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The impact of China's new energy transformation on the carbon performance of industrial enterprises under the regulatory policy-driven mode

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Abstract

The combustion and utilization of traditional fossil fuels constitute the predominant origin of atmospheric carbon dioxide emissions. In the context of China's pursuit of "dual carbon" goals, leveraging the competitive carbon reduction potential of industrial enterprises is a key focus for accelerating the nation's transition to low-carbon energy. Drawing on a panel of 2,260 A-share manufacturing firms listed in China over 2008–2021, this study adopts a difference-in-differences (DID) design to identify the causal impact of the New Energy Demonstration City Policy (NEDCP) on enterprise carbon performance. It further examines the underlying competitive mechanisms and effective boundaries of the policy. The empirical results reveal that the introduction of NEDCP generates a pronounced improvement in the carbon performance of industrial enterprises. Furthermore, the NEDCP improves enterprise carbon performance through several competitive mechanisms, including increased total factor productivity, catalysis of green-technology innovation, and reduction of financing constraints. Moreover, the impact on corporate carbon performance is found to be heterogeneous across various contexts: it is markedly amplified among non-state-owned firms, in regions with underdeveloped cross-regional dispatch infrastructure for new energy power, in non-heavily polluting industries, and in areas with lower levels of renewable energy consumption. The findings extend the current understanding of corporate carbon reduction strategies, thereby informing governmental policy design and corporate initiatives aimed at competitiveness improvement.

Keywords: *new energy demonstration city, carbon performance, industrial enterprises, low-carbon transition, dual carbon goals*

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1 INTRODUCTION

Given the increasingly severe reality of global climate change and the trend of continuously strengthening global competitiveness, governments across the globe are formulating and implementing policies aimed at curbing greenhouse gas emissions. The "Dual Carbon" goals, introduced by the Chinese government in 2020, involve a national roadmap that targets a 2030 carbon-emission apex and subsequent net-zero status by 2060 (Luo & Lu, 2023). Since China embarked on its ecological civilization initiative, a discernible trajectory of structural transformation has emerged within the energy sector, characterized by a move from extensive consumption to increasingly low-carbon patterns. However, the transition process remains relatively slow. The official figures released by the National Energy Administration indicate that the weight of fossil fuels-namely coal, oil, and natural gas-in China's overall energy mix saw a pronounced decrease from 90.3% in 2012 to 82.5% in 2022. Simultaneously, the share of primary electricity-derived from nuclear, hydro, wind, and solar sources-saw a commensurate rise from 9.7% to 17.5% over the same period. In 2014, the NEA released the "Notice of the National Energy Administration on Announcing the List of the First Batch of New Energy Demonstration Cities (Industrial Parks)", which was launched with the selection of 81 cities and 8 industrial parks, constituting the first group of New Energy Demonstration Cities and Industrial Parks. This initiative employs an integrated policy toolkit designed to simultaneously promote energy development aligned with green objectives, implement corresponding green financial regulations, and facilitate grid upgrades, which collectively contribute to improved corporate environmental performance and regional decarbonization (Chai et al., 2023; Cheng et al., 2023; Liu et al., 2023).

Advancing the low-carbon transition has been elevated as a strategic priority in China's national energy system restructuring efforts. The government's policies promoting the transition to low carbon are shifting from a single-command control model to a multilevel market-oriented approach (Zhao et al., 2023; Zeng et al., 2023). A scholarly consensus has thoroughly identified the effectiveness of low-carbon policies, primarily focusing on the "compliance cost effect" and "innovation compensation effect" resulting from corporate pollution and emissions (Pang et al., 2019; Chen et al., 2024). The core criterion for these evaluations lies in the ability of energy-intensive, high-pollution firms to make a pivotal shift from post-treatment solutions to integrated cleaner processes through policy enforcement. Numerous studies identify policy design as the indispensable mechanism facilitating the advancement of China's green and low-carbon development (Pan et al., 2022; Wang et al., 2023a). However, concerns have been raised regarding insufficient synergy between existing low-carbon policies and energy market mechanisms in China, with scholars noting that fragmented policy design often compromises implementation effectiveness. Future policy directions emphasize enhancing institutional development, optimizing market environments, and leveraging market mechanisms to incentivize low-carbon transitions (Giraudet, 2020; Zeng et al., 2023).

During the "Eleventh Five-Year Plan" to "Thirteenth Five-Year Plan" periods, the Chinese government consecutively formulated "Renewable Energy Development Plans" and specific industry support policies for new energies such as wind, hydrogen, biomass, and solar energy (Hepburn et al., 2021). The NEDCP offers significant advantages in the low-carbon transition. Pilot cities under this policy deeply implement new energy infrastructures, such as smart grids, energy-efficient buildings, and clean power transmission. They demonstrate that these technologies promote clean energy use locally and in neighboring areas, reducing reliance on traditional fossil fuels through the rapid diffusion of clean technologies such as green electricity and electric vehicles. This effectively lowers carbon emissions (Wang & Yi, 2021; Yang et al., 2022). In practice, however, certain deficiencies in the policy initiative have been progressively revealed through its pilot advancement. On the one hand, low-carbon energy transformation often involves substantial initial investments in new energy infrastructure and low-carbon technology development, leading to significant fixed costs (Zhao & You, 2020; Prokop et al., 2024).

Meanwhile, technological constraints in renewable energy absorption limit their efficiency. The renewable generation is inherently intermittent, volatile, and subject to non-negligible instability, and effective utilization hours are heavily influenced by resource conditions, causing severe "wind and solar curtailment" issues in China's northwest region (Shair et al., 2021; Novan & Wang, 2024). Industrial enterprises, as significant consumers of energy and emitters of carbon dioxide, closely tie their carbon performance to the pace of China's energy low-carbon transformation (Haque & Ntim, 2022; Jin et al., 2023). Therefore, whether the NEDCP effectively promotes clean energy as a viable alternative to traditional fossil fuels, thereby improving carbon performance, or exacerbates inadequate adaptation of enterprise energy consumption structures, leading to increased energy waste and carbon emissions, remains subject to further debate.

As summarized in the literature, this study offers several potential innovations. First, the study is oriented towards China's dual-carbon commitment and focuses on the practical realities of energy low-carbon transformation. It conducts a quasi-natural experiment using the NEDCP, which encompasses comprehensive aspects such as innovation in new energy technologies, support from green finance, and auxiliary services in the electricity market. The study evaluates its influence on the corporate carbon performance of industrial firms. Second, it focuses on the carbon reduction behaviors of microeconomic entities, identifying the multiple causal pathways through which the NEDCP affects corporate carbon performance—from total factor productivity to innovation in low-carbon technologies and constraints in corporate financing. Finally, the study delves deeper into analyzing the effective boundaries of the NEDCP's impact on industrial enterprise carbon performance. It clarifies how its effects vary across heterogeneous attributes such as corporate property rights, industry pollution characteristics, and the regional establishment of new energy infrastructure. The findings provide a scientific theoretical framework for future policy refinement aimed at enhancing the emission mitigation effects of the NEDCP.

2 RESEARCH HYPOTHESES

2.1 The impact of the NEDCP on industrial enterprise carbon performance

Addressing the environmental externality of carbon emissions is crucial for incentivizing industrial enterprises to transform their energy consumption patterns and reduce energy consumption and carbon emissions (Yang et al., 2023). The strategic objective of the NEDCP aims to facilitate the low-carbon transition of industrial enterprise energy consumption patterns through deploying new energy infrastructure and implementing green financial support. From the perspective of infrastructure development, the NEDCP enhances smart grids, wind farms, photovoltaic facilities, and electric vehicle charging stations. This allows industrial enterprises to utilize wind and solar energy at lower production costs, thereby reducing their reliance on traditional fossil fuels (Yang et al., 2021; Lin & Zhang, 2023). Furthermore, the scale effect of widespread adoption reduces the average costs of renewable energy for industrial enterprises and mitigates the impact of price volatility in traditional fossil fuel (Luderer et al., 2022). From the perspective of green financial services, pilot areas under the NEDCP often receive complementary green financial support. Structured incentive mechanisms, such as targeted subsidies and tax advantages, are deployed to stimulate enterprise innovation in green technologies and facilitate energy transition processes. Moreover, the policy encourages structural adjustments in lending by financial institutions, directing financial flows toward environmentally sustainable industries. This alleviates critical barriers to corporate financing, enabling greater investment in renewable energy and sustainable technologies by industrial firms (Li & Umair, 2023; Putranto et al., 2023). Additionally, the demonstration effect of the NEDCP attracted more social capital into the new energy industry, accelerating corporate adoption of new energy technologies, subsequently elevating carbon performance across industrial enterprises. Accordingly, this study posits its primary Hypothesis H1.

H1: The NEDCP enhances industrial enterprise carbon performance.

2.2 Competitive Mechanisms of the NEDCP on Enterprise Carbon Performance

This section analyzes the competitive mechanisms through which the NEDCP primarily enhances enterprise carbon performance. First, the NEDCP aims to improve enterprise total factor productivity by reducing the production and transportation costs of renewables, thereby enabling industrial enterprises to reallocate resources from conventional fuels to new energy alternatives.. This transformation necessitates further enhancements in equipment efficiency, production process redesign, and the operational capabilities of smart and automated technologies. These advancements promote more efficient resource allocation, enabling firms to achieve a higher output-to-input ratio while using fewer material and energy inputs, thus effectively lowering resource-intensity and improving carbon performance (Trinks et al., 2020; Gao et al., 2021). Second, frontier research on low-carbon technologies includes energy storage, decarbonization technologies for fossil fuels, clean energy sources, greenhouse gas capture and utilization, energy efficiency, and energy recovery. However, the innovation in low-carbon technologies is risky and time sensitive. Its success heavily hinges critically on scaling up a portfolio of emerging energy infrastructures, which encompasses wind farms, photovoltaic plants, smart grids, new storage systems, and ultra-high-voltage transmission projects. The NEDCP enhances these infrastructures in pilot cities, providing foundational support for industrial enterprises to innovate and develop low-carbon technologies. Moreover, the construction of NEDCP cities adheres to strict environmental regulations and sustainable development goals, compelling industrial enterprises to transition toward eco-friendly and efficient production pattern through research and innovation in green technologies, thereby curbing both energy usage and carbon emissions (Qi et al., 2021; Li et al., 2021). Third, the NEDCP facilitates the integration of renewable energy infrastructure and industrial energy consumption through green financial measures. Governments provide direct financial subsidies to encourage industrial enterprises to invest in green initiatives and indirectly require financial institutions to offer low-interest loans and green bonds for new energy projects. This ensures more favorable financing conditions and funding sources for industrial enterprises. The mitigation of severe financing constraints encourages industrial enterprises to undertake environmental and energy-saving initiatives, thereby enhancing their performance on carbon emissions (Li et al., 2024; Zhao et al., 2024). Following these reasonings, the study advances Hypothesis H2.

H2: The NEDCP enhances industrial enterprise carbon performance through multiple competitive mechanisms.

H2a: The NEDCP enhances industrial enterprise carbon performance by improving total factor productivity.

H2b: The NEDCP enhances industrial enterprise carbon performance by stimulating innovation in low-carbon technologies.

H2c: The NEDCP enhances industrial enterprise carbon performance by alleviating financing constraints.

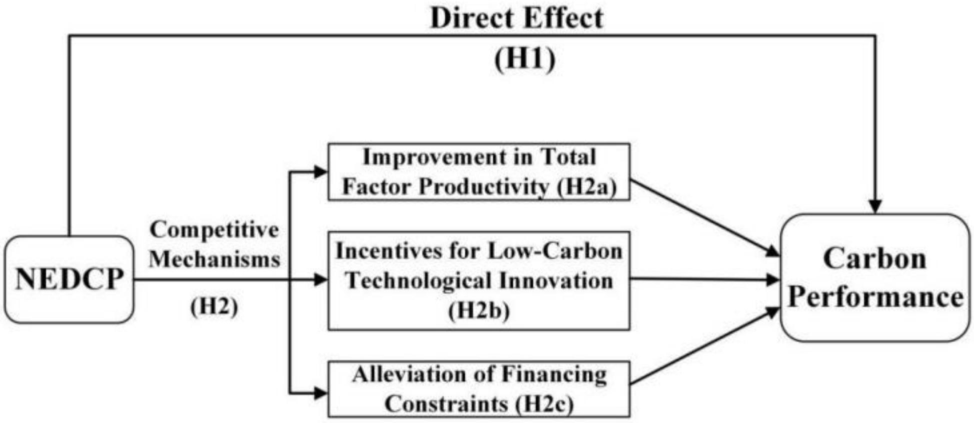


Fig. 1 – Theoretical framework. Source: own research

3 DATA SOURCE, EMPIRICAL MODEL DESIGN, AND VARIABLES

3.1 Data sources

This study selects listed firms from the Shanghai and Shenzhen A-share markets over the period 2008 to 2021 in the mining, manufacturing, electricity, gas, and water production and supply industries in China. The sample selection follows these principles: (1) exclude companies marked as ST or *ST during the study period; (2) exclude samples with fewer than 3 years of observations for individual listed companies; and (3) exclude samples with a significant number of missing values for key variables. To address the potential influence of extreme values, all continuous variables undergo Winsorization at the 1st and 99th percentiles.A total of 21,687 samples were ultimately obtained. The firm-level data employed in this study are obtained from the CSMAR database, the regional-level data are procured from the "China Statistical Yearbook" and "China Energy Statistical Yearbook," and the industry-level data for carbon discharge and energy usage are procured from the CEADs.

3.2 Model design

The study leverages the policy release of the "Notice of the National Energy Administration on Publishing the List of New Energy Demonstration Cities (Industrial Parks) (First Batch)" by the NEA in 2014, and then applies the DID approach to establish causal identification of the NEDCP's effects on corporate carbon performance. The econometric model is formulated as Equation (1), where the coefficient α_1 captures the effect of the interaction between a treatment group dummy and post-policy period indicator ($Treat_i \times Time_t$). The model incorporates two-dimensional subscripts where i and t correspond to the individual and temporal dimensions, respectively;

X_{it} comprises a series of observed control variables; D_j and D_t account for industry and temporal fixed effects, respectively; and ε_{it} constitutes the random disturbance.

$$CP_{it} = \alpha_0 + \alpha_1 Treat_i \times Time_t + \gamma X_{it} + D_j + D_t + \varepsilon_{it} \quad (1)$$

3.3 Variable settings

Dependent variable

Owing to the lack of mandatory requirements from government regulatory agencies for enterprises to disclose corporate carbon emission information, accessing carbon emission data from listed companies is challenging. In response, the study adopts the methodology developed by Trinks et al. (2022). Energy-intensive sectors, such as mining, manufacturing, and utilities, display a cost structure where energy represents a dominant component of operating costs. Therefore, corporate operating costs are directly linked to energy consumption and carbon emissions (Zhou & Liu, 2024; Wang et al., 2023b; Wang et al., 2024). This study decomposes industrial sector carbon emissions data, which are calculated on the basis of the China Carbon Accounting Database (CEADs), to the enterprise level according to operating costs. Specifically, grounded in the analytical framework established by Pan et al. (2024), the study allocates enterprise carbon emissions through a proportional calculation: industrial-level emissions are divided by total operating expenses at the sector level and subsequently multiplied by the individual firm's operational costs. And then enterprise carbon performance is further evaluated by the natural logarithm of carbon emissions normalized by revenue, as calculated in Equations (2) and (3):

$$\text{Enterprise carbon emissions} = \frac{\text{Industry carbon emissions}}{\text{Industry operating costs}} \times \text{Enterprise operating costs} \quad (2)$$

$$\text{Enterprise carbon performance} = \ln \frac{\text{Enterprise operating revenue}}{\text{Enterprise carbon emissions}} \quad (3)$$

Independent variable

This study operationalizes its explanatory variables through the measured effects of the "Notice of the National Energy Administration on the Announcement of the First Batch of Lists for Establishing New Energy Demonstration Cities (Industrial Parks)." Enterprises are assigned to the treatment or control group according to their geographic presence within the boundaries of the newly designated pilot zones. Enterprises located within the pilot zones take the value of 1 for $Treat_i$, while those outside the zones constitute the control group, assigned a value of 0. The temporal demarcation is anchored to the year when the NEDCP officially takes effect. $Time_t$ takes a value of 1 if the observation year is 2014 or later, and is assigned a value of 0 otherwise. The net effect variable of the NEDCP is captured by interacting the treatment indicator with the post-implementation time dummy, labelled as $Treat_i * Time_t$.

Control variables

The econometric specification includes a vector of controls for other potential confounding factors to ensure an accurate estimation of the NEDCP's impact on corporate carbon performance. These variables encompass firm size, the leverage ratio, the asset turnover ratio, the return on equity, the management expense ratio, the firm age, the proportion of fixed assets, and equity balance. Detailed definitions for these variables are summarized in Table 1.

Tab. 1 – Variable definitions. Source: own research

Variable Type	Variable Name	Variable Symbol	Variable Definition
Dependent Variable	Enterprise Carbon Performance	*CP*	Ln(ratio of firm revenue to carbon emissions)
Independent Variable	The NEDCP	*Treat*	Treatment dummy variable: it equals 1 if the enterprise is located in a demonstration city pilot zone, and 0 otherwise.
		Time	Time dummy variable: it equals 1 if the year is 2014 or later, and 0 otherwise.
Control Variables	Enterprise Size	*Size*	Natural logarithm of total assets at the end of the year
	Asset-Liability Ratio	*Lev*	Total liabilities at the end of the year/Total assets at the end of the year
	Asset Turnover Ratio	*ATO*	Operating income/Average total assets
	Return on Equity	*ROE*	Net profit/Average shareholder equity
	Management Expense Ratio	*Mfee*	Management expenses/Operating income
	Enterprise Age	*Age*	Ln (Current year - Year of establishment of the enterprise + 1)
	Proportion of Fixed Assets	*Fixed*	Net fixed assets/Total assets
	Equity Balance	*Balance*	Proportion of shares held by the second largest shareholder to the first largest shareholder

4 EMPIRICAL TESTS

4.1 Descriptive statistics of the variables

The descriptive statistics are detailed in Table 2. In terms of enterprise carbon performance, as evidenced by a standard deviation of 2.080 and a range between 7.273

and 15.568, the variable *CP* (mean = 12.461) indicates significant dispersion across the industrial enterprises in the sample. Some enterprises may rely heavily on traditional fossil fuels, whereas others tend toward cleaner energy sources. From the perspective of the NEDCP, the distribution of the interaction term (*Treat*Time*), having a mean of 0.234 and a standard deviation of 0.423, supports its validity as a policy identifier. The distribution is consistent with a quasi-natural experiment that effectively distinguishes the treatment group,thus fulfilling a critical precondition for applying the DID approach.

Tab. 2 – Descriptive statistics of the variables. Source: own research

Variable	Obs	Mean	Std. Dev.	Min	Max
CP	21687	12.461	2.080	7.273	15.568
*Treat*Time*	21687	0.234	0.423	0.000	1.000
Size	21687	22.123	1.253	19.857	25.976
Lev	21687	0.421	0.201	0.056	0.947
ATO	21687	0.675	0.395	0.101	2.344
ROE	21687	0.066	0.140	-0.690	0.442
Mfee	21687	0.085	0.059	0.010	0.366
Age	21687	2.856	0.337	1.792	3.497
Fixed	21687	0.251	0.151	0.021	0.698
Balance	21687	0.359	0.288	0.009	0.995

4.2 Baseline regression

This study first examines multicollinearity, and the Pearson correlation coefficient matrix reveals no significant multicollinearity among the variables (results omitted). Using the DID method, this study evaluates the policy effects of the NEDCP on the enterprise carbon performance. Table 3 presents the evolution of the baseline regression results, evolving from basic OLS in column (1) to a complete model in column (4) that includes industry and time fixed effects alongside firm-level control variables. The model fit progressively improves, indicating robustness. Across all specifications, Hypothesis H1 is thus confirmed, indicating that the NEDCP yields a tangible improvement in the carbon performance of industrial enterprises.

Tab. 3 – Outcomes of the baseline regression. Source: own research

	(1)	(2)	(3)	(4)
	CP	*CP*	*CP*	*CP*
*Treat*Time*	0.836^{***}	0.425^{***}	0.022^{***}	0.026^{***}
	(0.033)	(0.010)	(0.007)	(0.007)
Size				0.005^{*}
				(0.003)
Lev				-0.262^{***}
				(0.018)
ATO				-0.132^{***}

				(0.009)
ROE				0.399***
				(0.026)
Mfee				0.563***
				(0.073)
Age				-0.072***
				(0.009)
Fixed				-0.193***
				(0.023)
Balance				0.033***
				(0.010)
_cons	12.266***	12.362***	12.456***	12.710***
	(0.016)	(0.006)	(0.003)	(0.071)
Controls	No	No	No	Yes
Industry Fixed	No	Yes	Yes	Yes
Year Fixed	No	No	Yes	Yes
N	21687	21687	21687	21687
adj. R^2	0.029	0.885	0.960	0.963

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are robust to heteroskedasticity.Same as the table below.

4.3 Robustness test

Parallel trends test

The Parallel trends assumption states that before the introduction of the NEDCP, the carbon performance trajectories of industrial firms in the treatment and control groups need to follow a parallel pattern.On this basis, model (4) is designed to assess the policy's dynamic economic impacts, spanning six years prior to and five years following its implementation.

$$CP_{it} = \alpha_0 + \alpha_k \sum_{k=-6}^{k=5} D_{it}^k + \gamma X_{it} + D_j + D_t + \varepsilon_{it} \tag{4}$$

D_{it}^k represents the event-time indicator for year k, relative to the year t in which the city-level municipality where enterprise where enterprise is located implemented the NEDCP. The assignment rule is as follows: S_{it} indicates the specific year when enterprise i is located in a city under a policy trial. If $t - S_{it} = k$, then $D_{it}^k = 1$ is defined; otherwise, $D_{it}^k = 0$. The time span covers 6 periods before and 5 periods after policy implementation. α_k captures the evolving policy-induced impacts of the NEDCP on enterprise carbon performance over time. Figure 2 plots the dynamic policy impacts, indicating that prior to the NEDCP in pilot cities, the interaction coefficients for the treatment group remain non-significant at the 5% level. Post-policy implementation, these coefficients continued to be significant at the 5% level, demonstrating that the NEDCP has a sustained incentive effect on the carbon performance of industrial enterprises.

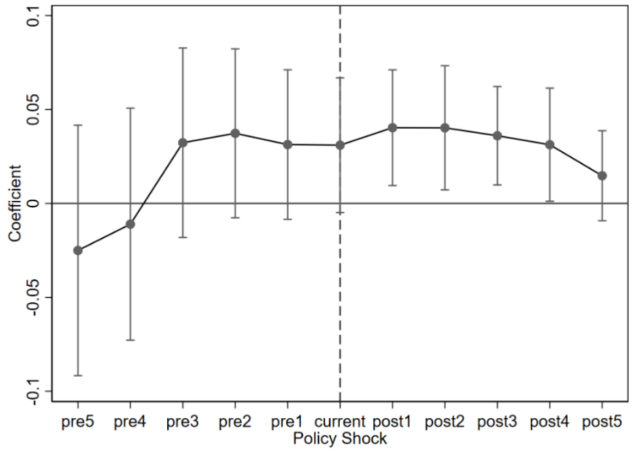


Fig. 2 – Policy dynamic economic effects of the *NEDCP*. Source: own research

Placebo test

The study further executes a placebo test on the baseline regression by randomly generating "pseudo-policy dummy variables". Figure 3 displays the p value distribution and coefficient estimation kernel density distribution from 500 repeated regressions based on randomly assigned pseudo-policy dummies. The placebo test indicates that both the p values and kernel density distribution of these coefficients are approximately normal and centered at 0. Additionally, the true estimated coefficients are largely independent of the estimated coefficient distribution of the "pseudo-policy dummy variables". This result confirms the robustness of the NEDCP's positive impact on enterprise carbon performance.

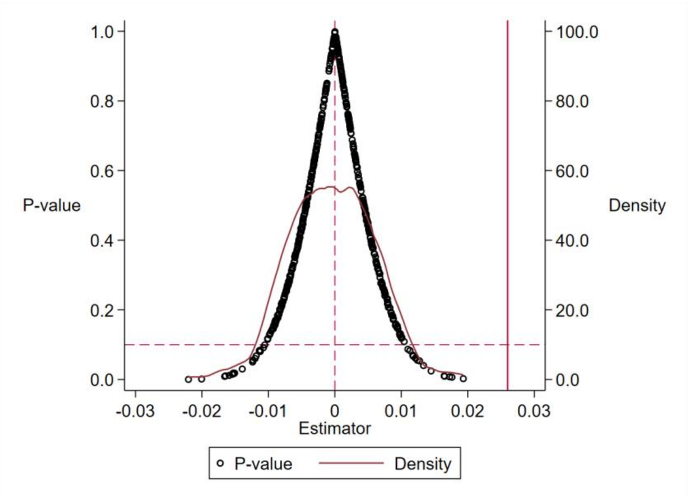


Fig. 3 – Placebo test of the *NEDCP*. Source: own research

Replace variable measures

This paper uses enterprise energy efficiency (*EE*) as a substitute variable for measuring enterprise carbon performance. Higher energy efficiency typically means that less energy is consumed in manufacturing an equivalent amount of goods or delivering identical services.Since industrial enterprises primarily consume traditional fossil fuels, enterprise energy efficiency can, to some extent, measure enterprise carbon performance. Referring to the method of Zhang and Zeng (2024), enterprise energy efficiency is calculated as the natural log of the ratio between firm revenue and energy use. Energy consumption at the industry level is transformed into standard coal equivalents and allocated to enterprises using a reverse calculation method. In Table 4, column (1) provides the robustness test outcomes by re-estimating the model with an alternative variable construction. Additionally, column (2) further clusters the standard errors at the firm level for robustness testing to eliminate intragroup correlation. The findings indicate that the NEDCP continues to significantly enhance industrial enterprises' carbon performance.

Control interference from nonrandom factors

The DID identification is most credible when treatment assignment approximates a randomized experiment. However, the selection of pilot areas for the NEDCP is plausibly shaped by conditions such as the geographical environment, administrative attributes, and locational factors, which could introduce a degree of non-randomness. Specifically, greater geographical slopes can increase the difficulty and cost of constructing energy infrastructure (e.g., wind farms and solar power plants). Municipalities, as political and economic centers, have a stronger policy demonstration effect. The economic development level and transportation network of the Yangtze River Economic Belt further facilitate the effective implementation of new energy industry policies. To address this, following the approach of Li et al. (2016), this study introduces interaction terms between time trends and variables related to geographical slope, administrative attributes, and locational factors. This approach controls the varying impacts of regional attributes over time on the carbon performance. The geographical slope is represented by the provincial average slope, while administrative characteristics are captured by a dummy variable denoting if the region is a municipality, and locational factors are captured by a dummy variable that denotes whether a region belongs to the Yangtze River Economic Belt. As presented in table 4, the column (3) reports that the *Treat*Time* coefficient is statistically significant. After accounting for an underlying nonrandom selection of the NEDCP pilot areas, the beneficial effect on carbon performance continues to be robust.

Exclude other relevant policies

Considering that during the observation period of the sample, the Chinese government also implemented various environmental and energy regulatory policies, including pilot programs for carbon emissions trading and energy rights trading, and low-carbon city pilots, these concurrent policies might enhance or weaken the evaluative effect of the target policy. These factors may confound the the observed effect of the NEDCP on enterprise carbon performance. Consequently, the study additionally incorporates dummy variables representing the carbon emissions trading pilot programs, energy usage rights trading pilots, and low-carbon city policies. The findings are displayed in Table 4, column (4). Controlling for the effects of additional low-carbon policies, the positive influence of the NEDCP on enterprise carbon performance remains strong.

Apply the PSM-DID approach

To further ensure the robustness of these findings, the study complements the baseline estimates with the PSM method. The study estimates the propensity score for each firm and match treated units to their nearest untreated counterparts. Results from the t test under the 1:1 nearest neighbor matching indicate that all standardized biases of the variables are below 5%. Column (5) presents the PSM-DID regression outcomes for samples with nonzero weights. The findings suggest that, after adjusting for underlying sample-selection distortions, the NEDCP continues to significantly promote the corporate carbon performance, confirming that the original model is largely free from serious sample selection bias.

Adopt the lagged effect model

This study further employs a lagged effect model to examine the effect of the NEDCP on enterprise carbon performance, with the aim of identifying the dynamic effects of the policy. The lagged effect model is frequently employed to examine the long-term consequences of policies or events on corporate behavior, especially when impacts emerge gradually after policy implementation. In this study, a one-period lag is applied to the *Treat*Time*, variable to assess the NEDCP's effect on enterprise carbon performance in the following period. Column (6) in Table 4 summarizes the lag-effect estimates, confirming the dynamic influence of the NEDCP.

Examine the environmental effect

To address measurement errors could undermine the accuracy of the policy effect estimation, the research additionally investigates the environmental impacts of the NEDCP to confirm the robustness of the baseline findings. An improvement in enterprise carbon performance ultimately manifests as an enhancement in the ecological environment, meaning that if enterprise carbon performance improves, it should lead to a reduction in CO_2 emissions in the surrounding area. This study uses panel data on CO_2 emissions from various provinces, cities, districts, and towns in China, along with fence data (EDGAR v8.0), to estimate CO_2 emissions within a 1 km radius of the company's office and registered addresses. Columns (7) and (8) of table 4 quantify the impact of the NEDCP on CO_2 concentrations around the company's office address and registered address, respectively. The findings show that the NEDCP substantially lowers CO2 levels in nearby regions, providing additional support for the baseline model's effectiveness.

Tab. 4 – Regression outcomes of the robustness tests. Source: own research

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EE	*CP*	*CP*	*CP*	*CP*	*CP*	CO_2	
*Treat*Time*	0.016***	0.026***	0.020***	0.020***	0.020**	0.027***	-0.565**	-0.747***
	(0.004)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.225)	(0.216)
_cons	12.116***	12.710***	12.690***	12.700***	13.211***	12.761***	-2.318	-2.192
	(0.046)	(0.071)	(0.071)	(0.071)	(0.114)	(0.094)	(2.243)	(2.169)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21687	21687	21687	21687	8127	19355	21687	21687
adj. R^2	0.960	0.963	0.963	0.963	0.965	0.943	0.026	0.022

Endogeneity test

Given the potential endogeneity issues arising from bidirectional causality and omitted variable problems, we further complement the instrumental variables method for robustness testing. This paper selects topographic undulation (*Undulation*) as the instrumental variable for the NEDCP (Cheng et al., 2023; Hu & Xu, 2025). On the one hand, topographic undulation is significantly correlated with the NEDCP. Topographic undulation can affect the extent and priority of new energy policy implementation, as regions with greater topographic undulation are more suitable for developing renewable energy (e.g., wind, solar). Therefore, the government is more likely to formulate and implement new energy demonstration policies to promote the use of clean energy (Liu et al., 2024). On the other hand, topographic undulation has a weak direct link to enterprise carbon performance. The degree of topographic undulation mainly influences the potential for renewable energy development rather than the energy efficiency or carbon emissions of enterprises themselves. The strong correlation between topographic undulation and the NEDCP, along with the lack of direct linkage to enterprise carbon performance, satisfies both the relevance and exogeneity requirements for an instrumental variable. Column (1) in Table 5 reports the first-stage IV-2SLS regression, revealing a significant positive association between the instrumental and endogenous variables. Column (2) shows the second-stage results. The relevant statistics support the validity of the selected instrument, confirming that Hypothesis H1 remains supported.

Tab. 5 – Endogeneity test. Source: own research

	(1)	(2)
	*Treat*Time*	*CP*
Undulation	0.000***	
	(0.000)	
*Treat*Time*		0.165**

		(0.074)
Identification test	191.538***	
	{0.000}	
Weak identification test	<174.637>	
	[16.38]	
Controls	Yes	Yes
Industry Fixed	Yes	Yes
Year Fixed	Yes	Yes
N	19302	19302

Note: ( ) parentheses indicate heteroskedasticity-robust standard errors, < > parentheses indicate the Cragg–Donald Wald F statistic, [ ] parentheses indicate Stock–Yogo critical values at the 10% significance level, and { } parentheses indicate the p value of the Kleibergen–Paap rk LM statistic.

4.4 Mechanism analysis

The previous sections validated the NEDCP effects on the carbon performance of industrial enterprises. However, traditional mediation analysis methods may yield unreliable results due to endogeneity biases and other factors. Following Jiang (2022), this study analyzes the impact mechanisms by observing how core explanatory variables affect mediator variables. Furthermore, it elucidates the specific mechanisms through which the regional NEDCP influences the carbon performance of industrial enterprises by emphatically examining three pathways: total factor productivity, low-carbon technological innovation, and financing constraints. Specifically, in consideration of potential endogeneity issues arising from bidirectional causality and omitted variables, on the one hand, the study mitigates the possible bidirectional causality problem by introducing a lagged effect model. This assumes that future enterprise-level variables do not influence the government's current policy decisions. On the other hand, the study further incorporates time–region interaction fixed effects and time–industry interaction fixed effects to address potential omitted variable issues (e.g., regional economic development level, environmental regulations, industry productivity, etc.). The model for mechanism testing is shown in Equation (5).

$$Mechanism_{i,t+1} = \alpha_0 + \alpha_1 Treat_i \times Time_t + \gamma X_{it} + D_j \times D_t + D_p \times D_t + \varepsilon_{it} \quad (5)$$

Mechanism analysis of enterprise total factor productivity

The theoretical hypothesis suggests that the NEDCP can increase enterprise total factor productivity (TFP), thereby improving their carbon performance. To examine this, various methods for calculating TFP have been applied, referencing existing research. Using listed companies, we employ OLS, FE, GMM, LP and OP methods to compute *TFP*. In these calculations, the natural logarithms of operating revenue serve as the output variables of the production function, the natural logarithms of employee numbers serve as labor inputs, and the net fixed assets serve as capital inputs. Table 6 reports the mechanism test results for enterprise total factor productivity (TFP), with columns (1)–(5) presenting regressions of the NEDCP's impact on TFP using various approaches. Across all methods, the results indicate that the NEDCP efficiently allocates production resources in industrial enterprises, which in turn reduces carbon emissions and improves carbon performance.

Tab. 6 – Regression outcomes of the mechanism tests: Enterprise total factor productivity. Source: own research

	(1)	(2)	(3)	(4)	(5)
	TFP_ols	*TFP_fe*	*TFP_gmm*	*TFP_lp*	*TFP_op*
*Treat*Time*	0.021***	0.021***	0.021***	0.017**	0.019**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
_cons	-7.415***	-8.032***	-5.008***	-2.346***	0.129*
	(0.069)	(0.070)	(0.070)	(0.069)	(0.076)
Controls	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes
Industry#Year Fixed	Yes	Yes	Yes	Yes	Yes
Province#Year Fixed	Yes	Yes	Yes	Yes	Yes
N	18640	18640	18640	18640	18640
adj. R^2	0.931	0.935	0.894	0.811	0.681

Mechanism analysis of enterprise low-carbon technology innovation

The theoretical framework proposes that the NEDCP encourages firms to pursue low-carbon technological innovation, thereby improving carbon performance in industrial enterprises. To test this mechanism, the number of low-carbon patents (LCP) held by enterprises is used as the mechanism variable. The definition of low-carbon patents follows the "Classification Standards for Green and Low-Carbon Technology Patents" published by the National Intellectual Property Administration, which mainly includes five categories: energy storage technology, decarbonization technologies for fossil fuels, clean energy, greenhouse gas capture, utilization and storage technologies, and energy saving and utilization technologies. Since some enterprises have not yet applied for low-carbon patents, the indicator adds 1 to the count of low-carbon patent applications before taking the natural logarithm. The results of the mechanism test for enterprise low-carbon technology innovation are summarized in table 7. Columns (1) and (2) show regression results based on filtering low-carbon patent applications by classification number, whereas columns (3) and (4) present results based on filtering by main classification number. In all model specifications, the coefficients remain significantly positive, suggesting that the NEDCP successfully motivates firms to pursue green and low-carbon technological innovations, which in turn enhance carbon performance.

Mechanism analysis of enterprise financial constraints

The theoretical hypothesis section suggests that the NEDCP can improve industrial enterprise carbon outcomes through easing firms' financial limitations. To test this, the study uses the KZ index (Kaplan & Zingales, 1997) to assess financing limitations, with higher values representing more severe constraints experienced by the firm. The mechanism test results for corporate financing constraints are presented in columns (5) and (6) of table 7. The findings show that the *Treat*Time* coefficients are significantly negative, indicating that the NEDCP can reduce the uncertainty risks faced by enterprises and improve their financing conditions, thus easing financing limitations and improving carbon performance in industrial firms.

Tab. 7 – Regression outcomes of the mechanism tests: Enterprise low-carbon patents and enterprise low-carbon patents and financial constraints. Source: own research

	(1)	(2)	(3)	(4)	(5)	(6)
	LCP_c	*LCP_c*	*LCP_mc*	*LCP_mc*	*KZ*	*KZ*
*Treat*Time*	0.032^{***}	0.020^{**}	0.021^{***}	0.013^{*}	-0.092^{*}	-0.100^{**}
	(0.010)	(0.010)	(0.007)	(0.007)	(0.050)	(0.039)
_cons	0.111^{***}	-2.215^{***}	0.066^{***}	-1.429^{***}	0.992^{***}	4.584^{***}
	(0.004)	(0.101)	(0.003)	(0.074)	(0.020)	(0.319)
Controls	No	Yes	No	Yes	No	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Industry#Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Province#Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	19342	19342	19342	19342	18522	18522
adj. R^2	0.081	0.150	0.074	0.132	0.136	0.496

4.5 Heterogeneity analysis

Heterogeneity analysis based on cross-regional dispatch of new energy electricity

Viewed through the perspective of cross-regional renewable transmission, new energy generation, such as wind and solar power, exhibit pronounced intermittency, volatility, and instability. The effective utilization hours of these new energy sources are severely impacted by resource conditions. For example, wind resources are not consistently high throughout the day, and there is no sunlight at night, leading to many periods where wind and solar units operate at low or zero output levels. This situation results in significant curtailment issues, particularly in regions such as Northwest China. Ultra-high voltage (*UHV*) transmission projects, exemplified by cross-regional dispatch of new energy, aim to increase power transmission capacity. These projects facilitate the efficient transmission of electricity from large-scale new energy generation bases across regions to load centers, thereby promoting the cross-regional utilization of new energy (Wang et al., 2023c). Additionally, high-voltage direct current (HVDC) transmission lines exhibit lower transmission losses, reducing energy losses during long-distance transmission and improving the efficiency and cost-effectiveness of cross-regional electricity transmission. Compared with those without operational UHV transmission projects, cities with well-developed levels of new energy cross-regional dispatch face challenges in supplying sufficient new energy to industrial enterprises. Therefore, the incentive impact of the NEDCP on local industrial firm carbon performance is stronger when new energy cross-regional dispatch capabilities are limited. In this study, we construct a dummy variable on the basis of whether the located city has operational HVDC transmission projects (HUV). Furthermore, interaction terms between explanatory variables and HVDC transmission projects (*Treat*Time*HUV*) are set to examine the heterogeneous effects of the NEDCP on enterprise carbon performance due to the bias arising from differentiated cross-regional energy dispatch infrastructures. The test findings in table 8, the negative moderating role of cross-regional new energy dispatch infrastructure demonstrates that the NEDCP's incentive effect on industrial enterprise carbon performance is stronger in areas with less developed cross-regional energy transmission systems.

Heterogeneity analysis on the basis of industry pollution characteristics

Based on industry pollution attributes, the production patterns of heavily polluting industries often involve extensive processes with high energy consumption and emissions. Relative to non-heavily polluting industries, heavily polluting industries face greater difficulties, higher costs, and longer cycles in adopting low-carbon technology innovations and transitioning to low-carbon energy. The financial and tax support provided by the NEDCP may not necessarily meet the funding requirements for transforming production patterns in heavily polluting industries. In contrast, the green transformation costs for non-heavily polluting industries are relatively lower, and their production processes are easier to adjust and optimize to accommodate clean energy utilization. In this study, a dummy variable is constructed on the basis of the pollution characteristics of the industry where the enterprise operates (*Pollute*). According to the "List of Classified Management of Environmental Inspections for Listed Companies" published by the Chinese MEE, if the industry where the enterprise operates is classified as the heavily polluting one, *Pollute* is assigned a value of 1; if it is classified as the non-heavily polluting industry, *Pollute* is assigned a value of 0. Furthermore, interaction terms between explanatory variables and industry pollution characteristics (*Treat*Time*Pollute*) are constructed to identify the heterogeneous effects of the NEDCP on enterprise carbon performance on the basis of differences in industry pollution characteristics. The test results in Table 8, column (2), the negative moderation effect of industry pollution characteristics suggests that the incentive effect of the NEDCP on industrial enterprise carbon performance is amplified within non-heavily polluting industries.

Heterogeneity analysis based on enterprise property rights

Viewed through the perspective of corporate property rights, state-owned enterprises (SOEs), because of their close political ties with the government, often receive governmental policy assistance and administrative safeguards, which gives them certain advantages regarding resource allocation and competitive positioning in the market (Yang et al., 2024). However, such administrative shielding could result in insufficient competitive pressure within the market, which can affect their efficiency. Owing to local government protection and administrative monopolies, SOEs often do not need to increase their efficiency or innovate to meet market demands, resulting in insufficient motivation for optimizing resource allocation and low-carbon technology innovation. Moreover, administrative monopolies and bureaucratic inefficiency may cause SOEs to be slow in responding to fiscal and tax incentives from the NEDCP, making it difficult for them to seize policy opportunities in a timely manner. In contrast, non-state-owned enterprises confront fiercer competitive pressures in the marketplace and must continuously optimize production factors distribution, improve efficiency, and innovate in green technologies to maintain their competitiveness. Without administrative protection, non-state-owned enterprises will show their faster reflexes to policies and swiftly realign their production models and technological trajectories to align with the mandates of the NEDCP. Non-state-owned enterprises typically have shorter decision-making chains, with management possessing greater decision-making authority and execution power in low-carbon transformation and technological investment. Therefore, the incentive effect of the NEDCP on industrial enterprise carbon performance is more pronounced in non-state-owned enterprises. To analyze the heterogeneous effects of the NEDCP on enterprise carbon performance based on property rights, this study constructs a dummy variable according to enterprise property rights (*SOE*). If an enterprise is state-owned, *SOE* is assigned a value of 1; if it is non-state-owned, *SOE* is assigned a value of 0. Furthermore, interaction terms combining explanatory variables with ownership structure (*Treat*Time*SOE*) are employed to examine how the NEDCP influences corporate carbon performance under different property rights. As reported in column (3) of Table 8, it implies a negative moderating effect of ownership, suggesting that the motivational policy effect in enhancing carbon performance is stronger for non-state-owned enterprises.

Heterogeneity analysis based on regional renewable energy absorption

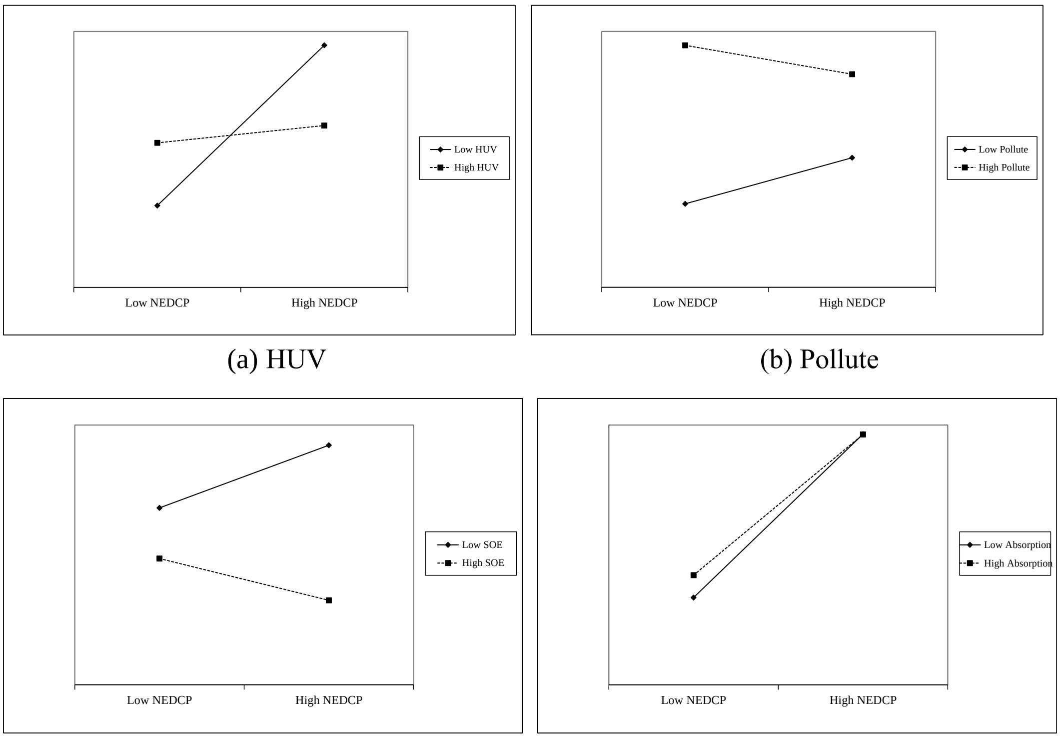
From the perspective of regional renewable energy absorption. In areas with a high degree of renewable energy integration,the infrastructure and technological applications of new energy have become relatively mature. Additional investments and policy support exhibit diminishing marginal effects on improving industrial carbon performance, thus making the enhancement in carbon performance less significant. Conversely, regions with low levels of renewable energy integration have greater potential for improvement in new energy technologies. Industrial enterprises have not fully utilized new energy technologies and facilities, enabling the policy impacts of new energy demonstration cities to more efficiently improve industrial carbon performance. This study calculates the level of renewable energy absorption (*Absorption*) in provinces where enterprises are located, taking the natural logarithm of this value. The absorption level of renewable energy is computed by measuring the renewable energy generation within each province, adding externally imported renewable energy, and deducting the renewable energy transmitted out of the region (including hydroelectric, wind, solar, and biomass energy generation). Furthermore, explanatory variables are constructed with the interaction term Absorption (*Treat*Time*Absorption*) to analyze the heterogeneous effects of the policies across different levels of regional renewable energy absorption. The examination results in Table 8, column (4) demonstrates that the level of regional renewable energy absorption plays a negative moderating role, indicating that the policy impacts of demonstration cities on carbon performance are stronger in regions with lower renewable energy absorption levels.

Tab. 8 – Regression outcomes from the heterogeneity analysis. Source: own research

	(1)	(2)	(3)	(4)
	CP	*CP*	*CP*	*CP*
*Treat*Time*	0.037***	0.083***	0.057***	0.223***
	(0.008)	(0.007)	(0.008)	(0.053)
HUV	0.006			
	(0.008)			
*Treat*Time*HUV*	-0.033**			
	(0.015)			
Pollute		0.216***		
		(0.078)		
*Treat*Time*Pollute*		-0.135***		
		(0.014)		
SOE			-0.057***	
			(0.007)	
*Treat*Time*SOE*			-0.095***	
			(0.013)	
Absorption				0.020***
				(0.006)
*Treat*Time*Absorption*				-0.031***
				(0.008)
_cons	12.703***	12.593***	12.497***	13.203***
	(0.071)	(0.080)	(0.072)	(0.088)
Controls	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
N	21687	21687	21687	13946

adj. R^2	0.963	0.963	0.963	0.971

To provide a clearer view of how the variables moderate the relationship between the NEDCP and corporate carbon performance, we also plot the moderating effects of HUV, Pollute, SOE, and Absorption on the NEDCP and enterprise carbon performance. In the moderation effect plots shown in Figure 4, the horizontal axis indicates the level of NEDCP implementation, while the vertical axis shows enterprise carbon performance. The two sloped lines represent the different impacts of the NEDCP on enterprise carbon performance when the moderating variable changes by one level or decreases by one level. Figure 4(a) indicates that in regions where HUV construction is still incomplete, the NEDCP has a stronger incentivizing effect on industrial enterprise carbon performance. Figure 4(b) illustrates the positive impact of the NEDCP on industrial enterprise carbon performance is mainly concentrated in non-heavily polluting industries, whereas its effect is less significant in heavily polluting industries. Figure 4(c) shows that the NEDCP's promoting effect on industrial enterprise carbon performance is evident in non-state-owned enterprises, while its impact on state-owned enterprises is comparatively weaker. Figure 4(d) illustrates that the incentivizing effect of the NEDCP on industrial enterprise carbon performance becomes more pronounced in regions with lower renewable energy absorption levels. The examination of the moderating effect diagrams aligns with the heterogeneity regression findings reported earlier.



(a) HUV (b) Pollute

(c) SOE (d) Absorption

Fig. 4 – Moderating effect diagram. Source: own research

5 DISCUSSION

The establishment of a climate governance framework and the spearheading of a green, low-carbon transition in the global economy constitute primary objectives of China's energy system reform. To achieve these goals, governmental policy mechanisms for decarbonization have evolved from singular command-and-control approaches to a multitiered, market-oriented policy framework (Zeng et al., 2023; Zhao et al., 2023). The Renewable energy policies has been served as pivotal levers within China's low-carbon transition, spanning the full energy value chain from production to end-use. Following the articulation of the "carbon peaking" and "carbon neutrality" objectives, these policies have increasingly become pivotal drivers of green transformation (Shair et al., 2021; Luo & Lu, 2023). During the 11th to 13th Five-Year Plan periods, China formulated renewable energy development plans and implemented sector-specific industrial support policies for emerging energy sectors, including wind, hydrogen, biomass, and solar energy (Hepburn et al., 2021; Wang & Yi, 2021; Yang et al., 2022).In 2014, the Chinese government identified 81 cities and 8 industrial parks as the inaugural group of new energy demonstration zones. This initiative aims to promote regional low-carbon transformation by empowering renewable energy development models aligned with green and low-carbon growth, implementing green finance policies, and upgrading grid infrastructure, thereby enhancing corporate energy efficiency and carbon reduction performance (Chai et al., 2023; Liu et al., 2023).

Current studies on renewable energy policies mainly concentrate on assessing the impact of new energy demonstration city programs on regional economic growth and ecological management. Current studies demonstrate that these policies effectively accelerate regional energy transitions (Hou et al., 2024), enhance energy utilization efficiency (Cheng et al., 2023; Zhou et al., 2023), stimulate green economic growth (Wang & Yi, 2021), reduce pollutant emissions (Guo et al., 2024), achieve coordinated pollution–carbon mitigation governance (Ding et al., 2024), and foster urban green technology innovation (Liu et al., 2024). Nevertheless, scholarly consensus remains elusive regarding whether such policies facilitate the effective substitution of clean energy for traditional fossil fuels to simultaneously increase regional economic and ecological quality or conversely induce structural incompatibility in energy consumption patterns that exacerbate energy waste and carbon emissions (Wang & Yi, 2021; Yang et al., 2022; Shair et al., 2021). Resolving this debate necessitates focused investigations into corporate carbon mitigation behaviors under policy shocks. As industrial enterprises constitute primary agents of energy consumption and CO_2 emissions, their carbon performance critically determines the pace of China's low-carbon energy transition (Haque & Ntim, 2022; Yang et al., 2023). This study constructs a quasi-natural experiment based on China's NEDCP—a comprehensive program that integrates technological innovation, green finance, and power market ancillary services—to systematically examine its impact mechanisms, effect boundaries, as well as the causal mechanisms affecting industrial carbon performance in the context of China's dual-carbon transition.

6 CONCLUSIONS AND IMPLICATIONS

6.1 Conclusions

Under China's "dual carbon" goals, the NEDCP significantly enhances industrial enterprises' carbon performance, as evidenced by panel data analysis of Shanghai/Shenzhen A-share listed firms (2008–2021) and robustness checks. The policy operates through three channels: improving total factor productivity, incentivizing low-carbon innovation, and alleviating financing constraints. Heterogeneity analysis reveals stronger effects in non-state-owned firms, regions with underdeveloped cross-regional new energy infrastructure, non-heavily-polluting industries, and areas with lower renewable energy absorption capacity.These results underscore the significance of the NEDCP in promoting energy decarbonization and provide actionable insights for optimizing regional green transition policies.

6.2 Implications

Drawing on these findings, this study offers the following policy recommendations:

(1) To increase the effectiveness of the NEDCP, pilot areas should prioritize phased smart grid deployment (e.g., integrating distributed renewables and energy storage) and AI-driven energy management platforms for real-time industrial consumption monitoring and grid optimization. Concurrently, tiered green finance mechanisms should be implemented, such as offering interest-subsidized loans (e.g., 15% discount for solar/wind adoption) and performance-linked fiscal incentives (e.g., 150% R&D tax deductions for top carbon performers). Carbon-linked bonds should be introduced at rates tied to verified emission reductions. Government-industry-academia hubs should be established to accelerate low-carbon technology transfer (e.g., hydrogen retrofitting), and executive carbon management training should be mandated to align decision-making with decarbonization goals. This integrated approach bridges infrastructure gaps, alleviates financing constraints, and institutionalizes data-driven, incentive-aligned carbon governance.

(2) The NEDCP should be dynamically tailored to regional characteristics by leveraging local resource endowments and absorption capacities. Solar-rich regions should prioritize large-scale photovoltaic parks with agrivoltaic systems (e.g., dual-use solar farms over croplands), whereas wind-rich areas should deploy integrated onshore wind farms coupled with green hydrogen production. Biomass-abundant zones can focus on biogas plants that utilize agricultural/forestry waste and biofuel refinement for heavy transport. Regions with low renewable absorption capacity require targeted

interventions, including subsidizing ultrahigh-voltage grid upgrades, implementing flexible industrial demand–response programs (e.g., time-based pricing), and enforcing renewable portfolio standards (30% by 2030). Cross-regional energy trading platforms should balance surpluses (e.g., Inner Mongolia's wind power to Guangdong's factories), ensuring policy flexibility and spatial equity.

(3) For heavily polluting industries (e.g., steel and cement), carbon intensity-based emission caps aligned with international benchmarks (e.g., EU CBAM) should be enforced, continuous emission monitoring systems (CEMS) should be mandated, and provincial-level decarbonization funds (e.g., 2% of fiscal revenue) should be allocated to subsidize retrofits such as electric arc furnaces or carbon capture retrofits. Additionally, 3% low-interest transition loans contingent on verified annual emission reductions (e.g., 5% YoY decline) should be provided. State-owned enterprises (SOEs) can integrate carbon metrics into executive KPIs—link 30% of senior management bonuses to carbon intensity targets—and establish cross-SOE alliances to share best practices (e.g., Sinopec's green hydrogen projects). SOEs should be required to publish annual carbon neutrality roadmaps and participate in carbon trading pilots, leveraging their scale to pilot scalable decarbonization models.

6.3 Research Limitations and Prospects for Future Studies

The corporate carbon emissions are estimated through reverse calculations based on industry data and operating costs, which could introduce measurement errors. The absence of direct use of actual corporate carbon emissions data could influence the precision of the findings. Additionally, the dynamic nature of the policy remains insufficiently investigated. In future research, it would be worthwhile to consider promoting legislation on corporate environmental information disclosure or integrating satellite remote sensing and IoT technologies to obtain more accurate carbon emission data. Moreover, employing event study methods or dynamic panel models could help capture the time-varying characteristics of policy effects, such as immediate effects and long-term balance.

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