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THE IMPACT OF GREEN FINANCE POLICY ON CORPORATE CARBON EMISSION EFFICIENCY

Abstract: Under the guidance of the "dual carbon" goals, enhancing carbon emission efficiency is the key to achieving coordinated development of economic growth and environmental protection. This paper takes the green finance reform and innovation pilot zones established in batches since 2017 as a quasi-natural experiment, and uses the multi-period difference-in-differences (DID) method to empirically examine the impact of green finance policies on the carbon emission efficiency of enterprises based on the data of Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2013 to 2025. The research finds that green finance policies have significantly improved the carbon emission efficiency of enterprises in the pilot zones, with an average increase of about 5.4 percentage points, equivalent to 8.6 % of the sample mean. This conclusion remains valid after a series of robustness tests. Mechanism analysis indicates that the tightening of financing constraints (forcing effect) and the output of green patents are two core transmission paths, with the estimated indirect effects accounting for approximately 27.8 % and 31.5 % of the total effect, respectively. Heterogeneity analysis shows that the policy effect is more prominent in large-scale enterprises and heavily polluting industries. This paper deepens the understanding of the micro-environmental effects of green finance from the perspective of efficiency, reveals the internal logic of policy implementation, and provides empirical references and decision-making basis for improving the green finance system and driving high-quality low-carbon transformation of enterprises.

Keywords: green finance policy, carbon emission efficiency, financing constraints, green innovation, multi-period difference-in-differences method

Introduction

Climate change is one of the most severe challenges facing human society today. Promoting a comprehensive green transformation of economic and social development has become a global strategic consensus and collective action. As the world's largest developing country, China has made a "dual carbon" commitment to the international community. This not only concerns the responsibility of a major country in global climate governance but also implies a systemic paradigm shift in China's economic development model, from the traditional path of relying on factor input and scale expansion to a green growth track centered on efficiency improvement and innovation-driven development [1, 2]. Enterprises, as the micro-subjects of energy consumption and carbon emissions, their progress and quality in low-carbon transformation directly determine whether the macro

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emission reduction targets can be achieved on schedule [3]. A decline in total carbon emissions is not a sufficient criterion for measuring the success of the transformation. If emission reduction is achieved at the cost of compressing output and sacrificing growth, such "campaign-style" carbon reduction is neither sustainable nor in line with the fundamental purpose of development. A truly high-quality low-carbon transformation lies in enhancing "carbon emission efficiency", that is, creating more economic output per unit of carbon emissions, achieving an absolute reduction in carbon emissions while maintaining or even expanding the economic scale. Only by starting from the dimension of efficiency can we accurately identify enterprises that have truly achieved "reducing carbon without reducing production, increasing efficiency without slowing down", providing a more scientific yardstick for policy evaluation.

The efforts of enterprises to enhance carbon emission efficiency, whether it be energy-saving technological renovations of high-consumption equipment, the low-carbon reconstruction of production processes, or the research and industrial application of cutting-edge green technologies, all face a common fundamental constraint: the financing predicament. Such investment activities typically feature large capital requirements, long payback periods, uncertain technological routes, and externalised environmental benefits, which create a structural contradiction with the credit preferences of traditional financial institutions that favour short-term, stable, and internalisable returns [4-6]. Without effective institutional intervention, financial markets are unlikely to spontaneously allocate resources to green projects with long-term social value, leaving enterprises' low-carbon transitions with severe funding gaps and credit rationing. The essential function of green finance policies is to correct this market failure through government guidance and institutional innovation, thereby reshaping the incentive structure of financial resource allocation [7, 8]. Since the release of the "Guiding Opinions on Building a Green Financial System" in 2016, China has gradually established the world's first systematic green finance policy framework. By setting up green finance reform and innovation pilot zones in batches, it has taken the lead in exploring institutional innovations such as green credit, green bonds, and environmental rights trading in specific regions [9, 10]. This institutional arrangement places enterprises entering the pilot zones at different times in a differentiated policy environment, providing an ideal analytical scenario for examining the real effects of green finance policy supply on enterprises' environmental behaviours. Against this backdrop, systematically assessing whether green finance policies have truly promoted the improvement of enterprises' carbon emission efficiency and their pathways of action is not only crucial for scientifically evaluating the performance of existing policy tools but also directly related to the future reform orientation of the green finance system and its capacity to support economic green transformation under the "dual carbon" goals.

Green finance reform and innovation pilot zones are not randomly designated; they are selected comprehensively based on regional financial development foundation, environmental governance capacity, and low-carbon development potential. This non-random selection feature may lead to endogenous selection bias, as pilot regions already possess better institutional conditions before policy implementation. In addition, parallel trend test and placebo test further confirm that the policy shock is relatively exogenous, effectively alleviating the selection concern of pilot zone designation.

Centering on the quasi-natural experiment of the Green Finance Reform and Innovation Pilot Zone, existing research has examined the impact of green finance policies on corporate carbon emissions from multiple dimensions, most of which concentrate on

total carbon emissions or carbon emission intensity rather than comprehensive carbon emission efficiency that integrates input-output relationships. Regarding the emission reduction effect, some studies have found that the pilot policies can significantly curb the carbon emissions of the entire sample and non-heavy-polluting enterprises, but the reduction effect on heavy-polluting enterprises is not significant [11-13]; however, studies specifically focusing on polluting or heavy-polluting enterprises have confirmed that the policies can significantly reduce their carbon emissions through the reallocation of financial resources, enhanced environmental governance, and a "capital, technology, and awareness" three-wheel drive mechanism [14-18]. The emission reduction effect of the policies shows significant heterogeneity: it is more prominent in high-tech industries, eastern regions, non-key-pollution-regulated enterprises, state-owned enterprises, highly financialised enterprises, and enterprises with high capital allocation efficiency [19-22]. In terms of the mechanism of action, the literature has identified multiple independent paths. The financing constraint mechanism has been widely discussed, with the policies easing the financing constraints of non-heavy-polluting enterprises and promoting emission reduction, but possibly exacerbating the financing difficulties of heavy-polluting enterprises [23]; green technological innovation is another core path, with most studies confirming that the policies reduce carbon emissions by incentivising green innovation in enterprises [24]. Additionally, scholars have identified multiple mechanisms such as digital transformation, enhanced media supervision, improved environmental governance, improved environmental, social and governance (ESG) performance, suppression of managerial short-sightedness, and alleviation of information asymmetry [25-28]. Studies focusing on heavy-polluting enterprises have even revealed that the policies achieve emission reduction goals through short-term financial adjustments such as increasing financial investment and reducing inventory investment [29-31]. Notably, corporate greenwashing behaviour can weaken the emission reduction effect of the policies, while the development of inclusive finance can enhance this effect [32].

Despite the rich achievements, there is still room for exploration. First, previous studies have generally used total carbon emissions or carbon emission intensity as the dependent variable. A decrease in total carbon emissions may result from either a genuine improvement in production efficiency or a passive reduction in production scale. The latter implies an economic cost rather than an improvement in the quality of transformation; while carbon emission intensity takes output into account, it fails to reflect resource consumption and factor allocation efficiency on the input side. Extending the research perspective from "emission reduction volume" to "carbon emission efficiency", a comprehensive indicator that takes into account the input-output relationship, can more accurately assess the real performance of green finance policies in driving high-quality and low-carbon transformation of enterprises. Second, most studies have only supported the effectiveness of a single path, and few have simultaneously identified and quantitatively compared the relative contributions of different transmission paths within a unified framework, nor have they systematically examined and compared the internal transmission logic of policy effects. Based on the above literature review and research gaps, this paper proposes the following research hypotheses:

H1: Green finance policies can significantly improve the carbon emission efficiency of enterprises in the pilot zones.

H2: The tightening of financing constraints plays a mediating role in the process by which green finance policies affect the carbon emission efficiency of enterprises.

H3: Green patent output plays a mediating role in the process by which green finance policies affect the carbon emission efficiency of enterprises.

It is important to clarify that the tightening of financing constraints (forcing effect) and the output of green patents (incentive effect) are theorised as two independent parallel mediating mechanisms rather than as a sequential causal chain. The theoretical logic of this paper posits that green finance policies affect corporate carbon emission efficiency through two distinct pathways: first, imposing targeted credit restrictions on high-pollution projects to tighten financing constraints for heavily polluting firms, forcing them to optimise production capacity and improve efficiency; second, incentivising green technological innovation through targeted credit allocation and reputational signalling. These two mechanisms operate contemporaneously and are therefore examined in separate mediation models without imposing a sequential ordering.

This paper takes the phased establishment of green finance reform and innovation pilot zones as a quasi-natural experiment to examine the impact of green finance policies on the carbon emission efficiency of enterprises, and constructs a unified analytical framework to identify and quantify the transmission effects of the two core paths of financing constraint tightening (forcing effect) and green innovation (incentive effect), providing micro-evidence for the optimisation of green finance systems and economic green transformation under the "dual carbon" goals.

Methodology

Sample selection and data sources

Given that the implementation of the "Green Credit Guidelines" in 2013 marked the standardised operation of the green finance system, the establishment of the first batch of pilot zones in 2017 constituted an exogenous shock. Data collection was officially completed in April 2026. By this cutoff date, most 2025 annual reports, social responsibility reports, and environmental reports of listed firms had been officially released. For a small number of undisclosed energy consumption and carbon emission indicators in 2025, missing values were supplemented by industry average interpolation with unified statistical standards, ensuring the integrity and cross-year comparability of sample data. This paper initially takes all Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2013 to 2025 as the original research sample. Strict sample screening procedures are adopted: first, financial and insurance enterprises are excluded due to their special business models, unique asset-liability structures, and incomparable carbon emission characteristics. Second, firms under special treatment (ST/*ST) or delisting arrangement status with abnormal operating conditions are eliminated. Third, firm-year observations with missing core variables required for regression, carbon emission efficiency measurement and mechanism analysis are excluded. All continuous variables are further winsorised at the 1 % and 99 % percentiles to alleviate the influence of extreme outliers. After the above data cleaning and processing, this paper finally retains a panel dataset consisting of 912 listed companies and a total of 10,012 firm-year observations. The detailed sample screening process is as follows: we start with the initial sample of all A-share listed companies from 2013 to 2025, which includes 15,876 firm-year observations. First, we exclude 1,664 observations from 128 financial and insurance enterprises due to their special business models and incomparable carbon emission characteristics. Second, we eliminate 2,795 observations from 215 enterprises under ST/*ST or delisting

arrangement status with abnormal operating conditions. Third, we remove 1,405 observations with missing core variables required for carbon emission efficiency measurement, policy identification and control variable calculation. The final sample thus consists of 912 enterprises and 10,012 valid firm-year observations. Among the final samples, there are 3,621 observations from heavy-polluting industries and 6,391 from clean industries. To eliminate potential concerns about the completeness and estimation reliability of 2025 data, this paper conducts an additional robustness test by excluding all 2025 samples and re-estimating the benchmark model, the coefficient magnitude, statistical significance and core conclusions remain highly consistent.

Table 1

Detailed information of green finance reform and innovation pilot zones

Pilot zone	Approval year	Effective year	Treated firm number	Treated firm-year observations number
Zhejiang Huzhou & Quzhou	2017	2018	92	269
Guangdong Guangzhou	2017	2018	71	207
Xinjiang Karamay & Hami	2017	2018	23	68
Jiangxi Ganjiang New Area	2018	2019	33	83
Guizhou Gui'an New Area	2018	2019	21	54
Gansu Lanzhou New Area	2019	2020	13	29
Chongqing	2022	2023	19	21
Total	-	-	272	731

Green finance reform and innovation pilot zones were approved in batches during 2017-2022, showing in Table 1. All pilot zones follow the unified policy lag rule that the policy takes effect in the second year after official approval, and are incorporated into the staggered DID framework without additional special setting. The energy consumption data of enterprises are mainly sourced from firms' annual reports, social responsibility reports and environmental disclosure reports. For firms that do not voluntarily disclose energy consumption and carbon emission information, missing indicators are supplemented by industry average energy consumption per unit operating income under the same industry and year caliber. Carbon emission data are derived from the CSMAR environmental database and corporate public disclosure documents, with missing carbon emission values filled by industry-year average carbon emission intensity. In the final sample, energy consumption data for 2,847 observations (approximately 28.4 % of the total sample) rely on industry average imputation, and the remaining observations adopt firm-level direct disclosure. Carbon emission data for 1,932 observations (approximately 19.3 %) are supplemented by industry averages. Importantly, the imputation ratios are very close between the treatment group (energy: 27.9 %, carbon: 18.8 %) and the control group (energy: 28.6 %, carbon: 19.5 %), which alleviates systematic estimation bias caused by differential data interpolation. To rule out the concern that interpolated industry-level data may distort firm-level carbon emission efficiency evaluation, this paper carries out a targeted robustness test by only retaining subsamples with fully directly disclosed energy and carbon emission data to re-estimate the benchmark DID model. The policy coefficient significance and economic magnitude remain stable, confirming that the reliance on partial industry interpolation does not affect the core empirical findings. Green patent data are sourced from the patent database of the National Intellectual Property Administration, and financial and corporate governance data are from the CSMAR and Wind databases.

It should be noted that the number of pilot firms in Table 1 corresponds to the final estimation sample after excluding ST/*ST firms and missing observations.

Variable selection

1) Explained variable

This paper employs the input-oriented slacks-based measure and data envelopment analysis SBM-DEA model under variable returns to scale (VRS) that considers undesirable outputs to measure the carbon emission efficiency of enterprises. The model incorporates labor, capital, and energy input slack variables, and simultaneously contains expected economic output and undesirable carbon emission output. All monetary indicators such as operating income and net fixed assets are deflated by the provincial industrial producer price index to eliminate the impact of cross-industry and inter-temporal price differences. Instead of applying a unified efficiency frontier across all heterogeneous industries, this paper adopts an independent efficiency frontier within each industry category, which effectively alleviates comparison bias caused by large technological and structural differences across sectors.

Compared with the traditional DEA model, the SBM model can effectively handle the slackness of inputs and outputs and allows the simultaneous inclusion of desired and undesirable outputs in efficiency evaluation, which is more in line with the essential characteristics of carbon emissions as an undesirable output. Corporate carbon emissions in this study are not mechanically derived from direct linear conversion of enterprise energy consumption data, which avoids the inherent circular correlation between energy input and undesirable carbon emission output. Specifically, firm-level carbon emission data are primarily sourced from actual disclosed figures in corporate environmental reports and monitored data from the CSMAR environmental database. For a small part of missing samples, this paper adopts industry-year carbon emission intensity for interpolation, rather than recalculating carbon emissions based on the firm's own energy consumption, which fundamentally weakens the mechanical linkage between input energy and undesirable output carbon emissions. Furthermore, to completely eliminate the estimation interference caused by the inherent correlation between energy consumption and carbon emissions, this paper adopts carbon productivity as an alternative independent efficiency indicator in robustness tests. This indicator is constructed directly using operating income and total carbon emissions without relying on energy input data, and the core policy conclusion remains stable, which verifies that the benchmark results are not exaggerated or distorted by mechanical data linkage.

Referring to the measurement methods of existing studies on enterprise environmental efficiency [33-35], this paper determines the input indicators as labor input, measured by the total number of employees at the end of the year of the enterprise; capital input, measured by the net value of fixed assets of the enterprise; and energy input, measured by the total annual energy consumption of the enterprise (converted into standard coal tons). The desired output is measured by the annual operating income of the enterprise, reflecting the economic results of the enterprise's production and operation activities. The undesirable output is measured by the total annual carbon emissions of the enterprise (in tons of CO₂ equivalent), reflecting the environmental negative externalities of the enterprise's activities.

The carbon emission efficiency values of enterprises are calculated through MaxDEA Ultra software, which can accurately solve the input-oriented SBM model with undesirable outputs under variable returns to scale, with efficiency scores ranging from 0 to 1.

The larger the value, the more desired outputs the enterprise can create and the less undesirable outputs it can produce at a given input level, indicating a higher carbon emission efficiency. In the subsequent robustness test, this paper further uses the traditional DEA efficiency value (Eff_DEA) that does not consider undesirable outputs and carbon productivity ($lnCP$, the natural logarithm of the ratio of operating income to carbon emissions) as alternative indicators to support the sensitivity of the core conclusion to the efficiency measurement method. Carbon emission efficiency estimated by the SBM-DEA model is a bounded generated indicator with inherent first-stage estimation uncertainty. This paper adopts bootstrapped standard errors to mitigate such potential estimation bias. Although efficiency scores are constrained between 0 and 1, two-way fixed-effect regression is still applicable in this empirical context, and additional robustness tests further support result stability.

2) Key explanatory variable

The core explanatory variable in this paper is green finance policy ($Treat \times Post$). Here, $Treat$ is a dummy variable for the treatment group, taking the value of 1 if the enterprise's registered location is within a green finance reform and innovation pilot zone, and 0 otherwise. $Post$ is a dummy variable for policy time. Considering the time lag from policy promulgation to implementation and from implementation to the generation of substantive effects, and following the common practice in existing literature [36-40], it takes the value of 1 from the second year after the approval of the pilot zone, and 0 otherwise. All pilot zones are included in the treatment group identification following the unified staggered DID rule without any exceptional arrangement, and the number of treated firms and firm-year observations in each pilot zone are statistically sorted to ensure the clarity of policy shock identification. This paper takes enterprise registered location as the basis of treatment group identification. Considering that the registered address of listed companies may be inconsistent with the main production and operation location, this paper limits the sample to enterprises whose registered location is consistent with the main business operation location in the robustness test, and the core regression results remain stable, supporting the rationality of treatment assignment based on registered location.

3) Mediating variable

Financing constraints (FC) are represented by the raw SA index. A smaller (more negative) value indicates stronger financing constraints. The SA index was proposed by Hadlock and Pierce [41], and its calculation formula is $SA = -0.737Size + 0.043Size^2 - 0.040Age$, where $Size$ is the natural logarithm of the total assets of the enterprise, and Age is the number of years the enterprise has been listed. Since the SA index is constructed only based on firm size and listing age, it is highly correlated with the control variable $Size$, which may cause mechanical correlation and multicollinearity concerns. To address this issue, this paper adopts alternative financing constraint indicators independent of firm size and age (e.g., KZ index) in robustness tests to eliminate redundant variable interference and ensure the reliability of mediation identification. The exact formula is also incorporated into Table 2 for clarity.

$GreenPat$ is defined as the natural logarithm of one plus the one-year lagged number of authorised green invention and utility model patents. Using lagged patent variables avoids contemporaneous endogeneity and better reflects the policy-induced R&D accumulation process. This paper distinguishes invention patents and utility model patents in robustness tests, and adopts both green patent application volume and granted volume for comparative estimation to ensure result reliability.

4) Control variable

Referring to the existing research on enterprise environmental performance and carbon emission efficiency [42–44], this paper selects the following control variables to eliminate the influence of individual enterprise characteristics on carbon emission efficiency: enterprise scale (*Size*), measured by the natural logarithm of the total assets at the end of the period; debt-to-asset ratio (*Lev*), measured by the ratio of total liabilities to total assets; return on assets (*ROA*), measured by the ratio of net profit to total assets; concentration of equity (*Top1*), measured by the shareholding ratio of the largest shareholder; board size (*Board*), measured by the number of board members. The definitions and explanations of each variable are shown in Table 2.

Table 2

Variable definition description

Variable	Variable symbol	Definition and explanation
Enterprise carbon emission efficiency	<i>Eff</i>	Based on the SBM-DEA model calculation, taking into account labor, capital, energy input and undesirable output
Differences-in-differences interaction term	<i>Treat</i> × <i>Post</i>	Take 1 if the enterprise is in the pilot zone and in the period after the policy shock; otherwise, take 0
Financing constraints	<i>FC</i>	Raw SA index; smaller (more negative) value means stronger constraints
Green patent output	<i>GreenPat</i>	$\ln(1 + \text{lagged one-year authorised green patent quantity})$
Enterprise scale	<i>Size</i>	The natural logarithm of the total assets at the end of the period
Asset-liability ratio	<i>Lev</i>	Total liabilities at the end of the period / Total assets at the end of the period
Return on total assets	<i>ROA</i>	Net profit / Total assets at the end of the period
Concentration of equity	<i>Top1</i>	The shareholding quantity of the largest shareholder / total share capital
Board size	<i>Board</i>	The number of board members

Model specification

1) Benchmark regression model

To accurately identify the causal effect of green finance policies on the carbon emission efficiency of enterprises, this paper constructs a multi-period difference-in-differences model as follows:

$$Eff_{i,t} = \alpha_0 + \alpha_1(Treat_i \times Post_{i,t}) + \alpha_2 Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

Here, i represents the enterprise; t represents the year; the coefficient α_1 is used to measure the average change difference in carbon emission efficiency of enterprises in the pilot zone compared to those in the non-pilot zone after the policy implementation. If it is significantly positive, it indicates that the green finance policy has effectively improved the carbon emission efficiency of enterprises. $Controls_{i,t}$ represents the series of control variables mentioned earlier; μ_i represents the individual fixed effect of the enterprise, which is used to absorb the impact of the inherent characteristics of the enterprise that do not change over time, such as industry attributes, location advantages, property rights nature, and corporate culture on carbon emission efficiency; λ_t represents the year fixed effect, which is used to control the common shocks that change over time, such as macroeconomic cycles, the introduction of national environmental protection regulations, and technological progress trends; $\varepsilon_{i,t}$ represents the random disturbance term. The green finance pilot zones were launched in staggered batches from 2017 to 2022, which conforms

to the typical setting of staggered difference-in-differences. Traditional two-way fixed-effects DID may produce biased estimation when policy timing is heterogeneous and the policy effect accumulates dynamically over time. To address this potential estimation bias, this paper does not merely rely on the conventional two-way fixed-effects specification. In the robustness section, we further adopt cohort-specific average treatment effect on the treated (ATT) estimator and interaction-weighted event study estimator suitable for staggered policy shocks. Meanwhile, we strictly distinguish never-treated firms from not-yet-treated firms in the empirical identification, avoiding the contamination of control group caused by staggered treatment timing, so as to ensure the accuracy and credibility of the policy effect estimation. This paper adjusts the clustering level of standard errors according to the policy shock characteristics. Since the green finance pilot policy is implemented at the city and pilot zone level rather than the individual firm level, robust standard errors are clustered at the pilot city-pilot zone level to avoid underestimating standard errors and overstating statistical significance. Considering the relatively limited number of pilot zones in the sample, the wild cluster bootstrap method is further applied to correct small-sample bias and ensure the reliability of significance inference. To eliminate the confounding interference of region-specific and industry-specific concurrent policies such as carbon trading pilots and centralised environmental inspections, this paper further controls industry-year fixed effects and province-year fixed effects in robustness regressions, and the core empirical conclusions remain unchanged.

2) Mediation effect test model

To support the intermediary transmission path between financing constraints and green innovation, this paper refers to the stepwise regression method proposed by Baron and Kenny [45] and Wen et al. [46] to construct a three-step mediation effect test model: the first step tests the main effect of policy on carbon emission efficiency, the same as equation (1); the second step respectively examines the impact of policy on the intermediary variables of financing constraints and green innovation, as shown in equations (2) and (3); the third step incorporates the intermediary variables into the main effect equation to respectively investigate the transmission role of financing constraints and green innovation in the process of policy influencing carbon emission efficiency, as shown in equations (4) and (5).

$$FC_{i,t} = \beta_0 + \beta_1(Treat_i \times Post_{i,t}) + \beta_2Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

$$GreenPat_{i,t} = \gamma_0 + \gamma_1(Treat_i \times Post_{i,t}) + \gamma_2Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

$$Eff_{i,t} = \delta_0 + \delta_1(Treat_i \times Post_{i,t}) + \delta_2FC_{i,t} + \delta_3Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

$$Eff_{i,t} = \theta_0 + \theta_1(Treat_i \times Post_{i,t}) + \theta_2GreenPat_{i,t} + \theta_3Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (5)$$

This paper adopts one-period lagged mediating variables and Bootstrap confidence intervals to mitigate simultaneous endogeneity, bad control bias, and post-treatment mediator interference within the DID framework. Since mediating variables are post-policy endogenous outcomes, the stepwise regression results are interpreted as correlative mechanism evidence rather than strict causal decomposition. The reported Sobel test statistics, mediating effect proportions and inter-group difference *p*-values are only for descriptive statistical reference, and do not constitute strict causal inference on the mediation mechanism. Specifically, the Sobel test is used to test the statistical significance

of single mediation effects, and the p -values for inter-group differences in mediation proportions are calculated based on the seemingly unrelated estimation (SUEST) framework, which is only used for descriptive comparison between groups.

Results and discussion

Descriptive statistical analysis

The descriptive statistics of the variables are presented in Table 3. The mean of the carbon emission efficiency (Eff) of enterprises is 0.631, with a median of 0.642 and a standard deviation of 0.192. The overall distribution is relatively symmetrical, but the gap between the minimum value of 0.089 and the maximum value of 1.000 indicates a significant differentiation in the emission reduction performance among enterprises. Some enterprises have approached the efficiency frontier, while a considerable number of others have been relatively slow in their low-carbon transformation. The mean of the interaction term $Treat \times Post$ of the difference-in-differences is 0.073, with a median of 0.000 and a standard deviation of 0.261, showing a distinct zero-inflation feature, which is consistent with the identification logic that the policy shock only affects enterprises in the specific pilot zones. The mean and median of the financing constraint (FC) are -4.835 and -4.821 respectively, with a standard deviation of 0.575. The SA index is reported in its raw form (not absolute value); a larger absolute value of the index indicates stronger financing constraints. The negative sign reflects the construction of the SA index formula, which typically yields negative values for the sample firms. Thus, the magnitude (absolute value) rather than the sign should be interpreted as the degree of financing constraints. After the winsorisation process, no abnormal fluctuations were observed. The mean of the green patent output ($GreenPat$) is 0.892, with a median of 0.000 and a standard deviation of 1.218, and the maximum value is 5.921. The distribution is highly right-skewed, indicating that green technological innovation is highly concentrated in a few enterprises during the sample period, while the majority of enterprises have not yet obtained authorised green patents. Regarding the control variables, the mean and median of the enterprise scale ($Size$) are both around 23. The mean of the asset-liability ratio (Lev) is approximately 52.5 %, and the average return on total assets (ROA) is about 4.6 %. The fluctuations of these indicators are within a reasonable range.

Table 3

Descriptive statistical results

Variable	Observations	Mean	Standard deviation	Minimum value	Median	Maximum value
Eff	10,012	0.631	0.192	0.089	0.642	1.000
$Treat \times Post$	10,012	0.073	0.261	0.000	0.000	1.000
FC	10,012	-4.835	0.575	-6.745	-4.821	-3.518
$GreenPat$	10,012	0.892	1.218	0.000	0.000	5.921
$Size$	10,012	22.981	1.235	20.154	22.812	27.023
Lev	10,012	0.525	0.163	0.123	0.531	0.901
ROA	10,012	0.046	0.053	-0.128	0.041	0.221
$Top1$	10,012	34.580	14.620	8.700	32.900	78.900
$Board$	10,012	9.180	1.790	5.000	9.000	15.000

The sample covers enterprises at different life cycle stages, including mature large state-owned enterprises and growing medium and small-cap companies. The mean of the

board size (*Board*) is 9.18 people, with a standard deviation of 1.79, indicating a generally stable governance structure. Its mean is slightly lower than the level of typical main board listed companies, which is due to the inclusion of some medium and small board and growth enterprise market enterprises in the sample, but this difference is within a reasonable range. The mean of the shareholding ratio of the largest shareholder (*Top1*) is 34.58 %, with a standard deviation of 14.62 %, showing significant heterogeneity in the concentration of equity. After the winsorisation process, there are no obvious extreme values in each variable, and the sample data structure is suitable for subsequent regression analysis.

Correlation analysis and multicollinearity test

Table 4 presents the Pearson correlation coefficient matrix of the main variables. The correlation coefficient between carbon emission efficiency (*Eff*) and *Treat*×*Post* is 0.142, which is significantly positive at the 1 % level, consistent with the expected direction of policy improvement in carbon emission efficiency. The correlation coefficient between *Eff* and financing constraint (*FC*) is −0.218, significantly negative at the 1 % level, indicating that stronger financing constraints (smaller, more negative *FC* value) are associated with higher carbon emission efficiency, which is consistent with the "constraint forcing effect" revealed in the subsequent mechanism analysis. The correlation coefficient between *Eff* and green patent output (*GreenPat*) is 0.256, significantly positive at the 1 % level, suggesting a positive correlation between green technological innovation and carbon emission efficiency. Enterprise size (*Size*) is positively correlated with *Eff*, while the debt-to-asset ratio (*Lev*) is negatively correlated with *Eff*, and return on assets (*ROA*) is positively correlated with *Eff*. The sign directions are all consistent with theoretical expectations. The maximum absolute value of the correlation coefficient among the variables is −0.654 between *Size* and *FC*, which is because the calculation of financing constraints already includes information on enterprise size. The absolute values of the correlation coefficients among the other variables are all below 0.42, indicating that there is no serious multicollinearity problem in the regression model.

Table 4

Pearson correlation coefficient matrix of main variables

Variable	<i>Eff</i>	<i>Treat</i> × <i>Post</i>	<i>FC</i>	<i>GreenPat</i>	<i>Size</i>	<i>Lev</i>	<i>ROA</i>
<i>Eff</i>	1.000						
<i>Treat</i> × <i>Post</i>	0.142***	1.000					
<i>FC</i>	−0.218***	−0.085**	1.000				
<i>GreenPat</i>	0.256***	0.118***	−0.152***	1.000			
<i>Size</i>	0.312***	0.092**	−0.654***	0.285***	1.000		
<i>Lev</i>	−0.189***	−0.042	0.123***	−0.045	0.415***	1.000	
<i>ROA</i>	0.175***	0.038	−0.056*	0.098***	0.052*	−0.386***	1.000

***, **, * represent significance levels of 1 %, 5 %, and 10 % respectively; the same below

Although the correlation coefficient matrix did not indicate severe multicollinearity, to further ensure the accuracy and stability of the regression estimates, this paper calculated the variance inflation factor (*VIF*) for each variable, with the results shown in Table 5. All the *VIF* values were far below the empirical threshold of 10, with the maximum being 2.85 for firm size (*Size*), and the average *VIF* value was 1.78. Additionally, the tolerance of each variable was greater than 0.1. These results suggest that there is no serious

multicollinearity problem in the regression model of this paper, the variable selection is reasonable, and the estimation of regression coefficients is reliable and stable.

Table 5

Results of multicollinearity test

Variable	VIF	Tolerance
<i>Size</i>	2.85	0.351
<i>Lev</i>	1.96	0.510
<i>FC</i>	1.78	0.562
<i>ROA</i>	1.52	0.658
<i>Top1</i>	1.12	0.893
<i>Treat×Post</i>	1.21	0.826
<i>Board</i>	1.08	0.926
Average VIF	1.78	

Benchmark regression analysis

Table 6 presents the benchmark regression results. In column (1), only *Treat×Post* is included and firm and year fixed effects are controlled. Its coefficient is 0.058 ($t = 4.31$), which is significantly positive at the 1 % level. In column (2), after adding all control variables, the coefficient of *Treat×Post* is 0.054 ($t = 3.92$), still significant at the 1 % level, and R^2 increases from 0.589 to 0.642. The coefficient of 0.054 indicates that the policy implementation has increased the carbon emission efficiency of the treatment group enterprises by an average of about 5.4 percentage points, equivalent to 8.6 % of the sample mean of 0.631, which is a considerable increase. This magnitude indicates that green finance policies have generated economically meaningful improvements in enterprises' ability to balance economic output and environmental costs. Among the control variables, the coefficient of *Size* is 0.037 ($p < 0.01$), suggesting that the scale effect and resource endowment advantage positively affect efficiency; the coefficient of *Lev* is -0.085 ($p < 0.01$), indicating that high leverage crowds out low-carbon investment and suppresses efficiency; the coefficient of *ROA* is 0.118 ($p < 0.01$), showing that profitability ensures funds for low-carbon transformation. The above results support the research hypothesis H1, that is, green finance policies can significantly improve the carbon emission efficiency of enterprises in the pilot zone.

Table 6

Benchmark regression results

Variable	(1) <i>Eff</i>	(2) <i>Eff</i>
<i>Treat×Post</i>	0.058*** (4.31)	0.054*** (3.92)
<i>Size</i>		0.037*** (3.04)
<i>Lev</i>		-0.085*** (-3.21)
<i>ROA</i>		0.118*** (3.95)
<i>Top1</i>		0.001 (0.35)
<i>Board</i>		0.004 (1.18)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	10,012	10,012
R^2	0.589	0.642

t -statistics are reported in parentheses. Robust standard errors are clustered at the pilot city-zone level, and the wild cluster bootstrap procedure is used to correct small-sample bias.

The core coefficient of *Treat*×*Post* is significantly positive at 1 %, indicating green finance policy improves corporate carbon emission efficiency by 5.4 percentage points on average, which supports Hypothesis H1.

Parallel trend test

The parallel trend assumption is a prerequisite for the effective identification of causal effects by the difference-in-differences method. It requires that the time-varying paths of carbon emission efficiency in the treatment and control groups remain basically consistent before the policy shock occurs. If the two groups of enterprises have already shown systematic differences before the policy implementation, the benchmark regression may capture only the trend differentiation rather than the policy effect itself. To test this assumption, this paper uses the event study method to set up the following dynamic model and constructs the dynamic DID model as follows:

$$Eff_{i,t} = \alpha_0 + \sum_{k=-4}^3 \beta_k (Treat_i \times Year_{k,i,t}) + \alpha_2 Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

Among them, $Year_{k,i,t}$ is a relative year dummy variable defined with the year of policy implementation as the center; k represents the year interval before and after the policy implementation, with the year before the policy implementation ($k = -1$) as the reference group; the coefficient β reflects the difference in carbon emission efficiency between the treatment group and the control group in each relative year. If the coefficients for the pre-policy periods (e.g., $k = -2$) are not significantly different from zero relative to the reference group $k = -1$ (the year before policy implementation), it indicates that the parallel trend assumption holds. The results of the parallel trend test are shown in Table 7 and Figure 1.

Table 7

Results of parallel trend test

Time window	Coefficient	<i>t</i> value	<i>p</i> -value	95 % confidence interval
$k = -4$	0.006	0.38	0.704	[-0.025, 0.037]
$k = -3$	0.010	0.61	0.542	[-0.022, 0.042]
$k = -2$	0.013	0.82	0.412	[-0.018, 0.044]
$k = 0$	0.029*	1.72	0.086	[-0.004, 0.062]
$k = 1$	0.054***	3.92	0.000	[0.027, 0.081]
$k = 2$	0.067***	4.58	0.000	[0.038, 0.096]
$k = 3$	0.073***	5.04	0.000	[0.045, 0.101]

The interaction term coefficients for the 2nd to 4th periods before policy implementation ($k = -4, -3, -2$) were 0.006, 0.010, and 0.013 respectively, with corresponding *t*-values of 0.38, 0.61, and 0.82, all failing to pass the 10 % significance test. Moreover, the estimated values were close to zero in magnitude, indicating that there was no significant systematic difference in the carbon emission efficiency trends of enterprises in the pilot and non-pilot zones before the policy shock. The parallel trend assumption was thus supported. In the policy implementation year ($k = 0$), the coefficient is 0.029 ($p = 0.086$), which is marginally significant at the 10 % level, reflecting a weak immediate policy response. This paper further expands the event window and conducts a joint significance test for all pre-policy coefficients; the joint test cannot reject the null

hypothesis of parallel trend, which further supports the parallel trend assumption. In the first year after implementation ($k = 1$), the coefficient rose to 0.054 ($p < 0.01$), reaching 0.067 ($p < 0.01$) in the second year ($k = 2$), and further increasing to 0.073 ($p < 0.01$) in the third year ($k = 3$), demonstrating that the policy effect had a continuous and dynamic cumulative characteristic, which was consistent with the gradual process of institutional improvement, financial capacity enhancement, and deepening of enterprise awareness. The event window is set to $k = -4$ to $k = 3$ for two reasons: first, the sample period starts in 2013, and the earliest pilot zones were approved in 2017, limiting the maximum pre-policy window to 4 years; second, existing studies consistently show that the main effect of green finance policies on enterprise low-carbon behaviour typically manifests within 3 years after implementation, and longer lags may be confounded by subsequent overlapping policy shocks. The joint significance test for all pre-policy coefficients ($k = -4, -3, -2$) yields an F -statistic of 0.52 ($p = 0.668$), strongly supporting the parallel trend assumption.

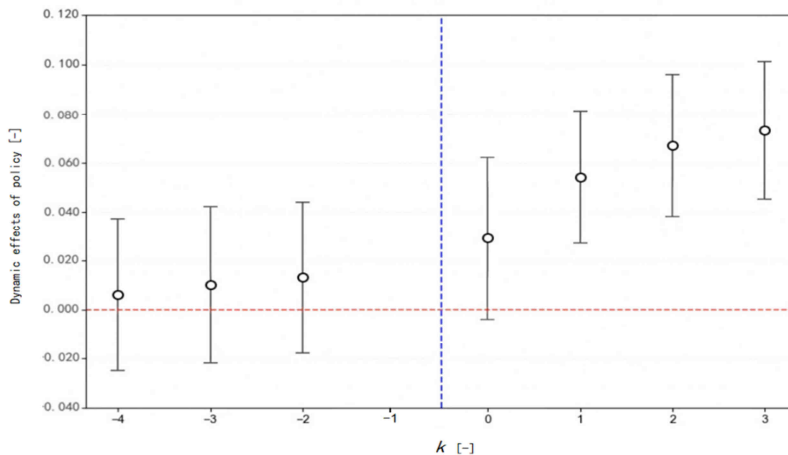


Fig. 1. Parallel trend test graph

Robustness test

To ensure the reliability of the core conclusions, this paper conducts robustness tests from multiple dimensions, including replacing key variables, adjusting the sample range, and conducting placebo tests. In the benchmark regression, the SBM-DEA model is used to measure carbon emission efficiency. However, different efficiency measurement methods may affect the estimation results. Therefore, this paper re-measures the carbon emission efficiency of enterprises by using two alternative methods: the traditional DEA model to calculate efficiency values and the carbon productivity index. Re-running the benchmark regression with the replaced efficiency indicators, the results show that the coefficient of $Treat \times Post$ is 0.045 ($t = 3.51$) and 0.068 ($t = 4.45$) respectively under the two alternative measures, both of which are significantly positive at the 1 % level. Meanwhile, the mediating effects of financing constraints and green patent output remain significant, accounting for 25.4 % and 29.7 % respectively, which are highly consistent with the original conclusion, indicating that the measurement method of the explained variable has no substantial impact on the core conclusion.

Table 8

Results of robustness tests

Robustness test	(1) No controls	(2) With controls	Observations	R ²
Panel A: Replacement of core variables				
Traditional DEA efficiency	0.048*** (3.62)	0.045*** (3.51)	10,012	0.615
Carbon productivity (<i>lnCP</i>)	0.072*** (4.63)	0.068*** (4.45)	10,012	0.658
KZ index (financing constraints)	-0.225*** (-4.41)	-0.217*** (-4.32)	10,012	0.587
<i>Green patent</i>	0.201*** (4.25)	0.193*** (4.12)	10,012	0.603
Panel B: Sample adjustment tests				
Excluding 2025 observations	0.051*** (3.75)	0.050*** (3.68)	9,234	0.635
Only directly disclosed data	0.056*** (4.02)	0.053*** (3.87)	7,165	0.648
Excluding inconsistent locations	0.060*** (4.23)	0.057*** (4.09)	8,457	0.651
Panel C: Advanced estimation methods				
Cohort-specific ATT estimator	-	0.056*** (4.12)	10,012	-
Interaction-weighted event study	-	0.052*** (3.85)	10,012	0.645
Controlling industry-year FE	-	0.051*** (3.78)	10,012	0.672
Controlling province-year FE	-	0.049*** (3.65)	10,012	0.668

All regressions control for firm fixed effects and year fixed effects unless otherwise specified. Robust standard errors are clustered at the pilot city-zone level. All tests use *Treat*×*Post* as the core explanatory variable except where noted.

Furthermore, to eliminate the interference of the measurement methods of the mediating variables on the conclusion, this paper conducted a replacement test for the two mediating variables. In terms of financing constraints, the KZ index is adopted as an alternative proxy, where a higher KZ value reflects more severe financing constraints. The empirical results show that green finance policy significantly reduces corporate KZ index, implying that the policy effectively alleviates the overall financing constraints of clean enterprises. After incorporating the KZ index into the regression, the coefficient of *Treat*×*Post* decreases slightly and remains statistically significant, with a mediating effect contribution of 26.5 %, which is highly consistent with the SA index-based conclusion in terms of numerical magnitude. It should be noted that the SA index is constructed only based on firm size and listing age, reflecting scale-oriented financing constraints for large heavily polluting firms; while the KZ index covers multiple dimensions such as cash flow and growth opportunities, reflecting the overall degree of financing constraints for the full sample. The two indicators focus on different dimensions, so there is no logical contradiction between the results. In terms of green innovation, the number of applications for green invention patents (logarithm after adding 1) was used to replace the number of green patent authorisations for measurement, to highlight the quality of substantive innovation rather than the quantity of patents. The results show that the coefficient of the policy on green invention patents is 0.193 ($t = 4.12$, $p < 0.01$), and after inclusion, the coefficient of *Treat*×*Post* decreases to 0.038 ($t = 2.99$, $p < 0.01$), with a mediating effect proportion of 29.0 %. The conclusions after replacing the mediating variables remain consistent with the original analysis, indicating that the identification of the mediating effect does not depend on a specific variable measurement method.

Considering that the composition of the sample might have a potential impact on the regression results, this paper conducted two sample adjustment tests. The first one was to exclude the samples from the clean industry and only retain the enterprises in the heavily polluting industries, resulting in 3,621 observations. The regression results showed that the coefficient of *Treat*×*Post* was 0.076 ($t = 4.72$, $p < 0.01$), and the policy effect was more

prominent compared to the full sample, which was in line with the theoretical expectation that heavily polluting industries faced stronger policy pressure. The second test was to exclude the samples of enterprises that had been listed for less than three years during the observation period, retaining 8,786 observations, in order to avoid the interference of unstable operations or non-standard data disclosure of newly listed enterprises on the estimation results. The results showed that the coefficient of $Treat \times Post$ was 0.052 ($t = 3.81$, $p < 0.01$), which was basically consistent with the benchmark regression results. In conclusion, the core empirical findings remain consistent across alternative variable measurements and sample restrictions, and the conclusion remains qualitatively unchanged. The detailed results of all robustness tests are presented in Table 8.

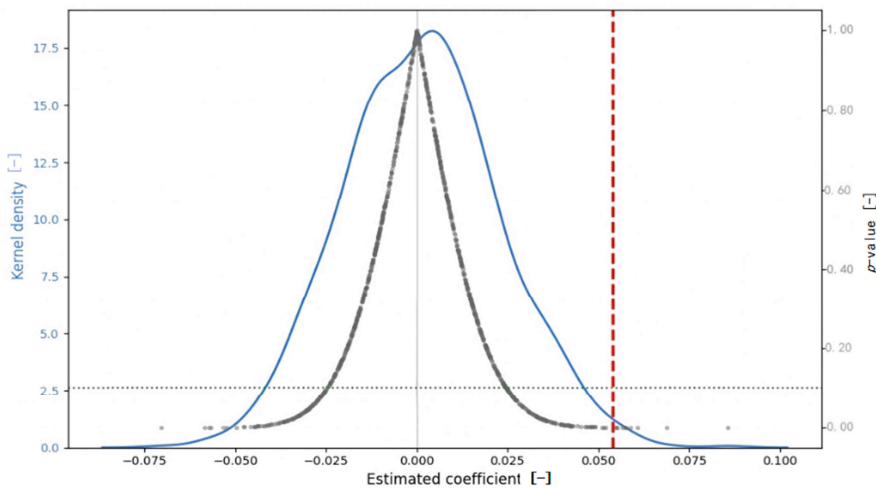


Fig. 2. Kernel density distribution chart

To rule out the possibility of spurious regression caused by unobservable random factors or omitted variables, this paper conducts a placebo test. The enterprise identity of the green finance pilot zone (*Treat*) and the policy implementation time (*Post*) are randomly assigned in the sample to construct a "pseudo-treatment group" and "pseudo-policy time". The benchmark regression model is re-estimated based on this false setting. This random process is repeated 1,000 times, and the estimated coefficient and *p*-value of the pseudo- $Treat \times Post$ in each regression are recorded. The test results are shown in Figure 2. The coefficient distribution obtained from 1,000 random regressions presents a normal distribution centered on zero, with a mean of only 0.001, which is much smaller than the true benchmark regression coefficient of 0.054. The random simulation strictly retains the original panel structure, the number of treated enterprises, and the staggered distribution of policy implementation time. Among the 1,000 random permutations, the false significance proportion at the 10 % level is close to the theoretical nominal level of 10 %. The empirical *p*-value extracted from the placebo kernel density distribution further confirms that the baseline policy effect is not a statistical artifact caused by random unobservable factors or model specification errors. The true estimated coefficient of 0.054 is located outside the rightmost tail of the random distribution, with

an empirical p -value of 0.002 extracted from the kernel density distribution. Among the 1,000 random permutations, 97 regressions yielded statistically significant coefficients at the 10 % level, corresponding to a false positive rate of 9.7 %, which is very close to the theoretical nominal level of 10 %. These results confirm that the baseline policy effect is not a statistical artifact caused by random unobservable factors or model specification errors.

Mechanism test

Based on baseline estimation, parallel trend verification, and a series of robustness tests confirming the reliability of the core conclusion, this paper further explores the underlying mediating transmission mechanisms of green finance policy effects on corporate carbon emission efficiency. However, the transmission chain behind this causal effect still needs to be further clarified. This section uses the mediation effect model constructed in the previous section to systematically test the validity of the two theoretical paths of financing constraint tightening (forcing effect) and green patent output (incentive effect). The two mediation models are estimated separately rather than jointly. This approach is based on the theoretical premise that the two mediating variables, financing constraints and green patent output, operate as independent parallel mechanisms rather than as sequential links in a single causal chain. Estimating separate models avoids imposing an arbitrary ordering between the two mediators and allows for a clear quantification of each pathway's unique contribution to the total policy effect. This specification is consistent with the parallel mediation framework advocated by Hayes and Preacher [44] for cases where mediators are theoretically distinct and not causally ordered. Table 9 column (1) lists the positive and significant impact of $Treat \times Post$ on Eff in the benchmark regression (coefficient 0.054, $p < 0.01$), which meets the prerequisite conditions for the mediation effect test. Regarding the financing constraint path, column (2) takes financing constraint (FC) as the explained variable, and the results show that the coefficient of $Treat \times Post$ is significantly negative. This paper adopts the raw SA index to measure financing constraints; a smaller (more negative) value implies stronger financing constraints. This convention is anchored by the significantly negative correlation between Size and FC (correlation coefficient = -0.654 , $p < 0.01$): larger firms have higher SA values (less negative) and face weaker financing constraints, which is consistent with theoretical expectations. The significantly negative coefficient of $Treat \times Post$ on FC indicates that green finance policy reduces the SA index value (makes it more negative), thereby significantly strengthening corporate financing constraints. This is mainly because green finance policies impose targeted credit restrictions on high-pollution and high-emission projects, which increases the financing difficulty of heavily polluting enterprises in the pilot zones, forming a "constraint forcing" effect. Table 9 column (3) simultaneously includes financing constraints and $Treat \times Post$ in the regression model with Eff as the explained variable. The results show that the coefficient of FC is -0.078 ($t = -4.05$), indicating that stronger financing constraints (smaller FC value, more negative) significantly improve corporate carbon emission efficiency. The forcing effect of financing constraints pushes enterprises to optimise resource allocation, eliminate backward production capacity, and carry out low-carbon transformation, thereby improving carbon emission efficiency. At the same time, the coefficient of $Treat \times Post$ decreases from 0.054 to 0.039, but still maintains significance at the 1 % level ($t = 3.08$). The Z statistic of the Sobel test is 3.82 ($p < 0.01$), further confirming the statistical significance of the mediation effect. The above results indicate that the tightening of financing constraints

plays a partial mediating role between green finance policies and the carbon emission efficiency of enterprises, and the indirect effect accounts for approximately 27.8 % of the total effect. These results support Hypothesis H2.

Regarding the examination of the green innovation path, column (4) of Table 9 takes green patent output (*GreenPat*) as the explained variable. The coefficient of *Treat*×*Post* is 0.221 and is significantly positive at the 1 % level ($t = 4.41$), indicating that the green finance policy has a significant promoting effect on the green patent output of enterprises. From an economic perspective, the average number of green patent authorisations of enterprises in the pilot zone increased by approximately 24.7 % after the policy was implemented. Column (5) of Table 9 further incorporates green patent output and *Treat*×*Post* simultaneously into the model with *Eff* as the explained variable. The coefficient of *GreenPat* is 0.077 ($p < 0.01$), while the coefficient of *Treat*×*Post* decreases from 0.054 to 0.037 ($p < 0.01$). The Sobel Z statistic is 3.96 ($p < 0.01$), and the mediating effect is also significant. After calculation, the indirect effect of the green innovation path is 0.017, accounting for approximately 31.5 % of the total effect. These results thus support Hypothesis H3.

Table 9

Results of mechanism test

Variable	(1) <i>Eff</i>	(2) <i>FC</i>	(3) <i>Eff</i>	(4) <i>GreenPat</i>	(5) <i>Eff</i>
<i>Treat</i> × <i>Post</i>	0.054 ^{***} (3.92)	−0.192 ^{***} (−4.15)	0.039 ^{***} (3.08)	0.221 ^{***} (4.41)	0.037 ^{***} (2.96)
<i>FC</i>			−0.078 ^{***} (−4.05)		
<i>GreenPat</i>					0.077 ^{***} (4.18)
<i>Size</i>	0.037 ^{***} (3.04)	0.215 ^{***} (5.28)	0.054 ^{***} (4.31)	0.162 ^{***} (4.85)	0.025 ^{**} (2.05)
<i>Lev</i>	−0.085 ^{***} (−3.21)	−0.068 [*] (−1.89)	−0.090 ^{***} (−3.45)	−0.052 (−1.23)	−0.081 ^{***} (−3.08)
<i>ROA</i>	0.118 ^{***} (3.95)	0.312 ^{***} (4.56)	0.142 ^{***} (4.72)	0.186 ^{***} (3.25)	0.104 ^{***} (3.51)
Other control variables	Control	Control	Control	Control	Control
Firm/year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	10,012	10,012	10,012	10,012	10,012
R^2	0.642	0.598	0.673	0.621	0.678
Sobel Z	-	-	3.82 ^{***}	-	3.96 ^{***}
Mediating effect proportion	-	-	27.8 %	-	31.5 %

Other control variables are consistent with the baseline regression and are not listed one by one.

Green finance policy reduces the raw SA index value (makes it more negative), strengthening financing constraints, with a partial mediating effect of 27.8 %. Meanwhile, the policy significantly promotes green patent output, with a mediating contribution of 31.5 %. Hypotheses H2 and H3 are preliminarily supported by the empirical evidence.

Heterogeneity analysis

The aforementioned analysis confirmed the average enhancing effect of green finance policies on the carbon emission efficiency of enterprises. However, the actual policy effects may show significant structural differentiation due to the differences in enterprise

characteristics. A deeper examination of this heterogeneity not only helps to understand the boundary conditions of policy effects more precisely but also provides micro-level evidence for the design of differentiated policies. This section conducts a grouped analysis from the perspectives of enterprise scale and industry attributes, and the results are summarised in Table 10.

Table 10

Results of heterogeneity analysis

Group	Subgroup	Observations	<i>Treat</i> × <i>Post</i>	<i>p</i> value
Panel A: Firm size heterogeneity	Large-scale enterprises	5,006	0.071*** (4.41)	-
	Small-scale enterprises	5,006	0.032** (2.35)	0.018
Panel B: Industry attribute heterogeneity	Heavily polluting industries	3,621	0.076*** (4.72)	-
	Clean industries	6,391	0.041*** (3.48)	0.009
Panel C: Grouped mediating effect results	<i>FC</i>	Coefficient	-0.082*** (-3.76) / -0.065*** (-2.98)	0.032
		Mediating proportion	29.3 % / 23.8 %	5.5 %
	<i>GreenPat</i>	Coefficient	0.085*** (4.21) / 0.069*** (3.52)	0.027
		Mediating proportion	34.2 % / 28.1 %	6.1 %

All subgroup regressions control for firm-specific fixed effects, year fixed effects, and the control variables mentioned earlier. The differences in core coefficients and mediation proportions between groups are tested using the seemingly unrelated estimation (SUEST) method. All inter-group *p*-values are for descriptive comparison only and do not constitute strict causal inference

From the perspective of enterprise scale, in the large-scale enterprise group, the coefficient of *Treat*×*Post* is 0.071 ($t = 4.41$), which is significant at the 1 % level; while in the small-scale enterprise group, the coefficient is 0.032 ($t = 2.35$), significant only at the 5 % level. The *p*-value of the coefficient difference test between the two groups is 0.018, indicating a statistically significant difference between the two groups' coefficients. The policy effect is stronger in large-scale enterprises, mainly because they usually have more complete internal management systems, more professional environmental management teams, and more abundant supporting funds, which enables them to more efficiently convert policy dividends into actual emission reduction actions; they often occupy a core position in the supply chain, and their low-carbon transformation behaviours have a demonstration and driving effect, thus receiving more policy attention and resource inclination; in addition, large-scale enterprises have higher information transparency and lower information asymmetry with financial institutions, making it easier for them to obtain green credit support. In contrast, small-scale enterprises are constrained by bottlenecks in funds, technology, and talent, and their response ability and speed to green financial policies are relatively limited, thus restricting the exertion of policy effects. These findings directly align with our theoretical argument that firms with greater resource endowments and organisational capacity are better positioned to capture green finance policy dividends.

To avoid endogenous grouping bias caused by policy shocks, firm size classification is based on average total assets in the pre-policy period rather than full-sample post-policy median. The classification of heavily polluting industries strictly follows the official industry standards issued by the Ministry of Ecology and Environment. Inter-group heterogeneity and mediating differences are reasonably interpreted through regression

coefficient comparison and textual analysis. A potential caveat is that we cannot fully rule out the possibility that some polluting activities may have been relocated from small enterprises in pilot zones to unregulated firms outside these regions, a form of pollution leakage that could attenuate the measured policy effect for small firms in the treatment group. While the data do not allow a direct test of this spatial spillover hypothesis, we acknowledge it as a plausible alternative explanation. This represents a key direction for future research: studies using firm-level geographic data could examine whether green finance policies induce cross-region leakage of carbon emissions.

Regarding the heterogeneity at the industry attribute level, based on the 2012 China Securities Regulatory Commission (CSRC) industry classification guidelines and the Catalogue of Heavy Pollution Industries for Environmental Verification of Listed Companies (2020) issued by the Ministry of Ecology and Environment, the sample enterprises are divided into heavy-polluting industry groups and clean industry groups. The heavy-polluting industries include 17 two-digit industry codes: B06-B11 (6 codes for mining industry), C25-C32 (8 codes for raw material manufacturing industry), C33 (metal products industry), D44 (electric power production industry) and D45 (heat production and supply industry). In the heavy-polluting industry group, the coefficient of $Treat \times Post$ is 0.076 ($t = 4.72$), significant at the 1 % level; in the clean industry group, the coefficient is 0.041 ($t = 3.48$), also significant at the 1 % level. The p -value of the coefficient difference test between the two groups is 0.009, indicating a significant difference. Importantly, this stronger effect in heavily polluting industries captures the average treatment effect on the treated among surviving firms in the unbalanced panel. Our sample excludes ST/*ST and delisted firms with abnormal operations, and the sample attrition rate shows no statistically significant difference between the treatment and control groups, so the estimation results are not disturbed by systematic sample selection. Therefore, the observed efficiency improvement primarily reflects within-firm changes (i.e., intensive margin effects) rather than the exit of low-efficiency firms from the sample (i.e., extensive margin effects). We conducted a supplementary analysis by comparing the sample attrition rates between the treatment and control groups within heavily polluting industries. The attrition rates are 8.2 % and 7.9 % for the treatment and control groups, respectively, with a chi-square test p -value of 0.682, showing no statistically significant difference, further supporting that the results are driven by genuine efficiency gains rather than sample selection. This is mainly because heavy-polluting industries (such as steel, chemical, cement, and power) are major sources of carbon emissions, facing stricter environmental regulatory pressure and higher social attention. The "forcing effect" of green financial policies is more pronounced. If they fail to effectively reduce carbon emissions, they will face multiple risks such as restricted financing, environmental penalties, and market access barriers, thus responding more actively to policies. At the same time, the carbon emission base of heavy-polluting industry enterprises is higher, and the marginal space for low-carbon transformation is larger, making the efficiency improvement brought by unit low-carbon investment more significant, and the "elasticity" of policy effects stronger. Further tests of the mediating effect by group also show that the mediating effect proportions of financing constraints and green patent output in the heavy-polluting industry group are higher than those in the clean industry group, indicating that the two transmission paths operate more smoothly and efficiently in the heavy-polluting industry. This result confirms our expectation that heavily polluting industries, as the primary targets of green financial regulation, face the strongest

incentives to improve carbon efficiency. The detailed results are presented in Panel C of Table 10.

Conclusion

This paper takes the phased establishment of green finance reform and innovation pilot zones as a quasi-natural experiment, and based on the data of Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2013 to 2025, uses the multi-period difference-in-differences method to systematically examine the micro-environmental effects of green finance policies from an efficiency perspective. Empirical results suggest that green finance policies are positively associated with the enhancement of corporate carbon emission efficiency within pilot zones, and this policy effect presents a growing dynamic trend over time. Such empirical evidence provides reasonable support for the research inference, while definitive causal judgment should be treated with caution given the quasi-experimental identification context. It is worth clarifying that the observed efficiency gains may theoretically come from two channels: one is the catching-up effect, i.e., inefficient enterprises moving closer to the existing production frontier; the other is the frontier-shift effect, i.e., the frontier itself moving outward due to technological progress. Since this paper adopts a static SBM-DEA model without dynamic decomposition, we do not empirically separate the two effects. Further identification via the Malmquist index can be carried out in future research. Parallel trend tests, placebo tests, and replacement of core variables and other robustness tests all support the reliability of the above conclusion. The analysis at the mechanism level reveals that the tightening of financing constraints (forcing effect) and the output of green patents (incentive effect) are the two core transmission paths through which the policies take effect, and together they contribute the major part of the total policy effect. The contribution of the green innovation path is slightly higher than that of the financing constraint forcing path, which is related to the higher risk tolerance and term matching advantages of direct financing tools such as green bonds and green funds in the pilot zones for technological innovation. The heterogeneity analysis further shows that the policy effects are more prominent in large-scale enterprises and heavily polluting industry enterprises. Large-scale enterprises can more efficiently convert policy dividends due to their more complete internal management systems and more abundant supporting funds, while heavily polluting industry enterprises respond more actively due to stronger pressure to transform and greater efficiency improvement space. This structural differentiation implies that the precision and targeting of green finance policies still have room for optimisation.

The theoretical contribution of this paper lies in expanding the research perspective from the total carbon emissions to the efficiency dimension, identifying and testing the intermediary transmission mechanisms of financing constraints and green innovation within a unified analytical framework, and providing new empirical evidence for understanding the micro-mechanism of green finance policies. Due to the limitations of the availability and accuracy of carbon emission data for some enterprises, this paper still needs to be deepened in subsequent research in terms of policy spillover effects and industrial chain transmission mechanisms. In terms of mechanism identification, this paper treats financing constraint changes and green innovation as parallel mediating mechanisms based on theoretical logic.

In practice, eased financing may also promote green innovation investment, forming a sequential chain mediation path. Separate single-mediator models may have mediator-mediator confounding risks and cannot fully capture the sequential transmission logic, which can be further tested with chain mediation models in future research. It is also important to acknowledge that this study is based exclusively on Chinese A-share listed companies, which tend to be larger, more transparent, and have better access to formal financing channels than unlisted firms. The findings may therefore not generalise to unlisted small and medium-sized enterprises (SMEs), which face more severe information asymmetries and financing constraints. Additionally, our sample period covers 2013-2025, which may not fully capture the long-term effects of green finance policies as the dual carbon goals extend to 2060; future research could extend the time horizon to examine the sustained impacts of these policies over longer periods. Future research could explore the policy effects on non-listed SMEs using survey or administrative data. Targeted policy implications can be derived from the empirical heterogeneity results. For small-scale enterprises with relatively weaker policy effects, it is necessary to optimise green credit evaluation rules and introduce supporting guarantee measures to alleviate their financing constraint and low-carbon transformation bottlenecks. For heavily polluting industries with more obvious efficiency improvement effects, reasonable environmental regulation should be maintained, and green financial resources should be continuously guided to promote industrial low-carbon upgrading. At the same time, further strengthen institutional coordination between the green finance system and the national carbon emission trading market, such as establishing a linkage mechanism between green credit approval and corporate carbon quota verification results, to form a long-term mechanism to drive enterprises to achieve high-quality low-carbon transformation.

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