
Impact of Carbon Emission Trading Policy on Green Innovation Behavior of High-energy Consuming Enterprises Based on Difference-in-Difference Model and PSM-DID

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Abstract

Affected by global climate change, the carbon emission trading policy, as a vital market-based environmental regulatory tool, plays a crucial role in promoting carbon reduction. To explore the impact of this policy on the green innovation quality of high-energy-consuming enterprises, this study combines the difference-in-difference model with propensity score matching to conduct an empirical analysis. Propensity score matching results show that the covariate balance between the treatment group and control group is significantly improved, verifying the reliability of the sample matching. The core explanatory variable $Treat*P$ has a positive and significant coefficient at the 1% level, indicating that high-energy-consuming enterprises in pilot areas tend to adopt high-value green innovation strategies after

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implementing the Carbon Emission Trading policy. This study reveals the net effect of the carbon emission trading policy on enterprises' green innovation behavior, provides a theoretical basis for optimizing the Carbon Emission Trading mechanism, and offers practical references for promoting the green transformation of high-energy-consuming industries.

Keywords: Difference-in-difference, PSM-DID, CET policy, green innovation, high-energy consuming enterprises.

1 Introduction

Whether the Carbon Emission Trading (CET) policy can achieve green innovation. Emission reduction is a crucial exploration to promote green development [1, 2]. The CET policy guides enterprises to reduce Carbon Emissions (CE) through market mechanisms, promotes green innovation, and thus promotes high-quality economic development. However, existing research has mostly focused on macro or meso levels, with limited exploration on micro level green innovation behavior of enterprises [3]. Existing PSM-DID studies on the CET policy mainly focus on macro emission reduction effects or single-dimensional innovation outputs, lacking in-depth exploration of the moderating mechanisms of enterprise internal factors (knowledge breadth, knowledge depth, and cost pass-through ability) and regional differences in policy effects. This paper fills this research gap by constructing a PSM-DID model incorporating moderating variables, which not only verifies the net effect of the CET policy on enterprises' green innovation quality, but also clarifies the boundary conditions of policy effectiveness, thus enriching the research on the micro-impact mechanisms of the CET policy. S. et al. analyzed the impact of purchasing new energy vehicles on urban green innovation and emissions reduction using two methods: Propensity Score Matching-DID (PSM-DID) test, Difference-in-Differences (DID) test, and fixed effects model. The new energy vehicle project had policy effects, but had a negative impact on green innovation [4]. Achieving Carbon Neutrality (CN) is a challenge faced by countries around the world. Y. et al. divided green development performance into green total factor productivity and CE intensity. The influence of CET policies on green development performance was analyzed. Reducing CE requires optimizing energy structure, and CET policies did not effectively improve green productivity or reduce CE [5]. The Porter hypothesis theory displays that environmental requirements can generate Porter effects and promote corporate innovation. However, few

studies examined the causal relationship between environmental regulations and regional Porter effects. X. et al. conducted quasi experimental tests on China's CET. A dynamic panel data model was tested to check if environmental regulations stimulated regional Porter effects. Appropriate environmental goals were crucial for each province and match them with local resources [6]. To alleviate the enormous pressure of CE, China has launched a pilot policy for CET. G. et al. took PSM-DID to evaluate the effectiveness of CE policies. Technological progress contributed to reducing CE, but the contribution of industrial structure was not significant. The CET policy significantly reduced regional CE and carbon intensity [7].

CET can promote high-quality economic development. W. et al. used a method called "differences within differences" to explore how CE trading affects green technology innovation. Controlling CE, establishing more carbon trading entities, and making market incentives and environmental regulations more effective are because CE trading reduces green technology innovation, but also reduces CE and intensity [8]. The current operating model needs to be adjusted to improve market efficiency. These targets in reducing emissions and using renewable energy mean that the CET and Tradable Green Certificate (TGC) markets are crucial. X. Guo and X Zhang created a model for the power industry through deep reinforcement learning. The CET mechanism linked the TGC market with the green electricity market, and the incentive mechanism increased the trading volume and prices, leading to significant CE reduction [9]. Carbon trading is a crucial way to achieve CN. The research on ETS policies mainly focuses on how they affect emissions and the economy. To measure efficiency and fairness in incorporating environmental equity into green development, Y. Wang and L He created a balanced green development index. The balance of China's green development was not strong. The global spatial agglomeration effect existed. The DID was applied to explore the influence of CET on green balance [10].

To adapt to the new energy market, reduce emissions, and improve investment returns, H. et al. proposed a new dual layer distribution network model with new energy as the core. NDN planning was compared with traditional distribution network planning. The impact of green power certificate trading and CET mechanisms on investment planning at different price levels was studied. The model was proven to be applicable and logical [11]. Given the uncertainty of renewable energy, S. et al. proposed a model that combined game theory, emissions trading, and green certificates. This strategy guided investment and grid planning, promoted renewable energy consumption,

reduced emissions, improved cross regional system economy, and reflected the value of renewable energy [12]. China is reducing energy use and emissions to address climate change. However, these measures may affect each other in unpredictable ways. J. et al. used a multi-regional approach to estimate the economic impact of China's national carbon market and renewable energy subsidies. If there is a carbon tax, the costs of reducing greenhouse gas emissions and lowering carbon prices will increase [13]. In September 2020, China announced that it would achieve CN by 2060. CET is a market-based way to reduce CE. X. Chen and B Lin analyzed the operation of CET in two stages. Taking China's CN pilot as an example, carbon trading reduces CE and saves energy [14].

In summary, the impact of CET policies on data processing, PSM, and DID analysis has undergone some research. The content is mainly based on the needs of climate change and environmental protection, the rise of CET policies, the necessity of green innovation, and the applicability and advantages of PSM-DID law. However, there is little research on the policy effects of PSM-DID and the moderating variables of green innovation factors. Based on the above research gaps, this study proposes the following research design: taking high-energy-consuming enterprises as the research object, taking the implementation of China's CET pilot policy as a quasi-natural experiment, a PSM-DID model is constructed to determine the net effect of CET policy on the quality of green innovation. Enterprise knowledge base (breadth and depth), cost transmission capability and geographical location are introduced as moderating variables to explore the heterogeneous impact of policies.

The practical contributions of this study are as follows: First, it provides micro-level empirical evidence for the effectiveness of the CET policy, which helps policymakers understand the actual response of enterprises to the policy. Second, it clarifies the moderating role of internal and external factors of enterprises, providing targeted decision-making references for enterprises to adjust green innovation strategies. Third, it reveals regional differences in policy effects, laying a foundation for formulating differentiated CE reduction policies.

The article structure is as follows. The first part reviews existing research. The second part elaborates on the method and process of the CET policies on green innovation behavior based on the PSM-DID, which is also the focus and innovation point. The third part tests the designed model. The fourth part draws conclusions and shortcomings, as well as the directions that need to be further explored in the future.

2 Methods and Materials

Firstly, the study analyzes the influence of CE policies on the green innovation of high-energy consuming enterprises and proposes regulatory variables for these enterprises in response to the policy. Secondly, the research innovatively combines the PSM-DID model for data statistics and analysis on the impact of this policy.

2.1 CET Policies on Green Innovation

The CET policy plays an important role in controlling greenhouse gas emissions through market mechanisms [15]. To analyze the impact of CET on the green innovation of high-energy consuming enterprises, the study first analyzes the knowledge foundation, cost pass-through, and regional location. The research model diagram is displayed in Figure 1.

The theory foundation of enterprise knowledge refers to the unique knowledge system accumulated and formed by enterprises in the long-term production and operation process, which is the core competitiveness. In Figure 1, the enterprise knowledge foundation mainly includes knowledge breadth and knowledge depth. The theory of enterprise knowledge foundation emphasizes the continuous updating and learning of knowledge, which helps the enterprise to continuously launch new products, technologies,

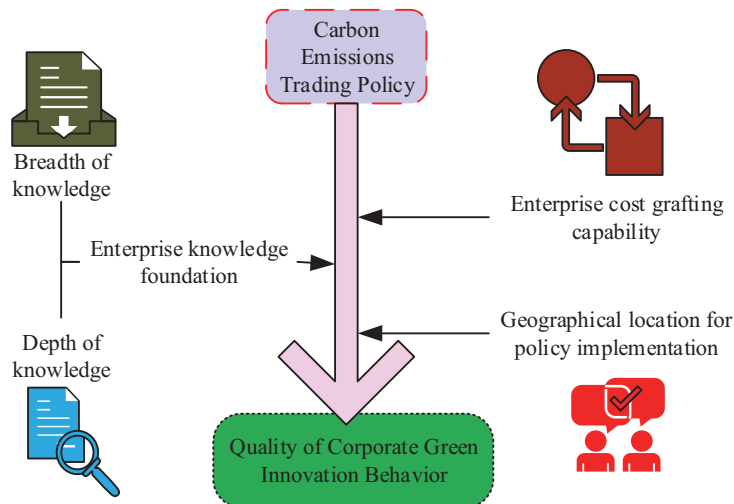


Figure 1 Research model diagram.

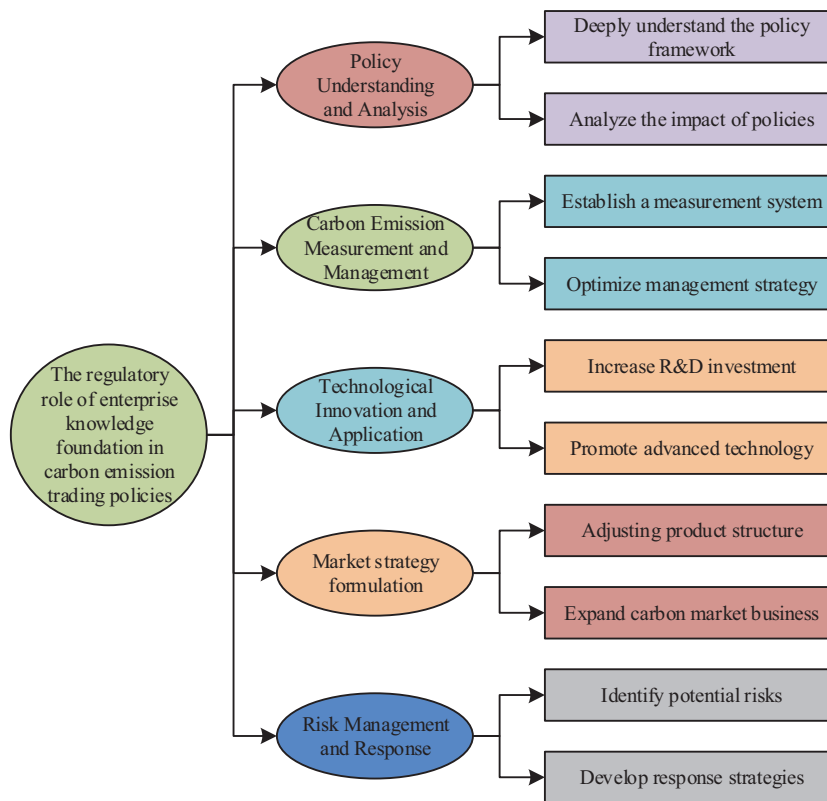


Figure 2 The moderating role of the corporate knowledge base for CET policies.

and services, maintain competitive advantages, and better adapt to market changes and external environments, and adjust strategies and business models in a timely manner [16]. The regulatory effect of enterprise knowledge foundation on CET policies is shown in Figure 2.

The transformation and sharing of enterprise knowledge is an important way to enhance the innovation capability and performance [17]. Through the transformation and sharing of knowledge, enterprises can better integrate internal resources, improve employee work efficiency, and enhance their competitiveness. Therefore, the higher the knowledge breadth and the lower the depth, the more effective the CET policy is in promoting the development of innovation quality in high-energy consuming enterprises [18]. The study constructs corresponding indices to describe knowledge breadth and knowledge depth. Knowledge breadth is described as the average

patent applications for some time, while knowledge depth is described in Equation (1).

$$D_{i,t} = \sum_j \left(\frac{P_{i,j}}{P_i} \right)^2 \quad (1)$$

In Equation (1), $P_{i,j}$ represents the number of patent numbers applied for by company i for some time. P_i represents the total number of patent applications for some time. $D_{i,t}$ is between 0 and 1. If the technology distribution is uneven, the value is close to 1. If the distribution is uniform, the value is close to 0. The HHI index to measure knowledge depth is supported by the corporate knowledge perspective. The depth of enterprise knowledge reflects the specialization in the core technology field, and the concentration of patent distribution (measured by the HHI index) can effectively characterize the specialization of enterprise knowledge. When concentration is high, knowledge in a specific field is deeper, while when concentration is low, knowledge is distributed more evenly.

Although CET promotes green technology innovation and environmental performance improvement for enterprises, it also increases their operating costs [19, 20]. The ability of enterprise cost pass-through affects the implementation effect of CET policies. Cost pass-through is resource integration, mainly through in-depth analysis of the enterprise's value chain and classification of its own operational activities, identifying those non-value-added and the parts of value-added activities with higher costs than competitors [21]. Cost pass-through refers to the ability of enterprises to transfer additional costs caused by policies to products, services, or other stakeholders through value chain adjustments, which can affect the implementation effectiveness of CET policies. The cost pass-through is displayed in Figure 3.

In Figure 3, the enterprise first needs to conduct a comprehensive analysis of its own value chain, clarifying the value-added and cost efficiency of each link. Secondly, homework activities have value-added and non-value-added activities, and the higher cost parts of value-added activities are further identified. Then the improved way is determined. Based on the analysis results, the enterprise seeks more efficient operational activities or technological achievements within or outside the strategic alliance in order to reduce cost. Finally, the identified improvement methods are introduced into the enterprise and integrated with its existing operational activities to achieve the cost pass-through. The study describes cost pass-through as the intensity of market competition, which is inversely proportional to the cost pass-through ability [22–24].

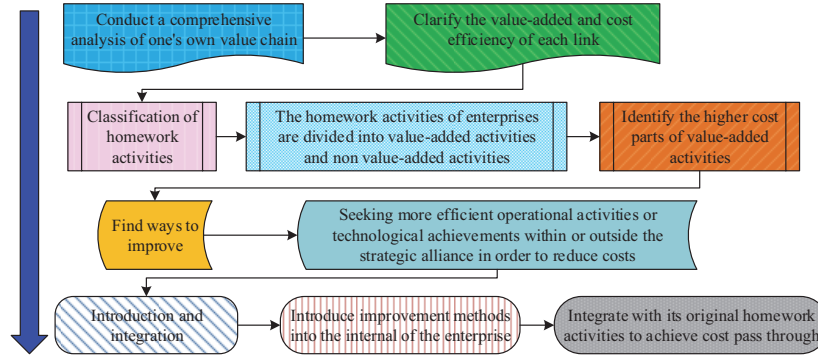


Figure 3 Specific processes for cost pass-through.

The effect of CET policies is related to geography and market conditions, so the innovation utility of enterprises varies in different regions. There are differences in economic, social, political, and technological factors in different areas like the central and western regions, and there are also significant differences in CE. Therefore, CET policies also have regional differences in influencing green innovation behavior [25]. Table 1 illustrates the variable explanation.

2.2 Analysis of the Policies on Green Innovation Behavior Based on PSM-DID

To effectively analyze the influence of CET on the green innovation of high-energy consuming enterprises, the commonly used DID quantification policy implementation effect is adopted, and a PSM-DID is constructed by combining propensity score matching method in robustness testing [26]. The Robustness Test examines the robustness of the methods used to evaluate and explain the indicators. That is, whether the method and indicator still have a relatively consistent explanation for the results when certain parameters are varied [27]. The robustness test is conducted on CET policies, with implementation effectiveness as the dependent variable and policy replacement as the core explanatory variable for estimation. The dependent variable is displayed in Equation (2).

$$Qua_{i,t} = \frac{QuoNum_{i,t}}{GrePatNum_{i,t}} \quad (2)$$

In Equation (2), i signifies the company. t signifies time (year). $QuoNum_{i,t}$ signifies the efficiency of i company's green innovation behavior

Table 1 Variable explanation

/	Name	Symbol	Definition
Explained variable	Green Innovation Quality	Qua	Number of citations of corporate green patents
Explanatory variable	Processing group virtual variables	Treat	The value of the enterprise belonging to the processing group is 1. Conversely, it is 0
Adjusting variables	Year dummy variable	P	Year = 2012 is 1, <2012 is 0
	Enterprise knowledge breadth	B	Unique IPC quantity applied by enterprises within a 3-year time window
	Depth of enterprise knowledge	D	HHI index of enterprises within a 3-year time window
	Cost pass-through ability	T	In a regulated industry, Trans = 1, not at 0
Control variable	Geographical location	Loc	Located in the eastern region, Loc = 1, and 0 in the central and western regions
	Company size	Size	Natural logarithm of end-of-year total assets
	Asset liability ratio	Lev	Total liabilities/ assets
	Number of employees	Labor	Logarithmic number of employees at period end
	Corporate social wealth creativity	TobinQ	Enterprise TobinQ value
	Property pights nature	S	1 for state-owned enterprises. Otherwise, it is 0

in t time (year), and the study describes it using the green patents cited. $GrePatNum_{i,t}$ signifies the green behavior practice of t company in t time (year), which is described by patent usage.

DID is a statistical technique whose core idea is to use two differencing operations. The first differencing eliminates the influence of common time trends, and the second differencing eliminates inherent differences between groups, getting the net effect of the intervention [28]. The benchmark DID model is shown in Equation (3).

$$Y_{it} = \alpha_0 + \alpha_1 du + \alpha_2 dt + \alpha_3 du \cdot dt + \varepsilon_{it} \quad (3)$$

In Equation (3), the coefficient α_3 displays the net effect of policy implementation. dt signifies a dummy variable for policy implementation, used as a marker of whether the policy has been implemented. It is mainly set before

<i>i</i>	Before policy pilot ($P_t=0$)	After policy pilot ($P_t=1$)	Difference
Processing group ($Treat_i=1$)	$\beta_0 + \beta_1$	$\beta_0 + \beta_1 + \beta_2 + \beta_3$	$\beta_2 + \beta_3$
Control group ($Treat_i=0$)	β_0	$\beta_0 + \beta_2$	β_2
Difference	β_1	$\beta_1 + \beta_3$	β_3

Figure 4 Estimation principle of DID method.

and after policy implementation. The corresponding dt values are 0 and 1, respectively. du signifies a grouping dummy variable used as a marker to distinguish between the Treatment Group (TG) and the Control Group (CG). du is mainly set to 1, with individual i as the TG, indicating that individual i is affected by policy implementation. Conversely, if du is set to 0, individual i is the CG. The estimation principle of the DID is shown in Figure 4.

The policy impact model on green innovation behavior constructed is shown in Equation (4).

$$Qua_{i,t} = \beta_0 + \beta_1 Treat_i + \beta_2 P_t + \beta_3 Treat_i * P_t + \gamma X_{i,t} + u_i + \lambda_t + \varepsilon_{i,t} \tag{4}$$

In Equation (4), $Qua_{i,t}$ signifies the quality of a company’s green innovation behavior. $Treat_{i,t}$ represents whether i company is in the research area of the CET market. If the value is 1, it indicates that it is within the area. If the value is 0, it is not within the area. β_6 represents the estimated moderating effect, which is the main concern variable. P_t represents the dummy variable for the implementation of CET policies. u_i represents individual fixed effects. $X_{i,t}$ represents other variables that may promote green behavior in high-energy consuming enterprises. $\varepsilon_{i,t}$ represents the perturbation term. λ_i represents the time effect.

The dependent variable “green innovation quality” (measured by patent citation) is a count data, and Poisson or negative binomial models are commonly used for such data. However, the reason for choosing a linear model in this study is as follows: Firstly, the core objective of this study is to

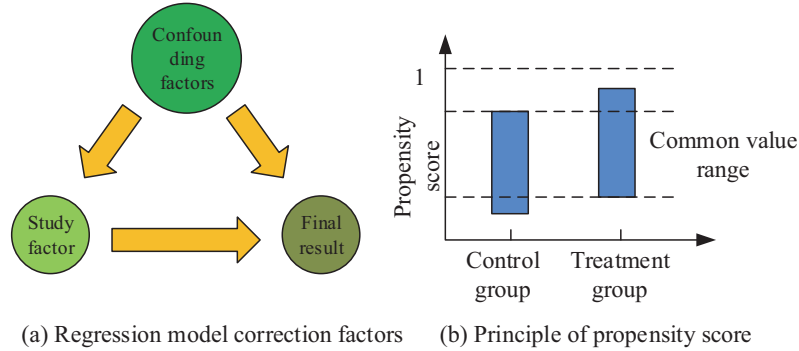


Figure 5 Regression model calibration and DID principle.

identify the net effects of CET policies through the DID framework. The linear model has the advantage of intuitively explaining the policy effect coefficients, making it easier to compare the policy impact under different adjustment conditions. Secondly, the sample size of this study is large (1,720 observations). When the count data is relatively scattered, the linear model can still obtain consistent and unbiased estimates. Thirdly, existing PSM-DID studies on similar topics also use linear models for policy effect estimation, ensuring the comparability of the research results with existing literature.

PSM is a statistical method for analyzing intervention effects using non-experimental or observational data [29]. Matching is performed between the CG and the TG based on propensity scores to match individuals in the TG with the highest possible degree of similarity in the CG, thus solving the sample self-selection [30, 31]. The regression model calibration and DID principle are shown in Figure 5.

Price-to-Sales Ratio (PS) value is the conditional probability that subject i ($i = 1, 2, \dots, n$) is assigned to a specific TG ($Z_i = 1$) or CG ($Z_i = 0$) under certain observable covariate (X_i). At this point, the probability of the i -th research subject being assigned to the TG can be expressed as Equation (5).

$$e(x_i) = P(Z_i = 1|X_i = x_i) \tag{5}$$

In Equation (5), if the given feature variable (x_i) is independent of the grouping variable (Z_i), then Equation (6) is used.

$$pr(z_1, z_2, \dots, z_n|x_1, x_2, \dots, x_n) = \prod_{i=1}^N e(x_i)^{z_i} \{1 - e(x_i)\}^{1-z_i} \tag{6}$$

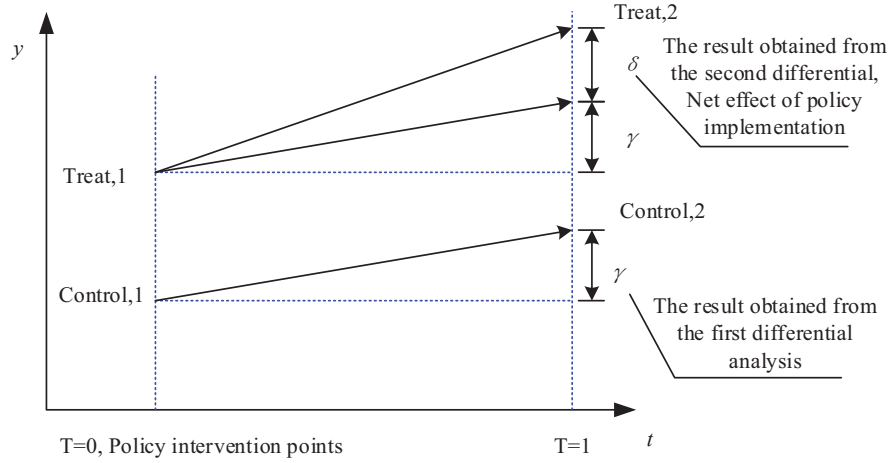


Figure 6 PSM hypothesis differential verification.

In Equation (6), propensity score signifies the conditional probability of assigning any research individual to TG ($Z_i = 1$) given a set of variables (x_i), as expressed in Equation (7).

$$e(x_i) = P(Z_i = 1|x_i) \tag{7}$$

The PSM-DID method needs to meet the Conditional Independence Assumption (CIA) and Parallel Trend Assumption (PTA), both of which cannot be directly tested and can only be verified through some indirect methods, as shown in Figure 6.

PSM has two conditions: independence and overlap of inter group scores, with independence represented by Equation (8).

$$(Y_i^T, Y_i^C) \perp T_i | X_i \tag{8}$$

In Equation (8), X represents the results of the TG. Y represents the results of the CG.

2.3 The Improved PSM-DID Model

The PSM-DID is a combination of PSM and DID, mainly used for quantitative evaluation of public policies and project implementation results. When the period before policy intervention is too short or even only one period, the parallel trend hypothesis is not fully satisfied, and robustness testing is

necessary, the PSM-DID model can be considered. According to the time period of panel data, PSM-DID can be divided into two or more periods. The premise of this model is that the mean can be ignored, as shown in Equation (9).

$$E(y_{0t} - y_{0t'} | x, D = 1) = E(y_{0t} - y_{0t'} | x, D = 0) \quad (9)$$

In Equation (9), E signifies the pre-processed variable and D signifies the post processed variable. When executing PSM-DID model, the first is to assess propensity scores based on the processing variables. Next is to identify individuals in the CG, which correspond one-to-one with each individual in the TG. The changes in their outcome variables before and after are calculated, as shown in Equation (10).

$$C = (y_{1ti} - y_{0t'i}) \quad (10)$$

In Equation (10), $y_{0t'i}$ represents the pre-processed variable. C represents the amount of change in the outcome variable before and after. $y_{1t'i}$ represents the post processed variable. Finally, for each i in the TG, all matched individuals in the CG are calculated, as shown in Equation (11).

$$C_{all} = (y_{1tj} - y_{0t'j}) \quad (11)$$

In Equation (11), $y_{0t'j}$ represents the pre-processed variable. $y_{1t'j}$ represents the processed variable. Propensity score kernel matching or local linear regression matching are performed on two types of changes to obtain estimated values. The robustness and reliability of the PSM-DID recognition results depend on the comparability and stability of the selected CG. Firstly, the matching variables have regular matching variables x_n and special class variables x_s . As shown in the following equation, this is because the matching will no longer be based solely on the PS -value, but will take special variables with a double standard of x_s and PS , with x_s taking precedence over PS . In the same category, the corresponding matching objects are filtered, which need to be closest to the PS value to ensure that the categories of both matching parties are consistent, as shown in Equation (12).

$$\min_j |PS_j - PS_i|, \quad \forall j \in C_s, \quad i \in D_s, \quad s \in x_s \quad (12)$$

In Equation (12), j signifies an individual in the CG s . i signifies an individual in the TG s . A regulatory model is constructed based on the

provided regulatory factors, as shown in Equation (13).

$$\begin{aligned} Qua_{i,t} = & \beta_0 + \beta_1 Treat_i + \beta_2 P_t + \beta_3 Treat_i * Keyvar_{i,t} \\ & + \beta_4 P_t * Keyvar_{i,t} + \beta_5 Treat_i * P_t + \beta_6 Treat_i * Keyvar_{i,t} \\ & + \beta_7 Keyvar_{i,t} + \gamma X_{i,t} + u_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \quad (13)$$

In Equation (13), $Keyvar_{i,t}$ represents a series of regulatory variables, including $B_{i,t}$, $D_{i,t}$, $T_{i,t}$, and $L_{i,t}$. $L_{i,t}$ represents the geographic location of the i company during t period. $T_{i,t}$ signifies the cost pass-through ability of i company during t . $B_{i,t}$ and $D_{i,t}$ respectively represent the breadth and depth of knowledge of i company in year t . The successfully matched i and e will be bound throughout the entire sample period to prevent changes in CG before and after the impact. Finally, according to the following equation, a matching object e is found for the processed individual i in CG, as shown in Equation (14).

$$\min_j \left\{ \frac{1}{T} \sum_t (PS_{j,t} - PS_{i,t})^2 \right\}, \quad \forall j \in C_s, \quad i \in D_s, \quad s \in x_s \quad (14)$$

In Equation (14), for all matching variables ($x_n + x_s$) in each regression section, the panel data needs to be split into $n(n > 1)$ -period section data. Then the PS -value for each individual in each period is calculated. $PS_{i,t}$ represents the PS -value of each individual in each period. t represents time (period). T represents the total periods. For unbalanced panels, the total periods T is also different because each individual in the TG has a different existence time, which can be matched according to the following equation.

$$\min_j \left\{ \frac{1}{T_i} \sum_{t \in t_i} (PS_{j,t} - PS_{i,t})^2 \right\}, \quad \forall j \in C_s, \quad i \in D_s, \quad s \in x_s \quad (15)$$

Overall, the model is improved as follows. Firstly, x_s represents a special class variable that needs to be determined for existence after completing the search for matching variables. Then, in order to calculate the $PS_{i,t}$ -value of each object for each period, the panel data for each period is regressed. Finally, individual samples are matched between PS -value sequences.

3 Results

To verify the influence of the CET policy based on the PSM-DID analysis on the green innovation of high-energy consuming enterprises, this research

Table 2 Descriptive statistical results of the research sample

Variable	Sample Size	Mean	Standard Deviation	Minimum	Maximum
Qua	1720	5.155	19.112	0	155
P	1720	0.652	0.481	0	1
D	1720	0.168	0.192	0.002	1
B	1720	17.559	26.374	0.333	236.333
TobinQ	1720	1.667	0.846	0	4.951
Treat	1720	0.234	0.426	0	1
Lev	1720	0.498	0.198	0.066	0.879
Size	1720	22.723	1.474	20.192	27.145
Labor	1720	8.354	1.287	5.566	11.602
S	1720	0.553	0.495	0	1

validates it by analyzing the corresponding design parameters and experimental data results, verifying the advantages and feasibility of the method, and providing reference for policy implementation and adjustment.

3.1 The Impact of CET Policies on Green Innovation Behavior

Data on green innovation patents of a high-energy consuming enterprise after implementing CET policy are analyzed to validate the proposed PSM-DID analysis method. The study uses PSM to compare enterprises that have implemented CET policies with other enterprises, divided into a CG and a TG. The TG has 464 observed values, while the CG has 1,256 observed values. The variable data of the enterprise is processed, and the statistical results of the data description are displayed in Table 2.

In addition, to examine the relationship between variables, Pearson correlation coefficient is used, which measures the strength and direction of the linear relationship in two variables. Coefficients range from -1 to 1 . 1 signifies a complete positive correlation. -1 signifies a complete negative correlation. 0 means no correlation. Table 3 displays the results.

3.2 Impact Analysis of CET Policies on Green Innovation Behavior

Figure 7 shows the propensity score matching equilibrium test of control variables. Figure 7(a) shows the mean values of control variables in the CG and TG before and after matching. The standard deviations of Lev, Labor, TobinQ, and S were less than 10%, and the standard deviations of all covariates were lower than those of before matching. Figure 7(b) shows

Table 3 Pearson correlation coefficient results

/	Qua	Treat*P	Size	Lev	Labor	TobinQ	S
Qua	1	/	/	/	/	/	/
Treat*P	0.321***	1	/	/	/	/	/
Size	0.349***	0.188***	1	/	/	/	/
Lev	0.022	0.023	0.491***	1	/	/	/
Labor	0.261***	0.117***	0.862***	0.433***	1	/	/
TobinQ	-0.0333	-0.0011	-0.44***	-0.36***	-0.35***	1	/
S	0.098***	0.084***	0.499***	0.387***	0.421***	-0.15***	1

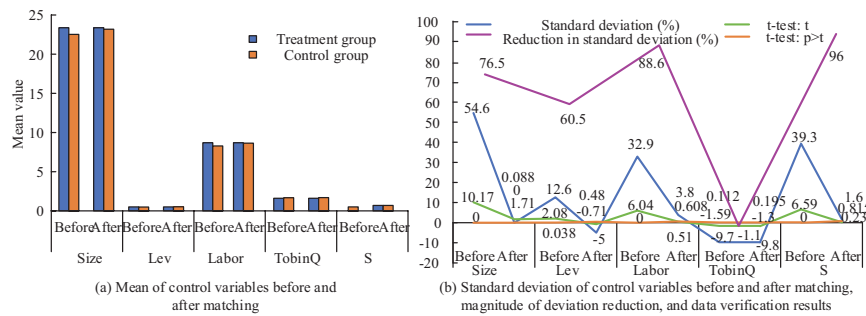


Figure 7 Balance test of propensity score matching for control variables: (a) Comparison of mean values of control variables before and after matching; (b) Standard deviation and deviation reduction of control variables before and after matching.

the standard deviation, reduction in deviation, and data test results of the control variables between the CG and the TG before and after matching. After matching, all t-tests for covariates were not significant at the 5% level, and the standard deviation decreased, indicating a good matching effect.

Figure 8 shows the influence of CET policies on the quality of green patents and a comparison of covariate standardization deviations. Figure 8(a) presents the dynamic impact of the CET policy on green patent quality. Taking the year of policy implementation as the benchmark period (excluding data from the year before implementation), the coefficients of the interaction term TreatP in the two years before policy implementation were within the 95% confidence interval (approaching 0) and were not statistically significant. This indicates that there is no significant difference in green innovation quality between the treatment group and the control group before the policy implementation, satisfying the parallel trend assumption of the DID model. After implementing the policy, the coefficients of TreatP were significantly positive and outside the 95% confidence interval, and the positive effect showed an increasing trend over the three years. This fully demonstrates that

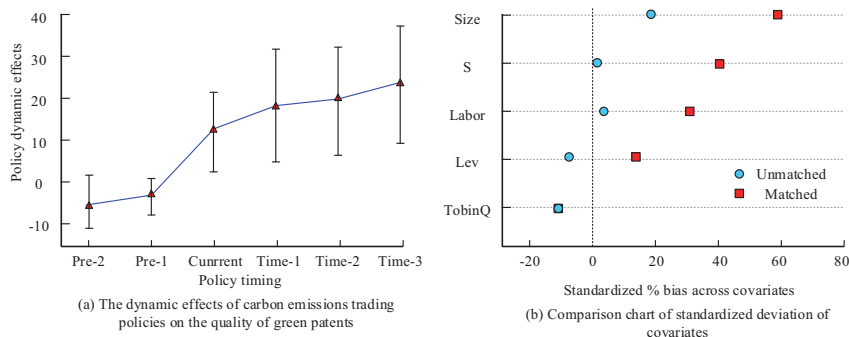


Figure 8 Dynamic impact of CET policy on green patent quality and covariate balance test: (a) Dynamic changes of policy effect coefficients (supporting parallel trend assumption); (b) Comparison of standardized deviations of covariates before and after matching.

the CET policy has a continuous positive impact on the green innovation quality of high-energy-consuming enterprises in pilot areas.

In Table 4, the t-value in parentheses, *, **, and *** represent significant differences at different levels. To analyze the impact of policy implementation on innovation quality, Table 4 presents the benchmark regression results of the policy’s influence on its quality. Columns a, b and c represent the addition of control variables and annual fixed effects, the addition of only company level control variables to the model, and the addition of fixed effects, respectively. The estimated coefficients of Treat*P were 12.2611, 12.3352, and 19.2122, all of which were significant at the 1% level. After controlling for fixed effects, the coefficients were omitted due to the presence of covariates. The fixed effects absorbed and reduced the impact of Treat. Overall, the Treat*P is positive at the 1% level, demonstrating the adopted different fixed effects. This indicates that energy-intensive enterprises in pilot areas are more willing to adopt high-value green innovation strategies after implementing emission trading policies.

Figure 9 shows the adjustment results of two factors on the influence of CET policies on the quality of enterprise innovation. In Figure 9(a), the estimated coefficients of Treat*P in columns a, b, and c were 12.2609, 12.3349, and 19.2042, respectively. After implementing CET policies, enterprises in pilot areas were more inclined to adopt better and more efficient green innovation strategies, mainly manifested as the coefficient of Treat*P always being positive when different fixed effects were adopted. In Figure 9(b), the coefficient of the third interaction term of D*Treat* was always less than 0, indicating that when high-energy consuming enterprises had more

Table 4 Benchmark regression of the influence of CET policies on the innovation quality

/	a	b	c
P	0.7083	1.0066	15.1521***
	-0.334	-0.98	-6.6333
Treat*P	12.2611***	12.3352***	19.2122***
	-6.25	-6.06	-11.48
Treat	0.4976	0.4301	0
	-0.301	-0.32	(.)
Size	6.0412***	6.0544***	-2.8426*
	-10.58	-10.94	(-1.72)
Lev	-13.9105	-14.0401***	-3.5321
	(-5.44)	(-5.52)	(-0.68)
Labor	-0.5233	-0.556	-1.3567
	(-0.92)	(-0.99)	(-1.21)
TobinQ	2.1419***	2.0668***	0.2459
	-3.533	-3.667	-0.349
S	-1.9987**	-2.0212**	4.81778
	(-2.06)	(-2.11)	-1.13
Year	Yes	No	Yes
Firm	No	No	Yes
Constant	-125.2641***	-125.8213***	68.2149***
	(-12.93)	(-13.25)	-2.18
Observations	1720	1720	1720
F	32.5678	56.8974	29.1998
	/	/	0.5926
Adj.R ²	0.2153	0.2171	/

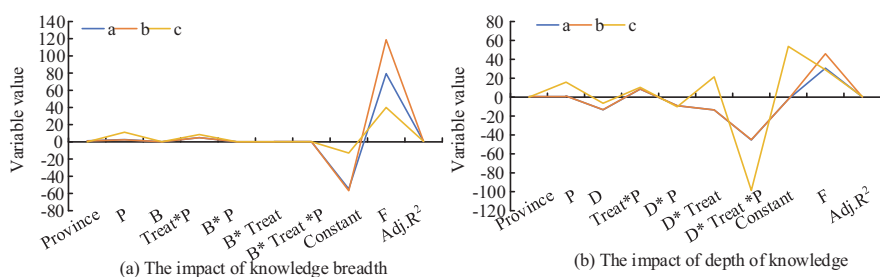


Figure 9 Moderating effect of knowledge breadth and depth on the impact of CET policy on corporate green innovation quality: (a) Positive moderating effect of knowledge breadth; (b) Negative moderating effect of knowledge depth.

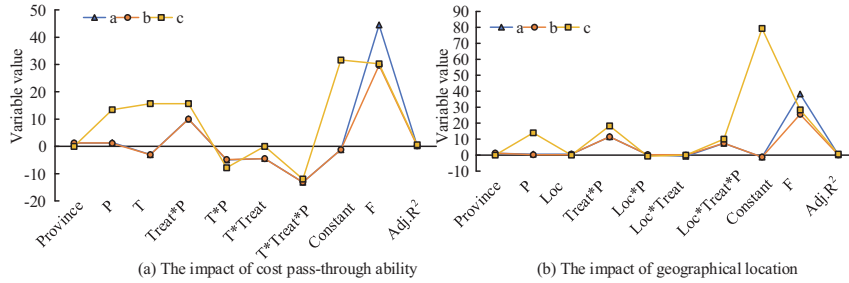


Figure 10 Moderating effect of cost pass-through ability and geographical location on the impact of CET policy on corporate green innovation quality: (a) Negative moderating effect of cost pass-through ability; (b) Stronger positive effect in eastern regions.

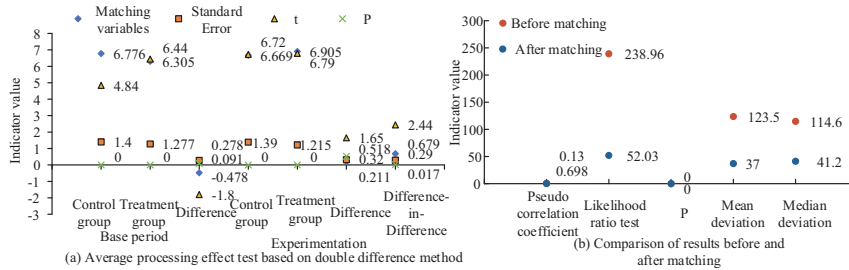


Figure 11 DID-based average treatment effect test and matching performance comparison: (a) Average treatment effect of policy implementation (0.679); (b) Comparison of matching performance indicators before and after matching.

knowledge, they couldn't accept new policies, or accept new things, making CET policies unlikely to have obvious impacts on the green innovation.

Figure 10 shows the impact of cost pass-through ability and geographical location on the quality of enterprise innovation behavior. In Figure 10(a), the strength of cost pass-through ability affected its quality. The stronger its capability, the less it promotes green innovation. The coefficient on the third interaction term of $T*Treat*P$ represented the observed coefficient, which was negative in cases a, b, and c. In Figure 10(b), the $Loc*Treat*P$ coefficient represents the main observation coefficient. Compared with energy-intensive enterprises in the central and western, the impact of CET policies on promoting green innovation in energy-intensive companies in the eastern region was more significant.

Figure 11 shows the balance test based on DID and the performance comparison before and after matching. In Figure 11(a), the average processing effect was 0.679, indicating that policy implementation had effects. In

Figure 11(b), compared with before matching, the values of various indicators decreased after matching. The pseudo-correlation coefficient, likelihood ratio test, mean deviation, and median deviation decreased by 0.568, 186.93, 86.5, and 73.4, indicating better matching effects.

The negative moderating effect of knowledge depth on the impact of CET policies on the quality of green innovation is an interesting counterintuitive finding. This can be explained by the theory of “knowledge rigidity”: Enterprises with profound professional knowledge often form path dependence in long-term technology research and development, and their resource allocation and technological capabilities are highly concentrated in existing core areas. When CET policies require companies to carry out green innovation in new technology fields such as low-carbon technology and renewable energy utilization, the deep professional knowledge accumulated by companies may become obstacles to technological transformation. Companies are unwilling to invest resources in unfamiliar fields, resulting in insufficient investment in green innovation. In addition, existing technological conventions and cognitive patterns hinder the absorption and application of new green technologies. In contrast, enterprises with lower knowledge depth have a more balanced distribution of knowledge and stronger flexibility in resource allocation, which enables them to quickly respond to policy changes and allocate resources to the field of green innovation. This finding reminds enterprises that while accumulating professional knowledge, they should also pay attention to knowledge breadth and technological diversity to avoid knowledge rigidity and better adapt to environmental regulatory policies such as CE trading.

4 Discussion and Conclusion

To effectively discuss the impact and effects of CET on the green innovation, a method based on the PSM-DID was applied. The PSM-DID was used to regulate corporate innovation behavior. The coefficient on the third interaction term of $T*Treat*P$ was negative in cases a, b, and c. Under the CET policy, high-energy consuming enterprises with weaker cost pass-through abilities improve the quality of green innovation to a greater extent than energy-intensive enterprises with stronger cost pass-through abilities. The $Loc*Treat*P$ coefficient represented the main observation coefficient. Compared with energy-intensive enterprises in the central and western, the impact of CET policies on promoting green innovation in energy-intensive companies in the eastern was more obvious. The average processing effect was

0.679, indicating that policy implementation had a certain effect. Compared with before matching, the values of various indicators decreased after matching. The pseudo-correlation coefficient, likelihood ratio test, mean deviation, and median deviation decreased by 0.568, 186.93, 86.5, and 73.4, indicating that the matching effect was good. The CET can effectively advance the low-carbon and green behavior, which has obvious positive effects. However, the innovative behavior of high-energy consuming enterprises mainly focuses on patent applications. The citation frequency and novelty of patents need to be more comprehensively considered. Therefore, follow-up research should explore other innovative behaviors of enterprises.

Based on the research results, this study proposes the following policy recommendations: For the eastern region, given that the CET policy has a more significant promoting effect on green innovation of high-energy consuming enterprises in the east, policy makers should further improve the carbon trading market mechanism in the eastern region. Meanwhile, encourage eastern enterprises to carry out green technology cooperation and knowledge sharing, and give full play to the exemplary and leading role of the eastern region in green innovation. Central and Western regions: Develop differentiated support policies: Increase financial subsidies for green innovation of high-energy consuming enterprises in the central and western regions to alleviate the cost pressure brought by CET policies; Build green technology innovation platforms, introduce advanced green technologies from the eastern region, and enhance the green innovation capabilities of local enterprises; Optimize regional industrial structure, reduce dependence on high-energy consuming industries, and create a favorable institutional environment for green innovation.

For enterprises with different knowledge foundations, those with deeper knowledge should break through knowledge rigidity, increase investment in cross disciplinary green technology research and development, strengthen cooperation with research institutions, and enhance their ability to absorb new green technologies. Enterprises with narrow knowledge breadth should expand their knowledge accumulation scope, focus on multi-disciplinary knowledge integration, and lay a solid foundation for green innovation. For enterprises with different cost transmission capabilities: Enterprises with strong cost transmission capabilities should not overly rely on cost transfer, but should actively carry out green technology innovation to achieve sustainable development. Enterprises with weaker cost transmission capabilities can receive policy support such as tax incentives and CE quota subsidies to reduce the cost of green innovation.

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