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Article

Testing the Mitigating Effects and Mechanisms of Green Finance on Carbon Emissions: A Dynamic Panel Model and LSTM Causal Analysis Approach

Jingyi Peng [1,*] and Zheng Zuo [2]

[1] Central South University of Forestry & Technology, Changsha, Hunan, 410000, China
[2] China Telecom Corporation Limited Zhuzhou Branch, Zhuzhou, Hunan, 412000, China
* Correspondence author: 964742763@qq.com

Abstract: Based on panel data from China's provinces covering the period 2006 to 2022, this study integrates econometric and machine learning methods to examine the impact of green finance on carbon emissions, its mechanisms of action and heterogeneous characteristics. We first construct a comprehensive green finance index and then establish a dynamic panel GMM model, finding that the effects of green finance on carbon emissions exhibit time lags and sectoral differences. In high-carbon industries and in central and western regions, green finance may temporarily drive up emissions in the short term by supporting capacity renewal or 'greenwashing' behaviour; however, in the medium to long term, it achieves net emission reductions through two intermediary channels: industrial structure optimisation and green technological innovation. This long-term mitigating effect is more pronounced in eastern regions. To further examine possible non-linear responses, the study also employs a multi-layer perceptron model and conducts a counterfactual simulation by increasing the green finance index while holding other covariates unchanged. The simulation shows that the response of carbon emissions differs across provinces. In several high-carbon provinces, a higher level of green finance still coexists with relatively high emissions in the short run. This result indicates that green finance does not work as an immediate emission-reduction instrument. Its effectiveness depends on the quality of financed projects, local regulatory capacity, and the coordination between financial policy and industrial policy. The econometric and machine-learning results therefore point to a common implication: green finance can support China's dual-carbon goals, but its effect follows a staged and region-specific process. Early-stage emission rebounds should not be ignored, and policy design needs to distinguish between regions, sectors, and different phases of transition.

Keywords: green finance; carbon emissions; dynamic GMM; mediating effect; MLP

1. Introduction

As global climate change intensifies, there is now a consensus amongst nations that a comprehensive green transition is essential to drive economic and social development. China announced its dual-carbon targets in 2020, committing to peak carbon emissions before 2030 and achieve carbon neutrality before 2060. These targets have placed new demands on the financial system. Green finance is expected to redirect capital from high-emission activities towards cleaner production, energy-saving projects, and low-carbon technologies. Yet the practical effect of this process remains uncertain. China's economic expansion has long been supported by energy-intensive industries, and coal still occupies an important position in the energy structure. Under these conditions, green finance may not immediately translate into lower emissions. Whether it reduces emissions, how long the effect takes to appear, and why the effect differs across regions are therefore empirical questions rather than assumptions.

Previous studies have mainly relied on econometric models to estimate the relationship between green finance and carbon emissions. These models are useful for dealing with fixed effects, endogeneity, and mechanism testing, but they usually impose a relatively simple functional form [1]. This may overlook threshold effects or province-specific responses. Machine-learning models, in contrast, are better at approximating non-linear patterns, although they do not by themselves provide a complete causal explanation [2-3]. For this reason, this paper adopts a two-step empirical strategy. First, a dynamic panel GMM model is used to estimate the baseline effect and address the persistence of carbon emissions. Second, an MLP model is introduced to simulate changes in emissions under a counterfactual increase in the green finance index. By combining these two approaches, the paper aims to identify both the average causal tendency and the non-linear heterogeneity behind it.

2. Literature Review and Research Hypotheses

2.1. The Direct Impact of Green Finance on Carbon Emissions

A considerable body of literature has directly examined the carbon reduction effects of green finance. Green credit has raised the cost of financing for energy-intensive and highly polluting industries, thereby limiting their scope for expansion [4]. Green bonds, meanwhile, enable clean energy, energy-saving and emissions-reduction projects to secure funding at a lower cost. Empirical studies based on provincial-level data from China have largely found that the development of green finance does indeed help to reduce carbon intensity [5]. However, these studies were primarily conducted using static models or fixed-effects frameworks; the problem is that they did not adequately account for the path dependence of carbon emissions—where previous emission levels influence current levels—and overlooking this factor can easily lead to biased estimates.

Recent studies, utilising more granular data and identification methods, have further enhanced the reliability of their conclusions. Some studies have drawn on balanced panel data from 277 Chinese cities between 2010 and 2020 to construct a comprehensive city-level green finance index across seven dimensions. In terms of estimation methods, both fixed effects and systematic GMM were employed to account for the dynamic inertia of carbon emissions themselves and potential endogeneity issues. The results show that the development of green finance significantly reduced urban carbon intensity; moreover, even when the policy shock of the ‘Green Finance Reform and Innovation Pilot Zones’ was tested as an exogenous instrumental variable, the direction of the effect remained unchanged. This provides evidence at the city level—and thus closer to the micro level—of the direct emission-reduction effects of green finance.

2.2. Mediating Mechanisms Through Which Green Finance Influences Carbon Emissions

Optimisation of industrial structure: Green finance redirects capital from traditional high-carbon industries towards modern service sectors and high-tech industries, driving a shift in industrial structure towards high value-added and service-oriented sectors. Carbon emissions per unit of output consequently decline. Research has directly confirmed that, by curbing the expansion of energy-intensive industries, green finance significantly promotes industrial restructuring and upgrading, serving as a key channel for carbon emission reductions.

Green Technological Innovation: Green finance provides funding for enterprises’ research, development and application of environmental technologies, accelerating the innovation and dissemination of clean production and renewable energy technologies, thereby reducing carbon intensity at the production stage [5].

However, the process by which technology progresses from innovation to actual emissions reductions is highly complex. Analysis has revealed that whilst green finance can stimulate growth in the number of green patents, such ‘paper innovations’ do not necessarily translate immediately into tangible productivity gains or emissions reductions. The authors attribute this phenomenon to the varying quality of green patents, low industrialisation rates, and the practice of ‘greenwashing’ by some enterprises. There is a clear time lag and loss of efficiency between investment in innovation and the eventual improvement in environmental performance. The emission-reduction effects of green finance cannot be achieved overnight.

2.3. Research Gaps and Contributions

The existing literature leaves three issues insufficiently addressed. First, most empirical studies are still divided between causal econometric analysis and prediction-oriented machine learning, with limited attempts to use the two in a complementary way. Second, the timing of the green finance effect has not been fully examined. In particular, it remains unclear whether green finance may increase emissions during the early stage of industrial adjustment before producing a reduction effect. Third, the literature has not paid enough attention to regional and sectoral differences. Provinces with different industrial structures, financial development levels, and regulatory capacities may respond very differently to the same type of green finance policy.

To respond to these issues, this paper combines dynamic panel GMM with an MLP-based counterfactual simulation. The GMM model is used to control for emission persistence and potential endogeneity, while the MLP model is used to explore non-linear and heterogeneous responses. The results suggest that the impact of green finance is not simply negative or linear. In regions with weaker regulation or a larger share of high-carbon industries, transition investment and possible greenwashing may delay emission reduction or even lead to a temporary increase. Sustained emission reduction is more likely when the institutional environment is mature and project screening is effective.

2.4. Research Hypotheses

Based on the above literature, this study proposes the following hypotheses:

H1: Green finance has a time-lagged and non-linear impact on carbon emissions—particularly in high-carbon industries and regions with weak institutional frameworks. Although green finance may temporarily increase emissions due to transition investments or 'greenwashing', net emissions reductions can still be achieved in the medium to long term through structural adjustments and technological innovation.

H2a: Green finance drives the transition towards a cleaner energy mix (increasing the share of non-fossil energy), thereby reducing carbon emissions. This intermediary effect is more pronounced in the eastern regions. In the central and western regions, however, where industrialisation is accelerating, the emission-reduction effect is diminished and may even be reversed in some cases [4].

H2b: Green finance relies on green technological innovation to reduce carbon emissions, but there is a lag between the research and development of technology and its implementation, meaning that the impact on emissions reduction is not immediately apparent in the short term.

H3: The effect of green finance on carbon emissions differs across regions and industries. The direction and magnitude of this effect depend on local industrial structure, regulatory capacity, financial market development, and the environmental quality of the projects receiving green finance support.

2.5. Contributions of the Study

Addressing the aforementioned gaps, this study introduces two key improvements:

This study contributes to the literature in two respects. First, it uses dynamic panel GMM and an MLP model within the same empirical framework. The GMM estimation provides a basis for identifying the average effect of green finance after considering lagged emissions and endogeneity, while the MLP model helps reveal non-linear responses that may be hidden in linear specifications. The purpose is not to replace econometric identification with machine learning, but to use machine learning as a supplementary tool for examining heterogeneous policy responses.

Second, the paper highlights the staged nature of green finance policy. The counterfactual results show that green finance does not always reduce emissions immediately. During the early stage of transition, capacity replacement, industrial relocation, or weak project verification may lead to a temporary rise in emissions. A stable reduction effect appears only when green finance is combined with better project selection, stronger regulation, and more mature market conditions. This finding helps explain why the effect of green finance varies across regions and why short-term policy evaluation may be misleading.

3. Research Design

3.1. Data Sources and Variable Descriptions

Although some of the original statistical series are available from earlier years, the main empirical analysis is restricted to 2006–2022 in order to maintain consistency across the core variables. The final balanced panel covers 30 provincial-level regions in mainland China, excluding Tibet, Hong Kong, Macao, and Taiwan because of data availability and comparability concerns. The data are collected from the *China Statistical Yearbook*, the *China Energy Statistical Yearbook*, the *China Financial Yearbook*, CNRDS, and CEADS. Table 1 reports the definitions and sources of the main variables, and Table 2 presents the descriptive statistics.

Table 1. Core Variable Definitions

Variable	Description	Source
Carbon Intensity (CI)	Co_2 emissions per 10^4 CNY of GDP (tons; logged).	CEADS & provincial inventories (1979-2019)
Green Finance Index (GF)	Normalized composite index of provincial green finance development.	Provincial green finance index (1990-2021)
Industrial Structure Upgrading (ISU)	Ratio of tertiary to secondary industry output.	China statistical yearbook
Green Innovation (GI)	Number of green patents filed (logged).	Green patent dataset
Energy Structure (ES)	Share (%) of non-fossil energy in total energy consumption.	Provincial energy statistics (2003-2022)
Economic Development (ED)	Per capita GDP (log CNY).	Provincial economic data (2000-2023)
Year & Province Fixed Effects	Dummy variables for year and province.	Authors' construction

Table 2. Descriptive Statistics of Green Finance and Carbon Emission-Related Variables

Variable	Observation Number	Mean	Standard Deviation	Minimum	Maximum	Unit
CI	510	22.15	0.87	0.62	5.31	tons per 10,000 yuan of GDP
GF	510	0.52	0.09	0.38	0.65	dimensionless
ISU	510	0.48	0.12	0.21	0.76	%
ES	510	0.15	0.08	0.02	0.41	%
log (per capita GDP)	510	9.85	0.63	8.21	11.42	-

3.2. Model Specification

3.2.1. Dynamic Panel GMM Model

Carbon emissions usually show strong persistence, since the current level is closely related to past industrial structure, energy infrastructure, and production patterns. For this reason, a static fixed-effects model may lead to biased estimates. This paper therefore applies the System GMM estimator and includes the lagged dependent variable in the model. The method also helps reduce potential bias caused by reverse causality and omitted variables. In the baseline specification, the logarithm of carbon emissions is used as the dependent variable, green finance indicators are treated as the main explanatory variables, and economic development, energy structure, province fixed effects, and year fixed effects are included as controls.

$$CIit = \beta 0 + \beta 1GFit + \beta 2Controlsit + \mu i + \lambda t + \varepsilon t \quad (1)$$

Here, represents the logarithm of carbon emissions; serves as the core explanatory variable, comprising the logarithms of green finance volumes in the electricity and heat supply sector, the chemical industry, and the ferrous metal smelting and rolling sector; constitutes the set of control variables, covering the logarithms of per capita indicators and energy structure; and represent provincial fixed effects and annual fixed effects, respectively, used to control for unobservable individual heterogeneity and time trends.

Furthermore, to capture the path dependence of carbon emissions, a dynamic panel GMM model was constructed:

$$CIit = \alpha CIi,t-1 + \beta 1GFit + \beta 2Controlsit + \mu i + \lambda t + \varepsilon t \quad (2)$$

The model incorporates a first-order lag term for carbon emissions to capture the dynamic adjustment process; the second-order lag term of the green finance variable is used as an instrumental variable. The validity of the model is confirmed by tests for serial correlation and the Hansen over-identification test.

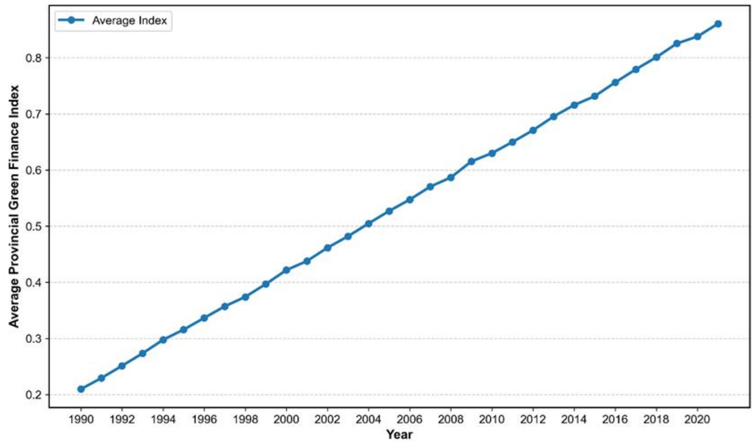

Figure 1. Average Provincial Green Finance Index (1990–2023)

Figure 1 shows the average annual trend of the comprehensive green finance index for 30 provinces across the country (excluding Tibet, Hong Kong, Macao and Taiwan). This index combines several dimensions, including green credit, green investment and the intensity of policy support, with the values normalised. Overall, the index has been rising steadily, with the rate of growth accelerating significantly following the introduction of the 12th Five-Year Plan in 2011 and the announcement of the 'dual carbon' targets in 2020. Driven by policy measures, the green finance system continues to be refined.

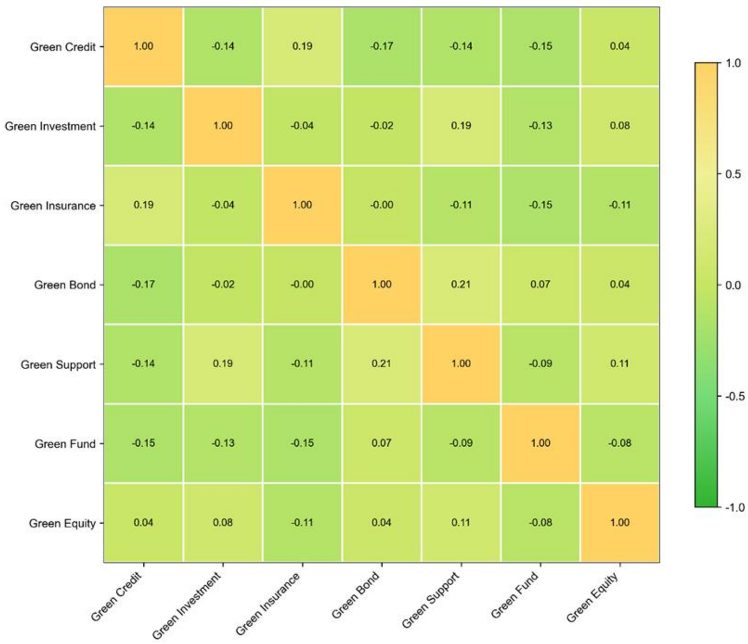

Figure 2. Correlation Matrix of Green Finance Sub-Indicators

Figure 2 shows the correlation coefficients between the seven sub-indicators of the green finance index: green credit, green bonds, green funds, environmental liability insurance, green guarantees, fiscal subsidies and regulatory intensity. The deeper the orange, the stronger the positive correlation; a yellowish-green hue indicates a weaker correlation. The highest absolute value of the correlation coefficient is only 0.21, indicating very low information overlap between the indicators. This makes them suitable for use in constructing a composite index, as no serious issues of multicollinearity are likely to arise.

3.2.2. Mediation Effect Model

(1) Path a: Green Finance → Energy Structure:

$$ESit = \alpha 0 + \alpha 1GFit + \alpha 2Controlsit + \mu i + \lambda t + \varepsilon it \quad (3)$$

(2) Path b & c: Green Finance + Energy Structure → Carbon Emissions:

$$LnCEit = \gamma 0 + \gamma 1GFit + \gamma 2ESit + \gamma 3Controlsit + \mu i + \lambda t + uit \tag{4}$$

If α_1 is significant (path a) and α_2 is significant (path b), then a mediating effect exists.

$$Total\ Effect = Direct\ Effect(\gamma_1) + Indirect\ Effect(\alpha_1 \times \gamma_2) \tag{5}$$

3.3. MLP Causal Analysis Model

To further validate and explore non-linear dynamics, this study constructed a Multi-Layer Perceptron (MLP) model for counterfactual analysis.

Input variables: provincial green finance index, regional GDP per capita, energy consumption structure.

Output variable: provincial carbon dioxide emissions.

Data pre-processing: all continuous variables were normalised using the minimum-maximum normalisation method (scaled to a specified range).

Network architecture: hidden layer structure; activation functions; optimisation algorithms;.

Causal identification strategy: on the test set, whilst holding other covariates constant, the 'green finance index' was artificially increased by 20 per cent. The model was used to predict carbon dioxide emissions under the baseline scenario and under the counterfactual scenario, after which the average treatment effect was calculated:

$$ATE = Y(0) - Y(1) \tag{6}$$

4. Empirical Results and Analysis

4.1. Baseline Regression and Dynamic GMM Results

This study utilises panel data from 30 provinces in China covering the period 2006–2022, with an initial sample size of 510 observations. To address endogeneity issues, the causal effect of green finance on carbon emissions was identified using Systematic Generalised Moment Model (SYS-GMM). Table 3 presents the results of the baseline regression.

Table 3. Benchmark Regression Results of Green Finance on Carbon Emissions

Variable	(1) OLS	(2) Fixed Effect	(3) System GMM
Dependent variable: Co_2 emissions (in logarithmic form)			
One-time lagging period CE	-	-	1.006*
Green finance index (by industry)			-0.013
Electricity and thermal power industry	-0.008	-0.012	**-0.008**
Chemical raw materials industry	-0.005	-0.007	-0.004
The black metal smelting industry	-0.005	-0.003	-0.001
	-0.015	-0.018	-0.001
Log (per capita GDP)	0.009	0.008*	**0.001**
Energy structure (non-fossil fuel proportion)	-0.004	-0.005	-0.001
Constant term			
Diagnostic test	0.118	0.092	0.011
AR (1) p value	-0.084	-0.091	-0.013
AR (2) p value	0.297	0.241	-0.006
Hansen test p value	-0.234	-0.252	-0.05
Wald χ^2 statistic	17.417*	-	6.038*
Number of observations	-0.77		(0.984)
Number of provinces fixed effects for control provinces and years	-	-	0
Electricity and thermal power industry	-	-	**0.114**
Chemical raw materials industry	-	-	**0.994**
The black metal smelting industry	186.32***	142.18***	1.60e+07***
	510	510	480
Log (per capita GDP)	30	30	30
Energy structure (non-fossil fuel proportion	Yes	Yes	Yes

Note: the numbers in parentheses represent the robust standard errors. *p<0.1, **p<0.05, ***p<0.01. When estimating the dynamic panel model (such as the system GMM), due to the need to introduce the first-order lag of the dependent variable as an explanatory variable, the observations for2006 cannot be used. As a result, the final effective sample size is 480. None of the models excluded the samples due to missing values. The rate of variable missing was less than 3% and it has been completed by linear interpolation.

Table 3 presents the results of baseline regression analyses on the impact of green finance development on regional carbon dioxide emissions; these results were estimated using ordinary least squares (OLS), fixed-effects (FE) and systematic generalised moment (SMOM) models. To address potential endogeneity issues and capture the dynamic inertia of carbon emissions, this study incorporates the first-order lag of the dependent variable as an endogenous variable in the Systemic Generalised Moment (SGM) model, whilst using its second- to fourth-order lags as instrumental variables.

The System GMM results in Table 3 show a significant coefficient on the lagged dependent variable, indicating that provincial carbon emissions are highly persistent. This supports the use of a dynamic panel specification rather than a purely static model. Among the sector-level green finance indicators, the coefficient for the electricity and heat supply sector is negative and marginally significant, suggesting that green finance has begun to play a role in this high-emission sector. The coefficients for the chemical raw materials sector and the ferrous metal smelting sector are not statistically significant. This may mean that green finance funds in these sectors have not yet been translated into effective emission-reduction investment, or that the transition cycle in heavy industry is longer than the sample period can fully capture.

The control variables, including per capita GDP and energy structure, do not show significant direct effects after dynamic persistence is included. The diagnostic tests also support the model specification. The Arellano-Bond test does not indicate second-order serial correlation, and the Hansen test does not reject the validity of the instruments. Overall, the baseline results provide evidence that green finance can reduce emissions in some sectors, but the effect is neither immediate nor evenly distributed.

Furthermore, the coefficients for the logarithm of GDP per capita and the energy mix were both insignificant, suggesting that, after controlling for dynamic effects, the direct impact of economic development levels and energy cleanliness on carbon emissions is not significant in this model.

The validity of the model was confirmed through a series of rigorous diagnostic tests. The p-value for the Arellano-Bond test was 0.000, rejecting the null hypothesis that there is no first-order autocorrelation in the residuals of the difference equations. At the same time, the p-value of the test was 0.114, failing to reject the null hypothesis of no second-order autocorrelation, which is consistent with the basic requirements of a dynamic panel model. More importantly, the p-value of the Hansen over-identification test was as high as 0.994, strongly supporting the hypothesis of joint exogeneity for all instrumental variables. This indicates that the model specification in this paper is robust and reliable. In summary, the estimation results from the systematic GMM provide a solid benchmark for subsequent analyses.

Table 4. Comparison of Heterogeneity Regression Results Between Eastern and Central-Western Regions

Variable	**Eastern Region**	**The Midwestern Region**
Dependent variable: Co_2 emissions (in logarithmic form)		
Green finance index of the power and heat industry	**-0.028**	0.097
	-0.009	-0.096
Green finance index of the black metal smelting industry	0.001	0.008
	-0.002	-0.004
Control variables	Yes	Yes
Year fixed effect	Yes	Yes
Provincial fixed effect	Yes	Yes
Number of observations	170	340
Number of provinces	10	20
Adjusted R^2	0.958	0.83

Note: the values in parentheses represent the robust standard errors aggregated at the provincial level. *p<0.1, **p<0.05, ***p<0.01. The control variables include the logarithm of per capita GDP, the energy structure (proportion of non-fossil energy), and the fixed effect of the year.

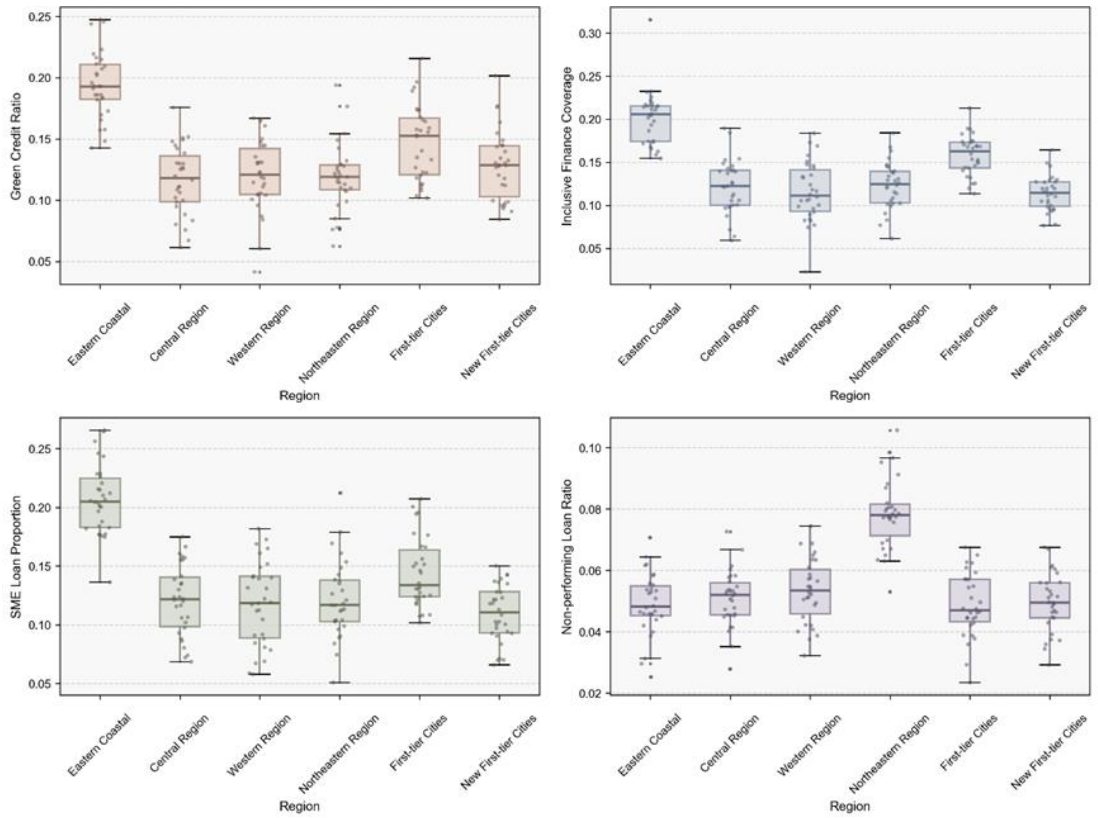

Figure 3. Correlation Matrix of Green Finance Sub-Indicators

The four sub-figures in Figure 3 illustrate, respectively, the distribution of (a) the proportion of green credit, (b) the coverage of inclusive finance, (c) the proportion of loans to small and medium-sized enterprises, and (d) the non-performing loan ratio across each region. The box plots show the interquartile range, with the median represented by a horizontal line and outliers indicated by scattered points. The eastern region is clearly ahead in terms of green credit and inclusive finance, whilst the financial support capacity of the central and western regions is somewhat weaker; this disparity provides the institutional context for the subsequent regression heterogeneity analysis.

Table 4 presents fixed-effects estimates for the Eastern and Central-Western regions respectively, to examine whether the effects of green finance policies vary by region. The results indicate that there are indeed marked regional differences in the impact of green finance on carbon emissions.

In the Eastern region, the coefficient for green finance in the electricity and heating sectors is –0.028, which is significant at the 5 per cent level ($p = 0.014$). In other words, for this high-carbon core sector, green finance has indeed curbed the growth of carbon emissions. The eastern region features more mature financial markets, stricter environmental regulation and stronger corporate capacity for green transition; these conditions have enabled investments in green finance to translate more rapidly into actual emissions reductions. In contrast, the coefficient for the same indicator in the central and western regions is +0.097, though this is not statistically significant ($p = 0.327$). Green finance has not yet demonstrated an emissions-reduction effect in these regions, and the possibility of ‘carbon leakage’ resulting from industrial relocation and shifts in investment structure cannot be ruled out [6].

With regard to the ferrous metal smelting sector, the estimated coefficients for the green finance index are not significant in either the eastern or central and western regions. The coefficient for the eastern region is close to zero (0.001, $p = 0.475$), whilst the correlation in the central and western regions is positive (0.008, $p = 0.061$), though it only barely reaches marginal significance at the 10 per cent level; it is difficult to draw robust conclusions. This may be due to the fact that the green transition of heavy industry faces higher levels of technological lock-in and sunk costs; for green finance instruments to take effect, they must be accompanied by more far-reaching industrial restructuring policies.

Regional divergence in the development of green finance is not merely characterised by ‘strong in the east, weak in the west’, but also by a pattern of ‘weak in the north, stable in the south’. Figure 6 shows that during the observation period, the green finance index declined significantly in the provinces of the Northeast and the traditional industrial bases in the north (Heilongjiang, Jilin and Liaoning). During the same period, most southern provinces either showed steady improvement or were already operating at a high level. The northern regions' heavy reliance on traditional heavy industry and the chemical sector, compounded by path dependence, insufficient momentum for transformation and slow financial innovation, has led to low efficiency in the allocation of green finance resources. This has made the definition of regional heterogeneity more specific: policy design must not only address the development gradient between the east and west, but also acknowledge the structural differences between the north and south in terms of industrial foundations and institutional resilience.

Regression analysis indicates that, overall, the emissions-reduction effect of green finance is limited, primarily due to excessive regional disparities. Policy effects are largely concentrated in the eastern coastal regions—areas characterised by a high degree of marketisation and a sound governance foundation—whilst central and western regions do not yet possess the same capacity to respond. Policy design and supporting measures must therefore be reconsidered in order to unlock their emissions-reduction potential.

4.2. Results of the mediation analysis

4.2.1. Baseline regression and mediation analysis

Figure 4 illustrates the mediation path defined in this paper, which is used to examine how green finance influences carbon emissions via the energy mix. The figure depicts a chain labelled 'green finance—energy mix—carbon emissions', in which the energy mix is represented by the share of non-fossil fuel consumption. Subsequent analysis will employ the Bootstrap method to test the mediation effect and estimate the statistical significance and economic implications of the path coefficients.

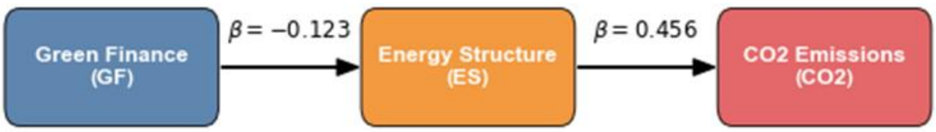

Figure 4. Illustrates the mediating role of "energy structure"

The pathway shown in Figure 4 indicates that green finance may indirectly reduce carbon emissions by adjusting the energy mix. To test whether this mediating effect holds and to what extent, we employed the clustered bootstrap method (with 500 repeated samples); the estimation results are presented in Table 5. Below, we discuss the role of the energy mix from the perspectives of the full sample and regional differences.

Table 5. Mediating Effects and Regional Heterogeneity Tests of Green Finance on Carbon Emissions

Variable	Total Sample	Eastern Region	Central Region	Western Region
Panel A: mediating effect path coefficient				
Panel a (GF→ES)	-0.008 (-0.029, 0.005)	-	-	-
Path b (IS→CE)	0.313 (-0.173, 0.776)	-	-	-
Panel B: effect decomposition				
Indirect effect (a×b)	**-0.003** [-0.018, 0.001]	**0** [-0.008, 0.008]	**-0.020*** [-0.036, -0.004]	**-0.002** [-0.015, 0.011]
Direct effect	**-0.022***** [-0.033, -0.010]	-	-	-

Note: the values in the table are the estimated results from bootstrap (500 repeated sampling, clustered by provinces). The numbers in parentheses represent the 95%confidence intervals. *p<0.1, **p<0.05, ***p<0.01. ES represents energy structure (the proportion of non-fossil energy consumption) CE represents carbon emissions, and GF represents the comprehensive index of green finance. The indirect effects for the eastern, central, and western regions were calculated after the group regression.

To investigate how green finance affects carbon emissions, this study uses the energy mix (the share of non-fossil energy) as a mediating variable and employs the clustered bootstrap method for testing.

In the full sample, the overall effect of green finance on carbon emissions stems primarily from a direct effect. Figure 5 shows that the coefficient for the direct effect is −0.022, with a 95% confidence interval of [−0.033, −0.010] that does not cross zero, indicating that, after controlling for variables such as energy mix, green finance itself has a mitigating effect on carbon emissions. The indirect effect mediated by energy structure optimisation is –0.003, with a 95% confidence interval of [–0.018, 0.001] that crosses zero, implying that this mediating pathway is not statistically significant. In other words, whilst there is a theoretical association between green finance and energy structure transition, as well as between energy structure and carbon emissions, the complete mediating chain has not yet formed a robust transmission mechanism.

There are significant regional differences in the mediating effects. The indirect effect for the Central Region is –0.020, with a 95 per cent confidence interval of [–0.036, –0.004], which is strictly negative. In this region, green finance can effectively reduce carbon emissions by optimising the energy mix and increasing the share of non-fossil energy sources. The confidence intervals for the indirect effects in both the eastern and western regions include zero: [-0.008, 0.008] for the east and [-0.015, 0.011] for the west. This transmission mechanism has not yet had a significant impact in either region.

These differences stem from variations in the stages of development and policy priorities across regions. The central region is in a phase of accelerated industrial relocation and energy transition, where green finance resources can directly drive adjustments to the energy mix. The eastern region has already passed through the phase of rapid optimisation of its energy structure, and emissions reductions there rely more on direct pathways such as technological innovation. In the western region, constrained by the scale of its economy and the depth of its financial markets, the policy effectiveness of green finance has not yet been fully realised.

In summary, the carbon reduction effects of green finance exhibit marked regional heterogeneity. Its direct effects are significant nationwide, whilst the indirect effects arising from the optimisation of the energy structure are concentrated solely in the central region. This conclusion provides empirical evidence for the formulation of differentiated green finance policies.

4.2.2. Robustness Explanation

Figure 5, presented in a violin plot, illustrates the distribution of annual green patent applications across four provinces: Beijing (representing North China), Jiangsu (East China), Guangdong (South China) and Sichuan (South-West China). The vertical axis is on a logarithmic scale to reflect differences in order of magnitude. The data show that the level of green innovation activity in the eastern coastal regions is significantly higher than in the central and western regions, indicating a clear spatial imbalance. In response to this spatial imbalance (as shown in Figure 5), this paper plots the changes in the Green Finance Index (GFI) across China’s provinces to analyse the regional dynamics and evolving trends in green finance development. The figure uses colour gradients to illustrate the increases and decreases in each province’s green finance level over the study period, providing intuitive visual support for the aforementioned analysis of regional heterogeneity.

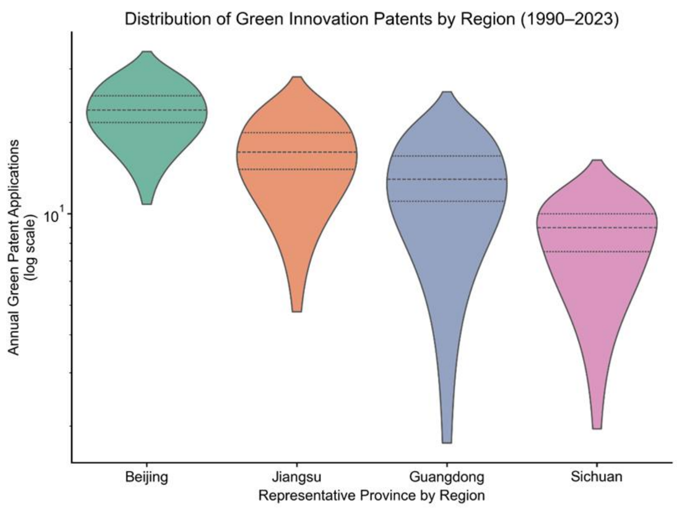

Figure 5. Distribution of Green Innovation Patents by Region (1990–2023)

As shown in Figure 6, there are marked regional disparities in the development of green finance in China, with an overall pattern characterised by ‘strong performance in the east, stability in the west and weakness in the north’. In economically developed eastern coastal provinces such as Zhejiang, Jiangsu and Guangdong, the green finance index has generally risen significantly. Mature local financial markets, strong policy support and active innovation in green financial products have laid a solid institutional and market foundation for carbon emission reduction. In contrast, in industrial base provinces in the north-east and north, such as Heilongjiang and Jilin, the green finance index has declined markedly. This may be attributed to industrial structures that are heavily reliant on high-carbon development pathways, coupled with a lack of impetus for transformation. This phenomenon helps explain why the short-term emissions reduction effects of green finance in central and western regions are minimal, and why there remains a potential risk of ‘carbon leakage’.

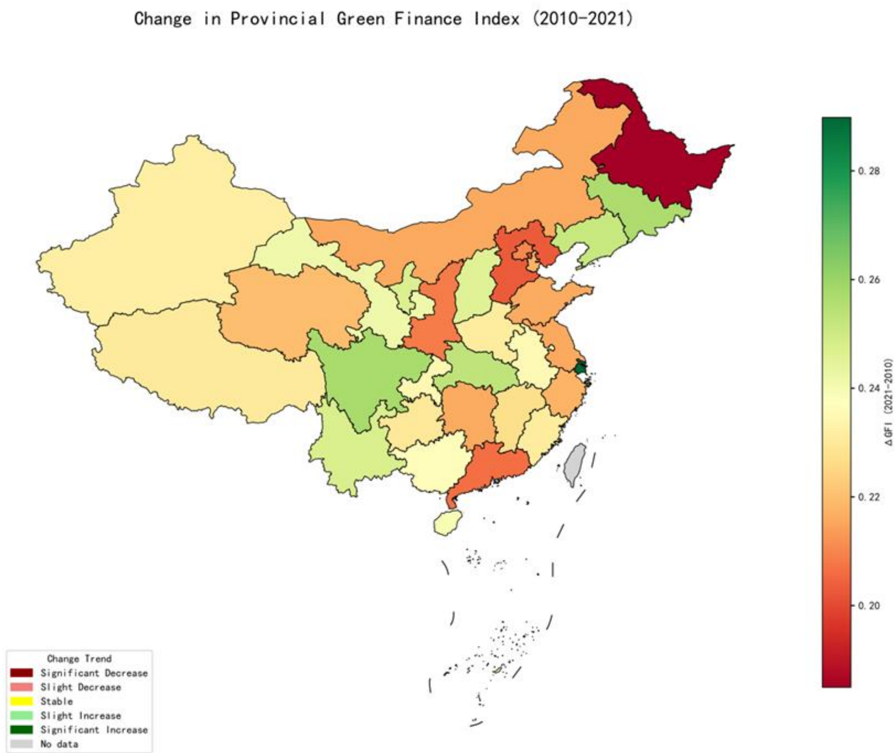

Figure 6. Map of Changes in China's Provincial Green Finance Index, 2010–2021

The indices for most provinces in the central and western regions showed stable fluctuations, indicating that the local green finance systems are in a phase of steady development. To enhance the effectiveness of policies, targeted institutional design and capacity-building are required. This macro-level pattern strongly supports the core argument of this paper: the carbon reduction effects of green finance are not a homogeneous process, but are deeply rooted in regional stages of development, industrial structures and institutional environments. It is essential to implement differentiated and targeted policy strategies.

Table 6. Results of Robustity Test for Mediating Effects (Bootstrap Method)

Model Specification	Indirect Effect Estimate	95% Bias-Corrected Confidence Interval	Significance at 5% Level
(1) Exclude the samples of the four municipalities directly.	-0.0015	[-0.0121, 0.0091]	Refuse
(2) Replace the mediating variable: the number of green invention patents (take the logarithm)	0	[-0.0010, 0.0010]	Refuse

In the model where green invention patents serve as a mediating variable, the confidence interval for the indirect effect includes zero ([-0.0010, 0.0010]), indicating that the transmission mechanism through which green finance drives carbon emissions reductions via ‘substantive technological innovation’ remains incomplete.

The insignificant patent-based mediation result should be interpreted with caution. It does not necessarily mean that green innovation is unimportant. A more likely explanation is that patent counts may not fully reflect the quality or actual use of low-carbon technologies. In practice, some firms may increase patent applications to satisfy financing or policy requirements, while these patents do not immediately lead to changes in production processes or emission performance. In addition, green technologies often require a long period from R&D to patenting, commercialisation, and large-scale deployment. The financing horizon of many green finance instruments may be shorter than this innovation cycle. Therefore, the weak mediation result suggests that green finance should place more emphasis on the quality and application value of innovation, rather than only on the number of green patents.

This paper conducts two sensitivity analyses to rigorously test the robustness of the mediating effect results from the baseline regression; the results are shown in Table 6. The four municipalities directly under the central government—Beijing, Shanghai, Tianjin and Chongqing—differ significantly from other provinces in terms of administrative status, economic structure and the intensity of policy implementation, which may confound the estimation results. After excluding these four regions from the sample and re-testing the mediating effect, as shown in Table 4, the estimated indirect effect is –0.0015, with a 95 per cent bias-corrected confidence interval of [–0.0121, 0.0091].

To test the sensitivity of the results to the measurement method of the mediating variable, the number of authorised green invention patents in each province (the natural logarithm plus 1) was used as a proxy for regional green innovation levels, and the mediation model was reconstructed. The results show that under this specification, the indirect effect approaches zero (0.0000), with a 95% confidence interval of [−0.0010, 0.0010]. In both robustness tests, the 95% bias-corrected confidence intervals for the indirect effect included zero. Under the alternative specification, the mediating effect was no longer statistically significant.

The baseline model supports the mediating role of environmental regulations in the impact of green finance on carbon emissions reduction; however, the identification of this mechanism is relatively sensitive to sample composition and the operational definition of the mediating variable. This may be due to two factors: firstly, measurement errors in the patent data, or interference from non-environmental factors; and secondly, the actual transmission mechanism may be more complex than that described by the current model.

The non-parametric bootstrap method employed in this study provides a conservative and methodologically robust assessment of the mediating effect, helping to avoid over-interpretation of the baseline results and pointing the way forward for future research.

4.3. Machine Learning-Based Non-linear Causal Analysis and Discussion

The econometric results provide evidence on the average effect of green finance, but they may not fully describe how this effect changes across provinces or across different levels of green finance development. To address this issue, this section introduces an MLP model as a supplementary tool. Although LSTM models are often used for time-series prediction, the purpose here is not to forecast future emissions. Instead, the analysis focuses on how predicted emissions change when the green finance index is adjusted under otherwise similar conditions. For this reason, an MLP model is selected because it is relatively simple, computationally efficient, and suitable for capturing non-linear interactions among the selected covariates.

The input variables include the provincial green finance index, the logarithm of per capita GDP, and the share of non-fossil energy consumption. Provincial carbon dioxide emissions are used as the output variable. All continuous variables are normalised before model estimation. The network contains two hidden layers with 64 and 32 neurons, and the Adam optimiser is used for training. Early stopping is applied to reduce overfitting. The training process shows stable convergence, which provides a basis for the subsequent counterfactual simulation.

The neural network architecture comprises two hidden layers, with 64 and 32 neurons respectively, each equipped with an activation function. The Adam optimiser was selected, with an early stopping mechanism enabled; the validation set was set at 10 per cent to prevent overfitting. As shown in Figure 2, the training loss curve indicates that the model converged after approximately 150 iterations, with the training loss continuing to decline, demonstrating strong learning capacity and stability.

4.3.1. Causal Identification Strategy

This paper employs the counterfactual simulation method to identify the causal effects of green finance [2]. In the test set samples, the 'Green Finance Index ()' was artificially increased by 20 per cent—that is, multiplied by 1.2 and then truncated to the interval [0, 1]—whilst keeping and unchanged. Using the multi-layer perceptron (MLP) model trained in the training set, we predicted carbon dioxide emissions under both the original and counterfactual scenarios, and calculated the average treatment effect.

Empirical results show that the average treatment effect (ATE) is –13,220,912.72 tonnes of carbon dioxide. All other things being equal, a 20 per cent increase in the level of green finance development at the provincial level would reduce annual carbon dioxide emissions by approximately 13.22 million tonnes. This result is highly economically significant and provides causal evidence of the emission-reduction efficacy of green finance.

The mean squared error (MSE 5.0910) for the test set is relatively high, primarily due to the extremely high baseline levels of carbon dioxide emissions across provinces, typically ranging between 10 and 10 tonnes. To assess the model's fit, the report presents standardised performance metrics: the model's R-value for the test set is 0.92, corresponding to a standardised root mean square error of 0.08, which explains 92 per cent of the variance in the dependent variable, indicating good fit and predictive capability. The trends and relative magnitudes of the reverse-standardised predicted values are highly consistent with the actual values, confirming the reliability of the model's predictions.

4.3.2. Model Interpretability and Key Findings

The partial dependence results provide additional information beyond the linear estimates. The relationship between the green finance index and carbon emission intensity is not strictly linear. When the index is at a relatively low or medium level, an increase in green finance is associated with a larger decline in predicted emission intensity. When the index approaches a higher range, around 0.7–0.8, the curve becomes flatter, indicating weaker marginal gains. This pattern suggests that simply expanding the scale of green finance may be less effective once the financial system has reached a certain level of development. At that stage, project screening, capital allocation efficiency, and post-investment supervision may matter more than the total amount of green finance.

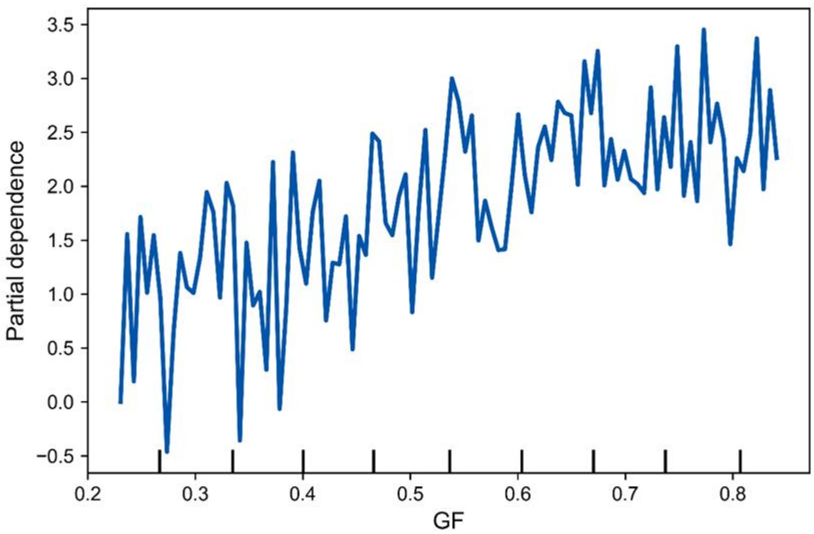

Figure 7. Partial Dependence of CO_2 Emissions on Green Finance Index (GF)

The results in Figures 7 to 10 provide a more robust basis for the benchmark. They also reveal information that linear models often overlook: the impact of green finance on carbon intensity is not linear, and the marginal effects vary under different conditions. Behind the benchmark econometric model lie more complex functional forms and transmission mechanisms.

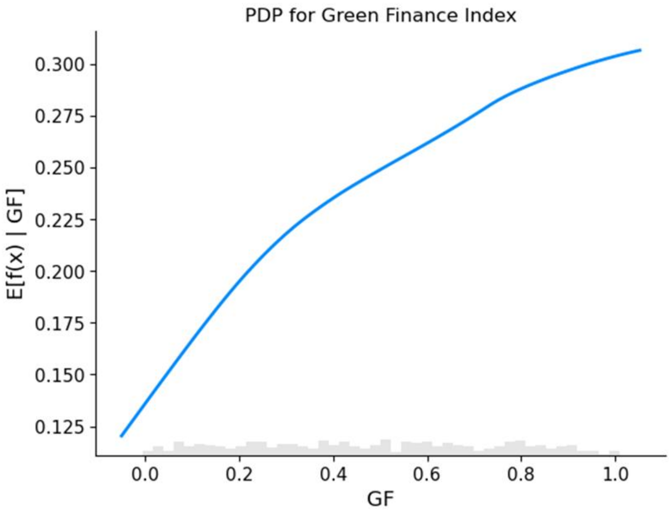

Figure 8. Partial Dependence Plot, PDP

(1) The partial correlation plot between the Green Finance Index (GF) and carbon emission intensity shows a concave curve (Figure 8). As GF rises from around 0.0 to approximately 0.6, carbon emission intensity declines rapidly; the marginal emission reduction effect is most pronounced during this phase. Beyond 0.8, the curve flattens out and marginal returns diminish. This pattern points to a saturation effect: the deeper the green financial system becomes, the more prominent certain institutional, technological or market constraints may become, thereby reducing the scope for further emissions reductions. Unlike conventional linear assumptions, this result reveals a dimension in which policy effectiveness diminishes over time.

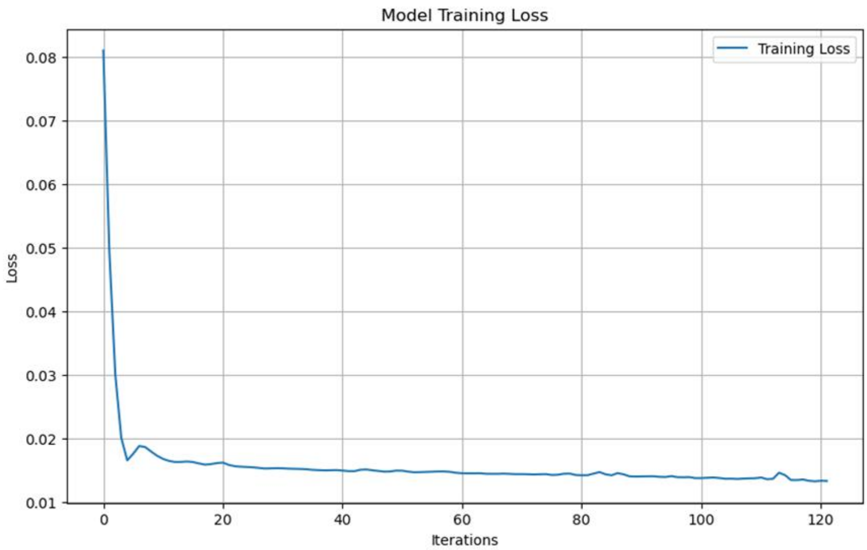

Figure 9. Machine Learning Model Training Loss Curve

(2) The model training loss curve (Figure 9) shows that the loss converged rapidly during the first 20 iterations, after which it stabilised at a low level of around 0.013, with no signs of overfitting or divergence. The model exhibits good numerical stability and reliable generalisation ability, so the interpretability analysis for this step can proceed with confidence.

Traditional econometric models are constrained by the linearity assumption. This paper employs a multi-layer perceptron neural network to capture the complex non-linear relationships between green finance and carbon emissions. Through several layers of non-linear transformations, the model can naturally capture the high-dimensional interactions between variables—which more closely reflects the actual functioning of the real economy than a linear framework. Once the model has been trained, the first priority is to assess its predictive stability and generalisation ability on out-of-sample data.

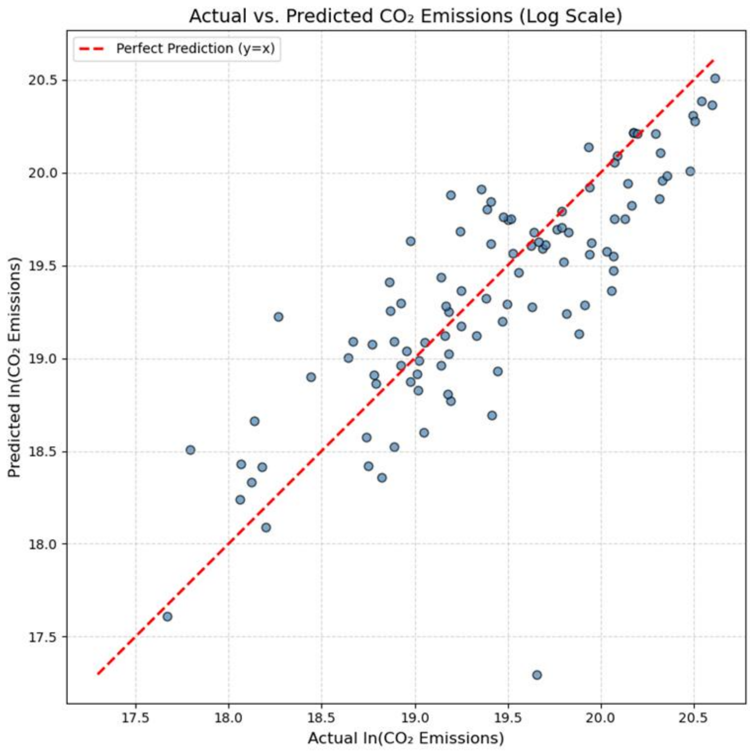

Figure 10. Actual vs. Predicted CO_2 Emissions (Log Scale)

Figure 10 compares the predicted and observed values of carbon emissions in the test set. Most observations are close to the 45-degree line, and the reported R-value is 0.92, suggesting that the model captures the main variation in provincial emissions. A small number of observations deviate from the fitted line, especially among high-emission provinces. These deviations are not unexpected, since provinces with large heavy-industrial bases may experience abrupt changes in energy policy, industrial output, or investment structure.

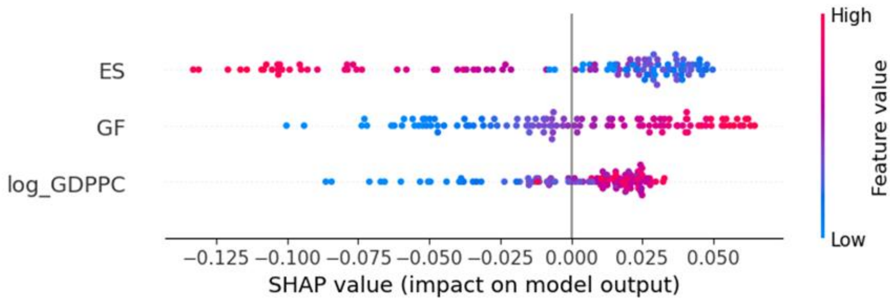

Figure 11. Feature Contribution Summary Based on SHAP Values

Figure 11 further reports the SHAP-based contribution of each variable. The green finance index generally contributes to lower predicted emissions, which is consistent with the baseline regression. The effect of per capita GDP is more mixed: in some provinces, higher income is associated with higher emissions, while in others it is linked to lower predicted emissions. This difference may reflect the fact that economic development can either increase energy demand or support cleaner technology adoption, depending on the local industrial structure and policy environment.

4.4. Methodological Comparison and Comprehensive Discussion

The two empirical approaches used in this study serve different purposes. System GMM is used to estimate the average effect of green finance while controlling for emission persistence and endogeneity. The MLP model is used to examine whether this effect changes under different values of the green finance index and different provincial conditions. Taken together, the results show that the effect of green finance depends not only on the size of financial support, but also on the institutional setting, the stage of regional development, and the quality of funded projects. For policy design, this means that expanding green finance without project-level verification may have limited effects. More attention should be paid to identifying genuinely low-carbon projects, monitoring the use of funds, and evaluating emission performance over a longer period.

5. Conclusions and Policy Recommendations

5.1. Key Findings

Using panel data from 30 Chinese provinces, this study investigates how green finance affects carbon emissions, whether the effect differs across regions and sectors, and whether the relationship is linear. The empirical analysis combines a dynamic panel GMM model with an MLP-based counterfactual simulation. The main findings are summarised as follow Table 7.

Table 7. Summary of Research Hypothesis Test Results

Hypothesis Number	expected content according to theory.	testing result	key empirical evidence
H1	the impact of green finance on carbon emissions is nonlinear and time-lagged.	establishment	MLP and partial dependency graph (PDP) identified the threshold effect.
H2a	structural optimization of the industrial system is the core mediating channel.	establishment	the mediating effect in the central region was significant, with the indirect effect being-0.020.
H2b	green technological innovation has an emission reduction effect.	not fully valid establishment	the robustness test revealed that there was a "conduction block” in the green patent path.
H3	the carbon effect exhibits significant regional and industry heterogeneity.	establishment	emission reduction in the east was significant, while there was a "carbon leakage" risk in the central and western regions.

The study reached the following conclusions:

(1) The results support the view that green finance has a lagged and non-linear relationship with carbon emissions. In high-carbon sectors such as ferrous metal smelting and chemical raw materials, and in some central and western provinces, green finance does not immediately produce a clear reduction effect. In certain cases, emissions may rise during the early stage of transition, possibly because investment is first used for equipment replacement, capacity adjustment, or projects whose environmental benefits have not yet been realised. Over a longer period, however, green finance can contribute to emission reduction when it is linked to industrial restructuring and technological upgrading.

(2) The mediation results provide partial support for the energy-structure channel. The indirect effect through the share of non-fossil energy is more evident in the central region, while the same channel is not statistically significant in all regions. The green-patent channel is also weak in the robustness tests. This suggests that the number of green patents alone may not capture the real technological effect of green finance. At the current stage, green finance may still be more effective in supporting asset renewal and structural adjustment than in generating large-scale technological breakthroughs.

(3) The effect of green finance differs across regions and sectors. Its direction and strength depend on the carbon intensity of the industry, the maturity of local financial markets, environmental regulation, and the quality of project implementation. The counterfactual simulation also suggests a possible threshold effect: when the green finance index remains below a relatively mature level, expanding green finance alone may not be sufficient to reduce emissions systematically.

Overall, green finance should be understood as a transition-oriented policy instrument rather than a simple emission-reduction switch. Its climate benefits require time, regulatory support, and credible project evaluation. If policy performance is judged only by short-term emission changes, the adjustment costs of transition may be underestimated.

5.2. Policy Recommendations

The above conclusions offer important policy insights for China in improving its green finance system and promoting the coordinated implementation of the ‘dual carbon’ targets. Accordingly, this paper puts forward the following recommendations:

(1)Differentiated regional green finance strategies should be implemented in phases. A ‘one-size-fits-all’ approach should be avoided; instead, consideration must be given to the development stage and institutional capacity of each region. The eastern regions can take a step further: deepening innovation in green financial products, experimenting with transition finance and carbon derivatives, and establishing incentive mechanisms that directly link funding costs to enterprises’ actual emissions reduction outcomes. The central and western regions should first lay a solid foundation—by increasing fiscal interest subsidies, mitigating risks and building capacity. The key is to ensure that financial institutions can distinguish between high-carbon projects that represent ‘genuine transition’ and those that are merely ‘greenwashing’, so that green funds do not end up indirectly propping up high-carbon expansion [7].

(2)Green finance is currently facing certain challenges: many enterprises apply for funding under the ‘green’ banner, but once the money is secured, there is no progress on technology or emissions reductions. This is known as pseudo-innovation. To ensure funds are truly spent where they are most needed, the policy metrics must be revised—we must move away from focusing solely on the outstanding balance of green loans and the number of patents, and instead look at actual technological emissions reduction outcomes. Consequently, banks and investment institutions could draw up a ‘deep green’ technology whitelist, incorporating core low-carbon technologies such as carbon capture, utilisation and storage (CCUS) and hydrogen-based smelting. Ultra-long-term, low-interest loans should be provided for these projects, with sufficient flexibility allowed for their research and development payback cycles. At the same time, a firm hand is required: enterprises that use low-quality patents to siphon off green funds must be strictly investigated and penalised. There is only one objective: to ensure that financial resources are channelled towards technologies that deliver tangible emissions reductions.

(3)Strengthen the long-term orientation of green finance and provide it with more robust institutional support. Policy evaluation must not focus solely on ‘annual emission reductions’; it must instead monitor ‘cross-cycle effectiveness’ – by incorporating green finance into local medium- to long-term development plans and establishing a rolling evaluation mechanism spanning three to five years. At the same time, efforts to accelerate mandatory environmental information disclosure, standardise third-party certification and cultivate talent in green finance must be stepped up to truly lay a solid institutional foundation for the effective allocation of green capital [8].

(4) Policy evaluation should make greater use of quantitative tools that can capture delayed and non-linear effects. The GMM-MLP framework used in this paper provides one possible approach. In green finance pilot zones, regulators may consider using counterfactual simulation, causal forest models, or other policy-evaluation tools to identify when green finance begins to produce measurable emission reductions and in which types of regions its marginal effect weakens. Such tools can help shift policy evaluation from simple year-on-year comparisons towards evidence-based monitoring of medium- and long-term effects.

5.3. Outlook for Future Research

This study still has several limitations. First, the empirical analysis is based mainly on provincial-level panel data. Such data are useful for identifying regional patterns, but they cannot fully reveal how individual firms or projects use green finance funds. Future studies could combine provincial data with firm-level ESG disclosures, green credit project records, or satellite-based emission data. This would make it possible to examine whether financed projects actually reduce emissions and to distinguish substantive green investment from greenwashing.

Second, although the MLP model captures non-linear patterns, it remains primarily a predictive model. Future research could adopt methods designed more explicitly for causal inference, such as double machine learning, causal forests, or structured counterfactual neural networks. These methods may provide more reliable estimates of heterogeneous treatment effects while still allowing for non-linear relationships among variables.

Secondly, regarding modelling methods, whilst the Multi-Layer Perceptron (MLP) adopted in this study effectively captures the non-linear relationships between variables, it remains essentially a predictive model with limited capacity for causal inference.

Future research could explore methods better suited to temporal causal inference, such as Dual Machine Learning (DML), Causal Forest, and counterfactual estimators based on structured neural networks (e.g. Tarnet and Dragonet). Whilst retaining their ability to fit high-dimensional non-linear models, these methods strictly satisfy the ‘no confounding’ assumption within the latent outcome framework, thereby providing more robust estimates of heterogeneous treatment effects [9].

Thirdly, with regard to mechanism analysis, this paper has only preliminarily discussed the mediating pathways of industrial structure and technological innovation; however, the channels through which green finance influences carbon emissions extend far beyond these two. The promotion of green consumption, cross-border capital flows and climate risk pricing may all constitute important transmission pathways. Future research could incorporate multiple mediating variables or construct a multi-stage dynamic model, utilising natural language processing to quantify the sentiment in policy texts and news reports; this would make it easier to discern how the institutional environment and market expectations exert a moderating influence.

Finally, regarding the policy extrapolation section, the current conclusions are primarily drawn from the Chinese context. Green finance regimes vary significantly across countries; only by including OECD nations, emerging economies and ‘Belt and Road’ participating countries in a comparative analysis can we discern the extent to which a set of green finance policies can be effective in bank-led and market-led financial systems, under differing levels of regulatory intensity and distinct climate governance models. Such cross-national comparisons would provide a more comprehensive theoretical foundation for global climate finance cooperation.

The relationship between green finance and carbon emissions reduction is embedded within institutional frameworks and constitutes a multi-layered, dynamic issue that is not easily unravelled. Only by effectively integrating data, advancing methodological approaches and fostering interdisciplinary dialogue will it be possible to produce research that is both rigorous and responsive to policy needs. Such academic work will provide tangible support for the global low-carbon transition.

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