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Examining the Effects and Operational Mechanisms of Green Credit on Carbon Emissions in Chinese Regions

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Abstract: The utilization of a green financial system, particularly through the implementation of green credit, plays a pivotal role in fostering environmentally sustainable, low-carbon economic growth and facilitating the transition toward a more ecologically responsible economy. This paper employs a two-way fixed-effects model, utilizing provincial panel data spanning from 2012 to 2020, to investigate the influence of green credit on regional carbon emissions within different regions of China. The results reveal a significant reduction in carbon emissions as a consequence of the green credit program's implementation. The analysis of the pathway indicates that green credit is instrumental in mitigating carbon emissions by instigating shifts in the energy mix, with evidence suggesting a partial mediating effect. Furthermore, a heterogeneity analysis discovered that the suppressive impact of green credit on carbon emissions is more pronounced in the eastern and western regions of China, while it is less significant in the central and northeastern areas. The implications of this study provide robust evidence in support of the role of green credit in reducing carbon emissions and can serve as a valuable resource for policymakers aiming to promote the expansion of green credit programs and, in turn, contribute to substantial reductions in carbon emissions.

Keywords: Carbon emission; Green credit; Intermediary effect

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1. Introduction

China's remarkable economic growth following its reform and opening-up policies stands as a global economic growth milestone. Nevertheless, the conventional concept of economic growth, characterized by excessive resource consumption, high pollution levels, and heavy environmental degradation, has given rise to profound environmental and pollution issues. China has long held the inevitable position of being the world's foremost contributor to total carbon emissions. As a result, there is a pressing and substantial need to curtail emissions. China's role as a major player in global emission reduction efforts is evident in its adoption of the "dual carbon" target.

The implementation of green credit exerts credit controls over industries characterized by "high energy consumption and high pollution," curtailing their expansion through mechanisms such as project access restrictions, elevated interest rates, and quota limitations, all aimed at compelling a shift away from their high energy consumption and high pollution business models. Meanwhile, through the provision of preferential credit policies and credit products, it fosters the growth of low-carbon, recycling, energy-saving, and environmentally friendly sectors, leading to significant ecological gains and ultimately realizing a symbiotic relationship between ecology and finance. The interplay between green credit, energy conservation, emission reduction, and the support of local low-carbon economic transformation has emerged as a key challenge in the pursuit of sustainable green development.

2. Literature review

2.1. Exploration of carbon emissions

The study of carbon emissions is a multifaceted field influenced by numerous factors, with a primary focus on environmental regulation, technological advancements, and industrial structure. Substantial research efforts have been devoted to strategies for reducing carbon emissions. Lin and Liu (2010) advocated the reduction of carbon emissions by maintaining GDP growth while controlling the urbanization rate and diminishing energy consumption intensity [1]. Sun *et al.* (2016) highlighted the optimization of industrial and energy structures to enhance carbon emissions efficiency, with government intervention playing a pivotal role in achieving energy target constraints [2]. Wang *et al*. (2018) revealed a significant inverted U-shaped curve relationship between economic growth and carbon emissions, while population agglomeration, technological advancements, openness to global markets, and intensified highway transportation together inhibit the increase in the level of urban carbon emissions [3]. Liu *et al*. (2019) unveiled the impact of technological innovation, foreign trade, and industrial concentration on both the carbon intensity of local high-energy-consuming industries and neighboring areas through the spatial spillover effect, while energy and industrial structures, as well as enterprise-scale primarily affect the carbon intensity of the local high-energy-consuming industries [4]. It is important to note that the factors influencing carbon emissions can differ greatly across industries and regions, necessitating the development of region-specific policies [5-8].

2.2. Exploration of green credit mechanisms

Scholarly investigations support the notion of a financing penalty and investment inhibition effect on high-energy and high-pollution firms as a result of green credit policies. Zhou and Luo (2017) observed that, following the implementation of green financial policies, non-heavily polluting enterprises gradually matched or even exceeded heavily polluting counterparts in obtaining new and long-term borrowings. Companies with a stronger green reputation were more successful in securing new borrowings and long-term financial support in their analysis of heavily polluting A-share listed enterprises [9]. Su and Lian (2018) employed a double difference method to conclude that green credit policies hinder interest-bearing debt financing and long-term liabilities for heavy polluters, with new investments exhibiting a declining trend [10]. Ding and Hu (2020) ascertained that green credit policies effectively curtail the credit financing of heavy polluters, with a stronger impact on long-term credit financing [11]. Wang *et al.* (2021) researched Chinese listed firms and determined that green financing policies enhance the investment effectiveness of high-polluting companies [12].

Moreover, studies confirm the role of green credit in promoting the development of environmental protection industries. Ding *et al*. (2020) utilized the data envelopment analysis (DEA) model to analyze the efficiency of green credit in supporting ecological economic development in Zhejiang Province and found a gradual improvement in the overall efficiency of green credit support for ecological economic development.

Specifically, they observed that energy-saving, environmental protection, medicine, and health industries attract substantial green credit inputs with high output efficiency [13]. Song *et al*. (2022) highlighted the significant impact of green finance on the dissemination of environmental protection technologies at the national level, with cleaner production technologies outweighing end-of-pipe technologies [14]. Shu *et al*. (2023) discovered that green credit policies play a substantial role in stimulating green innovation in enterprises [15].

2.3. Investigation of green credit's impact on carbon emissions

Research on the impact of green credit on carbon emissions is divided. He *et al*. (2023) discovered that green credit effectively contributes to carbon emissions reduction, with a more pronounced impact in the eastern region compared to the central and western regions [16]. Yin *et al*. (2019) contended that green credit lowers carbon emission intensity through the transmission chain of research and development expenditures in high-tech enterprises [17].

Conversely, some researchers assert that the influence of green credit is conditional. Huang *et al*. (2023) conducted a threshold effect analysis and revealed that the progress of environmental technology needs to surpass a certain threshold for green credit to significantly promote the manufacturing industry. Within a reasonable range of green credit intensity, it can notably enhance the efficiency of carbon emissions [18]. According to Wang and Huang's analysis in 2022, the impact of green credits on carbon emissions is dependent on environmental regulation. Green credit can greatly reduce carbon emissions when environmental regulations are stringent [19].

Based on this classification, this study employs two-way fixed-effects panel models, mediation effect analysis, and regional heterogeneity analysis to investigate the effects and impact pathways of green credit on carbon emissions in China, encompassing the eastern, central, western, and northeastern regions. The findings from this study hold valuable insights for the development and implementation of policies.

3. Research hypotheses

The green credit policy increases the loan difficulty and interest rates for enterprises with high pollution and high energy consumption, while incentivizing industries to transition towards energy conservation, environmental protection, low energy consumption, and reduced pollution. This shift contributes to the reduction in carbon emission intensity. Additionally, the concurrent development of low-carbon recycling industries enhances support for energy efficiency and environmental protection, resulting in greater ecological benefits. Under the regulatory guidance of green credit, social capital is more likely to flow into green sectors, expediting industrial transformation and carbon emission reduction. Therefore, the initial hypothesis of this study is as follows:

Hypothesis 1: Green credit facilitates a reduction in carbon emission intensity.

Green credit fosters the decarbonization of the energy consumption structure through expansion, technological advancement, and feedback effects [20]. Conventional energy sources like coal pose significant environmental threats, and enterprises heavily reliant on coal often generate substantial carbon emissions. Such businesses may encounter challenges in obtaining financial support within the green credit framework. Conversely, green credit promotes investments in new energy sources, accelerates their technological progress, reduces the cost of adopting new energy sources, and enables enterprises to utilize these sources cost-effectively. This ensures profitability while achieving low-carbon development and fostering a virtuous cycle. As a result, the following hypothesis is proposed:

Hypothesis 2: Green credit affects carbon emissions by reshaping the energy mix.

Given the substantial variation in carbon emissions, energy structures, the degree of green credit system maturity, and environmental objectives across China's provinces and regions, the effectiveness of green credit implementation exhibits regional disparities. Thus, the third hypothesis is formulated:

Hypothesis 3: Regional variability exists in the impact of green credit on carbon emissions, as well as in the transmission pathways from green credit to carbon emission reduction through the energy structure.

4. Selection of variables and modeling

4.1. Selection of variables

Explained variable: carbon intensity (CO_2gdp). Carbon intensity is the number of carbon emissions per unit of GDP. The measurement of carbon emissions used is based on the total amount of eight major energy sources consumed when converted to standard coal, together with the coefficient of carbon produced during the complete combustion of standard coal. Coal, crude oil, coke, gasoline, kerosene, diesel, fuel oil, and natural gas are the eight main energy sources. The specific formulas are:

$$CO_{2it} = \sum_{j=1}^{8} E_{itj} \times m_j \times n_j \tag{1}$$

$$CO_2gdp_{it} = \frac{CO_{2it}}{GDP_{it}} \tag{2}$$

Here, E_{itj} denotes the consumption of j types of fossil energy in province i in year t, whereas m_j and n_j represent the conversion factor of the jth type of fossil energy standard coal and the carbon emission factor of energy, respectively, and GDP_{it} denotes the real gross domestic product in province i in year t.

Core explanatory variable: green credit level (GC). According to Zhang and Zhao (2019) [21], the interest expense ratio of the six high-energy-consuming industries is used as the inverse indicator to ensure the continuity and completeness of the data at the provincial level. Therefore, the green credit level was measured using "1 - the interest expense ratio of 6 high-energy-consuming industries."

Mediating variable: energy structure (ES). The traditional energy source on which China currently relies most is coal, and the inefficient use of coal has caused great pressure on the environment; one of the most important goals of energy structure transformation is to reduce the reliance on coal and develop new types of energy. This paper adopts the method of Zhang and Li (2022) to measure the degree of energy structure transformation by using the proportion of coal consumption to total energy consumption [22].

Control variables: urbanization rate (URL), expressed as the ratio of urban population to total population; foreign direct investment (FDI), expressed as the ratio of FDI to total investment in fixed assets; degree of technological advancement (TI), expressed as the total amount of technological contract turnover; industrial structure (IND), expressed as the ratio of tertiary to secondary industries; level of economic development (PGDP), using regional GDP per capita.

4.2. Data sources

Carbon emission intensity is computed based on data encompassing eight energy consumption categories derived from the "China Energy Statistics Yearbook." "Gross Regional Product" data are sourced from the statistical yearbook of respective regions, and the nominal GDP is adjusted to real GDP using the GDP deflator with the year 2000 serving as the base period. Data pertaining to interest expenses are extracted from the "China Industrial Statistical Yearbook" and "China Economic Census Yearbook." The turnover of technology contracts is drawn from the "China Science and Technology Statistics Yearbook." Information on urban population, total population, foreign direct investment, investment in fixed assets, and output value of secondary and tertiary industries is obtained from the "China Statistical Yearbook."

To address heteroscedasticity, this paper employs a logarithmic transformation for variables such as carbon intensity, green credit level, urbanization rate, foreign direct investment, GDP per capita, and technological progress. The sample for this research encompasses panel data from 30 provinces, autonomous regions, and municipalities across China, excluding Hong Kong, Macao, Taiwan, and Tibet. The data covers the period from 2012 to 2020. A comprehensive overview of variable definitions and descriptive statistics can be found in **Table 1**.

Table 1. Variable definitions and descriptive statistics

Variable	Meaning	N	Mean	Std	Min	Max
$lnCO_2$ gdp	The logarithm of carbon intensity	270	0.947	0.732	-1.068	2.852
lnGC	Logarithm of (1 - Percentage of Interest Expenditures in the Six Major Energy-Consuming Industries)	270	3.805	0.405	2.240	4.392
ES	Share of coal consumption in total energy consumption	270	4.401	0.645	0.691	6.145
lnFDI	Logarithm of the ratio of foreign direct investment to total fixed investment	270	3.614	1.177	1.588	8.556
lnURL	Logarithm of the ratio of urban population to the total population	270	4.055	0.192	3.595	4.495
lnTI	Logarithm of total technology contract turnover	270	4.825	1.798	-0.568	8.751
lnPGDP	Logarithm of GDP per capita	270	1.258	0.464	0.087	2.405
IND	The ratio of tertiary to secondary output	270	1.257	0.703	0.549	5.310

4.3. Modeling

This research uses carbon emission intensity as an explanatory variable, green credit level as a core explanatory variable, and other variables impacting energy consumption intensity as control variables to investigate the effect of green credit on carbon emission intensity. In the end, a panel model (3) is established:

$$\ln CO_2gdp_{it} = \alpha_0 + \alpha_1 \ln GC_{it} + \alpha_2 Control_{it} + \delta_i + \varepsilon_{it} \quad (3)$$

Here, the explanatory variable ln CO_2gdp_{it} is the carbon emission intensity, the core explanatory variable ln GC_{it} is the level of green credit in each region, $Control_{it}$ is the control variable, δ_{it} is the regional effect, and ε_{it} is the random error term.

The mediating effect refers to the explanatory factor's indirect impact on the explained variables via the intermediary variables. Models (4) and (5) are created as stepwise regression is typically used to examine the intermediate effect, and both equations examine the impact of green credit on energy structure, the intensity of carbon emissions, and the direct impact of green credit on carbon emission intensity. ES_{it} stands for the energy structure. If both β_1 and γ_2 are significant, the product of the two reflects the indirect effect of green credit on carbon emission through energy structure.

$$ES_{it} = \beta_0 + \beta_1 \ln GC_{it} + \beta_2 Control_{it} + \varphi_i + \varepsilon_{it} \quad (4)$$

$$\ln CO_2gdp_{it} = \gamma_0 + \gamma_1 \ln GC_{it} + \gamma_2 ES_{it} + \gamma_3 Control_{itt} + \varphi_i + \varepsilon_{it} \quad (5)$$

5. Analysis of regression results

5.1. Baseline regression results

It is important to decide beforehand whether to use a fixed effects model or a random effects model. The article additionally controls the temporal effect and establishes a two-way fixed effect model after the Hausman test demonstrating that the data in this research are better suited for the fixed effect model.

The regression outcomes for model (3) are displayed in **Table 2**. **Table 2**'s column (1) displays the results when no controls are added, columns (2) through (5) display the results when control variables are gradually added, and column (6) displays the regression results when all control variables have been included. As can be observed, the calculated coefficients of green credit are all significantly negative, meaning that green credit has a considerable positive impact on reducing carbon emissions. Hypothesis 1 of the article is verified.

Using the estimation results in **Table 2**'s column (6) as the baseline for analysis, the coefficients of the degree of technological progress, industrial structure, and level of economic development are significantly negative, indicating that improving the level of technology, optimizing the industrial structure, and promoting the green development of the economy can help to reduce carbon emissions, which is in line with expectations. Foreign direct investment and the rise of urbanization level will bring about an increase in carbon emission intensity, which may be related to the impacts of laxity in the gatekeeping of foreign investment and the transfer of the rural population brought about by urbanization.

Table 2. Benchmark regression results

	(1)	(2)	(3)	(4)	(5)	(6)
	lnCO_2 gdp	**lnCO_2 gdp**	**lnCO_2 gdp**	**lnCO_2 gdp**	**lnCO_2 gdp**	**lnCO_2 gdp**
lnGC	-0.321^{***} (-5.443)	-0.265^{***} (-4.549)	-0.263^{***} (-4.499)	-0.297^{***} (-5.037)	-0.233^{***} (-4.352)	-0.203^{***} (-4.000)
lnFDI		0.0739^{***} (4.379)	0.0746^{***} (4.387)	0.0750^{***} (4.469)	0.0286^{*} (1.764)	0.0457^{***} (2.919)
lnURL			0.0816 (0.396)	0.174 (0.847)	0.968^{***} (4.555)	0.555^{**} (2.584)
lnTI				-0.0338^{***} (-2.752)	-0.0373^{***} (-3.387)	-0.0361^{***} (-3.469)
lnPGDP					-1.695^{***} (-7.544)	-1.683^{***} (-7.929)
IND						-0.195^{***} (-5.339)
Constant	2.454^{***} (11.021)	1.994^{***} (8.347)	1.661^{*} (1.899)	1.555^{*} (1.801)	-0.0194 (-0.024)	1.610^{**} (1.973)
Province fixed effects	YES	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES	YES
Adjust R^2	0.753	0.771	0.770	0.776	0.820	0.840

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2. Robustness analysis

To ensure that the relationship between the explained variables and explanatory variables in the empirical results of the model is accurate and reliable, it is necessary to do the robustness test of the model. In this paper, the model empirical results are tested for robustness in two ways. The first is to replace the explanatory variables. To eliminate the possible influence of introducing real GDP, total carbon emissions are selected as the explanatory variable to do the robustness test. Secondly, considering the possible endogeneity of the variables, the difference GMM method is used to re-estimate the benchmark regression.

After utilizing total carbon emissions as an explanatory variable, (1) in **Table 3** displays the regression findings. The final regression results reveal that the amount of green credits has a negative impact on overall carbon emissions. It is consistent with the benchmark regression's findings and demonstrates the benchmark regression's robustness.

The output of building a dynamic panel model for differential GMM estimation is shown in **Table 3** at (2). The first-order autocorrelation *p*-value is 0.01 and the second-order autocorrelation *p*-value is 0.20, which supports the notion that there is just a first-order autocorrelation and no second-order autocorrelation. Hansen's test yields a value of 0.294, which shows that the model's instrumental variables were reasonably well chosen and that the differential GMM estimate results are trustworthy. According to the estimation results, the coefficient of green credit is significantly negative at the national level, and the significance of the other variables is similar. This suggests that even after accounting for the model's potential endogeneity issue, our main conclusions are still valid.

Table 3. Robustness analysis

	(1)	**(2)**
	$lnCO_2$	**$lnCO_2$ gdp_GMM**
$lnCO_2$ gdp		0.381^{***} (9.290)
lnGC	-0.225^{***} (-4.515)	-0.128^{***} (-5.744)
lnFDI	0.0367^{**} (2.398)	0.0484^{***} (4.058)
lnURL	0.735^{***} (3.496)	-0.169 (-1.553)
lnTI	-0.0327^{***} (-3.215)	-0.0131^{**} (-2.648)
lnPGDP	-0.971^{***} (-4.679)	-0.186^{**} (-2.401)
IND	-0.227^{***} (-6.361)	-0.220^{***} (-9.461)
Constant	9.493^{***} (11.897)	
Province fixed effects	YES	YES
Time fixed effect	YES	YES
AR(1)		0.010
AR(2)		0.200
Hansen		0.294

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3. Analysis of intermediation effects

Table 4 (1) shows the overall impact without taking into account energy structure, and the result is markedly negative, with a coefficient of -0.203. (2) shows, with 99% certainty, that green credit has a detrimental impact on energy structure. Green credits can enhance the energy structure and lower the percentage of coal use. Given that energy structure is a reverse indication, the coefficient of energy structure in (3) is noticeably positive, demonstrating that the change of energy structure contributes to a decrease in carbon emissions. Additionally, the coefficient in (3) is -0.133, with a substantially lower absolute value than in the total effect model (1) and a lessened negative impact on carbon emissions. This suggests that there is a partial mediating effect of energy structure in the effect of green credit on carbon emissions, and the partial mediating effect is -0.7, indicating that hypothesis 2 is validated. Green credit's carbon emission reduction effect helps to optimize the energy structure by forcing high-polluting enterprises to use more environmentally friendly and clean energy for production, replacing the original crude production mode dominated by coal resources, which reduces carbon emissions.

Table 4. Analysis of intermediation effects

	(1) **$lnCO_2$ gdp**	(2) **ES**	(3) **$lnCO_2$ gdp**
lnGC	-0.203^{***} (-4.000)	-0.505^{***} (-3.248)	-0.133^{***} (-2.823)
ES			0.139^{***} (7.036)
Control variable	YES	YES	YES
Province fixed effects	YES	YES	YES
Time fixed effect	YES	YES	YES
Adjust R^2	0.840	0.156	0.868

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.4. Analysis of regional heterogeneity

It is necessary to further investigate the different performance of the relationship between green credit and carbon emission intensity in different geographic regions. According to the National Bureau of Statistics, China is divided into four regions: eastern, western, central, and northeastern. Group regression is carried out on the four subsamples to determine the heterogeneity. The regression findings from the heterogeneity analysis are displayed in **Table 5**. The estimation findings in **Table 5** show that there are quite obvious discrepancies between the coefficients of green credit. While the central and northeastern regions are not significant, the eastern region experiences the greatest reduction in carbon emissions via green credits, followed by the western region.

Table 5. Analysis of regional heterogeneity

	(1) **Eastern**	(2) **Central**	(3) **Western**	(4) **Northeastern**
lnGC	-0.268^{***} (-4.676)	0.227 (1.239)	-0.202^{**} (-2.266)	-0.0620 (-0.481)
Control variable	YES	YES	YES	YES
Province fixed effects	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
Adjust R^2	0.929	0.872	0.865	0.976

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The eastern region of China stands as the forefront of economic and cultural development, with the highest population density and environmental pressures. It faces an urgent need for economic transformation and development. In this region, financial institutions, enterprises, environmental awareness, and investments in emission reduction are relatively high. These favorable conditions contribute to the substantial inhibitory impact of green credit on carbon emissions in the eastern region.

The western region, on the other hand, has seen a more pronounced influence from national policies in recent years. It receives relatively greater support in terms of national policies and financial aid. The region's industrial development is largely centered around resource-based economies. Consequently, much of the green credit in this region is directed toward clean energy and sustainable development industries. However, due to a delayed initiation of green credit activities in the western region compared to the eastern region, its overall effectiveness in carbon emission reduction is somewhat lower.

The central and northeastern regions of China find themselves in an intermediate position regarding national policies and development. These regions receive comparatively less policy and financial support, possess relatively underdeveloped industrial research, and apply technology to a limited extent. Their industrial structures tend to be more homogeneous, resulting in a less significant impact on green credit on carbon emissions reduction.

Since the green credit policy significantly reduces carbon emission intensity in both the eastern and western regions, the next step is to delve into an analysis of the mediating role of energy structure in these regions. As shown in **Table 6**, all coefficients in the eastern region are statistically significant, indicating that energy structure plays a partial mediating role. This implies that green credit has not only improved the energy structure in the eastern region but has also spurred the growth of cleaner energy sources, ultimately leading to a reduction in carbon emissions. Conversely, in the western region, there is no significant correlation between green credit and energy structure, thereby negating any mediating effect. Thus, hypothesis 3 is validated.

Table 6. Analysis of regional mediating effects

	(1)	(2)	(3)	(4)
	ES_East	**lnCO_2 gdp_east**	**ES_West**	**lnCO_2 gdp_west**
lnGC	-0.883*** (-3.054)	-0.213*** (-3.631)	-0.0987 (-0.666)	-0.169** (-2.258)
ES		0.0630*** (2.698)		0.334*** (5.708)
Control variable	YES	YES	YES	YES
Province fixed effects	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
Adjust R^2	0.497	0.935	0.268	0.906

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6. Conclusions and recommendations

This study draws upon data from 30 Chinese provinces, autonomous regions, and municipalities spanning the years 2012 to 2020. It conducts a comprehensive analysis, encompassing basic regression, robustness testing, mediation effect analysis, and regional heterogeneity analysis, using a two-way fixed effect model. The study yields the following key findings.

First, the implementation of the green credit policy significantly reduces carbon emission intensity. This reduction is also influenced, to some extent, by technological progress, improvements in industrial structure, and economic development. In contrast, foreign investment and urbanization contribute to increased carbon emissions. Second, there is a partial mediating effect attributed to the energy structure. Third, the impact of the mediating role of the energy structure is particularly pronounced in the eastern region, while it is less significant in other regions. The suppression effect of green credit is more prominent in the eastern and western regions compared to the central and northeastern regions.

As a conclusion, this paper underscores the substantial role of scaling up green credit in reducing carbon emissions. To harness this potential, relevant state authorities should actively work on reinforcing the legal framework and the depth of green credit legislation to facilitate the seamless execution of green credit policies. This includes providing commercial banks with more flexibility within predefined standards, promoting transparency in green credit operations, streamlining the application process, and assisting in the establishment of regional green credit systems.

Based on the insights garnered from the mediation analysis, it is evident that green credit's capacity to reduce carbon emissions is largely attributed to improvements in the energy structure. Therefore, increasing the share of clean and low-carbon energy in energy consumption and optimizing the energy mix are crucial steps in mitigating carbon emissions. To encourage the development of new energy sources, green credit financing should be channeled effectively through investments in talent, technology, and capital. Gradually diminishing the role of "two highs and one leftover" industries in China's energy consumption and transitioning towards a high-quality energy system rooted in renewable sources such as hydropower, wind power, and natural gas is imperative.

Nonetheless, it is worth noting that the regional disparities in economic development, geographic location, resource endowment, and other factors result in variations in the implementation and impact of green credit across regions. Local governments should tailor green credit policies to align with their unique economic development, ecological environment, and industrial structure characteristics. By leveraging regional strengths, they can bolster the environmental protection industry and stimulate the coordinated development of the local ecological and economic environments.

This paper primarily focuses on the relationship between green credit and carbon emission intensity, laying the foundation for policy recommendations. Nevertheless, it has two main limitations. First, due to data constraints, the direct measurement of green credit across different provinces is challenging. Thus, the interest share of high-energy-consuming industries is employed as a proxy. Second, additional intermediary effects and influence mechanisms warrant further exploration and research.

Disclosure statement

The author declares no conflict of interest.

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