

Can National AI Pilot Zones Improve Corporate Carbon Performance? Evidence from China

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Abstract: This study utilizes the National AI Innovation Pilot Zone policy as a quasi-natural experiment to investigate how AI policies influence corporate carbon performance. By analyzing panel data from Chinese listed companies spanning 2007 to 2023 and applying difference-in-differences (DID) as well as triple-difference (DDD) models, we present comprehensive evidence regarding the effects of the policy and the mechanisms that underlie them. The findings indicate that the policy regarding AI pilots greatly enhances the carbon performance of corporations, and these results hold steady across various identification approaches. Analysis of the mechanism indicates that the policy functions via two primary channels: proactive innovation, which is demonstrated by a rise in green invention patents, and optimization of efficiency, indicated by enhancements in green total factor energy efficiency. Further analysis indicates that the policy effect is strengthened by supply chain coordination, industry digitalization, human capital, and government environmental attention, while it is weakened by higher capacity utilization. Moreover, we document substantial ownership heterogeneity: the policy effect is significantly stronger for state-owned enterprises (SOEs), with innovation channel being primarily driven by SOEs, whereas private firms rely more on government environmental attention and supply chain concentration. Overall, this study uncovers a dual-channel mechanism through which AI policies facilitate green transformation and highlights the critical role of institutional context in shaping policy effectiveness. The findings provide new micro-level evidence on the environmental implications of digital transformation and offer important policy insights for promoting low-carbon development.

Key words: Artificial Intelligence Experimental Area; Carbon Performance; Heterogeneity of Ownership; DID

1. Introduction

Global climate governance has long been grounded in the assumption that carbon mitigation is primarily driven by regulatory interventions, including command-and-control policies and market-based instruments such as carbon pricing (Wang et al., 2022; Berrone et al., 2013). Within this framework, firms are typically viewed as passive responders that adjust their production behavior to comply with external environmental constraints (Ju et al., 2024). However, the rapid development of artificial intelligence (AI) challenges this conventional paradigm by introducing a fundamentally different mechanism for achieving decarbonization—one that is rooted not in compliance, but in technological capability (Li et al., 2025).

As a versatile technology, artificial intelligence has the capability to transform production methods, enhance resource distribution, and facilitate instantaneous decision-making on a scale that has never been seen before (Han et al., 2024; Cai et al., 2025; Wang and Wei, 2020). From intelligent energy management systems to data-driven operational optimization, AI applications are increasingly embodied in firms' core activities, suggesting that carbon reduction may no longer rely solely on regulatory pressure, but also on endogenous technological transformation (Yu et al., 2025; Wei et al., 2025). This raises a yet underexplored question: can government-led AI policies systematically reconfigure firms' decarbonization pathways (Huang et al., 2024), and if so, through

what mechanisms?

Previous research offers valuable perspectives on how digital technologies influence environmental performance (Wang et al., 2024). A growing body of literature documents that AI and digital transformation can improve energy efficiency and promote green innovation at the firm level (Feng et al., 2025). Meanwhile, research on environmental regulation highlights the role of policy-induced innovation, as emphasized by the Porter Hypothesis. However, these two strands of literature remain largely disconnected. On the one hand, studies on digital technologies often treat AI adoption as a firm-level decision, overlooking the role of policy in shaping technological diffusion. On the other hand, research on environmental regulation predominantly focuses on compliance-driven mechanisms, failing to account for the transformative role of technology in redefining the production frontier (Chen et al., 2025). As a result, the broader question of whether and how AI policy can serve as a technology-driven institutional instrument for decarbonization remains insufficiently explored (Wang et al., 2025; Fang et al., 2025).

In addition, the role of institutional context in shaping the effectiveness of AI-driven decarbonization has received limited attention. In particular, firms embedded in different ownership structures may exhibit heterogeneous responses to policy incentives due to disparities in resource access, strategic objectives, and governance mechanisms (Acemoglu et al., 2012). Ignoring such institutional heterogeneity may lead to an incomplete assessment of the environmental consequences of AI policies (Lin et al., 2025; Fan, 2026).

To tackle these deficiencies, the current research investigates how AI Pilot Zones influence corporate carbon performance. Utilizing a quasi-natural experiment along with firm-level panel data spanning from 2007 to 2023, we apply a multi-period DID approach to discern the impacts of AI policy. More importantly, we go beyond average treatment effects to unpack the underlying mechanisms and institutional conditions that shape policy effectiveness.

This paper makes three main contributions. First, we reconceptualize AI policy as a technology-driven institutional instrument that enables a shift from compliance-based emission reduction to capability-driven decarbonization. Second, we propose a dual-path decarbonization framework, distinguishing between proactive green innovation and operational efficiency improvement as two parallel mechanisms through which AI policy affects carbon performance. Third, we reveal the institutionally embedded nature of AI-driven green transformation, showing that policy effects are significantly stronger for state-owned enterprises, reflecting the role of resource reallocation and institutional structures in mediating technological impacts.

By bridging the literature on environmental regulation and digital transformation, this study provides new insights into how emerging technologies reshape the logic of climate governance. Our findings suggest that the future of decarbonization may lie not only in stricter regulations, but also in the strategic deployment of technology-oriented policies that enhance firms' endogenous capabilities.

2. Research hypotheses

2.1. AI Policy and Capability-Driven Decarbonization

Building on the perspective of technology-driven decarbonization, this study argues that the establishment of AI Pilot Zones can enhance corporate carbon performance by reshaping firms' production processes and governance structures (Acemoglu et al., 2012). Unlike traditional environmental regulations that primarily rely on compliance pressure, AI pilot zone policies function as a form of technology-driven institutional intervention, which reduces uncertainty and adoption costs associated with advanced digital technologies. Through policy instruments such as fiscal subsidies, tax incentives, and the provision of computing infrastructure, these pilot zones encourage firms to integrate AI technologies into their production systems. This integration facilitates the deep coupling of digital intelligence with manufacturing and operational processes, thereby creating new opportunities for low-carbon transformation.

From an innovation standpoint, the diffusion of AI technologies driven by policy can encourage companies to participate in proactive green innovation. In line with the broadened Porter Hypothesis, effectively structured institutional incentives can activate an "innovation compensation" effect, leading firms to enhance their environmental performance via technological advancements. AI-enabled innovation, such as intelligent energy management and data-driven emission monitoring, can fundamentally alter production technologies and generate long-term carbon reduction benefits. From the perspective of operational efficiency, AI technologies enhance firms' ability to optimize resource allocation and energy utilization. Through the application of machine learning techniques and real-time data analysis, firms can improve production scheduling, reduce redundant energy consumption, and minimize inefficiencies across the value chain. These improvements contribute to a systematic reduction in carbon emission intensity, thereby enhancing overall carbon performance.

In addition, AI pilot zone policies strengthen environmental governance through data-driven regulatory mechanisms. The integration of digital technologies into regulatory systems improves the precision and effectiveness of environmental supervision, thereby increasing the external pressure on firms to reduce emissions. Under the joint effects of technological empowerment and institutional constraints, firms are more likely to undertake proactive green transformation. In light of the analysis presented, this research puts forward the subsequent hypothesis:

H1: The introduction of policies for the AI Pilot Zone notably enhances the carbon performance of corporations.

2.2. AI Policy and Proactive Green Innovation Pathway

Building upon the capability-driven perspective of decarbonization, this study argues that AI policy promotes corporate carbon performance through a frontier green innovation pathway, which fundamentally transforms firms' technological capabilities. Unlike incremental improvements in production efficiency, advanced green innovation includes the development and

application of advanced technologies that transform the production boundary and enable substantial reductions in carbon emissions. As a general-purpose technology, artificial intelligence enhances firms' capacity to process large-scale data, identify complex patterns, and generate novel solutions (Berrone et al., 2013), thereby significantly lowering the barriers to green innovation.

Building on the capability-driven perspective of decarbonization, this study argues that AI policy promotes corporate carbon performance through a proactive green innovation pathway (Berrone et al., 2013), which reflects firms' strategic shift from passive compliance to forward-looking technological upgrading. Traditional environmental regulations often induce reactive innovation, where firms engage in limited technological adjustments to meet regulatory standards. In contrast, AI pilot zone policies reduce uncertainty and enhance expected returns to innovation, thereby encouraging firms to undertake proactive and strategic green innovation. By providing institutional support such as R&D subsidies, digital infrastructure, and innovation platforms, these policies create an enabling environment for firms to explore and invest in long-term, high-risk green technologies.

Artificial intelligence, as a general-purpose technology, further strengthens this process by enhancing firms' ability to process complex information, identify innovation opportunities, and optimize R&D decisions. This not only lowers the cost of innovation but also increases the likelihood of breakthrough advancements in environmentally friendly technologies. As a result, firms are more likely to internalize environmental objectives into their core innovation strategies, rather than treating them as external compliance requirements. Therefore, AI policy induces a shift toward proactive green innovation, which serves as a key mechanism through which firms achieve sustained improvements in carbon performance.

H2: AI pilot zone policies improve corporate carbon performance by promoting proactive green innovation.

2.3. AI Policy and Process Reconfiguration Pathway

Complementing the proactive green innovation pathway, this study argues that AI policy also enhances corporate carbon performance through a process reconfiguration pathway, which improves firms' operational efficiency and resource utilization. While proactive innovation focuses on long-term technological breakthroughs, process reconfiguration emphasizes the real-time optimization of existing production systems. Artificial intelligence enables firms to integrate data analytics, machine learning, and intelligent control systems into their operational processes, thereby facilitating dynamic adjustments in production scheduling, energy consumption, and resource allocation. This transformation allows firms to move beyond static efficiency improvements toward adaptive and data-driven optimization.

The establishment of AI pilot zones accelerates this process by improving digital infrastructure and reducing barriers to technology adoption. Firms located in pilot zones gain access to advanced computing resources, data platforms, and technical support, which enable them

to embed AI technologies into core business operations. As a result, firms can identify inefficiencies more precisely, reduce redundant energy use, and minimize carbon-intensive activities across the production chain. Importantly, this pathway reflects a shift from end-of-pipe treatment to process-integrated decarbonization. Instead of relying on pollution control after production, firms leverage AI to optimize processes *ex ante*, thereby achieving simultaneous improvements in productivity and environmental performance. This aligns with the concept of capability-driven decarbonization, where emission reduction is embedded within firms' operational routines rather than imposed externally (Sueyoshi and Goto, 2011). Therefore, AI policy improves corporate carbon performance by enabling process reconfiguration and efficiency enhancement.

H3: AI pilot zone policies improve corporate carbon performance by facilitating process reconfiguration and operational efficiency improvement.

3. Model construction and variable description

3.1. Model Specification

To empirically investigate how AI policy affects corporate carbon performance and to assess the capability-driven decarbonization framework, this research utilizes a multi-period DID model informed by the quasi-natural experiment of China's AI Pilot Zones (equation (1)).

$$LnCP_{it} = \alpha_0 + \alpha_1 Pilot_r \times Post_t + \alpha_2 \bar{X}_{it} + \mu_j + \delta_t + \varepsilon_{ijrt} \quad (1)$$

where i represents the firm and t indicates the year. The dependent variable $LnCP_{it}$ reflects the carbon performance at the firm level. The primary independent variable $Pilot_r \times Post_t$ serves as a policy metric, which is assigned a value of one if firm i is situated in a city r recognized as an AI pilot zone starting in year t or later, and is given a value of zero otherwise.

The vector $\bar{X}_{it}$ captures various control variables that might influence corporate carbon performance. To account for time-invariant unobserved differences among firms, firm fixed effects (μ_i) are included, while year fixed effects (δ_t) help to control for common temporal shocks.

The coefficient of interest, α_1 , captures the causal effect of AI policy on $LnCP$. A significantly positive estimate of α_1 provides empirical support for the capability-driven decarbonization hypothesis, indicating that AI policy enhances firms' internal capacity to achieve carbon reduction.

3.2. Variables Definition

To empirically implement the capability-driven decarbonization framework and its underlying pathways, this study constructs variables that closely map to the theoretical concepts of carbon performance and AI policy exposure.

3.2.1. Dependent Variable: Carbon Performance

The variable that depends on other factors in this research is Carbon Performance, representing firm-level carbon efficiency from the viewpoint of carbon effectiveness (Wang et al., 2025).

Following the existing literature, carbon performance is measured as the inverse of carbon emission intensity, typically defined as carbon emissions relative to firm output. This measure

reflects how efficiently firms generate economic value while minimizing carbon emissions, thereby providing a comprehensive indicator of environmental performance.

Compared with absolute emission measures, Carbon Performance better aligns with the concept of capability-driven decarbonization, as it emphasizes firms' internal ability to optimize production processes and reduce emission intensity. In this sense, it captures not only the outcome of emission reduction but also the underlying efficiency and technological capability embedded in firms' operations.

3.2.2. Independent Variable: AI Policy

This research considers the AI Pilot Zone as an external policy shock. We construct a DID specification based on the interaction term $Pilot_r \times Post_t$, which captures firms' exposure to the policy.

Specifically, $Pilot_r$ serves as a treatment indicator, taking a value of one if firm r operates in a city classified as an AI pilot zone, and zero in other cases. $Post_t$ functions as a time indicator that equals one for the years following the policy's implementation in the relevant city, and zero in other instances. Consequently, the interaction term illustrates the varied impact of the policy on the treated firms in comparison to the control firms.

In 2019, 2020, and 2021, the Ministry of Science and Technology set up the pilot zones in three different phases, creating a variation in policy across various regions and time periods. This phased implementation allows us to discern the causal impacts of the policy while accounting for regional traits that do not change over time and shared macroeconomic disturbances.

To account for potential delays in policy implementation and firm responses, we modify the timing of policy implementation by allocating cities that receive approval after September to the subsequent year. This treatment ensures that the estimated effects reflect actual exposure to policy support rather than announcement timing.

3.2.3. Control Variables

To address the possible omitted variable bias, we incorporate a collection of control variables at the firm level that reflect economic traits, financial circumstances, and aspects of corporate governance. Initially, we account for firm fundamentals through metrics such as firm size ($LnSize$), firm age ($LnAge$), Tobin's Q ($TobinQ$), and leverage ($Debts$). Larger and more mature firms tend to have greater resource endowments and experience, which may facilitate both technological adoption and environmental performance. Tobin's Q captures firms' growth opportunities, while leverage reflects financial pressure that may constrain or incentivize environmental investment.

Second, we control for firms' profitability and production structure by including return on assets (Roa) and capital intensity ($LnCap_inten$). Firms that enjoy higher profitability typically have a stronger ability to invest in environmentally friendly technologies, whereas capital-intensive firms may face higher adjustment costs in reducing carbon emissions.

Thirdly, factors related to corporate governance include the shareholding percentage of the

largest stakeholder (*LnTop1*) and the ratio of independent directors (*Dependent*). The concentration of ownership can impact a firm's strategic direction and its propensity for risk-taking, whereas a higher level of board independence tends to correlate with enhanced monitoring and greater environmental accountability. Including these control variables allows us to distinguish the direct impact of AI policy on corporate carbon performance from potential confounding influences at the firm level (Supplementary Table S1).

The information utilized in this research is sourced from various credible references. Financial and accounting details at the firm level, along with indicators of carbon performance, are mainly gathered from the CSMAR database and the annual reports of the companies. Data regarding green innovation are derived from patent records provided by the CNIPA and WIPO. Second, considering the substantial revision of China's Accounting Standards for Business Enterprises implemented in 2007, which altered accounting items and measurement rules, this paper adjusts the sample period to 2007–2023. This treatment ensures consistent statistical caliber of panel data and mitigates measurement bias induced by the accounting regime change. Additionally, we eliminate ST and *ST firms to prevent possible biases stemming from irregular financial situations. Lastly, any observations lacking critical variables are disregarded. As a result of these steps, the final dataset comprises 1,438 publicly traded companies and 11,814 firm-year entries, creating an unbalanced panel dataset (Supplementary Table S2).

4. Results Analysis of empirical results

4.1. Baseline Regression

To evaluate the primary hypothesis, we begin by estimating the baseline model to assess the overarching influence of the AI pilot policy on corporate carbon performance. The regression findings are detailed in Table 1. In all modeled specifications, the coefficient for the DID term consistently shows a statistically significant positive value, suggesting that the AI Pilot Zone policy has a notable effect on enhancing firms' carbon performance. Overall, the empirical evidence provides strong support for Hypothesis 1.

Table 1 Benchmark estimation results of the full sample

Variable	(1)	(2)	(3)	(4)
	<i>Lncp</i>			
<i>DID</i>	0.5312*** (0.0350)	0.3852*** (0.0574)	0.0388*** (0.0083)	0.0363*** (0.0104)
<i>Lnsize</i>	0.8393*** (0.1267)	1.3911*** (0.3289)	-0.1038*** (0.0352)	0.5537*** (0.1402)
<i>Debts</i>	-0.1344*** (0.0449)	0.3125*** (0.0711)	0.0717*** (0.0168)	0.0675*** (0.0221)
<i>Roa</i>	-0.5078*** (0.0902)	-0.6292*** (0.1136)	0.1237*** (0.0349)	0.1348** (0.0476)

<i>lnCap_inten</i>	0.0276*** (0.0065)	0.0194* (0.0113)	0.0019 (0.0024)	-0.0106*** (0.0045)
<i>Dependent</i>	0.0050*** (0.0010)	0.0018 (0.0015)	0.0002 (0.0003)	-0.00003 (0.0004)
<i>LnTop1</i>	-0.1852*** (0.0348)	-0.2808*** (0.0873)	-0.0240 (0.0128)	0.0325 (0.0431)
<i>Tobinq</i>	-0.0139*** (0.0043)	-0.0244*** (0.0053)	-0.0003 (0.0007)	-0.0022** (0.0010)
<i>Age</i>	0.4547*** (0.0309)	0.9831*** (0.0583)	-0.0259*** (0.0071)	0.0469* (0.0245)
<i>Id</i>	N	Y	N	Y
<i>Year</i>	N	N	Y	Y
<i>_cons</i>	-4.8676*** (0.4004)	-8.0462*** (0.9300)	-0.4465*** (0.1099)	-2.6723*** (0.4300)
<i>N</i>	28184	28184	28184	28147
<i>adj. R²</i>	0.1600	0.2558	0.9225	0.9357

Note: *, ** and *** indicate significance at the levels of 10%, 5% and 1%, respectively, and the figures in parentheses are t values. The clustering standard errors are at the city level, and the following table is the same.

4.2. Robustness Checks

4.2.1. Parallel Trend Test

A key identification concern in this study is the potential selection bias in policy implementation. In order to tackle this issue, we perform a parallel trend analysis utilizing an event-study framework. The reliability of the DID method is predicated on the presumption that, without the intervention, both treated and control firms would have exhibited comparable trends in carbon performance.

Illustrated in Supplementary Fig. S1 are the dynamic impacts of the AI pilot policy on carbon performance. The coefficients estimated for the periods prior to treatment do not significantly differ from zero. In contrast, the coefficients in the post-treatment periods become significantly positive and exhibit a persistent upward pattern, suggesting that the policy leads to a sustained improvement in firms' carbon performance. The lack of pre-trends, coupled with the appearance of notable post-treatment effects, strongly supports the validity of the DID identification method, thus enhancing the reliability of the initial findings.

4.2.2. Placebo Test

To provide additional assurance that the baseline findings are not influenced by neglected variables or misleading correlations, we perform a placebo test utilizing random assignment. Specifically, from the full sample of 1,438 listed manufacturing firms, we randomly select 575 firms to form a "pseudo-treatment group," matching the size of the actual treated group. The remaining firms are assigned to the control group. For each pseudo-treatment group, we then randomly assign a policy implementation year from the period 2006–2019 to construct a "pseudo-policy" indicator.

Utilizing this methodology, we conduct the simulation 2,000 times and estimate the relevant DID models, thus creating a distribution of placebo coefficients along with their respective p-values (Supplementary Fig. S2). The estimated coefficients cluster around zero and show no consistent significance, indicating that randomly assigning treatment status and policy timing does not produce effects similar to those observed in the baseline results. This result indicates that the beneficial impact noted in the primary analysis is improbable to stem from unobserved variables or mere coincidence.

4.2.3. Goodman-Bacon Decomposition

To more thoroughly assess the robustness of the DID identification approach in the context of staggered policy implementation, we perform a Goodman-Bacon decomposition analysis.

The decomposition results, reported in Supplementary Table S3, show that the largest weight (0.957) comes from the comparison between treated units and never-treated units, with an average DID estimate of 0.047. This estimate is consistent with the baseline regression results. In contrast, comparisons between early-treated and late-treated groups receive very small weights (0.034 and 0.009, respectively), contributing negligibly to the overall estimate. Importantly, we do not observe evidence of substantial negative weights or conflicting estimates across different comparisons.

4.2.4. PSM-DID Test

To tackle the possible selection bias resulting from a non-random assignment of policies, we integrate PSM with the DID methodology.

Supplementary Fig. S3 shows the standardized bias plot of covariates to check the balance property of propensity score matching (PSM). The dots represent the standardized bias of covariates between the treatment and control groups before matching, while the crosses denote the standardized bias after matching. It can be observed that several covariates exhibited substantial between-group differences prior to matching. After propensity score matching, the standardized bias of all covariates falls below 5%, indicating no significant differences between the treatment and control groups across all covariates and verifying the balance assumption.

Illustrated in Supplementary Fig. S4 are the kernel density distributions, displayed before and after the matching process. Before the matching, there is a clear divergence between the two groups, indicating substantial differences in observable characteristics. After matching, the distributions largely overlap, suggesting that the matched samples are well balanced in terms of observed covariates.

This result indicates that PSM effectively reduces selection bias by constructing a comparable control group for treated firms. Utilizing the matched sample, we re-evaluate the DID model, yielding findings that align with the original results. In summary, the PSM-DID outcomes reinforce the idea that our primary conclusions are not influenced.

Table 2 further provides robustness evidence from alternative samples and model specifications. Specifically, Column (1) reports the estimation results based on samples without missing weights,

where the DID coefficient remains positive and significant. Column (2) restricts the sample to observations within the region of common support, and the estimated coefficient remains highly significant. Column (3) adopts a frequency-weighted regression, and the DID coefficient continues to be positive. Overall, the reliability of findings across various sample limitations and estimation methods suggests that the beneficial impact of the AI pilot zones on carbon performance is strong and remains unaffected by different specifications.

Table 2 Baseline Regression and Cross-Sectional PSM-DID Results

Variable	(1) Samples with Non-Missing Weights	(2) Samples Satisfying the Common Support Assumption	(3) Use frequency-weighted regression
<i>DID</i>	0.0370*** 0.0114	0.0360*** 0.0110	0.0409*** 0.0124
Year	Yes	Yes	Yes
Id	Yes	Yes	Yes
Control	Yes	Yes	Yes
N	20888	28166	31930
Adj. R ²	0.9361	0.9359	0.9413

4.2.5. Instrumental Variable Approach

In order to tackle possible endogeneity issues linked to reverse causality and the absence of certain variables, we utilize an instrumental variable (IV) approach grounded in the historical framework of communication infrastructure. More precisely, we consider the quantity of post offices per million residents in the mid-1980s as our instrumental variables (IV1) and the count of fixed-line telephones per 100 individuals (IV2). These historical indicators capture a region's early information infrastructure endowment, which shapes long-term patterns of information diffusion, commercial connectivity, and openness to technological adoption. As a result of path dependence, early infrastructure is intricately connected to the advancement of digital technologies and the probability of being chosen as a pilot zone for AI.

At the same time, these variables are plausibly exogenous to contemporary corporate carbon performance. Given the substantial institutional, technological, and structural transformations that have occurred over the past decades, it is unlikely that communication infrastructure from the 1980s directly affects current firm-level carbon outcomes, thereby satisfying the exclusion restriction.

To further mitigate dynamic selection concerns, we construct an interaction-based instrument by interacting lagged policy exposure with historical post office density. This specification captures the idea that historical infrastructure influences policy assignment rather than directly affecting current outcomes.

The first-stage results reported in Table 3 confirm the relevance of the instruments. The coefficients on the instrumental variables are significantly positive, with F-statistics exceeding the Stock-Yogo critical value (e.g., $F = 528.81$ and 559.19), rejecting the weak instrument hypothesis. The Kleibergen-Paap LM statistics are also significant, rejecting the null of under-identification. In

addition, the Anderson-Rubin test remains significant, further supporting the validity of the instruments. The second-stage estimates, reported in Table 3 (Columns 2, 4), indicate that the pilot policy improves carbon performance. The magnitude of the IV estimates is larger than that of the baseline DID results, suggesting the presence of attenuation bias or negative selection in the OLS estimates.

Table 3 IV test

Variable	(1)	(2)	(3)	(4)
	<i>DID</i>	<i>Lncp</i>	<i>DID</i>	<i>EnvrPat</i>
<i>IV1</i>	0.0086*** (0.0002)			
<i>IV2</i>			0.2668*** (0.0048)	
<i>DID</i>		0.8631*** (0.0245)		0.7636*** (0.0223)
Control	Y	Y	Y	Y
Year	Y	Y	Y	Y
Id	Y	Y	Y	Y
N	21515		21515	

4.2.6. Alternative Measures of Key Variables

To verify that our results remain robust regardless of how the key variables are measured, we substitute both the primary explanatory variable and the outcome variable with different proxies.

First, for the explanatory variable, we adopt several alternative measures of AI development. The firm-level AI intensity depicted in columns (1) and (2) of table 4 is derived from a textual analysis of annual reports (Merino et al., 2025) and is quantified as the logarithm of the frequency of AI-related keywords (plus one). In particular, we created a lexicon of 73 terms related to AI of the annual reports for publicly listed companies, informed by recent studies. In addition, Column (2) employs a city-level AI search index as an alternative proxy for regional digital development.

Second, to further capture technological adoption from a production perspective, Column (3) adopts alternative measures of AI-related technologies from the literature (Dirk et al., 2023; Daron Acemoglu and Pascual Restrepo, 2020).

Third, we replace the dependent variable with alternative measures of carbon performance. Column (4) employs an alternative carbon performance indicator based on different calculation methods (Le and Tang, 2014), while Column (5) uses carbon emissions (CO_2) as a direct proxy (Zhang & Wei, 2010).

$$CP_2 = \frac{\text{Firm's value}}{(\text{Firm's cost of sales industry's cost of sales}) * \text{industry's carbon emission}} \quad (2)$$

Table 4 The explained variable replaces the test result

Variable	(1)	(2)	(3)	(4)	(5)
	<i>Lncp1</i>	<i>Lncp1</i>	<i>Lncp1</i>	<i>Lncp2</i>	<i>CO₂</i>
<i>DID</i>				0.0493** (0.0246)	-5.0011** (2.3655)
<i>ln(Ai_wf + 1)</i>	0.0071** (0.0030)				
<i>Ai_si</i>		0.0028*** (0.0006)			
<i>Ai_tech</i>			0.0034** (0.0016)		
Control	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y
Id	Y	Y	Y	Y	Y
_cons	-1.5436*** (0.3815)	-1.9551 (0.4389)	-2.6741*** (0.4212)	34.3418*** (1.3861)	-5556.68*** (226.4198)
<i>N</i>	28147	18418	28147	28147	28417
adj. <i>R</i> ²	0.9525	0.9546	0.9356	0.6468	0.8742

4.2.7. Controlling for Concurrent Policy Shocks

To reduce the likelihood of bias that may result from simultaneous policy interventions, we also account for various policies enacted during the sample timeframe that could concurrently influence the carbon performance of firms. Specifically, we incorporate a series of policy controls related to low-carbon transition and digital economy development, including low-carbon pilot programs, smart city initiatives, carbon emissions trading schemes, new energy policies, big data pilot zones, and low-altitude economy policies.

The results show that the coefficient remains positive (Table 5). This indicates that the fundamental results we obtained are not influenced by intersecting policy effects or excluded policy factors.

Table 5 Excluded confounding policy interference test results

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Lncp1</i>					
<i>DID</i>	0.0354*** (0.0108)	0.0350*** (0.0108)	0.0370*** (0.0106)	0.0365*** (0.0104)	0.0371*** (0.0103)	0.0364*** (0.0098)
<i>DID_LCCP</i>	0.0058 (0.0067)	0.0073 (0.0066)	0.0108 (0.0074)	0.0105 (0.0074)	0.0097 (0.0075)	0.0099 (0.0075)
<i>DID_SCPP</i>		-0.0090 (0.0073)	-0.0077 (0.0073)	-0.0079 (0.0074)	-0.0079 (0.0074)	-0.0086 (0.0072)
<i>DID_CTPP</i>			-0.0136 (0.0083)	-0.0153* (0.0080)	-0.0127 (0.0080)	-0.0126 (0.0080)
<i>DID_NEPP</i>				-0.0153 (0.0080)	0.0111 (0.0075)	0.0114 (0.0075)

<i>DID_BDPP</i>					-0.0046 (0.0077)	-0.0049 (0.0076)
<i>DID_LAEPP</i>						-0.0086 (0.0146)
Control	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y
Id	Y	Y	Y	Y	Y	Y
_cons	-2.7521*** (0.4516)	-2.7368*** (0.4524)	-2.7460*** (0.4509)	-2.7328*** (0.4485)	-2.7326*** (0.4481)	-2.7383*** (0.4456)
<i>N</i>	24465	24397	24918	24397	24918	24887
adj. <i>R</i> ²	0.9359	0.9361	0.9362	0.9362	0.9362	0.9361

4.2.8. Additional Robustness Checks

To strengthen the validation of our results, we perform several more tests. Initially, taking into account the possible influence of the Global Financial Crisis on the economic context in China and the carbon performance of its firms, we limit the sample duration to 2010–2023. The regression findings presented in Table 6 (Column 1) indicate that the AI pilot policy still exerts a positive impact.

Second, given that administrative hierarchy may affect the allocation and concentration of innovation resources, differences in city administrative levels may bias the estimation results. To address this concern, we exclude municipalities, provincial capitals, and sub-provincial cities from the sample. The results remain significantly positive, indicating that our findings are not driven by administrative-level heterogeneity (Column 2).

Third, we further strengthen the model specification by incorporating industry fixed effects and clustering standard errors at the firm level. The estimated coefficients remain statistically significant, providing additional support for the robustness of our conclusions (Columns 3 and 4).

Table 6 Test results of adjusting sample time and excluding abnormal samples

Variable	(1)	(2)	(3)	(4)
<i>DID</i>	0.0638** (0.0276)	0.0363** (0.0077)	0.0365*** (0.0104)	0.0376*** (0.0106)
Control	Y	Y	Y	Y
Year	Y	Y	Y	Y
Id	Y	Y	Y	Y
Industry	N	N	N	Y
_cons	-2.6364*** (0.5730)	-2.6723*** (0.3968)	-2.6813*** (0.4445)	-2.8222*** (0.5318)
<i>N</i>	14430	28147	28147	28740
adj. <i>R</i> ²	0.9357	0.9357	0.9358	0.9371

5. Mechanism analysis

5.1. Proactive Innovation Channel

To investigate the fundamental mechanism, we analyze if the AI pilot policy enhances carbon performance by fostering proactive innovation activities within firms. As indicated in Column (1) of Table 7, the pilot area facilitates the enhancement of carbon performance via the number of green patents awarded.

There are two categories of green innovation—patents for green inventions and green utility models—that represent fundamentally different approaches to innovation. Green invention patents reflect substantial and novel technological breakthroughs that involve high R&D investment and long development cycles, representing firms’ forward-looking efforts to reshape production technologies. In contrast, patents for green utility models mainly capture incremental improvements in existing products or processes, typically associated with short-term, cost-saving adjustments.

This distinction allows us to differentiate between proactive innovation and adaptive innovation. The former is driven by strategic technological upgrading and long-term competitive positioning, while the latter reflects compliance-oriented or cost-minimizing responses to environmental regulations (Berrone et al., 2013; Qi et al., 2014).

The results shown in Table 7 demonstrate that the policy aimed at AI pilots increases the quantity of green invention patents, while its effect on green utility model patents is not significant. This pattern suggests that the policy primarily stimulates proactive, breakthrough-oriented innovation rather than incremental, compliance-based adjustments.

Table 7 Mediating effect test

Variable	(1)	(2) Active emission reduction	(3) Passive Emission Reduction
	<i>licenvrpat</i>	<i>licenvrinvp</i>	<i>licenvrutypat</i>
<i>DID</i>	2.6965*** (1.0066)	2.4563** (0.9991)	0.2401 (0.4045)
Control	Y	Y	Y
Year	Y	Y	Y
Id	Y	Y	Y
<i>_cons</i>	-418.3994*** (68.5249)	-238.4624*** (47.3465)	-179.9370*** (27.3000)
<i>N</i>	28147	28147	28147
adj. <i>R</i> ²	0.6321	0.5565	0.6696

5.2. Efficiency Optimization Channel

Table 8 shows that the pilot zone has improved carbon performance by optimizing the production process rather than promoting the substitution of clean energy. This study utilizes the green total factor energy efficiency as the primary metric to evaluate the effectiveness of the green operational process (Kaoru and Miki, 2014). In this paper, by linking the input of production factors with the regional gross product (GDP) as the desired output, and considering the undesirable environmental emissions such as industrial sulfur dioxide, smoke dust and wastewater, the

calculation method adopts super efficiency SBM and CCR (Fang et al., 2024; Gao et al., 2024). The traditional transformation is gradual optimization and improvement, while the AI demonstration zone enables enterprises to "jump" -- that is, bypass the traditional gradual path such as coal to gas, and directly enter the new technological paradigm, green energy and disruptive innovation. The "significant transformation of green energy efficiency" and "insignificant transformation of clean energy substitution" found by the mediating effect are perfect evidence of "transition." The improvement of green total factor energy efficiency proves that artificial intelligence technology has achieved the "technical decoupling" of economic growth and carbon emission reduction by optimizing production scheduling, predictive maintenance, and precise allocation of materials and energy. This validates the "Porter hypothesis" that appropriate policies can induce innovation that improves both efficiency and environmental performance. In this sense, the demonstration zone has successfully forged AI into a sharp tool to improve "green productivity".

Table 8 Mediating effect

Variable	(1) High-carbon production process	(2) Optimize operation process	(3) Optimize operation process
	<i>Recs</i>	<i>Gtfee1</i>	<i>Gtfee2</i>
<i>DID</i>	-0.0001 (0.0003)	0.1691*** (0.0471)	0.1129*** (0.0384)
Control	Y	Y	Y
Year	Y	Y	Y
Id	Y	Y	Y
_cons	0.8319*** (0.0149)	0.1589 (0.2286)	0.7817*** (0.2312)
<i>N</i>	21939	24525	24525
adj. <i>R</i> ²	0.1209	0.8316	0.8369

However, it is important to note that an efficiency-oriented pathway—rather than one based on fundamental energy substitution—may, to some extent, reduce the urgency of deep low-carbon transformation.

Specifically, improvements in green total factor energy efficiency primarily reflect optimization within existing production systems, rather than a structural shift away from carbon-intensive energy inputs. As such, this pathway may delay the transition toward cleaner energy structures.

In addition, efficiency gains typically rely on data availability, algorithmic capabilities, and digital infrastructure, implying heterogeneous firm capacities in leveraging such technologies. Firms with stronger technological and resource endowments are more likely to benefit from AI-driven efficiency improvements, while others may remain limited to incremental adjustments within existing production frameworks.

Overall, these findings suggest that the AI-driven pathway to improved carbon performance operates mainly through efficiency enhancement rather than structural energy transformation,

highlighting a pattern of “efficiency-based decarbonization” rather than “substitution-based decarbonization.”

5.3. Moderating Effects

To investigate the boundary conditions that influence how the AI pilot policy impacts corporate carbon performance further, we extend the baseline model by incorporating a set of moderating variables. Specifically, we introduce firm-level supply chain concentration (*Ssc*), capacity utilization (*Cur*), industry-level digitalization (*Digit*), the proportion of highly educated employees (*Lnhep*), and government environmental attention (*Erp*) as moderating variables Tj_{it} . Based on this, we construct a triple-difference (DDD) specification by interacting the policy variable with each moderating factor.

The frequency of keywords associated with low carbon initiatives in governmental reports is used to gauge environmental attention (*Erp*). Supply chain coordination (*Ssc*) is represented by the level of supply chain concentration, which is calculated as the average proportion of transactions involving a firm’s leading five suppliers and customers (Chen et al., 2023). Industry digitalization (*Digit*) is measured as the industry-level average degree of digital transformation. Specifically, firm-level digitalization is captured using a dictionary of 139 digital-related keywords—covering technological applications, organizational empowerment, and digital practices—constructed from listed firms’ annual reports. The industry average of this measure is then used to represent industry digitalization. Human capital (*Lnhep*) is quantified by the ratio of employees who possess a graduate degree or higher compared to the entire workforce, indicating the firm’s capability to absorb and apply advanced technologies. Capacity utilization (*Cur*) is determined through a stochastic frontier analysis (SFA) method and is described as the proportion of actual output relative to the maximum possible output. The production frontier is defined by utilizing operating revenue, total assets, and the number of employees as input factors.

This approach allows us to examine how firm characteristics, industry conditions, and external policy environments shape the effectiveness of the pilot policy in improving *lncp* (equation (2)).

$$Lncp_{it} = \lambda_0 + \lambda_1 Pilot_r \times Post_t \times Tj_{it} + \lambda_2 Pilot_r \times Tj_{it} + \lambda_3 Post_t \times Tj_{it} + \lambda_4 Pilot_r \times Post_t + \lambda_5 \bar{X}_{it} + \mu_j + \delta_t + \varepsilon_{ijrt} \quad (2)$$

To further explore the boundary conditions of the AI pilot policy, we examine moderating effects from five dimensions: supply chain coordination, production efficiency, industry digitalization, human capital, and institutional environment. The results are reported in Tables 11.

Initially, it can be seen in Column (1) of Table 9 that the significant positive nature of the DDD term suggests that the coordination within the supply chain enhances the beneficial impact of the AI pilot policy on carbon performance (Meng et al., 2023). This finding suggests that carbon performance improvements rely not only on internal process optimization but also on external

coordination. Stronger supply chain linkages enable leading firms to transmit technological standards and promote joint emission reduction along the value chain.

Second, Column (2) of Table 9 shows that capacity utilization negatively moderates the policy effect (Dong et al., 2021). Specifically, the impact of the AI policy on carbon performance is weaker for firms with higher or rapidly increasing capacity utilization. This implies that when firms operate close to full capacity, production expansion driven by demand may dominate, limiting the marginal contribution of technological upgrading to carbon efficiency improvements.

Third, Column (3) indicates that industry digitalization enhances the effectiveness of the AI pilot policy (Wang and Gao, 2025). The positive sign of the triple interaction term indicates that for the successful implementation of AI technologies, having robust digital infrastructure and accessible data is essential. In more digitalized industries, firms can better integrate AI into production processes, thereby improving carbon efficiency (Liu et al., 2025).

Fourth, Column (4) shows that the proportion of highly educated employees positively moderates the policy effect (Jiang et al., 2012; Kromann et al., 2024). Firms with a more skilled workforce are better able to absorb and apply AI technologies, translating them into green innovation and production optimization (Marin, G., & Vona, F., 2019).

Finally, Column (5) demonstrates that government environmental attention significantly strengthens the impact of the AI pilot policy (Țigănașu et al., 2025). In regions with stronger environmental policy signals, AI policies are more effectively aligned with regulatory objectives, encouraging firms to undertake long-term green investments and further improve carbon performance.

Table 9 Test results of moderating mechanism

Variable	(1) External synergy	(2) Capacity utilization rate	(3) Industry digitalization level	(4) Proportion of highly educated employees	(5) Environmental importance
<i>DID</i>	0.0087 (0.0161)	0.2233*** (0.0678)	-0.0253 (0.0171)	0.0062 (0.0174)	0.0270** (0.0107)
<i>Ssc</i>	0.0003 (0.0002)				
<i>Ssc × DID</i>	0.0009* (0.0005)				
<i>Cur</i>		0.3250*** (0.1086)			
<i>Cur × DID</i>		-0.2671*** (0.0960)			
<i>Digit</i>			0.0010 (0.0008)		
<i>Digit × DID</i>			0.0046*** (0.0014)		

<i>Lnhep</i>				0.0001 (0.0024)	
<i>Lnhep × DID</i>				0.0059** (0.0029)	
<i>Erp</i>					-0.0006 (0.0007)
<i>Erp × DID</i>					0.0038* (0.0023)
Control	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y
Id	Y	Y	Y	Y	Y
_cons	-2.8261*** (0.4239)	-3.2093*** (0.9359)	-2.6586*** (0.4228)	-3.0721*** (0.4690)	-2.9024*** (0.4692)
<i>N</i>	27812	28712	28135	26096	24305
adj. <i>R</i> ²	0.9364	0.9359	0.9359	0.9369	0.9363

6. Heterogeneity Analysis

This part analyzes the varying impacts of the AI pilot policy on carbon performance among diverse ownership categories. In general, the influence of the policy is notably more pronounced for SOEs compared to private companies, which indicates fundamental distinctions in resource allocations, innovation approaches, and positions within the supply chain.

6.1. Ownership Heterogeneity: The Dominant Role of SOEs

The data presented in Table 10 indicate that the AI pilot policy greatly enhances carbon performance for both state-owned enterprises (SOEs) and private companies; however, the impact is considerably greater for SOEs. A Fisher-type permutation test, consisting of 500 replications, demonstrates that the difference in coefficients observed between these two categories is statistically significant. Further mechanism analysis (Columns 5–6 of Table 10) reveals that proactive innovation channels are significant only for SOEs, while they are insignificant for private firms.

Table 10 Heterogeneity Analysis: State-Owned Enterprises

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Lncp1</i>		<i>Gffeel</i>		<i>licenvrinvp</i>	
	Private enterprise	State-owned enterprises	Private enterprise	State-owned enterprises	Private enterprise	State-owned enterprises
<i>DID</i>	0.0324*** (0.0100)	0.0508** (0.0216)	0.1481*** (0.0397)	0.2116*** (0.0665)	0.2405 (0.6427)	9.5104*** (2.1433)
Control	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y
Id	Y	Y	Y	Y	Y	Y
_cons	-2.8181*** (0.5849)	-3.1192*** (0.8271)	0.3045 (0.2642)	-0.0919 (0.3590)	-220.3483*** (47.5758)	-412.514** (164.3126)

adj. R^2	0.9438	0.9106	0.8408	0.8107	0.5799	0.5948
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6.2. Resource Allocation Advantage of State-Owned Enterprises

The results in Table 11 provide consistent evidence that state-owned enterprises (SOEs) possess significant advantages in accessing key resources under the AI pilot policy, as reflected in financing constraints (Kaikai et al., 2025), government subsidies (Lin and Yang, 2025), and R&D investment (Hengyu et al., 2024). These findings suggest that the policy operates, in part, as a mechanism of resource reallocation, with SOEs benefiting disproportionately from improved access to critical inputs.

Table 11 Advantages of state-owned enterprises from the perspective of resource reallocation

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Sa</i>		<i>Res</i>		<i>Sub</i>	
	Private enterprise	State-owned enterprises	Private enterprise	State-owned enterprises	Private enterprise	State-owned enterprises
<i>DID</i>	-0.0025 (0.0035)	0.0167** (0.0084)	7.6990 (4.8459)	37.5040*** (12.8184)	0.0518 (0.4716)	6.3310*** (2.0746)
Control	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y
Id	Y	Y	Y	Y	Y	Y
_cons	-2.2256*** (0.2745)	-4.7108*** (0.5754)	-1680.553*** (206.9952)	-2284.81*** (657.4185)	-285.2406*** (32.0983)	-459.8346*** (135.5125)
adj. R^2	0.9707	0.9568	0.4930	0.6931	0.5815	0.2744

6.3. Ownership Differences in Moderating Effects

To further examine how ownership shapes the moderating mechanisms, we conduct subgroup analyses for key moderating variables. The findings are detailed in Table 12. First, Columns (1)–(2) show that government environmental attention significantly strengthens the policy effect only for private firms, while the effect is insignificant for SOEs (Li et al., 2025). This suggests that private firms are more responsive to policy signals released by local governments.

Second, the results indicate that capacity utilization exhibits a significantly negative moderating effect for SOEs. This finding reflects an offsetting mechanism between efficiency gains and scale expansion: when firms operate at higher capacity levels, improvements in energy efficiency brought by AI may be partially offset by increased total energy consumption due to output expansion.

Third, supply chain concentration positively moderates the policy effect for private firms but not for SOEs (Ren et al., 2025). This suggests that private firms may benefit more from concentrated supply-chain relationships by strengthening coordination with upstream and downstream partners, thereby facilitating joint emission reductions and enhancing the policy effect (Hussain et al., 2025).

Finally, Columns (7)–(8) show that industry digitalization significantly enhances the policy effect for both SOEs and private firms, highlighting the importance of digital infrastructure as a

prerequisite for AI deployment. Further tests using the seemingly unrelated estimation (suest) indicate that the moderating effects differ significantly across ownership types ($\chi^2=8.84^{***}$, $p<0.001$), with stronger effects observed for SOEs.

Table 12 The heterogeneity test of firm ownership with respect to the moderating variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Private enterprise	State-owned enterprises	Private enterprise	State- owned enterprises	Private enterprise	State-owned enterprises	Private enterprise	State- owned enterprises
<i>DID</i>	0.0216** (0.0107)	0.0415*** (0.0146)	0.1132 (0.0783)	0.5470*** (0.1223)	-0.0022 (0.0179)	-0.0255 (0.0308)	-0.0204 (0.0189)	-0.0660 (0.0229)
<i>Erp</i>	-0.0012 (0.0008)	0.0003 (0.0017)						
<i>Erp × DID</i>	0.0046** (0.0023)	0.0023 (0.0086)						
<i>Cur</i>			0.2747** (0.1135)	-0.5824 (0.1794)				
<i>Cur × DID</i>			-0.1165 (0.1135)	-0.6964*** (0.1675)				
<i>Ssc</i>					0.0004** (0.0002)	0.00003 (0.0005)		
<i>Ssc × DID</i>					0.0011** (0.0004)	0.0008 (0.0012)		
<i>Digit</i>							0.0015 (0.0011)	0.0002 (0.0012)
<i>Digit × DID</i>							0.0039*** (0.0014)	0.0094*** (0.0021)
Control	Y	Y	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y	Y	Y
Id	Y	Y	Y	Y	Y	Y	Y	Y
_cons	-3.0774*** (0.6657)	-3.3496*** (0.8502)	-3.2832*** (0.6704)	-3.9822*** (0.9326)	-2.9663*** (0.5879)	-3.2271*** (0.8695)	2.8147*** (0.5842)	-3.0139*** (0.8314)
adj. R^2	0.9441	0.9142	0.9439	0.9117	0.9441	0.9124	0.9440	0.9111

7. Conclusion and Policy Implications

This research utilizes the policy of the AI Pilot Zone as a quasi-natural experiment and analyzes panel data from Chinese A-share listed companies spanning the years 2007 to 2023 to assess its influence on corporate carbon performance. Through the application of multi-period DID and DDD models, we present comprehensive evidence regarding the effects of the policy, the mechanisms involved, and the variations observed. The primary conclusions are outlined below.

Initially, the AI pilot policy greatly enhances corporate carbon performance. This finding consistently holds true across various tests, such as parallel trends, placebo examinations, PSM-

DID, instrumental variable estimation, alternative metrics, and adjustments for concurrent policies, thus validating the presence of a true policy effect.

Second, the policy operates through two primary channels: proactive innovation and efficiency optimization. On the one hand, the policy significantly increases green invention patents, indicating enhanced strategic investment in frontier green technologies. On the other hand, it improves green total factor energy efficiency by facilitating the intelligent upgrading of production processes. In contrast, the effect on utility-model green patents is insignificant, suggesting that the policy primarily stimulates forward-looking innovation rather than compliance-driven adjustments.

Third, the moderating analysis identifies key boundary conditions of the policy effect. Industry digitalization, human capital, supply chain coordination, and government environmental attention all strengthen the policy impact, highlighting the importance of complementary conditions such as digital infrastructure and institutional support. In contrast, capacity utilization exerts a significantly negative moderating effect, reflecting a potential offset between efficiency gains and output expansion.

Fourth, the policy effect exhibits pronounced ownership heterogeneity. The impact is significantly stronger for state-owned enterprises (SOEs), and the innovation channel is only significant within SOEs. This difference is primarily driven by disparities in resource access and allocation capacity. The policy alleviates financing constraints, increases government support, and enhances resource allocation more effectively for SOEs, whereas private firms rely more on external conditions such as government environmental attention and supply chain concentration.

Overall, our findings suggest that the AI pilot policy promotes carbon performance through a dual-channel mechanism, but its effectiveness depends critically on firm characteristics and institutional context. This highlights the importance of considering both technological and institutional factors in AI-driven green transformation.

Based on these findings, several policy implications emerge. First, for SOEs, reforming performance evaluation systems to emphasize carbon efficiency and green productivity can better translate resource advantages into sustainable outcomes. Second, for private firms, enhancing policy credibility and improving digital infrastructure are essential to reduce uncertainty and facilitate green transformation. Third, investing in human capital and promoting digitalization are fundamental to supporting broad-based low-carbon transition.

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Figure legends

Figure 1. Results of the parallel trend test.

The figure presents the dynamic treatment effects of the AI pilot-zone policy before and after policy implementation.

Figure 2. Results of the placebo test.

The figure presents the distribution of estimated coefficients from the placebo tests based on randomly assigned treatment groups. The vertical line indicates the baseline estimate.

Figure 3. Covariate balance before and after propensity score matching.

The figure compares the standardized differences in covariates between the treatment and control groups before and after propensity score matching.

Figure 4. Kernel density distributions of propensity scores before and after matching.

The figure presents the kernel density distributions of propensity scores for the treatment and control groups before and after propensity score matching.

Availability of data

The data and code are provided in the attachment.

Competing interests

The authors declare that we have no relevant or material financial interests that relate to the research described in this paper.

Figures

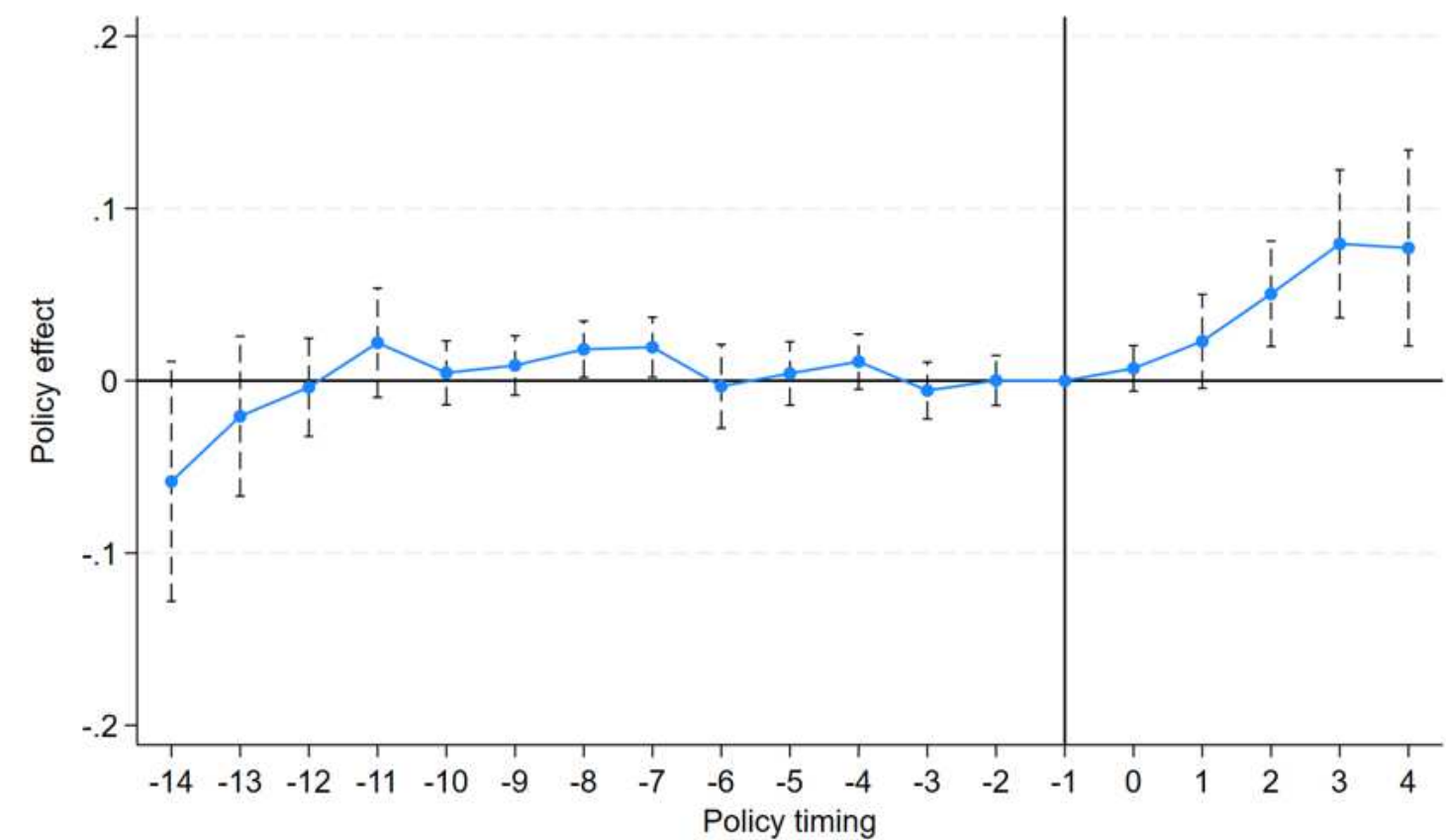


Figure 1

Results of the parallel trend test.

The figure presents the dynamic treatment effects of the AI pilot-zone policy before and after policy implementation.

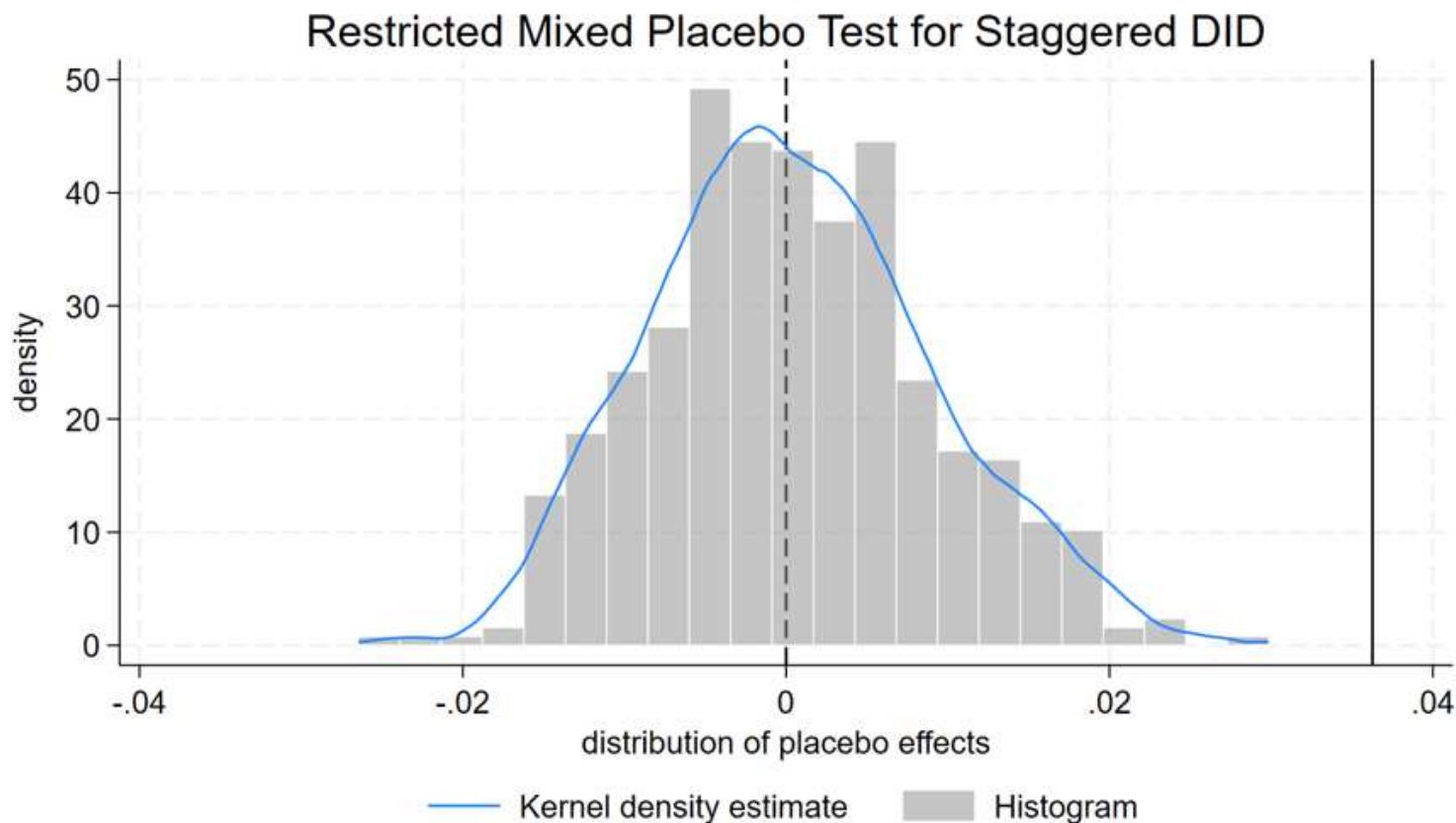


Figure 2

Results of the placebo test.

The figure presents the distribution of estimated coefficients from the placebo tests based on randomly assigned treatment groups. The vertical line indicates the baseline estimate.

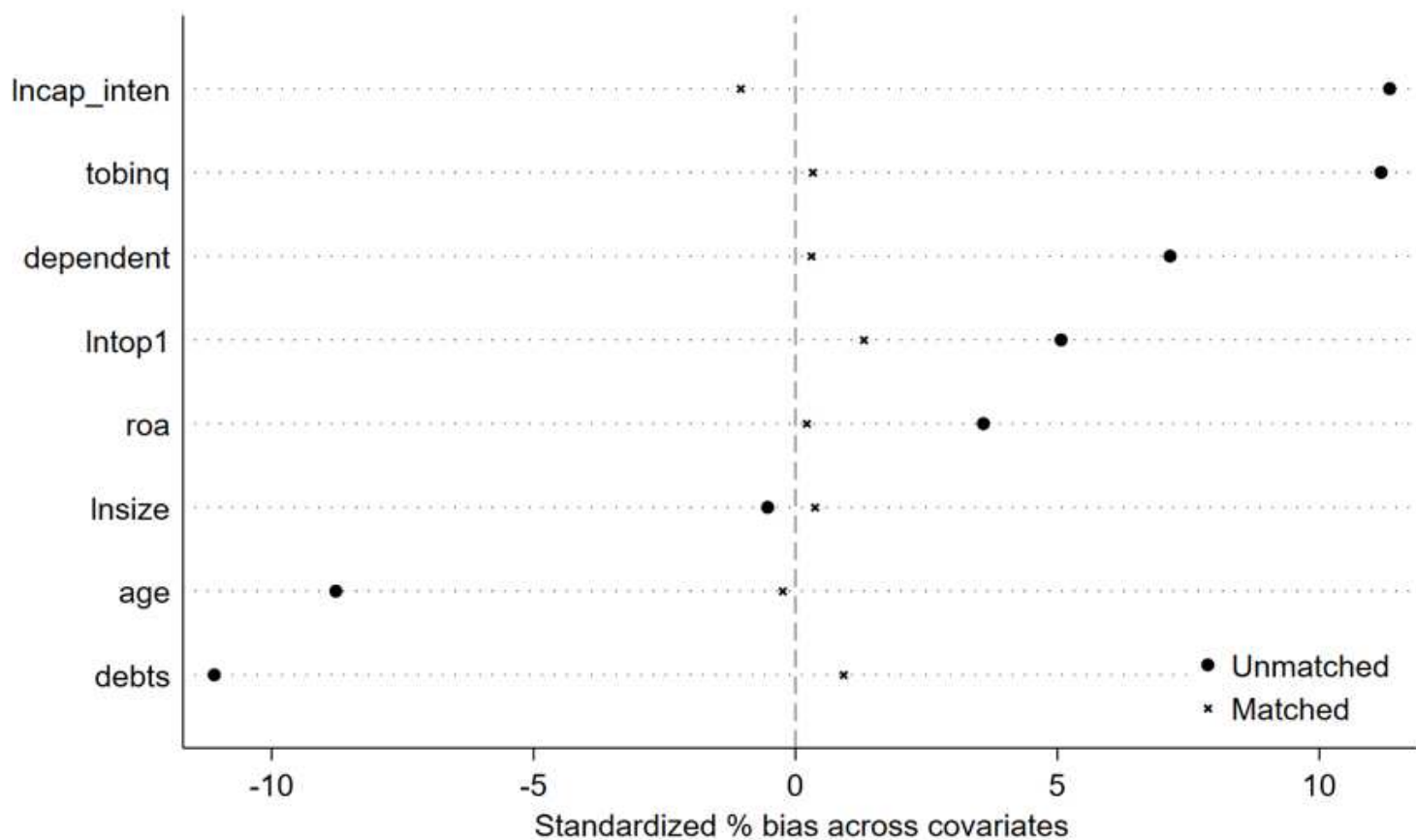


Figure 3

Covariate balance before and after propensity score matching.

The figure compares the standardized differences in covariates between the treatment and control groups before and after propensity score matching.

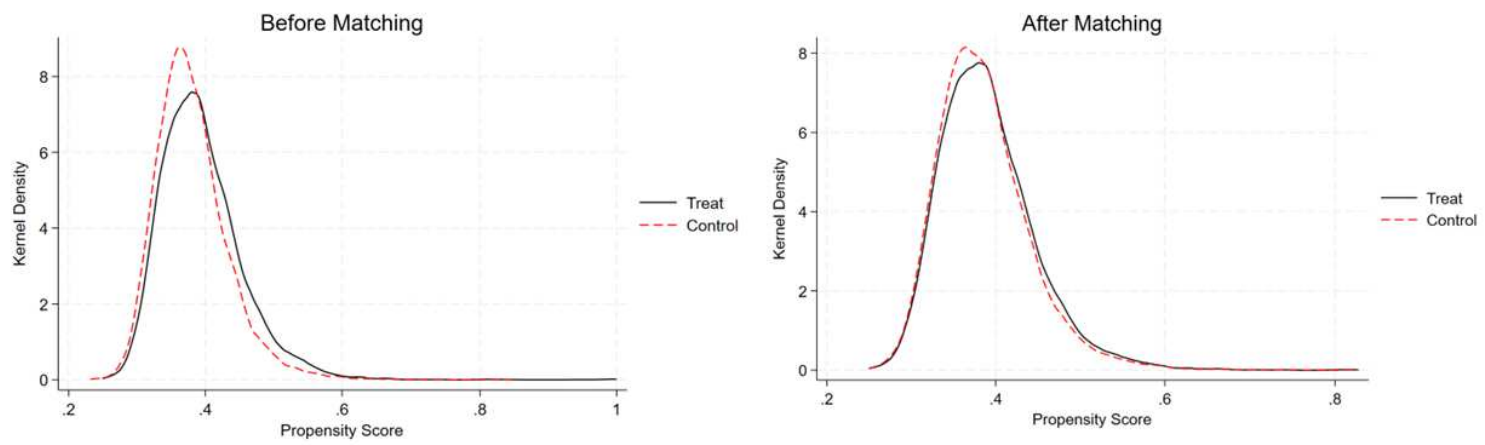


Figure 4

Kernel density distributions of propensity scores before and after matching.

The figure presents the kernel density distributions of propensity scores for the treatment and control groups before and after propensity score matching.

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