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Article

Research on the Sustainable Development Path of Green Finance Reform on Low-Carbon Transition of Enterprises Based on Multilayer Perceptual Machine Algorithm

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Abstract: This paper conducts a general study on the role, mechanisms, and characteristics of green finance in corporate low-carbon transformation and development from both theoretical and empirical perspectives. First, the paper reviews the concept of green finance and, based on the institutional characteristics and practical logic of green finance in China, proposes the basic research direction that green finance reform can facilitate corporate low-carbon transformation. Using panel data from 30 provinces (regions and municipalities) in China from 2014 to 2023, the study employs a multi-layer perceptron algorithm to calculate the annual green finance development levels across regions. A difference-in-differences model is then applied to test the effects of green finance policies on corporate low-carbon development. The findings indicate that green finance policies facilitate corporate low-carbon transformation, a conclusion that remains valid after testing for parallel trends, heterogeneity analysis, and robustness checks.

Keywords: multi-layer perceptron algorithm; difference-in-differences model; green finance; corporate low-carbon transition.

1. Introduction

The International Energy Agency (IEA) released its “2024 Carbon Dioxide Emissions Report,” which states that global CO₂ emissions related to energy reached 37.8 billion tons in 2024, an increase of 0.8%. The Global Carbon Project, an international climate science organization, analyzed that if countries do not significantly reduce emissions, the remaining “carbon emissions” budget will be exhausted within the next eight years, leading to global warming exceeding 1.5 °C and triggering catastrophic climate impacts [1-2]. Therefore, the transition to a low-carbon economy will be a systemic transformation and challenge that society and the economy will face in the long term, particularly for the eight high-emission industries such as thermal power, steel, and building materials. According to statistics, the carbon emissions of these eight industries accounted for approximately 80% of total carbon emissions in 2020, and they will be the first to face the rigid constraints of carbon reduction [3-5]. Achieving the “dual carbon” goals will undoubtedly drive the green and low-carbon transformation of the entire industrial chain, with enterprises being the key targets for transformation [6]. Green finance is an innovative carbon reduction policy tool and an important means of guiding enterprises toward low-carbon transformation, particularly high-emission enterprises [7-8]. Whether it promotes enterprise low-carbon transformation determines the effectiveness of green finance reform as an important exploration and whether the “dual carbon” goals can be achieved [9-10].

Since the implementation of green finance, its development and impact on enterprises have gradually become a topic of common concern at the academic research, local practice, and national governance



levels. Most scholars have found that green finance reforms can promote green technological innovation in manufacturing by alleviating financing constraints, driving technological and product upgrades, and enhancing corporate competitiveness [11-12]. By expanding financing channels and improving production efficiency, green finance can enhance corporate value. Environmentally oriented financial institutions and investors are more inclined to support environmental initiatives and establish partnerships with environmentally friendly enterprises, thereby enhancing the corporate reputation in both society and the market [13-15]. By providing green loans and preferential interest rates to incentivize enterprises to adopt clean technologies and renewable energy, reducing energy consumption and environmental emissions, enterprises can avoid hefty fines resulting from environmental pollution, reduce resource waste, and lower operational costs [16-18]. Since the carbon peaking and carbon neutrality strategy was proposed relatively recently, there has been limited research on the impact of green financial reforms on corporate low-carbon transitions. As a key initiative to empower green and low-carbon development in recent years, studying the impact and mechanisms of green financial policies on corporate low-carbon transitions holds significant theoretical and practical implications for financial institutions to better support businesses in achieving steady low-carbon transitions and advancing the dual carbon strategy in a prudent manner [19-21].

This paper starts from the actual situation of China's green finance development, establishes an appropriate indicator system, selects panel data from 30 provinces, autonomous regions, and municipalities from 2014 to 2023, measures the level of China's green finance development, and conducts a dynamic evolution analysis, aiming to scientifically measure the current level of China's green finance development, comprehensively and systematically present the development status and regional differences of China's green finance, and provide necessary policy reference for improving green finance policies to support the low-carbon transformation of economic development. A two-period DID model is constructed based on the measurement results of China's green finance development level to analyze the impact of green finance policy implementation on economic low-carbon transformation. Further benchmark analysis, heterogeneity analysis, and stage analysis are conducted to examine the regulatory mechanisms, heterogeneous factors, and influence channels involved in the process of green finance policies affecting economic low-carbon transformation.

2. Building a System to Measure How Green Finance Is Doing

2.1. Green Finance

The level of green finance development in a region is determined by its green finance model. In regions with relatively well-developed green financial infrastructure, the level of green financial development is higher than in regions where green financial infrastructure is slightly lagging behind. The paper provides an in-depth analysis of the five green financial models: green investment, green credit, green securities, green insurance, and carbon finance. It can be observed that although the transmission mechanisms and operational principles vary significantly across different models, the ultimate goal of all green financial models is to provide services for environmental protection, energy conservation and emissions reduction, and green industries.

The direct target of green finance policies is micro-enterprises. By providing interest rate subsidies for production capital in low-carbon sectors and research and development capital in green innovation sectors, capital allocation is encouraged to tilt toward low-carbon sectors, resulting in an increase in the relative financing costs of production capital for high-carbon enterprises. Although short-term emissions reduction investments may lead to an increase in production costs, but from a long-term cost-benefit perspective, enterprises not only gain access to financing support for green technological innovation, but also reduce their reliance on fossil fuels in the long term, lower compliance costs resulting from environmental regulations, and enhance their intrinsic motivation to reduce pollution emissions. Therefore, the following hypothesis is proposed:

H1: Green finance policy regulation is conducive to promoting enterprise low-carbon transformation.

2.2. Construction of the Indicator System

Taking into full consideration the current state of green finance development in China, and in accordance with documents such as the “Guiding Opinions on Establishing a Green Financial System,” this paper establishes an indicator system based on five aspects: green credit, green securities, green investment, green insurance, and carbon finance.

In terms of green credit, based on the characteristics of the six high-energy-consuming industries mentioned in the China Banking Regulatory Commission's “Green Credit Guidelines,” such as overcapacity, high consumption, and severe pollution, and considering that industry interest expenses are

related to loan scale and can reflect changes in loan scale, the paper selects the proportion of interest expenses in high-energy-consuming industries to reflect the level of green credit. Data sources include the “China Financial Yearbook” and the “Financial Operations and Development Report.”

In terms of green securities, the market capitalization share of high-energy-consuming industries can reflect the capital market financing situation of the six high-energy-consuming industries, thereby measuring the development level of green securities. Relevant data is sourced from the “China Statistical Yearbook” and the Wind database.

In terms of green investment, green investment can expand financing channels for green projects. The proportion of environmental pollution investment and the proportion of fiscal expenditures on energy conservation and environmental protection can respectively reflect the intensity of government investment in pollution control and support for energy-saving and environmentally friendly enterprises, thereby highlighting the financing capacity of green investment. The relevant data is sourced from the national economic and social development statistical bulletins of each province and municipality.

In terms of green insurance, green insurance can enhance environmental supervision and management levels, clearly define the entities responsible for compensation in pollution incidents, and play a role in improving the ecological environment. Agriculture is an industry significantly influenced by natural environmental factors, so the agricultural insurance claims ratio and the proportion of agricultural insurance scale are used as indicators to measure green insurance.

In terms of carbon finance, encouraging provinces to advance greenhouse gas reduction efforts can promote green and low-carbon development, so carbon intensity is selected as the metric for assessing the development level of carbon finance. The indicator system for measuring the development level of green finance is shown in Table 1.

Table 1. Green financial development level measure system.

Primary indicator	Secondary indicator	Tertiary index	Index definition	Index attribute	
Green financial development level	Green credit	Industrial interest ratio	Interest in industrial interest/industrial interest	-	
	Green securities	The market capitalisation of energy-consuming industries	The six high energy energy A stock market value/A stock market value	-	
	Green investment	Environmental pollution investment ratio		Pollution investment /GDP	+
		The ratio of energy conservation and environmental protection to expenditure		The total amount of energy conservation and environmental protection expenditure/fiscal expenditure	+
	Green insurance	Agricultural insurance loss rate		Agricultural insurance payment/agricultural insurance income	+
		Agricultural insurance size ratio		Agricultural insurance expenditure/insurance total expenditure	+
	Carbon finance	Carbon intensity		Carbon dioxide emissions /GDP	-

2.3. Evaluation Function

After establishing the metrics we need, we begin to build an MLP model for evaluating the level of green finance development. Multi-layer perceptrons are primarily used to solve classification and regression problems. A multi-layer perceptron network model (MLP) is a neural network with many hidden layers. Compared to shallow neural networks, it has more network parameters and can better solve local optimality problems, extracting more important information from massive amounts of data [22]. Figure 1 shows the basic structure of a multi-layer perceptron network. The first layer is the input layer, the last layer is the output layer, and the two intermediate layers are hidden layers. The layers are fully connected, and the basic unit they form is a neuron, which is a linear relationship $z = \sum w_i x_i + b$ plus an activation function $f(z)$.

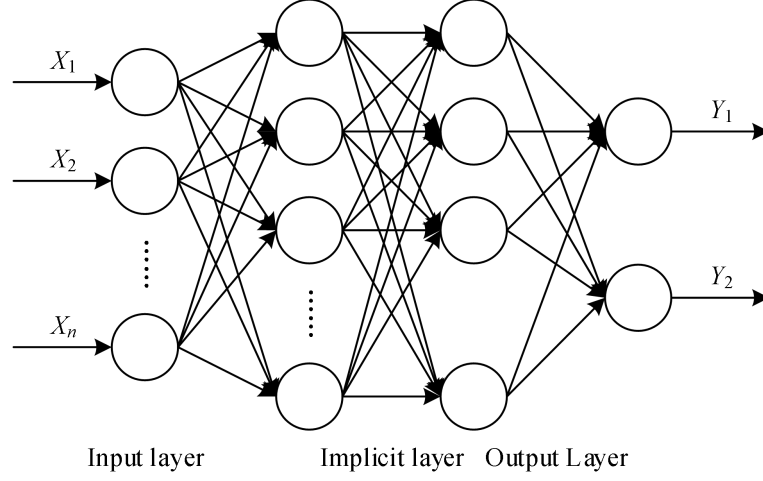


Figure 1. Multi-layer perceptron network model structure.

The training of a multi-layer perceptron network includes a forward propagation process and a backward propagation process. The forward propagation algorithm uses the output of the previous layer to calculate the output of the next layer, continuing until the output layer. Assuming that the training data is (x_i, y_i) , the total number of input layers is L , and the weight matrix W and bias vector b correspond to all hidden layers and output layers, the output of each layer is calculated as a^l , and the final output is a^L . f is the activation function, and z is the output after passing through the neuron:

$$a^l = f(W^l a^{l-1} + b^l) \quad (2 \leq l \leq L) \quad (1)$$

During forward propagation, the weight matrix W and bias vector b are both random values. The backpropagation algorithm is used to determine the appropriate weight matrix W and bias vector b . The backpropagation algorithm uses the loss function to optimize and find the extremum. The mean squared error is used to measure the loss, and for each sample, the following loss function is obtained:

$$J(W, b, x, y) = \frac{1}{2} \|a^L - y\|_2^2 \quad (2)$$

Output to the L th layer, where the W and b of the output layer satisfy the following equation:

$$a^L = f(z^L) = f(W^L a^{L-1} + b^L) \quad (3)$$

For the output layer parameters, the loss function becomes:

$$J(W, b, x, y) = \frac{1}{2} \|f(W^L a^{L-1} + b^L) - y\|_2^2 \quad (4)$$

Solve for the gradient by taking the derivative of W, b separately:

$$\frac{\partial J(W, b, x, y)}{\partial W^L} = \frac{\partial J(W, b, x, y)}{\partial z^L} \frac{\partial z^L}{\partial x} = (a^L - y)(a^{L-1})^T \odot f'(z) \quad (5)$$

$$\frac{\partial J(W, b, x, y)}{\partial b^L} = \frac{\partial J(W, b, x, y)}{\partial z^L} \frac{\partial z^L}{\partial x} = (a^L - y) \odot f'(z^L) \quad (6)$$

According to the forward propagation algorithm, we obtain:

$$z^l = W^l a^{l-1} + b^l \quad (7)$$

Then, the gradient of W^l, b^l in the l th layer can be obtained as follows:

$$\frac{\partial J(W, b, x, y)}{\partial W^l} = \frac{\partial J(W, b, x, y)}{\partial z^l} \frac{\partial z^l}{\partial x} = \delta^l (a^{l-1})^T \quad (8)$$

$$\frac{\partial J(W, b, x, y)}{\partial b^l} = \frac{\partial J(W, b, x, y)}{\partial z^l} \frac{\partial z^l}{\partial x} = \delta^l \quad (9)$$

Obtain the recursive relation for δ :

$$\delta^l = \delta^{l+1} \frac{\partial z^{l+1}}{\partial z^l} = (W^{l+1})^T \delta^{l+1} \odot \sigma'(z^l) \quad (10)$$

The recursive formulas for W, b are derived from the recursive relationship:

$$W^l = W^l - \alpha \sum_{i=1}^m \delta^{i,l} (a^{i,l-1})^T \quad (11)$$

$$b^l = b^l - \alpha \sum_{i=1}^m \delta^{i,l} \quad (12)$$

When the change values of W, b are both less than the iteration threshold, output the linear coefficient matrix W and the bias vector b for each hidden layer and the output layer. The entire neural network training is complete.

Step-by-step introduction to the MLP method. (1) Input layer: The input layer of a multi-layer perceptron accepts input data $x = (x_1, x_2, \dots, x_n)$, where n is the number of features. (2) Hidden layer: The hidden layer is the core part of an MLP and typically contains one or more neurons. Each neuron in the hidden layer performs a linear transformation on the input data to obtain an internal state value h_i , as shown in Equation (13):

$$h_i = \sum_{j=1}^n w_{ij} x_j + b_i \quad (13)$$

In particular, w_{ij} and b_i represent the weight and bias terms of the i th neuron, respectively. (3) Activation function: Each neuron in the hidden layer applies a nonlinear activation function $g(h_i)$ to the internal state value h_i to obtain the output value a_i , as shown in Equation (14):

$$a_i = g(h_i) \quad (14)$$

Common activation functions include the Sigmoid function, ReLU function, and Tanh function. This experiment uses the ReLU function. (4) Output layer: Finally, the output layer of the multilayer perceptron performs a linear transformation on the output values a_i of the hidden layer to obtain the final output value y , as shown in Equation (15):

$$y = \sum_{i=1}^m w_{iy} a_i + b_y \quad (15)$$

3. Measuring the Level of Green Finance Development

3.1. Data Sources and Processing

The data used in this research analysis are panel data from 30 provinces, autonomous regions, and

municipalities in China from 2014 to 2023. The data are sourced from the China Statistical Yearbook, China Environmental Statistics Yearbook, China Financial Yearbook, Financial Operations and Development Report, China Insurance Yearbook, Wind Database, and statistical reports released by relevant departments. The authority, scientific rigor, and reliability of the data are assured.

First, the paper employs mean interpolation to address missing data for certain base indicators in specific years. Second, since the evaluation indicator system includes a large number of indicators, involving issues such as positive and negative indicators and differences in indicator units, direct calculation of the raw data is meaningless. Therefore, the data requires preprocessing, with the calculation formula as follows:

To preserve the difference information of negative indicators, negative indicators are normalized using the following formula:

$$x'_{\theta ij} = \max(x_{\theta ij}) + \min(x_{\theta ij}) - x_{\theta ij} \quad (16)$$

Then perform standardization processing using the following formula:

$$Y_{\theta ij} = \frac{x_{\theta ij} - \min(x_{\theta ij})}{\max(x_{\theta ij}) - \min(x_{\theta ij})} \quad (17)$$

$$Y_{\theta ij} = \frac{x'_{\theta ij} - \min(x'_{\theta ij})}{\max(x'_{\theta ij}) - \min(x'_{\theta ij})} \quad (18)$$

In this context, θ represents the year, i represents the province, j represents the indicator of the measure, $x_{\theta ij}$ represents the raw data of the indicator, $x'_{\theta ij}$ represents the data obtained after normalizing the reverse indicator, $Y_{\theta ij}$ represents the dimensionless data of the indicator, $\max(x_{\theta ij})$ and $\max(x'_{\theta ij})$, and $\min(x_{\theta ij})$, $\min(x'_{\theta ij})$ represent the maximum and minimum values of the indicator across all years and provinces, respectively.

Since some data points may be zero after standardization, a small positive number slightly greater than zero is added to the original data after standardization to ensure that each indicator in the system has meaningful values. In this paper, 0.001 is added to all standardized data. That is:

$$Y_{\theta ij} = \frac{x_{\theta ij} - \min(x_{\theta ij})}{\max(x_{\theta ij}) - \min(x_{\theta ij})} + 0.001 \quad (19)$$

$$Y_{\theta ij} = \frac{x'_{\theta ij} - \min(x'_{\theta ij})}{\max(x'_{\theta ij}) - \min(x'_{\theta ij})} + 0.001 \quad (20)$$

3.2. Main Calculation Results

The level of green finance development in each province was calculated using an MLP model. The results of the green finance development level calculations for the period 2014–2023 are shown in Table 2. As can be seen from the table, although there were fluctuations in the green finance development levels of China's 30 provinces, autonomous regions, and municipalities between 2014 and 2023, overall there was an upward trend, indicating that under the backdrop of the state's strong support and advocacy for green finance development strategies, provinces, autonomous regions, municipalities have increasingly prioritized ecological resource protection and environmental pollution control, gradually increasing their investment efforts, thereby driving the overall development of green finance.

Specifically, the green finance development level showed slight fluctuations and a slow upward trend from 2014 to 2023, indicating that during this period, all provinces, autonomous regions, and municipalities were actively exploring and striving to enhance their green finance development levels. It can also be observed that the top five provinces in terms of green finance development levels are Shanghai, Beijing, Zhejiang, Guangdong, and Tianjin. Among these, Shanghai has the highest average

green finance development level at 0.416, followed by Beijing at 0.382, while Ningxia, the last on the list, has an average green finance composite index of only 0.276. This shows that the development levels of green finance vary significantly across regions, with notable disparities.

Table 2. The results of the green financial development level in 2014-2023.

Province	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Shanghai	0.393	0.397	0.392	0.414	0.427	0.413	0.420	0.419	0.436	0.446
Beijing	0.377	0.371	0.383	0.377	0.378	0.389	0.378	0.391	0.395	0.380
Zhejiang	0.360	0.369	0.374	0.373	0.376	0.361	0.384	0.397	0.391	0.382
Guangdong	0.372	0.358	0.376	0.364	0.369	0.380	0.378	0.380	0.402	0.380
Tianjin	0.352	0.356	0.341	0.370	0.368	0.403	0.390	0.366	0.401	0.395
Jiangsu	0.347	0.364	0.369	0.364	0.374	0.386	0.372	0.395	0.388	0.376
Chongqing	0.332	0.347	0.388	0.367	0.360	0.413	0.362	0.358	0.411	0.381
Heilongjiang	0.344	0.362	0.368	0.367	0.367	0.399	0.367	0.377	0.369	0.363
Fujian	0.397	0.359	0.352	0.435	0.338	0.364	0.356	0.340	0.356	0.353
Hainan	0.340	0.337	0.369	0.349	0.362	0.410	0.370	0.370	0.371	0.377
Anhui	0.339	0.350	0.360	0.363	0.362	0.363	0.369	0.370	0.374	0.376
Hunan	0.334	0.360	0.383	0.354	0.356	0.362	0.366	0.368	0.344	0.346
Shandong	0.316	0.323	0.352	0.348	0.343	0.377	0.357	0.373	0.371	0.355
Hupei	0.329	0.320	0.350	0.354	0.348	0.360	0.343	0.344	0.375	0.379
Jilin	0.347	0.341	0.356	0.345	0.364	0.342	0.341	0.345	0.340	0.336
Shaanxi	0.315	0.329	0.339	0.345	0.335	0.356	0.364	0.363	0.371	0.350
Henan	0.327	0.332	0.332	0.318	0.331	0.336	0.341	0.360	0.370	0.374
Sichuan	0.314	0.312	0.336	0.366	0.328	0.328	0.313	0.334	0.404	0.341
Xinjiang	0.271	0.295	0.318	0.346	0.372	0.347	0.331	0.351	0.381	0.369
Liaoning	0.292	0.309	0.329	0.334	0.349	0.338	0.331	0.360	0.348	0.341
Hebei	0.333	0.330	0.330	0.345	0.361	0.341	0.323	0.308	0.345	0.326
Guangxi	0.309	0.307	0.340	0.292	0.317	0.314	0.332	0.351	0.355	0.381
Shanxi	0.320	0.313	0.324	0.309	0.318	0.323	0.316	0.326	0.337	0.330
Guizhou	0.296	0.291	0.320	0.319	0.326	0.341	0.323	0.329	0.347	0.332
Jiangxi	0.284	0.298	0.310	0.311	0.295	0.310	0.286	0.326	0.296	0.322
Yunnan	0.204	0.264	0.258	0.279	0.286	0.333	0.291	0.298	0.326	0.365
Qinghai	0.266	0.293	0.284	0.295	0.300	0.323	0.296	0.287	0.276	0.292
Kansu	0.241	0.230	0.280	0.281	0.276	0.270	0.352	0.296	0.295	0.305
Inner Mongolia	0.196	0.232	0.308	0.392	0.268	0.385	0.269	0.262	0.222	0.226
Ningxia	0.393	0.397	0.392	0.414	0.427	0.413	0.420	0.419	0.436	0.446

3.3. Analysis of the Dynamic Evolution of Green Finance Development Levels

There are certain differences in the level of green finance development. In order to observe the evolution of these differences more clearly and intuitively, the kernel density estimation method was used to analyze the level of green finance development in China and its three major regions from 2014 to 2023, and Matlab software was used to draw a three-dimensional kernel density curve diagram.

3.3.1. National-Level Analysis

Figure 2 illustrates the distribution and dynamic evolution trends of green finance development levels across 30 provinces, autonomous regions, and municipalities from 2014 to 2023. From the figure, we can observe the following: (1) Based on the changes in the annual density curves, the overall distribution curve center and the range of changes for green finance development levels from 2014 to 2023 exhibit a noticeable shift to the right. The main peak height rapidly increased between 2016 and 2017 while the width remained largely unchanged, slowly decreased between 2018 and 2019 with an expanded width, and gradually increased between 2020 and 2023 with an expanded width. (2) From the evolution of the peak, the distribution of green finance development levels shows a trend of “double peak—single peak—double peak.” Specifically, from 2014 to 2015, there was one main peak and one side peak; in 2016, there was one main peak; and from 2017 to 2023, there was one main peak and one side peak, but the value of the side peak has significantly decreased, and the peak has become flatter. This indicates that the development levels of green finance across the 30 provinces, autonomous regions, and municipalities still exhibit a certain degree of gradient effect, but the phenomenon of polarization persists. (3) The

distribution's extensibility shows a widening trend, indicating that the spatial absolute differences in green finance development levels are continuously expanding, and the gap between provinces with higher development levels and the average level continues to widen.

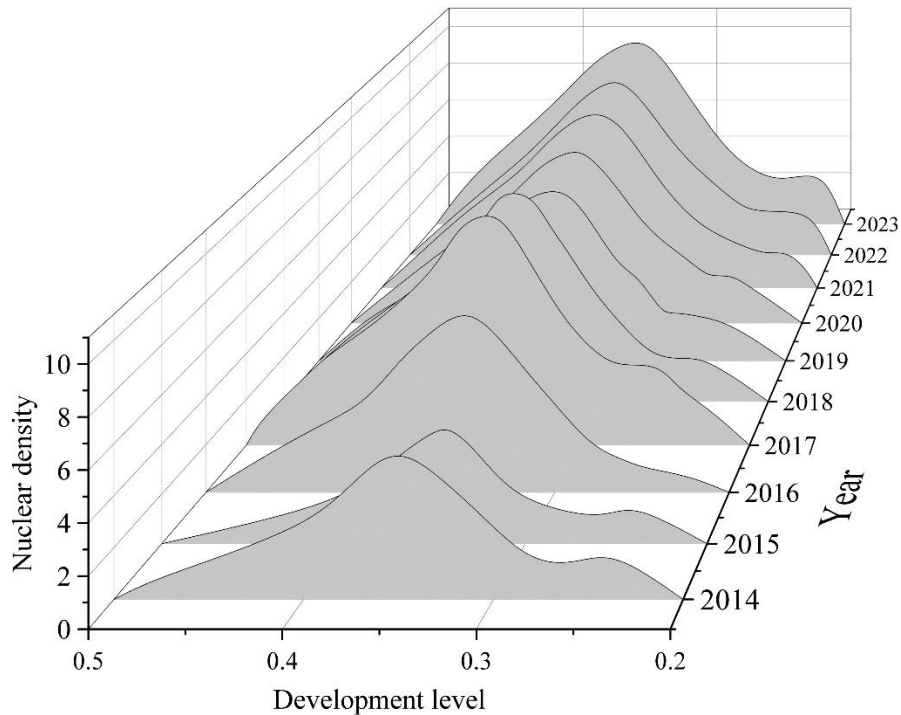


Figure 2. Green financial development level.

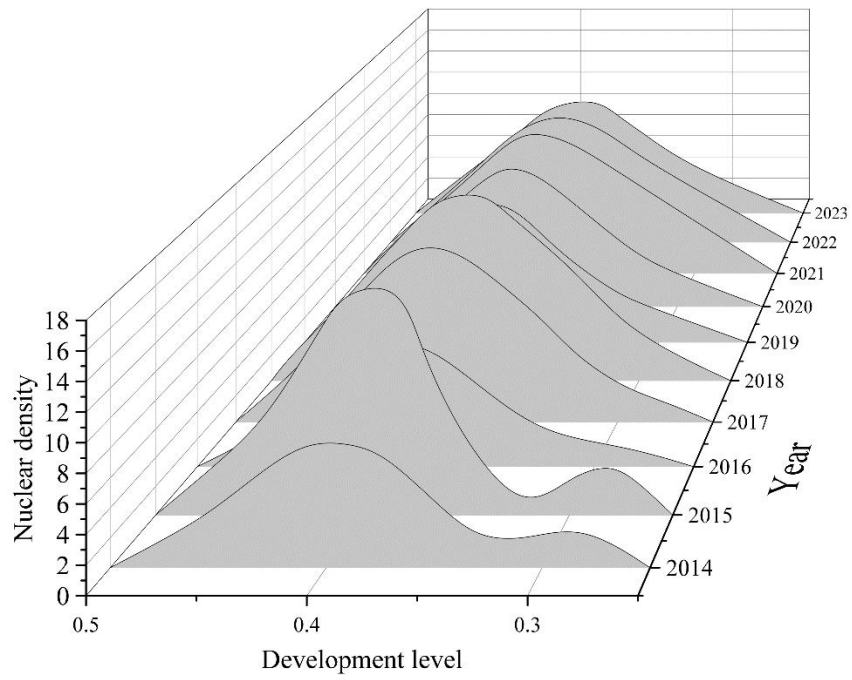
3.3.2. Regional-Level Analysis

Figure 3 shows the kernel density plots of green finance development levels in the eastern, central, and western regions from 2014 to 2023. First, from the distribution of the curves, the centers and ranges of green finance development levels in the eastern, central, and western regions are slowly shifting to the right, indicating that green finance development levels in the three regions showed a slow upward trend from 2014 to 2023.

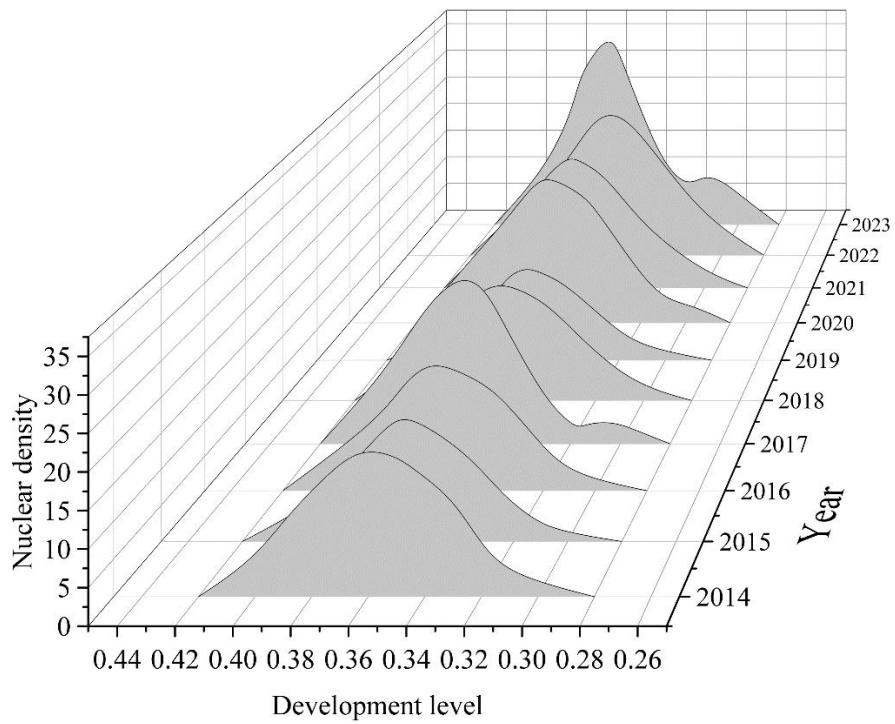
Second, from the perspective of the distribution pattern, the main peak in the eastern region first rises, then declines, and subsequently remains in a fluctuating state, with the curve width gradually narrowing. This indicates that the absolute difference in fluctuation trends in the eastern region is not particularly pronounced. The main peak height in the central region remained stable from 2014 to 2016, significantly increased from 2017 to 2018, slowly decreased in 2019, significantly increased again in 2020, and rapidly increased from 2022 to 2023 with a narrowing curve width, indicating that the absolute difference in the central region is continuously expanding. The peak height in the western region slowly increased from 2014 to 2016, remained stable from 2017 to 2018, rapidly increased and then decreased from 2019 to 2020, during which the curve width significantly expanded, and slowly increased again from 2021 to 2023 with the curve width narrowing, indicating that the absolute difference in the western region first expanded and then contracted.

Third, in terms of distribution extensibility, only the western region exhibits a noticeable right-tail phenomenon, while neither the eastern nor the central regions do. The extensibility of the eastern region showed a slow rightward expansion trend from 2014 to 2023, while the extensibility of the central and western regions began to gradually expand to the right after 2020. This indicates that provinces in the western region with higher levels of green finance development are still on an upward trend. In the eastern and central regions, the level of green finance development has slowly improved after 2020, and the gap between provinces with high and low levels of green finance development has narrowed to some extent, but the narrowing is not particularly significant.

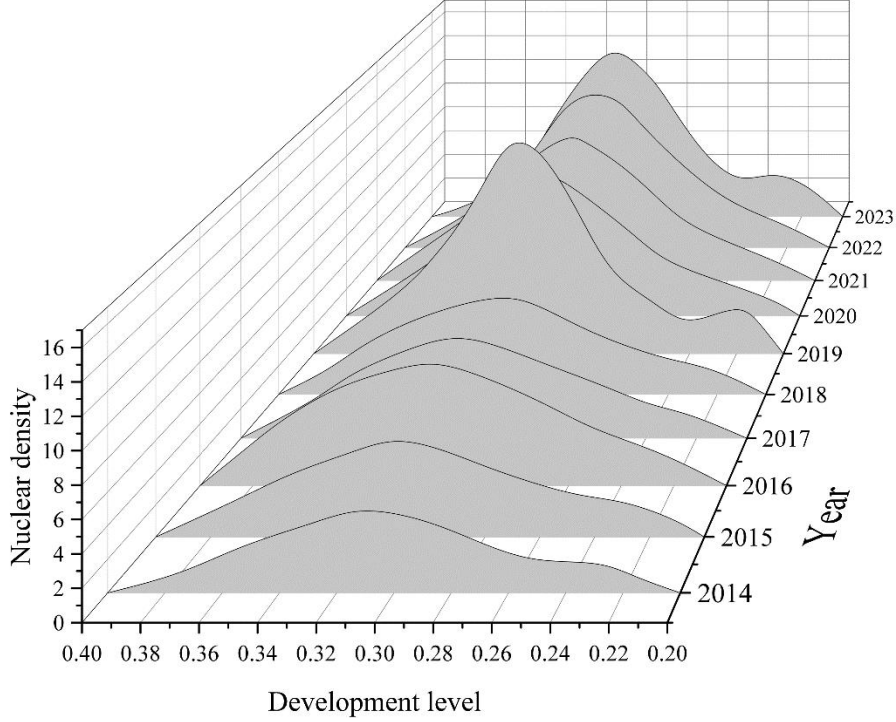
Overall, the eastern, central, and western regions have all shown varying degrees of diversification and clustering trends over time.



(a) Eastern region



(b) Central region



(c) Western region

Figure 3. Green financial development level of green financial development.

4. The Impact of Green Financial Reform on the Low-Carbon Transformation of Enterprises

4.1. DID Model Construction

The Difference-in-Differences (DID) model is based on the concept of counterfactual simulation, using external policy shocks as quasi-natural experiments. It constructs a treatment group subject to policy intervention and a control group not subject to policy intervention, eliminating factors that change over time and are unobservable. This approach mitigates endogeneity issues to some extent and is widely applied in policy effect evaluations [23]. This section uses the issuance of the “Guiding Opinions on Building a Green Financial System” in 2016 as a quasi-natural experiment and employs the DID model to assess the impact of green financial reforms on corporate low-carbon transformation. The “Guiding Opinions on Building a Green Financial System” is a uniform policy implemented across all regions nationwide. Drawing on the industry-based grouping method commonly used in existing research, treatment and control groups are established. When dividing the treatment and control groups, we further considered the extent to which each industry was affected by green finance policies, categorizing firms into high-carbon firms, low-carbon firms, and other types of firms. High-carbon firms and low-carbon firms were designated as the treatment groups, while the control group consisted of other types of firms not affected by the policy, thereby addressing the issue of sample self-selection to some extent. Based on this, the following baseline model was constructed:

$$LCT_{i,t} = \alpha_0 + \alpha_1 CGF_{i,t} \times HC_{i,t} + \alpha_2 X_{i,t,c} + \lambda_t + \gamma_i + \delta_d + \varphi_c + \varepsilon_{i,t,d,c} \quad (21)$$

$$LCT_{i,t} = \alpha_0 + \alpha_1 CGF_{i,t} \times LC_{i,t} + \alpha_2 X_{i,t,c} + \lambda_t + \gamma_i + \delta_d + \varphi_c + \varepsilon_{i,t,d,c} \quad (22)$$

In this model, i , t , d , c correspond to firm, year, industry, and city, respectively. LCT represents the firm's low-carbon transition level, CGF is a dummy variable indicating whether national green finance policies were implemented before or after the study period, HC is a dummy variable indicating whether the firm is a high-carbon firm, and LC is a dummy variable indicating whether the firm is a

low-carbon firm. $X_{i,t,c}$ denotes control variables at the firm and city levels. To mitigate omitted variable bias as much as possible, a series of fixed effects are also controlled: λ_t is the year fixed effect, γ_i is the firm-level fixed effect, δ_d is the industry fixed effect, and φ_c is the city fixed effect. These are intended to control for the interference of unobservable time, firm, industry, and city characteristic variables on the estimation results. $\varepsilon_{i,t,d,c}$ is the random disturbance term. α_1 is the coefficient of the core explanatory variable. When the treatment group consists of high-carbon enterprises, if it is significantly positive, it indicates that national green finance policies have a transformation effect on high-carbon enterprises. When the treatment group consists of low-carbon enterprises, if it is significantly positive, it indicates that national green finance policies have a development effect on low-carbon enterprises.

4.2. Variable Selection and Data Description

(1) Dependent variable. This chapter uses ESG ratings to measure a company's level of low-carbon transition. The better a company's ESG rating performance, the higher its level of low-carbon transition.

(2) Core explanatory variable. According to Equations (21) and (22), the core explanatory variable is the interaction term between the policy timing and the industry's dummy variable.

Regarding the timing of green finance policies (CGF), based on industry carbon emissions data from the China Emissions Database (CEADs), the following six industries—electricity, heat production, and supply; ferrous metal smelting and rolling; non-metallic mineral products; chemical raw materials and chemical products manufacturing; petroleum processing, coking, and nuclear fuel processing; and non-ferrous metal smelting and rolling—account for over 80% of total carbon emissions. These six industries are also defined as high-energy-consuming and high-polluting industries in existing research. Therefore, this chapter defines the above six industries as high-carbon industries. A two-digit industry code is used to match high-carbon industries with the industries to which listed companies belong. If a company's industry belongs to a high-carbon industry, the value is set to 1; otherwise, it is set to 0.

Regarding whether an industry is low-carbon (LC), this chapter defines the energy-saving, environmental protection, and clean industries listed in the “Statistical Classification of Energy-Saving, Environmental Protection, and Clean Industries (2021)” as low-carbon industries, primarily including the energy-saving and environmental protection industry, the clean production industry, and the clean energy industry. A four-digit industry code is used to match low-carbon industries with the industries to which listed companies belong. If the industry to which a company belongs is a low-carbon industry, the value is set to 1; otherwise, it is set to 0.

(3) Control variables. This chapter controls for the following company characteristics that influence a company's low-carbon transformation. Asset size (Size) is measured using the logarithm of total assets to reflect the size of a company's assets. The larger the company's asset size, the more it focuses on its social image and is more likely to pursue low-carbon transformation. Profitability (ROA) is measured using net profit divided by total assets, i.e., return on assets. Companies with stronger profitability have better sustainable development capabilities. Maturity (Age) is measured by the number of years since the company's establishment. The more mature a company is, the less likely it is to pursue green innovation and transformation due to expanded scale and redundant organizational structures and personnel. Economic environment (GDP) is measured by the logarithm of the city's gross domestic product. Industrial structure (Sec) is measured by the proportion of the city's secondary industry added value. Population density (Peo) is measured by the logarithm of the number of permanent residents per square kilometer of land area. The definitions of each variable are shown in Table 3.

Table 3. Variable definition.

	variable	symbol
Explained variable	Enterprise low-carbon transformation	LCT
Interpretation variable	High carbon policy interaction	$CGF \times HC$
	Low-carbon policy interaction	$CGF \times LC$
Control variable	Asset size	$Size$
	profitability	Roa
	maturity	Age
	Economic environment	GDP
	Industrial structure	Sec
	Population density	Peo

The research sample for this chapter consists of annual data from 2014 to 2023 for A-share listed

companies in China and their respective cities. The Huazheng ESG Rating Index is sourced from the WIND database, while data on listed companies and cities are obtained from the Guotai An database (CSMAR) and the EPS database. This yields a sample of 2,688 listed companies, including 422 high-carbon enterprises, 561 low-carbon enterprises, and 1,705 other types of enterprises. The descriptive statistics of the variables are shown in Table 4. The average LCT value for low-carbon enterprises is 4.2391, the highest among the three groups of enterprises. However, low-carbon enterprises have the smallest standard deviation among the three groups, indicating that the LCT values of low-carbon enterprises are more concentrated and exhibit smaller fluctuations. High-carbon enterprises also have higher LCT values than other types of enterprises, but their standard deviation is the largest among the three groups, indicating significant differences in LCT performance among high-carbon enterprises.

Table 4. Descriptive statistics of variables.

High carbon enterprise						
Variable	Sample Size	Mean	Standard deviation	Minimum value	Median	Maximum value
<i>LCT</i>	3268	4.1808	1.1000	1	3	7
<i>Size</i>	3268	13.2551	1.3589	8.1456	12.0834	16.5327
<i>Age</i>	3268	2.8233	0.3910	0.6922	2.8343	3.8107
<i>Roa</i>	3268	0.0497	0.0754	-1.3992	0.0250	0.3793
<i>GDP</i>	3268	11.3575	1.5341	8.7144	10.2373	19.1806
<i>Sec</i>	3268	0.4491	0.1015	0.1491	0.4468	0.8752
<i>Peo</i>	3268	0.0696	0.0544	-0.0065	0.0454	0.7872
Low-carbon enterprise						
<i>LCT</i>	4155	4.2391	1.0367	1	3	6
<i>Size</i>	4155	12.8526	1.3309	7.5921	11.6331	18.4388
<i>Age</i>	4155	2.7448	0.3894	0.0062	2.8270	4.1546
<i>Roa</i>	4155	0.0185	0.0547	-0.8273	0.0337	0.5928
<i>GDP</i>	4155	11.7431	1.7686	7.5399	9.5383	20.0402
<i>Sec</i>	4155	0.4207	0.1008	0.1345	0.4382	0.7402
<i>Peo</i>	4155	0.0925	0.0758	0.0078	0.0909	0.7754
Other types of enterprises						
<i>LCT</i>	12792	4.0550	1.0676	1	3	7
<i>Size</i>	12792	12.7303	1.1754	7.4303	11.5718	17.3369
<i>Age</i>	12792	2.7697	0.3889	0.0017	2.8325	3.9630
<i>Roa</i>	12792	0.0539	0.0818	-2.7649	0.0441	0.7925
<i>GDP</i>	12792	11.6697	1.7483	7.5622	10.4875	20.1749
<i>Sec</i>	12792	0.4222	0.1164	0.1540	0.4508	0.8875
<i>Peo</i>	12792	0.0750	0.0816	0.0103	0.0713	0.7927

4.3. Benchmark Analysis

4.3.1. Parallel Trend Test

The application of the double difference model requires that the treatment group and control group satisfy the parallel trend assumption. Therefore, prior to empirical regression, the differences between the treatment group and control group before the implementation of green finance policies are tested using the event analysis method. The parallel trend test method is shown in Equation (23):

$$LCT = \beta_0 + \beta_k (CGF \times LC)_{i0+k} + \rho \ln X_{it} + \delta_i + \varphi_i + \varepsilon_{it} \quad (23)$$

In this context, k represents the difference between each year and 2016, enabling an assessment of the impact of green finance policies on the low-carbon economic transition over the six years prior to and the three years following their implementation. To address the issue of perfect collinearity, this study uses the year preceding the formal implementation of green finance policies as the base year. Equation (23) focuses on the parameter β_k , which reflects the impact of green finance policies before and after implementation on the low-carbon economic transition of prefecture-level cities. If β_k is not significantly different from 0 during the period $k < 0$, it indicates that the study sample satisfies the

parallel trend assumption. When $k \geq 0$, β_k describes the dynamic effects of green finance policy implementation. The results of the parallel trend test are shown in Table 5. It can be seen that the policy effects on the level of economic low-carbon transformation and carbon intensity are significantly enhanced, and the extent of the impact also increases over time.

Table 5. Parallel trend test results.

	(1)	(2)
	<i>LCT</i>	<i>LCT</i>
pre_6	0.0221 (0.0413)	
pre_5	-0.0133 (0.0494)	
pre_4	-0.0047 (0.0437)	0.0895 (0.0503)
pre_3	-0.0368 (0.0461)	0.0626 (0.0266)
pre_2	-0.0425 (0.0525)	0.0153 (0.0240)
current	0.0415 (0.0607)	-0.0103 (0.0256)
post_1	0.1065** (0.0496)	-0.0937*** (0.0411)
post_2	0.1057** (0.0578)	-0.1345*** (0.0408)
post_3	0.1243** (0.0430)	-0.1499*** (0.0449)
Constant	-1.3903*** (0.0097)	-0.8916*** (0.0107)
Observations	3941	3942
R-squared	0.734	0.807

Note: The values in parentheses below the coefficients are their standard errors. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

It can be seen that when $k < 0$, the values of β_k are not significant at the 10% level, indicating that there is no significant difference in the economic low-carbon transition performance between the treatment group and the control group before the policy was announced, which satisfies the parallel trend assumption. When $k \geq 0$, the correlation coefficients all pass the 10% significance test, and the values of the coefficients increase year by year, indicating that the low-carbon transition effect of green finance policies is sustainable.

To further determine the effectiveness of green finance policies, a parallel trend test was also conducted on carbon emission intensity. Since carbon intensity is influenced by numerous factors, to ensure the accuracy of the test results, data from the first four years and the last three years were used for the test. The results in Column (2) generally indicate that the parallel trend assumption is satisfied. In the subsequent tests, carbon intensity was also selected as a single variable measurement indicator to provide supplementary clarification for the results of the core dependent variable.

4.3.2. Benchmark Regression

The impact of green finance policies on the level of economic low-carbon transition is shown in Table 6. Column (1) presents the regression results without control variables, column (2) presents the regression results after adding control variables, and column (3) presents the regression results after adding control variables and conducting 600 self-samples. It can be seen that the results in columns (2) and (3) are similar. The results indicate that green finance policies significantly enhance the performance of economic low-carbon transition. As the policies are implemented, the performance of economic low-carbon transition increases by 0.1893, which is statistically significant at the 1% level, indicating that the development of green finance has a certain low-carbon effect.

Table 6. The impact of green financial policy on the transition level of the economy.

Variable	(1)	(2)	(3)	(4)	(5)
	<i>LCT</i>	<i>LCT</i>	<i>LCT</i>	<i>LCT</i>	<i>tfcep</i>
<i>CGF</i> × <i>LC</i>	0.1893*** (0.0602)	0.2044*** (0.0286)	0.1968*** (0.0322)	0.2072*** (0.0648)	0.0112*** (0.0142)
<i>Size</i>		0.0372* (0.0225)	0.0487* (0.0188)	-0.0420 (0.0301)	0.0001 (0.0117)
<i>Roa</i>		-0.0986*** (0.0113)	-0.1132*** (0.0095)	0.1024*** (0.0158)	0.0174 (0.0068)
<i>Age</i>		-0.0515*** (0.0015)	-0.0536*** (0.0002)	0.0499*** (0.0111)	-0.0125** (0.0047)
<i>GDP</i>		-0.0169 (0.0125)	-0.0131 (0.0026)	-0.0263 (0.0234)	0.0022 (0.0117)
<i>Sec</i>		0.0201 (0.0237)	0.0085 (0.0174)	-0.0211 (0.0165)	-0.0044 (0.0049)
<i>Peo</i>		-0.0148** (0.0117)	-0.0187* (0.0223)	0.0113** (0.0050)	0.0083 (0.0080)
Constant		-0.1791 (0.1182)	-0.1999 (0.1169)	-2.3967*** (0.1737)	0.0506* (0.0130)
N	2289	1735	1735	1735	1735
R-squared	0.4983	0.5525	0.5728	0.6332	0.0322

From the perspective of controlling variables, changes in industrial structure, specifically an increase in the ratio of output between the secondary and tertiary industries, have a positive impact on transformation performance. The level of financial development has a negative impact on transition performance, likely because China's credit system has long prioritized support for the heavy industry sector, indirectly leading to large-scale carbon emissions. The strength of environmental regulations, measured inversely by sulfur dioxide emissions, also has a negative relationship with economic low-carbon transition, indicating that weaker environmental regulations hinder improvements in economic low-carbon transition levels. China's economic low-carbon transition still requires strict environmental regulations to constrain it.

To further illustrate the impact of green financial policy implementation on low-carbon economic development, Column (4) of Table 6 shows the impact of green financial policy implementation on carbon intensity. It can be seen that the impact is significantly negative at the 1% level, further confirming the low-carbon effects of green financial policy implementation from a single-variable perspective. The Luenberger productivity index is used to measure provincial carbon emission performance, represented by *tfcep*, to assess economic low-carbon transition performance. The results are shown in column (5) of the table. The test results indicate that the implementation of green finance policies has indeed improved the performance of the economy's low-carbon transition. The above tests demonstrate that green finance reforms can influence the performance of the economy's low-carbon transition, and that this influence is significantly positive.

4.3.3. Robustness Test

To enhance the reliability of the test results, this paper conducts robustness tests from several aspects, including the differences between the treatment group and the control group, the reliability of determining the policy implementation time, and the potential impact of other policies.

To overcome the systematic differences between the treatment group and the control group after the release of the green finance policy and reduce the estimation bias of the difference-in-differences model, the propensity score matching method is used for testing. First, a Logit regression was performed on the control variables using the treatment group's dummy variables, and matching was conducted at a 1:1 ratio to obtain propensity score values. The prefecture-level cities with the closest score values were selected as the matched groups for the treatment group. The PSM matching results are shown in Table 7, which indicates that the matching between the control group and the treatment group was effective.

Table 7. PSM matching results.

	Unmatched sample	Match sample	Total
Control group	0	1011	1011
Processing group	3	1050	1053
Total	3	2061	2064

Next, a balance test was conducted. The parallel hypothesis tests before and after propensity matching are shown in Table 8. It can be seen that there is no significant difference in the mean values of the control variables between the treatment group and the control group after matching, indicating that the results of propensity matching are reliable. Furthermore, the P-values of the control variables generally increase after matching, and the bias between the treatment group and the control group decreases after matching, suggesting that the matching effect is good.

Table 8. Parallel hypothesis testing before and after the preference match.

Variable	Match front and rear	Mean		Standardized deviation	P value
		Processing group	Control group		
Industrial structure	Before matching	0.145	0.237	-18.6	0.002
	After matching	0.163	0.185	-1.2	0.682
Financial development	Before matching	-0.448	-0.520	22.9	0.000
	After matching	-0.453	-0.457	-2.7	0.587
Environmental regulation	Before matching	10.749	10.281	36.1	0.003
	After matching	10.760	10.786	-1.5	0.618
Foreign strength	Before matching	-1.391	-1.930	38.8	0.000
	After matching	-1.377	-1.392	1.8	0.609
Human capital	Before matching	7.221	7.244	-3.9	0.448
	After matching	7.209	7.160	5.1	0.232
Government intervention	Before matching	7.250	7.233	1.3	0.791
	After matching	7.254	7.299	-4.5	0.297

Based on this, after matching using the PSM method, a double difference test was re-conducted on the main dependent variables. The results of the double difference estimation after matching are shown in Table 9. It can be seen that the policy implementation had a significant effect on both economic low-carbon transition performance and carbon intensity at the 1% level, indicating that green finance policies still significantly promoted the economic low-carbon transition of prefecture-level cities, and the results are robust.

Table 9. Match the double difference estimation result.

Variable	(1)	(2)	(3)	(4)
	LCT	LCT	LCT	LCT
CGF×LC	0.2078***	0.2017***	0.2132***	-0.2087***
	(0.0560)	(0.0285)	(0.0398)	(0.0552)
Size		0.1133**	0.0699	-0.1101**
		(0.0419)	(0.0441)	(0.0731)
Roa		-0.1192***	-0.0762***	-0.0867***
		(0.0015)	(0.0183)	(0.0041)
Age		-0.0430***	-0.0544***	-0.0451***
		(0.0099)	(0.0091)	(0.0063)
GDP		-0.0011	-0.0373	-0.0084
		(0.0238)	(0.0283)	(0.0017)
Sec		0.0082	0.0075	-0.0113
		(0.0116)	(0.0148)	(0.0146)

<i>Peo</i>		-0.0047*	-0.0276*	-0.0137**
		(0.0102)	(0.0198)	(0.0054)
Constant		-0.5919***	-0.9514***	-1.9379***
		(0.2020)	(0.2044)	(0.3226)
N	1735	1735	1735	1735
R-squared	0.5006	0.5626	0.5689	0.6450

4.4 Heterogeneity Analysis

4.4.1. Analysis of Heterogeneity in Economic Development Levels

Given that the role of green finance policies in promoting low-carbon transformation and development may vary across regions with differing levels of economic development, this study selected the median per capita GDP of each region over the years as the classification criterion. Regions with annual per capita GDP exceeding the median per capita GDP of all regions were classified as high-level economic development regions, while those below the median were classified as low-level economic development regions. Grouped regression analysis was conducted on the two sets of sample data to examine the heterogeneity of green finance policies' impact on corporate low-carbon transformation and development. The regression results are shown in Table 10, columns (1) and (2). Based on the results of the grouped regression analysis, it can be observed that green financial policies implemented in regions with higher levels of economic development have a more significant promotional effect on corporate low-carbon transformation and development compared to regions with lower levels of economic development. The reason for this phenomenon may be that regions with higher levels of economic development typically possess larger green financial market scales and more advantageous technological innovation environments. Therefore, compared to regions with lower levels of economic development, green financial policies are more easily implemented and achieve greater effectiveness in regions with higher levels of economic development, thereby driving the development of corporate low-carbon transformation.

Table 10. Heterogeneity test.

Variable	Economic development is high	Economic development is low	Green finance development is high	Green financial development is low
	(1)	(2)	(3)	(4)
Green financial policy(GFP)	0.135*** (0.051)	0.008 (0.019)	0.241*** (0.048)	0.016 (0.022)
Control variable	Control	Control	Control	Control
Time effect	Fixup	Fixup	Fixup	Fixup
Individual effect	Fixup	Fixup	Fixup	Fixup
Observed value	190	190	190	190
R ²	0.762	0.794	0.782	0.715

4.4.2. Analysis of Heterogeneity in Green Finance Development Levels

Differences in the development levels of green finance across regions may impact the effectiveness of green finance policies, thereby affecting their role in promoting enterprises' low-carbon transformation and development. Therefore, this study categorizes the 30 regions in the sample into two groups—regions with high levels of green finance development and regions with low levels of green finance development—based on the 2022 regional green finance development index rankings from the report “China Regional Green Finance Development Report (2023)” by scholars Wang Yao and Ren Yujie. Grouped regression analysis was conducted on the sample data from the two groups, with the results shown in columns (3) and (4) of Table 10. According to the results of the grouped regression analysis, in regions with higher levels of green finance development, green finance policies have a more significant promotional effect on the low-carbon transformation and development levels of enterprises. However, in regions with lower levels of green finance development, green finance policies do not have a significant promotional effect on the low-carbon transformation and development levels of enterprises. A possible reason is that higher levels of green finance development indicate that the green finance industry in the region is more mature, capable of providing a wider range of green finance products and services, and there is greater market demand for low-carbon and environmentally friendly products. Therefore, green finance policies are more likely to guide enterprises in regions with higher levels of green finance development to increase R&D investment, promote enterprise transformation toward green

and intelligent directions, and thereby facilitate the low-carbon transformation of enterprises in those regions.

4.5. Phases

The analysis revealed a single threshold effect for the levels of green finance development (LCT), urbanization (UR), and industrialization (IN). The likelihood ratio function plot is shown in Figure 4, illustrating the estimation and construction of the confidence intervals for the threshold variables. When the threshold value falls within the corresponding confidence interval, its LR value is less than the critical value at the 5% significance level (indicated by the dashed line in the figure). The estimated threshold value for green finance is 0.1907, with a 95% confidence interval of [0.1856, 0.2161]. The narrow confidence interval width indicates that the threshold value identification is effective. The threshold estimate for urbanization level is 0.7792, with a 95% confidence interval of [0.7453, 0.8008]. The threshold estimate for industrialization level is 0.2091, with a 95% confidence interval of [0.2036, 0.2189].

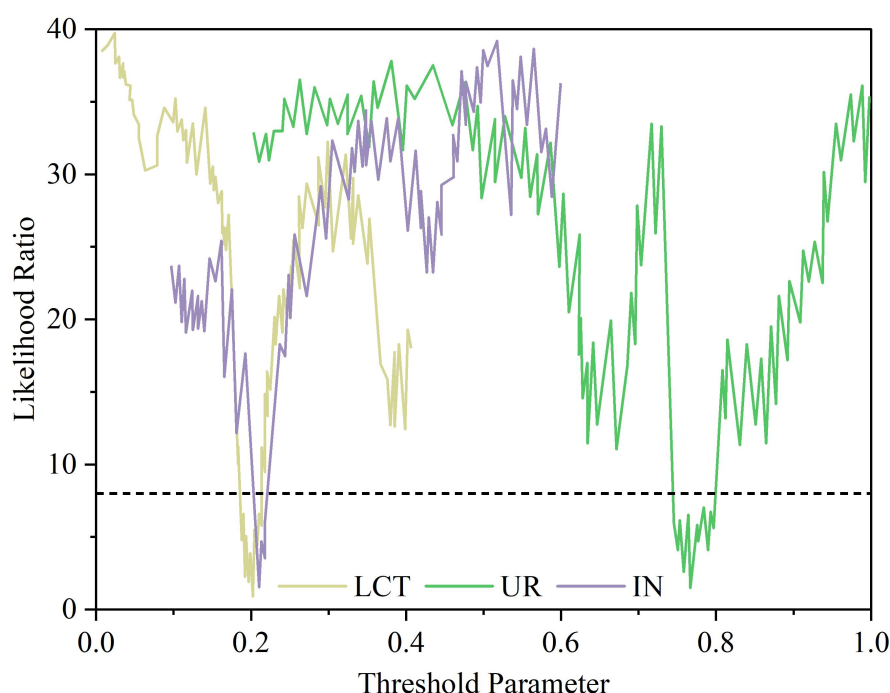


Figure 4. Threshold estimate and confidence interval.

The results of the panel threshold model regression are shown in Table 11. The results indicate that the impact of green finance on China's regional low-carbon economy exhibits distinct stage-specific characteristics:

(1) Green finance threshold effect: When LCT is less than 0.1907, the promotional effect of green finance on regional low-carbon economic development is 0.236. Once LCT exceeds the threshold value, the promotional effect reaches 0.359. This indicates that green finance requires a certain level of development in the green finance system as a foundation to exert a significant promotional effect on the low-carbon economy. There are spatial imbalances and regional development disparities in the level of green finance development across regions and provinces/cities in China. Building and improving green finance infrastructure can further enhance the promotional effect of green finance on the low-carbon economy.

(2) Urbanization level threshold effect: The promotional effect of green finance on regional low-carbon economic development exhibits distinct stage-specific characteristics as urbanization progresses. When the urbanization level exceeds the threshold value of 0.7792, the promotional effect reaches 0.392 at the 1% significance level, indicating that green finance facilitates a stage-based leap in low-carbon economic development. This suggests that enhancing urbanization levels can promote green finance's role in driving the transformation and upgrading of low-carbon economic development.

(3) Industrialization level threshold effect: Green finance can promote regional low-carbon economic development at different industrialization levels, but the promotional effect is not significant when the industrialization level is below the threshold value of 0.2091. Once the industrialization level exceeds the

threshold value, the promotional effect of green finance increases to 0.289 at the 5% significance level. This indicates that industrialization must reach a certain baseline to effectively promote the role of green finance in driving low-carbon economic development.

Table 11. The panel threshold model is estimated.

Variable	Threshold regression model		
	Green finance	Level of urbanization	Level of industrialization
λ	0.1907*	0.7792*	0.2091*
LCT	0.236**	0.211**	0.089
($X \leq \lambda$)	(2.44)	(2.26)	(1.09)
LCT	0.359***	0.392***	0.289**
($X > \lambda$)	(4.16)	(5.28)	(2.66)
Controls	Control	Control	Control
_cons	-0.626***	-0.422**	-0.308**
	(-3.33)	(-2.59)	(-2.26)
Adj-R ²	0.61	0.75	0.58
N	180	180	180

5. Conclusion

Based on the model construction and variable settings of empirical research, this paper selects panel data from China's provincial-level regions (including municipalities) from 2014 to 2023 as the research sample to analyze the significant promotional role of green financial policies in corporate low-carbon transformation and development. The empirical research results show:

From 2014 to 2023, the overall level of green finance development across China's 30 provinces, autonomous regions, and municipalities showed an upward trend, with a certain degree of gradient effect still present, though polarization persists. Over time, eastern, central, and western regions exhibited varying degrees of dispersed clustering trends.

Green finance policies can promote the low-carbon transformation of enterprises. In regions with lower levels of green finance development, the promotional effect of green finance policies on enterprise low-carbon transformation is relatively weak. In contrast, in regions with higher levels of economic development, the implementation of green finance policies has a more significant promotional effect on enterprise low-carbon transformation.

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