero. The absolute values of the coefficients were all below 0.05 standard deviations, indicating that there was no systematic deviation in the early trend of digital transformation between carbon trading pilot areas and non-pilot areas, and the benchmark DID identification was effective. After the implementation of the policy, the processing effect showed a continuous monotonous increase in the time series. During the policy preparation window period from 2011 to 2013, enterprises captured regulatory expectations in advance and prospectively arranged digital upgrading, forming a pre adjustment behavior, which can effectively eliminate the interference of mixed shocks in the same period, and further support the causal driving relationship between carbon trading pilot policies and digital transformation.

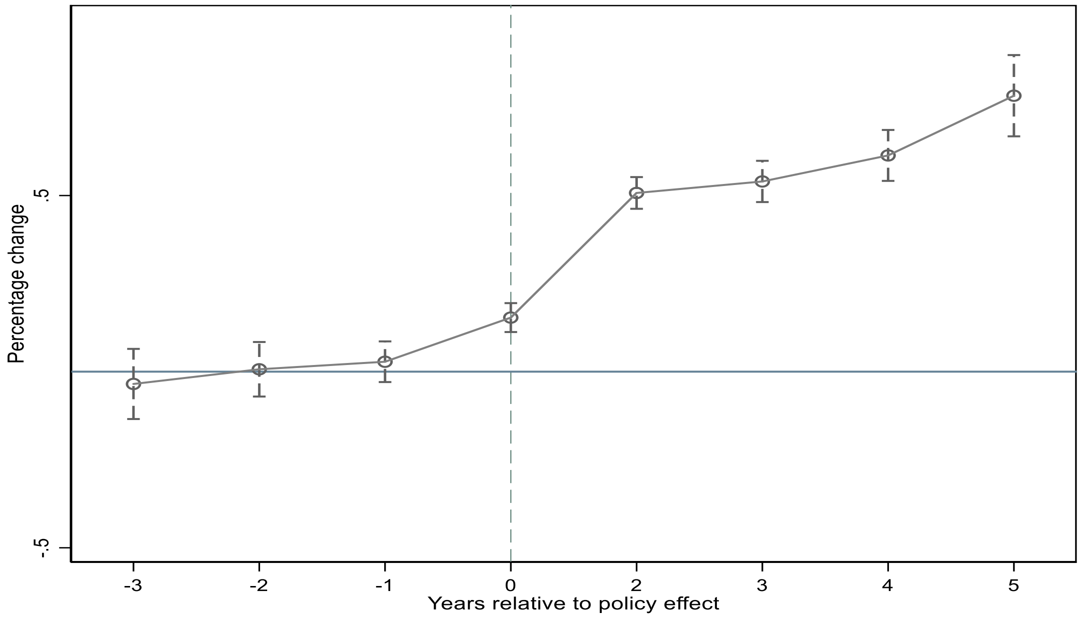

Figure 1: Research and analysis strategies for policy impact events

5.4 Comfort group policy evaluation

This article refers to the research paradigm proposed by La Ferrara et al. (2012) [45] and conducts a permutation comfort group test based on 500 random sampling iterations. The coefficient distribution pattern obtained from the random fictitious treatment group is shown in Figure 2: (1) At the level of central tendency, the mean coefficient of the comfort group is -0.002, and the standard deviation is 0.117; (2) At the level of statistical inference, 92.4% of the simulation results had p-values greater than 0.10 and did not show statistical significance; (3) At the level of distribution characteristics, the coefficient distribution follows a normal distribution pattern, that is, the Shapiro Wilk test value satisfies p=0.312.

The overall false processing effect highly converges around zero, i.e. around d=0.017, and there is a significant deviation from the true policy estimation coefficient of the benchmark regression, indicating that the policy effect identified by the benchmark regression is not caused by random fluctuations in data, inherent sample bias, or other accidental factors. This further verifies the robustness of the net effect of carbon trading pilot policies on enterprise digital transformation.

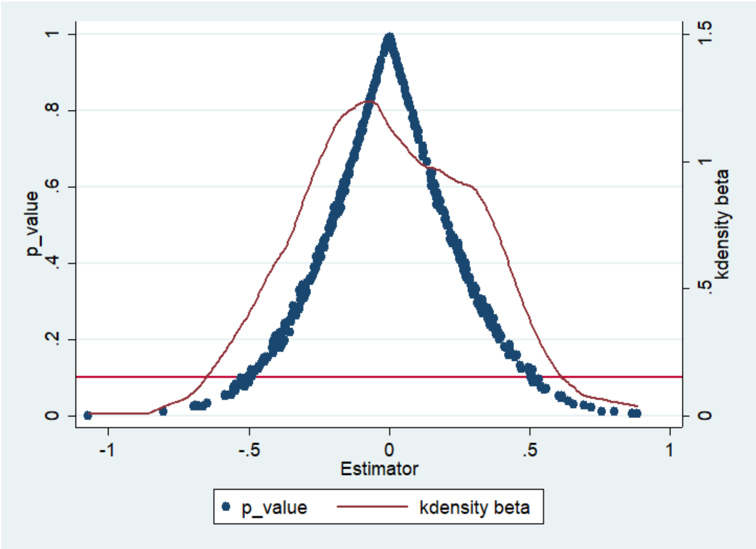

Figure 2: Distribution pattern of comfort group experimental coefficients

6 Mechanism analysis

6.1 Financing constraints channel

The digital transformation of enterprises can help improve operational efficiency and long-term core competitiveness, but the process of digital implementation has problems such as large capital investment scale, long transformation cycle, and prominent uncertainty in the early stage, which require stable and sufficient funding supply to promote the transformation. Therefore, this article mainly tests the mitigating effect of carbon emissions trading policies on corporate financing constraints, and the empirical verification results are shown in Table 5.

According to the regression results in the third column of Table 5, the core interaction term DID of carbon trading pilot policies can significantly reduce the cost of corporate debt financing COST at a significance level of 1%. The core coefficient β = -0.032 and t = -2.763, indicating that the carbon trading system can provide financial support for digital transformation by optimizing the external financing environment of enterprises, expanding capital acquisition channels, and reducing financing costs. This ultimately supports research hypothesis 2.

Table 5: Transmission channel analysis

	(1)	(2)	(3)
	ln_DT	GREEN	COST
did	0.220 ***	0.087 ***	-0.032 ***
	(4.266)	(2.871)	(-2.763)
_cons	0.470 ***	11.859 ***	0.119 ***
	(13.801)	(604.735)	(14.361)
Control Variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Id FE	Yes	Yes	Yes
N	16992	15038	16992
Adjusted R^2	0.725	0.877	0.722

t statistics in parentheses

***Represents its significance level p<0.1, * * represents its significance level p<0.05, * represents its significance level p<0.01

6.2 Green technology innovation channels

The continuous iteration of green innovation technology can provide underlying support for the deep integration of digital technology in production and operation, warehousing and circulation, organizational management, and other scenarios. According to the empirical verification results in column 2, the core policy interaction term *did* have a significant positive promoting effect on green innovation output, with a regression coefficient $\beta = 0.087$ and a $t = 2.871$, which is statistically significant at the 1% level. This indicates that the carbon trading pilot policy relies on cost internalization and innovation compensation effects to continuously promote breakthroughs in green technology research and development in enterprises, ultimately accelerating the overall digital transformation process, fully meeting the theoretical expectations and research settings of hypothesis 3.

7 Conclusions

This article takes Chinese A-share listed companies from 2010 to 2021 as research samples, integrates dual machine learning and difference in differences (DID) quasi experimental methods, and systematically tests the causal effects and internal transmission mechanisms of carbon trading policies on corporate digital transformation. The empirical results show that the carbon trading pilot policy can significantly promote the digital transformation of enterprises. The core policy coefficient remains highly robust under various algorithms and model settings and has passed the significance test at the 1% level. It can empower digital transformation through two paths: reducing the cost of corporate debt financing and improving the output of green technology innovation. This verifies the mediating role of financing constraint relief and green innovation drive, providing new empirical evidence for the micro governance effect of market-oriented environmental policies and practical reference for the coordinated promotion of the "dual carbon" strategy and enterprise digital upgrading.

Existing issues: (1) The long-term dynamic impact of the launch of the unified national carbon market in 2021 has not been covered, and the sample period can be extended in the future to reveal the long-term evolution of carbon trading policies on digital transformation. (2) The heterogeneous responses of different digital technologies such as artificial intelligence, big data, cloud computing, and blockchain have not been distinguished. In the future, the differential driving effects of carbon trading on the application of different digital technologies can be explored. (3) The regulatory effects of external factors such as regional digital infrastructure, industrial chain collaboration, and government subsidies have not been considered. In the future, a regulatory effect model can be introduced to further enrich the boundary condition research of policy transmission. (4) This article uses the text frequency method to measure digital transformation. Although it has objectivity, it is difficult to capture differences in transformation quality. In the future, a more comprehensive evaluation system for digital transformation quality can be constructed by combining multidimensional indicators such as data envelopment analysis. (5) Without considering the reverse effect of digital transformation on corporate carbon performance and carbon market participation behavior, a bidirectional causal and spatial spillover model can be constructed in the future to explore the coupling and collaborative mechanism between carbon market and digital transformation.

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