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Article

How do Green Credit Policies Affect Carbon Emissions? Evidence from 30 Provinces and Cities in China

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Abstract

The Green Credit (GC) policy is a government-mandated initiative designed to reconcile environmental governance with sustainable economic development. Examining the empirical impact of GC implementation on carbon emissions (CE) mitigation is a critical inquiry in environmental economics. Utilizing province-level panel data from 30 Chinese administrative divisions, this investigation employs three analytical frameworks: baseline regression modeling, mediation effect analysis, and spatial econometric estimation. The analysis empirically demonstrates that GC mechanisms facilitate CE reduction through three structural pathways: industrial restructuring (IS), technological advancement (TA), and energy efficiency optimization (EE). These findings provide an empirical basis for policymakers to refine GC regulatory frameworks, enhance policy efficacy in eco-economic coordination, and accelerate low-carbon transition processes.

Keywords: GC policies; CE; mediating effect; spatial spillover effect
JEL: C33, D24, G21, Q54

1. Introduction

Climate change is one of the most critical global challenges of the 21st century, exerting profound impacts on ecological systems, economic stability, and social welfare. Its significance lies in its pervasive and multidimensional consequences, encompassing rising global temperatures, accelerated polar ice cap melting, sea-level rise, heightened frequency and severity of extreme weather events, and biodiversity and ecosystem degradation. These phenomena threaten not only natural environments but also compromise food security, water resources, public health, and infrastructure systems, disproportionately impacting vulnerable communities and intensifying global inequities (Dafermos et al, 2018). The interconnection between climate change and global economic stability manifests through risks to agricultural output, energy networks, supply chain operations, and financial mechanisms. Notably, atmospheric carbon dioxide (CO_2) concentrations—the principal driver of climate change—have exceeded 420 parts per million, reaching levels unparalleled in human history. The cumulative nature of greenhouse gas emissions necessitate immediate mitigation efforts, as the prolonged atmospheric persistence of CO_2 amplifies its warming potential. Concurrently, the structural inertia of fossil fuel-dependent energy systems and industrial infrastructure highlights the urgency of rapid transitions toward renewable energy adoption, energy efficiency improvements, and low-carbon technology implementation (Campiglio, 2016). Under these circumstances, energy conservation and emission reduction objectives transcend environmental priorities, emerging as indispensable requirements for sustainable economic and social development.

In response to increasingly prominent ecological and environmental challenges, developed countries have actively pursued financial innovation to mitigate pollution, providing valuable references for contemporary green finance (GF) system development. The concept of sustainable development was formally introduced in the 1987 World Commission on Environment and Development report "Our Common Future", subsequently gaining global recognition. This period witnessed the integration of financial systems into national green development strategies, establishing the foundational framework for GF. The adoption of the United Nations Framework Convention on Climate Change and Kyoto Protocol significantly advanced GF development through institutional innovations such as carbon trading mechanisms and circular economy (CE) initiatives. The 2002 Equator Principles, jointly established by the World Bank and Dutch financial institutions, systematically incorporated environmental criteria into financial institutions' investment and financing operations, establishing an international standard for sustainable financing practices.

Green credit (GC) constitutes a critical component of GF mechanisms, designed to align financial resource allocation with environmental sustainability objectives. As defined by Lv et al (2023), GC represents a loan regulation framework implemented by commercial banks and financial institutions under national environmental policies, economic strategies, and industrial regulations (Hong et al, 2021). This mechanism imposes quota restrictions and punitive interest rates on financing for polluting production activities and environmentally detrimental projects (Hunjra et al, 2023). Conversely, it provides loan support and preferential rates for enterprises engaged in pollution control technology research and experimental development (R&D), ecological conservation, renewable energy development, circular economy practices, and sustainable agriculture (Chai et al, 2022). GC financing models primarily comprise government-subsidized loans and social capital financing (Afzal et al, 2022). The former reduces corporate borrowing costs through interest subsidies to stimulate green investments (Muganyi et al, 2021), while the latter enables enterprises to access favorable financing terms, with governments occasionally converting funds into specialized financing instruments. GC's core objective is to direct financial resources toward environmentally sustainable projects, catalyzing large-scale green investments, and promoting systemic transitions to sustainable development (Gao and Liu, 2023). This mechanism embodies scientific development principles and corporate social responsibility, incentivizing financial institutions to guide market entities in pollution reduction, ecological preservation, and resource conservation through environmental-economic decision integration.

GC represents a strategic banking sector initiative for environmental risk mitigation and international competitiveness enhancement (Mirza et al, 2023). As a crucial financial instrument for energy conservation and emission reduction, it aligns with the evolving trends of modern financial systems (Irfan et al, 2022; Zhang Z et al, 2022). Amid global prioritization of sustainable development, GC is becoming central to financial institutions' operational frameworks (Alharbi et al, 2023). Concurrently, ongoing GC policy refinements are establishing robust institutional support for green transitions (Bouchmel et al, 2024; Chen et al, 2024). CE implementation presents exceptional complexity among environmental challenges. Whether through carbon market mechanisms, taxation systems, or non-market regulatory approaches, substantial barriers remain to effective implementation (Xu and Li, 2020). Consequently, China requires a guided GC policy framework with service-oriented mechanisms to reduce green premiums, address critical environmental issues, accelerate dual-carbon target achievement, and transform ecological challenges into green development opportunities (Liu et al, 2017).

Currently, academic research on GC and its impact on CE remains underdeveloped, marked by significant gaps and fragmented understanding. This study aims to advance theoretical and practical knowledge by systematically investigating GC's role in CE reduction and sustainable environmental development. Regarding theoretical contributions, this research demonstrates three key innovations. First, it introduces a novel analytical perspective. While existing literature predominantly examines GC-CE relationships through policy frameworks or conceptual or qualitative, single-dimensional analyses, our study adopts a systematic methodology. We combine literature review, indicator calculation, theoretical deduction, and econometric modeling to comprehensively analyze GC's carbon reduction mechanisms. Second, the study enhances mechanistic comprehensiveness by incorporating three mediating variables into the GC-CE analytical framework. This approach enables empirical verification of mediation effects and their magnitude assessment. Furthermore, spatial correlation analysis reveals GC's significant positive spatial spillover effects on CE. Third, the methodology achieves multidimensional rigor. Building on existing research strengths while addressing limitations, we integrate mediation effect models with Spatial Durbin Models (SDM) to examine direct/indirect relationships and linear/spatial correlations between GC and CE. Endogeneity checks, robustness tests, and heterogeneity analyses ensure comprehensive and reliable conclusions. Practically, this research provides critical insights for China's green finance development. By evaluating GC's scale and structural impacts on CE, we elucidate pathways through which GC—as a core Green Finance (GF) component—influences carbon reduction. These findings offer an empirical foundation for policymakers to establish unified GC standards, diversify financing structures, enhance incentive mechanisms, and prioritize green industry investments. The analysis further provides actionable financial strategies to support China's low-carbon transition while expanding methodological approaches for GC development research.

In China, the implementation of green credit policies exhibits significant regional heterogeneity, primarily manifested in economic development, industrial structure, resource endowment, and the intensity of policy enforcement. First, in the eastern regions, due to their advanced economies and well-established financial systems, the enforcement of green credit policies is more robust, and financial institutions are more proactive in supporting green projects. In contrast, the central and western regions, with slower economic development and industrial structures dominated by high-energy-consuming and high-pollution industries, face greater challenges in implementing green credit policies. Second, enterprises in the eastern regions possess stronger technological innovation capabilities and exhibit higher willingness and capacity for green transformation, whereas enterprises in the central and western regions are more dependent on traditional industries, lacking sufficient motivation for green transformation. Additionally, the roles of local governments in the enforcement of green credit policies vary significantly. Local governments in the eastern regions generally possess stronger policy enforcement capabilities and resource allocation abilities, enabling them to effectively promote the

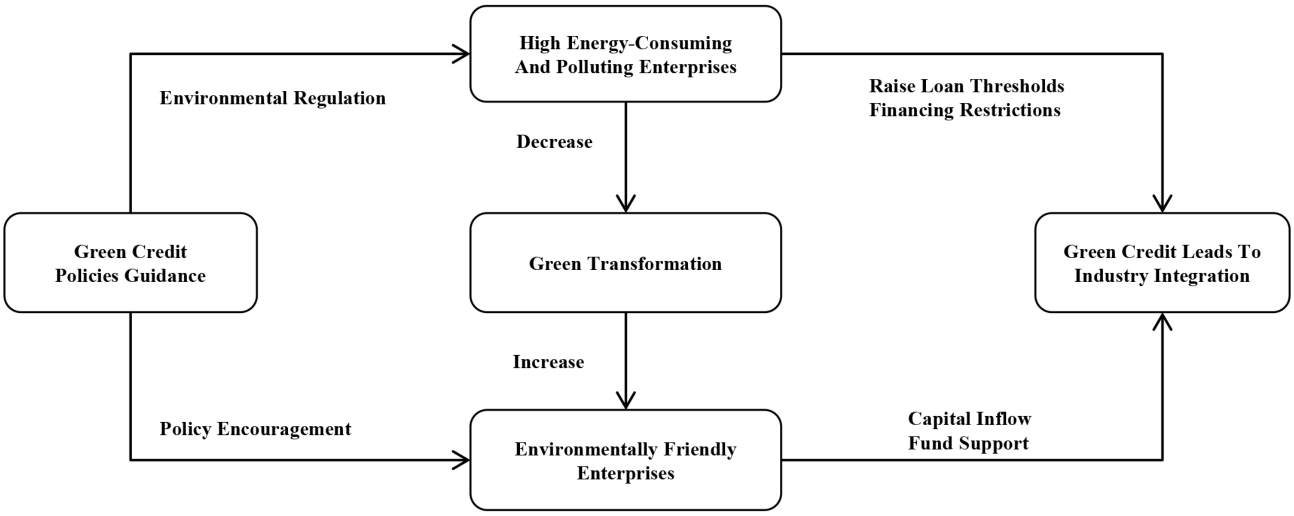

Fig. 1. The path of GC acting on CE through IS. GC, Green credit; CE, Carbon emission; IS, Industrial restructuring.

implementation of green credit policies. Conversely, local governments in the central and western regions, constrained by fiscal pressures and limited policy enforcement capabilities, often lead to suboptimal implementation of green credit policies. This regional heterogeneity not only affects the overall effectiveness of green credit policies but may also lead to disparities in carbon reduction achievements across different regions. Therefore, when studying the impact of green credit policies on carbon emissions, it is imperative to fully consider regional heterogeneity in order to develop more targeted policy recommendations for different regions.

The structure of this paper is as follows: Section 2 presents a review of the literature and the development of research hypotheses. Section 3 details data collection and modeling specifications. Section 4 reports empirical results including benchmark regressions, heterogeneity analysis, robustness checks, mediation effects, and spatial effects. Section 5 summarizes conclusions and policy recommendations. Section 6 discusses research limitations and future directions.

2. Literature Review and Hypothesis Development

2.1 The Direct Effect of GC on CE

GC influences CE through the following mechanisms as documented in academic literature. First, GC serves as an environmental regulation instrument within financial credit systems. Financial institutions establish environmental access criteria as fundamental credit allocation prerequisites, thereby restricting financing channels for high-pollution and high-energy-consumption enterprises through source-level controls (Lu et al, 2022; Zhang Y et al, 2022). By implementing stringent credit policies, exercising selective credit granting, and maintaining institutional reputation, financial institutions directly regulate corporate emission reduction behaviors (Taghizadeh-Hesary and Yoshino, 2020). Second, GC enhances enterprises' innovation efficiency and market competitiveness while improving environmental awareness (An et al, 2021; Taghizadeh-Hesary and Yoshino, 2019). This policy promotes green technology advancement with sustained effects, ultimately contributing to long-term CE reduction. Third, through capital formation mechanisms, GC controls fund allocation flows and implements differential interest rates. This facilitates short-term capital concentration in green sectors, promoting industry expansion and development. Subsequently, it accelerates industrial upgrading and reduces pollution sources (Cui et al, 2022; Fan et al, 2021). Fourth, through signaling transmission effects, GC operates via dual channels. Punitive and incentivizing measures send strategic adjustment signals to peer enterprises, while green industry development triggers industrial agglomeration effects, establishing a virtuous cycle of green signal transmission (Tian et al, 2024). Based on these arguments, hypothesis H1 is formed:

H1: GC can reduce CE.

2.2 The Indirect Effect of GC on CE

GC affects CE through industrial restructuring (IS) via two primary mechanisms according to contemporary research. First, policy-driven mechanisms create ecological protection externalities through top-down implementation, helping mitigate negative environmental effects (Wang and Wang, 2023). Diversified policy tools including government procurement, fiscal subsidies, and tax incentives guide IS optimization. These measures drive technological innovation in polluting enterprises while supporting sustainable development of green industries with long return cycles (Ma et al, 2023), thereby accelerating CE reduction. Second, financial mechanisms promote industrial integration. Banking institutions restrict loan availability and increase financing costs for high-pollution industries through

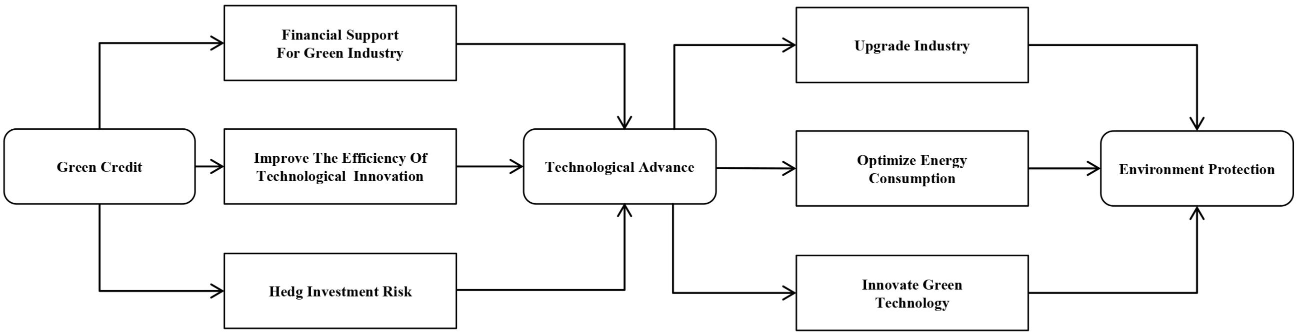

Fig. 2. The path of GC acting on CE through TA. TA, technological advance.

elevated approval thresholds and interest rates, redirecting capital to sustainable sectors (Hu et al, 2021; Zhang S et al, 2021). This dual approach constrains polluting enterprises while channeling resources to green industries, achieving balanced IS development and CE reduction objectives. In summary, GC policies enforce production model transitions towards energy efficiency and pollution control while directing financial resources to green industries, accelerating industrial focus shifts. This dual mechanism underscores GC's critical role in IS transformation and environmental protection. The pathway of GC's impact on CE through IS is illustrated in Fig. 1. Based on these arguments, hypothesis H2 is formed:

H2: GC can reduce CE through IS.

GC significantly influences CE through technological advance (TA) via three primary mechanisms. First, Chen (2020) examined the relationship between banking financial structures, technological innovation, and CE, emphasizing that green development fundamentally relies on innovative fund allocation, particularly in green technology innovation (Xing et al, 2021). As an innovative financial-sector instrument, GC policies offer fiscal support for corporate green technology initiatives. Research and development capital constitutes a critical initial investment component, with small and micro enterprises facing heightened financing challenges. Funding often favors sectors with short-term returns, limiting investment in green development areas with longer payback periods (Degryse et al, 2023). GC implementation provides financial support for eco-friendly projects and emerging industries, effectively distributing financing risks while enhancing technological capabilities (Su et al, 2022). Second, GC stimulates corporate innovation. Yu et al (2016) demonstrate that GC promotes green industry advancement and regional green economic growth by improving green technology innovation efficiency. Third, GC integrates risk-sharing mechanisms. Green financial institutions utilize professional risk management capabilities to implement comprehensive technical-level risk assessments for supported projects. This integration encourages enterprises to incorporate ecological considerations into production activities, thereby mitigating climate-related and environmental pollution risks (Zhang K et al, 2021). The pathway of GC's impact on CE through TA is illustrated in Fig. 2. Based on these arguments, Hypothesis H3 is formed:

H3: GC can reduce CE through TA.

The energy efficiency (EE)-mediated CE reduction mechanism of GC operates through three aspects. First, GC accelerates clean energy development through dedicated financing. Clean energy projects (e.g., wind/hydroelectric power) inherently generate lower CE than fossil fuel-based systems. GC-backed projects displace high-carbon energy sources, achieving CE reduction at source (Tian et al, 2022). Second, GC imposes credit constraints on high-energy/high-emission industries, mandating technological upgrades. To obtain green credit, enterprises must enhance energy efficiency and emission reduction capabilities, creating dual mechanisms that drive energy-saving technology investments (Wang et al, 2022). Third, GC fosters green financial instrument innovation. Carbon finance products enable corporate financing through carbon quota trading, incentivizing emission reduction behaviors. Financial institutions provide differentiated support through carbon accounting systems, offering preferential terms to enterprises demonstrating green achievements (Yao et al, 2021; Zhang, 2021). Collectively, GC improves EE and reduces CE through clean energy financing, industrial credit constraints, and financial innovation (He et al, 2019). This mechanism advances environmental sustainability while promoting green economic transformation. The pathway of GC's impact on CE through EE is presented in Fig. 3. Based on these arguments, Hypothesis H4 is formed:

H4: GC can reduce CE through EE.

3. Data and Models

We selected relevant economic data from 30 provinces and cities in China from 2008 to 2022 as our research sample. Owing to data availability, our study does not include Xizang, Hong Kong, Macao, and Taiwan.

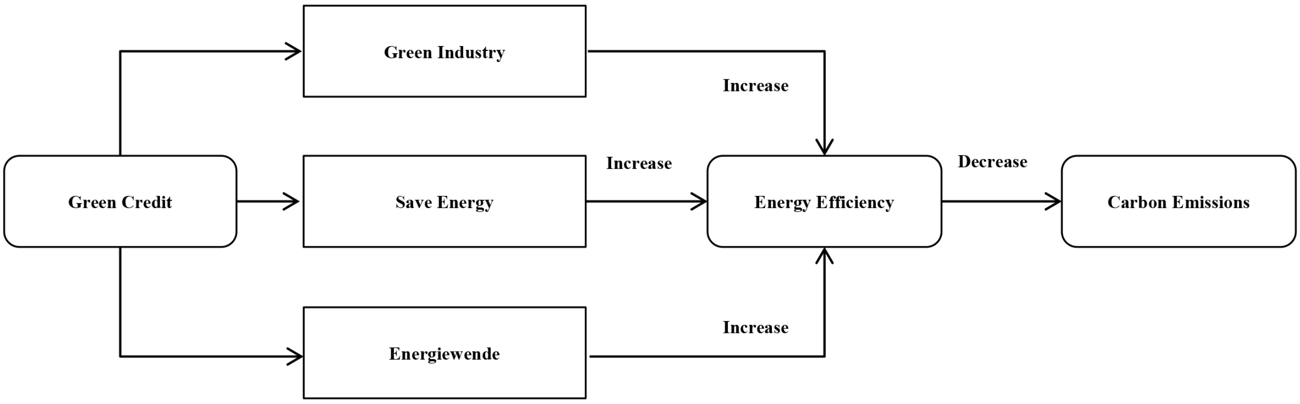

Fig. 3. The path of GC acting on CE through EE. EE, energy efficiency.

3.1 The Definition of Variables and Data Source

3.1.1 Dependent Variable

We selected CE as the dependent variable in this study. The indicator of CE was calculated through the material balance algorithm recommended by the Intergovernmental Panel on Climate Change (IPCC, 1990), which takes into account the consumption of several major fossil fuels, such as coal (including coal and coking coal), natural gas, and petroleum (including kerosene, diesel, crude oil, fuel oil, and gasoline). The CE calculation formula is presented in Eqn. 1:

$$\mathrm{CE} = \sum\nolimits_{\mathrm{i}} \mathrm{m_i} \times \delta_{\mathrm{i}} \times 12/44 \quad (1)$$

Where $\mathrm{m_i}$ is the annual consumption of the i-th major carbon emitting energy source. δ_{i} denotes the carbon emission factor (CEF) of the i-th fossil fuels, which is the average value provided in Table 1. The factor 12/44 is the mass fraction of carbon in one unit of carbon dioxide. Energy consumption data is sourced from the China Stock Market & Accounting Research (CSMAR) database and the China Energy Statistical Yearbook, while the CE coefficient is sourced from the CE coefficient guidelines of major authoritative energy accounting institutions. In addition, we calculate regional carbon emission intensity (CEI). Regional CEI is the amount of CE per unit of output, accounting for the level of gross domestic product (GDP). The formula for regional CEI is shown in Eqn. 2:

$$\mathrm{CEI} = \mathrm{CE}/\mathrm{GDP} \quad (2)$$

Where GDP denotes the annual gross domestic product of each provincial administrative unit, obtained from the National Bureau of Statistics of China.

3.1.2 Independent Variable

We chose GC as the independent variable of this research. Currently, scholars often use the proportion of interest expenses in six high energy consuming industries to the total interest expenses of industrial enterprises above designated size when measuring GC (Tan et al, 2022b). The effectiveness of utilizing the interest expenditure share of high-energy-consumption industries as a proxy variable for green credit policy intensity lies in the mechanism that when regulators tighten green credit policies, commercial banks will systematically reduce credit allocation to high-energy-consumption, high-pollution, and overcapacity sectors. This credit rationing mechanism directly results in decreased total loan volume accessible to high-energy-consumption industries, consequently diminishing their proportional share in aggregate interest expenditures. The reduction in this indicator value reflects the policy effect of structural reallocation of credit resources from traditional polluting industries to green and low-carbon sectors, with lower numerical values indicating stronger enforcement intensity of green credit policies. Therefore, we calculate GC according to this method. Moreover, these six high energy consuming industries include chemical raw material and chemical product manufacturing, electricity and heat production and supply, black metal smelting and rolling processing, petroleum processing coking and nuclear fuel processing, non-ferrous metal smelting and rolling processing, and non-metallic mineral products. The data used to calculate GC is primarily drawn from the China Statistical Yearbook, the China Industrial Statistical Yearbook, the China Energy Statistical Yearbook, and statistical yearbooks of various provinces and cities in China, as well as the Fourth National Economic Census of China. Interpolation was applied to supplement minor missing data from 2017.

3.1.3 Mediating Variables

We selected IS, TA and EE as the mediating variables in this study. Following the methodological framework established by Liu et al (2019), we operationalized industrial structure upgrading through the Industrial Structure Upgrading Index (ISUI). The index construction involves: (1) assigning differentiated weights to primary, secondary, and tertiary industries; (2) applying weighting coefficients

Table 1. The CEF.

Project/Institution	Coal (Tons of standard coal)	Natural gas (Tons of standard coal)	Petroleum (Tons of standard coal)
U.S. Department of Energy	0.702	0.389	0.478
Institute of Energy Economics of Japan	0.756	0.449	0.586
Chinese Academy of Engineering	0.680	0.410	0.540
Global Environment Facility	0.748	0.444	0.583
Asian Development Bank	0.726	0.409	0.583
Beijing Project	0.656	0.452	0.591
Ministry of Science and Technology of China	0.726	0.409	0.583
National Development and Reform Commission of China	0.748	0.444	0.583
Average	0.718	0.426	0.566

Source: The reports from various institutions.
CEF, Carbon emission factor.

Table 2. The definition of variables.

Type	Variable name	Variable measures
Dependent Variable	Carbon Emissions (CE)	Calculated through the material balance algorithm
Independent Variable	Green Credit (GC)	Interest expenses/Total interest expenses
Mediating Variables	Industrial Structure (IS)	ISUI
	Technological Advance (TA)	R&D/GDP
	Energy Efficiency (EE)	Total energy supply/GDP
Control Variables	Population Density (PD)	Total population/Area
	Openness Level (OPL)	Total import and export volume/GDP
	Economic Development Level (EDL)	GDP/Total population

ISUI, Industrial Structure Upgrading Index; R&D, Research and Development.

through multiplication by their respective proportions. The ISUI metric exhibits positive directional alignment, where elevated values correspond to enhanced industrial structure upgrading. The formal mathematical specification appears in Eqn. 3:

$$\mathrm{IS} = \sum \mathrm{q_i} \times \mathrm{i} = \mathrm{q_1} \times 1 + \mathrm{q_2} \times 2 + \mathrm{q_3} \times 3 \qquad (3)$$

Where q_i denotes the proportion of the i-th industry.

As for TA, we measured it by the sum of internal R&D expenditures within the region divided by GDP. R&D expenditure is divided into internal expenditure and external expenditure. Internal expenditure refers to all expenses actually used within the unit to carry out R&D activities, while external expenditure refers to the actual expenses incurred by outsourcing R&D activities to external entities. To avoid double counting between the implementing unit and the commissioning unit, the data refers only to internal R&D expenditures by implementing units.

As for EE, we measured it by total energy supply divided by GDP, which refers to energy consumption per unit of GDP in each province. This reflects the degree of energy utilization in a country's economic activities, indicating changes in economic structure and EE.

The data for mediating variables is from the Energy Database of China, the National Bureau of Statistics of China, the China Energy Statistical Yearbook, the China Science and Technology Statistical Yearbook and so on.

3.1.4 Control Variables

Control variables refer to variables that are not the main focus of the study but may affect the dependent variable. By introducing control variables, researchers can more accurately estimate the impact of independent variables on the dependent variable, reducing omitted variable bias. With reference to relevant studies, we chose population density (PD), openness level (OPL), and economic development level (EDL) as the control variables of this research. According to existing literature, these three control variables will have an impact on CE. As for PD, we measured it by the total population divided by the area of each province (Wang et al, 2023). PD will reflect the population density of a province and also reflect the level of urbanization. As for OPL, we used the proportion of the total import and export volume to the current GDP of each province as a representation (Lei et al, 2023). The higher the degree of OPL, the more advanced domestic and foreign technologies and development concepts can be introduced, and it can also contribute to the development of cross-border GF cooperation. As for EDL, we measured it by GDP divided by total population of each province (Sun and Zeng, 2023). EDL reflects the consumption level of the people in each province.

Table 3. The descriptive statistics of variables.

Variables	Observations	Mean	Std.Dev.	Min	Max
lnCE	450	5.493	0.751	3.076	6.843
lnGC	450	–0.654	0.283	–1.398	–0.125
lnIS	450	0.859	0.052	0.757	1.042
lnTA	450	4.886	0.607	3.049	6.446
lnEE	450	–0.096	0.528	–1.261	1.375
lnPD	450	5.438	1.322	1.540	8.257
lnOPL	450	–1.689	0.955	–4.360	0.513
lnEDL	450	10.542	0.557	8.959	11.988

CE, carbon emission; GC, Green Credit; IS, industrial restructuring; TA, technological advance; EE, energy efficiency; PD, population density; OPL, openness level; EDL, economic development level; Std.Dev., Standard Deviation; Min, Minimum; Max, maximum.

The data for control variables are obtained from the National Bureau of Statistics of China, the CSMAR database, the China Statistical Yearbook, the China Environmental Statistical Yearbook, the China Industrial Statistical Yearbook, the China Energy Statistical Yearbook, and statistical yearbooks of various provinces and cities in China, as well as the Fourth National Economic Census of China. For individual missing data, interpolation was used to fill gaps. For the convenience of browsing, each specific variable is defined in Table 2.

3.1.5 The Descriptive Statistics of Variables

For the convenience of calculation, we took the logarithm of all variables. The descriptive statistics of variables are shown in Table 3. Table 3 shows that the mean of lnCE is 5.493, the standard deviation is 0.751, the minimum value is 3.076 and the maximum value is 6.843. Additionally, there is a significant difference in lnEE, lnPD and lnOPL.

3.2 Model Setting

3.2.1 The Benchmark Regression Model

In order to test the direct impact of GC on CEI, we constructed the model in Eqn. 4:

$$\mathrm{lnCE}_{i,t} = a_0 + a_1 \ln \mathrm{GC}_{i,t} + \sum_{j=1} \beta_j X_{j,i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{4}$$

Where a_0 refers to the constant; a_1 and β_j denote the coefficients of the explanatory variables. Moreover, $\mathrm{lnCE}_{i,t}$, $\mathrm{lnGCL}_{i,t}$ and $X_{j,i,t}$ refer to the value of CE, GC and j-th variable for i-th province of China in year t. μ_i, γ_t, and ε_i denote the individual effects, time effects, and stochastic error term, respectively.

3.2.2 The Mediating Effect Model

The commonly used research methods for analyzing mediating effect are stepwise regression, the Sobel method, and the bootstrap method. This research uses the first method to analyze the relationship between GC and CE from the perspectives of the individual mediating effects of IS, TA, and EE. The mediating effect model based on stepwise regression is constructed in Eqns. 5,6,7,8,9,10:

$$\ln \mathrm{IS}_{i,t} = b_0 + b_1 \ln \mathrm{GC}_{i,t} + \sum_{j=1} \beta_j X_{j,i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{5}$$

$$\ln \mathrm{CE}_{i,t} = c_0 + c_1 \ln \mathrm{GC}_{i,t} + \ln \mathrm{IS}_{i,t} + \sum_{j=1} \beta_j X_{j,i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{6}$$

$$\ln \mathrm{TA}_{i,t} = d_0 + d_1 \ln \mathrm{GC}_{i,t} + \sum_{j=1} \beta_j X_{j,i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{7}$$

$$\ln \mathrm{CE}_{i,t} = e_0 + e_1 \ln \mathrm{GC}_{i,t} + \ln \mathrm{TA}_{i,t} + \sum_{j=1} \beta_j X_{j,i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{8}$$

$$\ln \mathrm{EE}_{i,t} = f_0 + f_1 \ln \mathrm{GC}_{i,t} + \sum_{j=1} \beta_j X_{j,i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{9}$$

$$\ln \mathrm{CE}_{i,t} = g_0 + g_1 \ln \mathrm{GC}_{i,t} + \ln \mathrm{EE}_{i,t} + \sum_{j=1} \beta_j X_{j,i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{10}$$

Where b_0, c_0, d_0, e_0, f_0, and g_0 refer to constants; b_1, c_1, d_1, e_1, f_1 and g_1 denote the coefficient of the variables. Moreover, $\mathrm{lnIS}_{i,t}$, $\mathrm{lnTA}_{i,t}$ and $\mathrm{lnEE}_{i,t}$ refer to the values of IS, TA, and EE for i-th province of China in year t. In order to eliminate the influence of heteroscedasticity, logarithmic transformation is applied to all variables.

3.2.3 The Spatial Effect Model

There are generally four types of matrices commonly used in the empirical literature on spatial econometrics: binary adjacency weight matrix (also known as 0-1 weight matrix), inverse distance weight matrix, economic weight matrix and nested matrix. The earliest spatial econometric model in foreign literature is the 0-1 weight matrix (Getis, 2009), which is also widely used in China. The 0-1 weight matrix is divided into two categories: first-order adjacency and high-order adjacency. The first-order adjacency matrix assumes that spatial interactions will occur as long as there are non-zero length common boundaries between spatial sections. Researchers believe that a spatial effect should also occur within a certain distance range around a given spatial cross-section, and beyond a given threshold distance, the spatial effect between regions can be ignored. Therefore, this research extends the definition of spatial weights as follows:

$$w_{i,j}\begin{cases}1, & \text{if } d_{i,j} < d\\ 0, & \text{if } d_{i,j} > d\end{cases} \tag{11}$$

where, $w_{i,j}$ is the spatial weight matrix, i and j are the spatial section number. i, j∈[1, n], and n is the number of spatial sections. Moreover, $d_{i,j}$ denotes the distance between i-th and j-th spatial section, and d denotes a certain distance range. This article adopts the above method, using the latitude and longitude of provincial administrative regions to create a 0-1 weight matrix, that is, if regions are adjacent within a threshold distance, it takes 1, otherwise it takes 0. In the construction of spatial econometric models, the selection of a binary adjacency weight matrix (0-1 matrix) fundamentally stems from its straightforward construction logic and suitability for characterizing strong spatial adjacency relationships. The investigation focuses on the geographical distribution characteristics of 30 Chinese provincial units, where administrative boundary adjacency demonstrates notable prominence. The adjacency matrix effectively captures direct spatial interdependencies between regions through its binary operationalization. By dichotomously assigning weights based on territorial contiguity, the 0-1 matrix circumvents potential estimation biases inherent in geographical distance matrices that may arise from topographical heterogeneity, transportation network disparities, or asymmetrical economic interactions. Furthermore, this matrix configuration has been extensively employed in seminal spatial econometric literature, possessing both classical theoretical underpinnings and empirical validation, thereby satisfying the preliminary verification requirements for spatial effect existence in exploratory research. Although geographical distance matrices can delineate the continuity of physical separation, their construction necessitates precise geospatial coordinate computations that may introduce superfluous complexity while inadequately reflecting practical pathways of policy transmission and economic spillover effects. Consequently, this study adopts the 0-1 matrix to streamline spatial relationship representation, achieving an optimal balance between model robustness and explanatory efficacy.

In addition, this study also requires the use of Moran's Index (Moran's I) for spatial autocorrelation test. The formula is shown in Eqn. 12:

$$\text{Moran's I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}\left(x_i - x_m\right)\left(x_j - x_m\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}\left(x_i - x_m\right)^2} \tag{12}$$

Where i and j refer to the i-th and j-th province of China, n denotes 30 provinces of China and $w_{i,j}$ is the spatial weight matrix. Additionally, x and x_m refer to a variable and its mean value. Moran's I ranges from 0 to 1.

The spatial econometric model is divided into Spatial Error Model (SEM), Spatial Lag Model (SLM), and SDM. For the convenience of calculation, this study currently uses the SDM with fixed effect and tests the rationality of the model settings in the following section. The construction of SDM is as follows:

$$\begin{aligned}\ln CE_{i,t} &= \beta_0 + \rho W \ln CE_{i,t} + \beta_1 GC_{i,t} + \sum \beta_j X_{j,i,t}\\ &+ W'GC_{i,t}\delta + \sum W'X_{j,i,t}\delta_j + \mu_i + \gamma_t + \varepsilon_{i,t}\end{aligned} \tag{13}$$

Where i and t denote province and year; β_0, ρ and β_1 refer to constant, the coefficient of spatial autoregression and the coefficient of independent variable. W is 0-1 weight matrix and W' denotes the spatial lag term of one variable. β_j and δ_j refer to the coefficient of control variables and spatial lag term. γ_t denotes the time fixed effect.

4. The Empirical Results

Based on Chinese administrative regional planning and academic conventions, this study divides China's 30 provincial-level administrative regions into three regions: eastern, central, and western. The eastern region comprises 11 provinces and municipalities: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region consists of 9 provinces: Shanxi, Nei Mongol, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region includes 10 provincial-level administrative regions: Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, Qinghai, and Xinjiang. It is particularly noteworthy that, given the pronounced heteroscedasticity of principal continuous variables, this study has applied a natural logarithmic transformation to all continuous variables. This treatment not only effectively mitigates heteroscedasticity in model error terms but, more critically, enables the regression coefficients to be interpreted directly as elasticity measures—indicating the percentage change in the dependent variable associated with a 1% percentage change in an independent variable.

4.1 The Results of Dependent and Independent Variables

4.1.1 The Results of CEI

To better understand the trend of CEI changes, we shifted the sample observation period forward by five years. Hence, we calculated the average CEI of 30 provincial-level administrative regions in China from 2003 to 2022. Regarding spatial distribution, the CEI of the northern part of China is higher than the southern part, and the CEI of the western part of China is higher than the eastern part, forming a geographical feature of "higher north and lower south, higher west and lower east" (Zhang A et al, 2022). Shanxi, Nei Mongol, Guizhou, and Ningxia consistently exhibit high CEI values. For example, as an old industrial zone and an important energy production base in China, Shanxi's

CEI reached 6.4 tons/10,000 yuan in 2020. However, under long-term environmental constraints, its CEI decreased by 48% compared to the initial level. In contrast, Guangdong, Sichuan, Chongqing and other regions have consistently maintained lower CEI levels, which reflects differences in regional CE and economic structures. The CEI of most other provinces is below 1 ton/10,000 yuan. It is worth mentioning that Xinjiang's CEI has remained relatively high and stable, with small fluctuations. However, in recent years, an upward trend has emerged, which cannot be ignored (Yu et al, 2021).

In terms of temporal trends, China's overall CE has shown a continuous upward trend, rising from 8.3 billion tons of standard coal in 2006 to over 11.4 billion tons of standard coal in 2022. This indicates that while China is rapidly developing its economy, its energy consumption is also increasing. From 2006 to 2008, the overall CE level in China remained relatively stable, with a modest growth rate. Between 2008 and 2012, China's economy expanded rapidly, and energy demand surged. During this period, the average annual growth rate of CE was 7.06%, and the total CE remained high. After 2012, the overall growth rate of China's CE slowed, and although the total CE continued to increase, the average annual growth rate dropped to only 0.67%. This suggests that in recent years, while China has continued to pursue economic growth, environmental awareness has become increasingly embedded in public consciousness. China's ecological focus on green development and the promotion of low-carbon production and lifestyles has yielded notable results (Su D et al, 2023; Tan et al, 2022a).

Compared to CE, CEI has shown a consistent downward trend. From 2006 to 2008, due to China's vigorous development of green and sustainable concepts, the decline was significant. Since 2009, the rate of decline has moderated but remained steady. This suggests that in recent years, for the same level of output, China's energy consumption and CE have continuously declined due to technological advances, IS adjustments, and improvements in EE.

4.1.2 The Results of GC

Consistent with the preceding analysis, we calculated the average GC of 30 provincial-level administrative regions in China from 2003 to 2022. Regarding the industrial interest expenses of China's six high-energy consuming industries, the electricity and heat production and supply industry has the largest share of interest expenses, while the petroleum, nuclear fuel processing, and smelting industry has the smallest share. In addition, energy consumption in the eastern region of China is generally higher than in other regions (Su T et al, 2023). Energy use in the power and heat industry, chemical products sector, and non-ferrous metal smelting industry is relatively high in the western region. The central region, dominated by coal-rich provinces, exhibits energy concentration in industries such as power generation, heating, and smelting. As for GC, detailed data are presented in Table 4. The proportion of GC in eastern Chinese provinces is relatively low, while in western provinces such as Gansu, Qinghai, and Yunnan, where energy development constitutes a large share of the economy, the proportion of GC is high. This may be due to the relatively advanced economy in eastern China, which features more large state-owned enterprises and listed companies, diverse financing channels, and a richer economic structure, with a lower reliance on indirect financing (Song et al, 2021). In contrast, there are relatively more small and medium-sized enterprises (SMEs) in the less developed central and western regions, where the economic structure is more concentrated. GC continues to play a key role in supporting the development of these SMEs.

Table 4. GC in provincial administrative regions of China from 2003 to 2022.

Rank	Province	GC	Rank	Province	GC
1	Qinghai	0.851	16	Tianjin	0.507
2	Yunnan	0.783	17	Hunan	0.500
3	Gansu	0.767	18	Heilongjiang	0.489
4	Guizhou	0.720	19	Henan	0.483
5	Nei Mongol	0.667	20	Chongqing	0.474
6	Ningxia	0.666	21	Fujian	0.446
7	Xinjiang	0.604	22	Jilin	0.446
8	Guangxi	0.584	23	Shanxi	0.445
9	Hebei	0.555	24	Beijing	0.439
10	Liaoning	0.551	25	Shandong	0.423
11	Sichuan	0.545	26	Guangdong	0.389
12	Hainan	0.539	27	Anhui	0.382
13	Jiangxi	0.532	28	Shanghai	0.371
14	Hubei	0.520	29	Jiangsu	0.365
15	Shaanxi	0.517	30	Zhejiang	0.285

Source: The author's calculation based on the China Industrial Statistical Yearbook and the Fourth National Economic Census of China.

4.2 Direct Effect Results

We have assessed multicollinearity among independent variables to ensure the reliability of regression outcomes. All variables have yielded variance inflation factor (VIF) values below 3, indicating the absence of severe multicollinearity in the model. Furthermore, inter-variable correlation coefficients remain under 0.6, confirming variable independence and demonstrating that the regression results are not compromised by multicollinearity issues.

The verification outcomes presented in Table 5 demonstrate that GC significantly reduces CE, thereby confirming Hypothesis H1 in this study. From models (1)–(4), we can observe that GC has a significant negative effect on CE, passing the significance test at the 1% level. The regression coefficients for models (1) and (4) with and without control variables are –0.871 and –0.837, respectively.

This indicates that for every 1% increase in regional GC levels, CE decreases by 0.837%. This is consistent with the theory of credit allocation, which suggests that countries and institutions selectively allocate credit funds by controlling credit interest rates to achieve a greener allocation of credit funds and reduce CE from the source (Umar et al, 2021). This result confirms Hypothesis 1, namely, that GC can significantly promote CE reduction.

In terms of control variables, model (2) introduces PD, which indicates the level of urbanization in each province. However, this control variable did not pass the significance test, so additional control variables are needed to describe in more detail the impact of GC on CE. Model (3) introduces the control variable of urban OPL based on model (2), with a regression coefficient of –0.166. It passes the significance test at the 1% level and makes the PD control variable significantly positive at the 5% level. This indicates that urban OPL can effectively promote CE reduction, while PD increases CE to a certain extent. This is due to the increasing openness of a city, which determines the introduction of more green innovative technologies and talents to reduce CE, while the increase in population leads to an increase in CE from daily life. Model (4) introduces the per capita GDP of each province with a coefficient of 0.103, which passed the significance test at the 10% level, indicating that as the per capita GDP of each province increases, CE also increases. This indicates that an increase in EDL will lead to an increase in CE, confirming the Environmental Kuznets Curve (EKC), which states that when the EDL is low, the environment will deteriorate with an increase in per capita income. This result suggests that a country should pay attention to environmental protection while developing its national economy, avoiding economic growth at the expense of the environment, and protect the environment to advance the turning point of the inverted "U" curve (Zakari et al, 2023).

Table 5. The results of the benchmark regression.

Variables/Statistics	(1)	(2)	(3)	(4)
lnGC	–0.871***	–0.784***	–0.920***	–0.837***
	(–6.23)	(–5.59)	(–6.71)	(–5.81)
lnPD		0.030	0.091**	0.091**
		(0.76)	(2.16)	(2.16)
lnOPL			–0.166***	–0.185***
			(–4.23)	(–4.22)
lnEDL				0.103*
				(1.74)
Constant	9.761***	9.654***	8.953***	7.892***
	(8.45)	(8.04)	(8.31)	(8.52)
Observations	450	450	450	450
R-squared	0.710	0.711	0.736	0.739
F-statistics	38.85	21.62	20.57	15.14

Notes: *, **, *** indicate significant at 10%, 5%, 1% confidence levels respectively, and *t*-value is in parentheses, same below.

4.3 Mediating Effects Results

Stepwise regression, also known as the causal stepwise method, is currently the most commonly used mediation analysis method (Baron and Kenny, 1986). The existence of mediating effect requires the following conditions: the regression coefficient of the independent variable to the dependent variable is significant, the regression coefficient of the independent variable to the mediating variable is significant, and the regression coefficient of the mediating variable to the dependent variable is significant while the regression coefficient of the independent variable to the dependent variable is significantly reduced or becomes non-significant (Baron and Kenny, 1986). This study analyzed the mediating effect of GC on CE through stepwise regression, and Table 6 shows the empirical results. Model (1) is the benchmark regression result, which is the same as the regression result of model (4) in Table 5. Models (2) and (3) are the regression results with the mediating effect of IS added, models (4) and (5) are the results with the mediating effect of TA added, and models (6) and (7) are the regression results with the mediating effect of EE added. The regression coefficient results of model (1) for GC demonstrate the significance of the independent variable on the dependent variable coefficient. Therefore, this study analyzes models (2)–(7) one by one.

As evidenced by the results in Table 6, GC indirectly influences CE through IS optimization, thereby validating Hypothesis H2 proposed in this research. From the perspective of IS, model (2) shows that GC has a positive impact on IS at a significance level of 1%, with an impact coefficient of 0.047. Model (3) shows that IS effectively promotes CE reduction at a significance level of 1%. GC can effectively reduce CE through IS, but IS has a certain "crowding out effect" on GC, which weakens the overall effect of GC on reducing CE. Therefore, it can be concluded that IS plays a mediating role and has a significant impact. With the optimization and upgrading of IS, GC can achieve the effect of reducing CE.

As evidenced by the results in Table 6, GC indirectly reduces CE via TA facilitation, thereby validating Hypothesis H3 proposed in this research. From the perspective of TA, model (4) shows that the impact coefficient of GC on TA is –1.014, which passed the significance test at the 1% level. Model (5) shows that TA is still significant, and the coefficient of the independent variable GC is significant after introducing TA.

As evidenced by the results in Table 6, GC indirectly diminishes CE through EE enhancement, thereby validating Hypothesis H4 proposed in this research. From the perspective of EE, model (6) shows that GC has a positive impact on EE at a significance level of 1%, with an impact coefficient of 0.355. Model (7) shows that EE promotes CE reduction at a significance level of 1%. GC can achieve CE

Table 6. The results of stepwise regression.

Variables/Statistics	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnCE	lnIS	lnCE	lnTA	lnCE	lnEE	lnCE
lnGC	–0.837***	0.047***	–0.419**	–1.014***	–0.184***	0.355***	–1.035***
	(–5.81)	(5.73)	(–2.53)	(–5.25)	(–3.45)	(4.54)	(–5.91)
lnIS			–0.950***				
			(–6.17)				
lnTA					0.652***		
					(4.18)		
lnEE							0.535***
							(4.81)
lnPD	0.091**	0.006***	0.175***	0.433***	–0.165***	–0.138***	0.191***
	(2.16)	(3.52)	(4.93)	(5.22)	(–5.45)	(–4.04)	(4.72)
lnOPL	–0.185***	0.007***	–0.167***	–0.133**	–0.142***	0.015	–0.236***
	(–4.22)	(2.79)	(–3.49)	(–2.31)	(–3.87)	(0.63)	(–4.65)
lnEDL	0.103*	0.073***	0.797***	1.178***	–0.636***	–0.438***	0.367***
	(1.74)	(4.42)	(7.73)	(6.24)	(–5.34)	(–6.18)	(3.96)
Constant	7.892***	0.100**	3.441***	–10.464***	9.347***	5.525***	–0.432
	(8.52)	(2.47)	(4.31)	(–7.89)	(6.42)	(6.23)	(–0.41)
Observations	450	450	450	450	450	450	450
R-squared	0.739	0.827	0.703	0.836	0.664	0.861	0.699

Notes: *, **, *** indicate significant at 10%, 5%, 1% confidence levels respectively, and *t*-value is in parentheses.

reduction by improving EE, and EE amplifies the overall effect of GC in reducing CE. Therefore, it can be concluded that EE plays a mediating role, that is, with the improvement of EE, GC can promote carbon reduction.

However, traditional mediating models may have shortcomings, such as ignoring the influence of omitted variables. In the mediating effect test, the Sobel test has greater statistical power than stepwise regression (MacKinnon et al, 2000). The Sobel test rigorously verifies the significance of mediation pathways through an ore robust statistical methodology, overcoming limitations inherent in traditional stepwise regression. Its critical advantages include: (1) quantifying the mediation effect significance via computation of indirect effect standard errors and Z-values, thereby eliminating subjective judgment bias; (2) precise identification of pathway contributions in complex mediation processes through integration with suppression-effect theory; and (3) enhanced result credibility through explicit reporting of statistical parameters (e.g., $p < 0.01$), providing a quantitative foundation for multi-path mechanism analysis. Therefore, we followed the approach of Wen et al (2004) to conduct the Sobel test on the mediating effect. The results are shown in Table 7.

According to the results in Table 8, after analyzing the three mediating variables using the Sobel test, the total effect passed the test at a significance level of 1%. In addition, regarding the proportion of the three mediating effects, both IS and TA have a significant proportion in the direct effect of GC on CE, accounting for 51.8% and 78% respectively. However, the indirect effect of EE is opposite in direction to the total effect, so the proportion result is negative. Wen and Ye (2014) proposed that if the Sobel test is used to test the mediating effect, and the sign of the indirect effect is opposite to that of the total effect, then the mediating variable has a certain masking effect, and only significance needs to be considered. Therefore, Hypotheses H2–H4 have been reconfirmed.

Table 7. The results of Sobel test.

Sobel Test	(1)	(2)	(3)
	lnIS	lnTA	lnEE
Indirect Effect	–0.447***	–0.673***	0.205***
	(–3.96)	(–4.58)	(–2.81)
Direct Effect	–0.414***	–0.189	–1.067***
	(–3.83)	(–1.54)	(–6.29)
Total Effect	–0.861***	–0.861***	–0.861***
	(–5.92)	(–5.86)	(–5.94)
Proportion	0.518	0.780	–0.238

Notes: *, **, *** indicate significant at 10%, 5%, 1% confidence levels respectively, and *t*-value is in parentheses.

4.4 Heterogeneity Analysis

This study selects regional heterogeneity and industrial structure heterogeneity as analytical dimensions, primarily based on two considerations. Firstly, there are significant disparities in economic development levels, resource endowments, and policy implementation intensity among the eastern, central, and western regions of China: the eastern region boasts a well-developed financial system and strong technological innovation capabilities, whereas the central and western regions exhibit a less diversified economic structure and a high reliance on traditional energy-intensive industries, which may lead to spatial differentiation in the effectiveness of GC policies. Secondly, the proportion of the secondary industry (degree of industrial dominance) in each province directly influences CE levels. Provinces with a high industrial proportion experience more concentrated energy consumption and pollution emissions, and the pathway of Green Credit in curbing financing for energy-intensive industries and promoting industrial upgrading may be more targeted. Therefore, this study categorizes the sample provinces into high and low industrial proportion groups based on the median value of the secondary industry's share in GDP (45%), which aids in revealing the mechanisms of GC policy under different industrial structures.

Table 8 indicates that the inhibitory effect of GC on CE exhibits a distinct regional gradient. The GC regression coefficient for the eastern region is –0.818, which is statistically significant at the 5% level, indicating the strongest emission reduction effect. This is attributed to its developed economy and mature financial market, where Green Credit resources are more readily directed towards low-carbon technology research and development and green industries. For instance, Guangdong and Jiangsu have accelerated the replacement of high-carbon industries by supporting the new energy sector. The central region has a GC coefficient of –0.517, also significant at the 5% level, with a moderate effect, as it serves as a traditional industrial base where Green Credit promotes technological transformation by restricting financing for energy-intensive industries such as steel and chemicals, albeit constrained by technological absorption capacity. The western region has a GC coefficient of –0.405, which is not statistically significant, due to its economic reliance on energy development (e.g., Xinjiang, Inner Mongolia), insufficient enforcement of Green Credit, and lagging clean energy infrastructure. Additionally, the positive effect of the economic development level (EDL) on CE (0.205, significant at the 10% level) suggests that the western region is still in the ascending phase of the "Environmental Kuznets Curve", where economic growth comes at the expense of environmental degradation.

After grouping by the proportion of the secondary industry, the emission reduction effects of GC show significant differences. The GC coefficient for the high industrial proportion group (secondary industry $\geq$45%) is –0.921, significant at the 1% level, indicating that in provinces dominated by heavy industries (e.g., Shanxi, Hebei), Green Credit significantly reduces carbon emissions per unit of GDP by restricting financing for high-pollution industries and supporting the application of green manufacturing technologies. Conversely, the GC coefficient for the low industrial proportion group (secondary industry $<$45%) is –0.312, only significant at the 10% level, with a weaker effect, as provinces primarily focused on services (e.g., Hainan, Zhejiang) have a lower base energy demand, resulting in limited marginal emission reduction effects of Green Credit, and smaller room for technological innovation (TA) and energy efficiency (EE) improvements, leaving policy potential not fully unleashed.

4.5 Spatial Effects

4.5.1 The Results of Moran's I

Table 9 shows the values of Moran's I of GC and CE from 2008 to 2022. It can be seen that there is a significant positive spatial correlation between GC and CE in the 30 provincial-level administrative regions of China during the sample period. Therefore, the next step of spatial effect analysis can be carried out.

4.5.2 The Results of Spatial Model Test

Model selection is required before constructing a spatial econometric model (Fischer and Getis, 2010). This study first conducted the Lagrange Multiplier (LM) test, as shown in Table 10, and found that the results of both the SEM and SLM were significant. Therefore, the SDM that combines the advantages of both models was selected. Then, this study conducted the Wald test. The result of the Wald test for SLM is 32.63, with a p-value of 0.000. Besides, the result of the Wald test for SEM is 34.19 while its p-value is 0.000. Thus, the null hypothesis that SDM can be degraded to SLM or SEM is rejected. Eventually, this study continued with the Hausman test and the result was 33.89, which led to the rejection of the null hypothesis of random effects at the 1% significance level.

Compared to SEM and SLM, SDM is capable of simultaneously capturing the spatial lag effect of the dependent variable and the spatial spillover effect of the independent variables, which is particularly crucial when examining the impact of green credit policies on carbon emissions. Green credit policies not only influence carbon emissions within the local region but may also generate spillover effects on neighboring regions through mechanisms such as technology diffusion and industrial linkages. By incorporating the spatial lag term of the independent variables, SDM provides a more comprehensive depiction of such spatial interactions. SDM can be regarded as a generalized form of SEM and SLM, as it can degenerate into either SEM or SLM when specific parameters are set to zero. This flexibility allows SDM to adapt to a broader range of research scenarios, especially when the sources of spatial dependence are uncertain. In this study, the Wald test confirmed that SDM cannot degenerate into SLM or SEM, further substantiating the rationale for selecting SDM. The estimation results of SDM not only decompose direct and indirect effects but also more accurately reflect the spatial spillover effects of green credit policies, offering significant guidance for formulating regionally coordinated green finance policies. Therefore, based on theoretical completeness and empirical considerations, this study selects SDM

Table 8. The results of regional and industrial structure heterogeneity.

Variables/Statistics	Eastern region	Central region	Western region	High industrial proportion	Low industrial proportion
lnGC	–0.818**	–0.517**	–0.405	–0.921***	–0.312*
	(–2.55)	(–2.15)	(–1.26)	(–5.23)	(–1.76)
lnPD	0.153**	–0.156***	0.167***	0.107**	0.053
	(2.02)	(–3.33)	(3.90)	(2.38)	(1.12)
lnOPL	–0.363**	–0.648***	0.163*	–0.189***	–0.125*
	(–2.55)	(–5.95)	(1.69)	(–3.84)	(–1.85)
lnEDL	–0.052	0.105	0.205*	0.141**	0.072
	(–0.26)	(1.01)	(1.85)	(2.19)	(1.23)
Constant	9.091***	8.483***	7.329***	8.632***	6.329***
	(4.86)	(8.09)	(6.48)	(7.54)	(5.82)
Observations	165	135	150	240	210
R-squared	0.676	0.756	0.728	0.752	0.683

Notes: *, **, *** indicate significant at 10%, 5%, 1% confidence levels respectively, and *t*-value is in parentheses.

as the primary analytical tool to more comprehensively reveal the mechanisms and spatial effects of green credit policies on carbon emissions.

4.5.3 The Results of Spatial Effect

Table 11 shows the results of spatial spillover effects. The direct effect refers to the degree of impact of a variable in the local area on CE in the local area, the indirect effect refers to the degree of impact of a variable in the surrounding area on CE in the local area, and the total effect refers to the overall degree of impact of a variable in the local area and surrounding areas on CE in the local area.

According to Table 11, the regression coefficients for the direct effect, indirect effect, and total effect of GC are –0.130, –0.287, and –0.417, respectively, and all passed the significance test at the 1% level. This indicates that the higher the proportion of GC, the more it can reduce CE. The possible reason for this is that GC guides funds towards low-carbon and environmentally friendly green industries and projects by providing preferential loan conditions, while limiting the development of high-pollution and high energy-consumption industries. This funding allocation method helps promote the green transformation of IS, reduce the proportion of high-carbon industries, and thus reduce regional CE. In addition, GC can promote exchanges and cooperation in green technology between the local and surrounding areas, and generate demonstration effects. By sharing green technology achievements and experiences, regions can promote the improvement of regional technological levels and reduce CE in surrounding areas. Therefore, GC can reduce CE in the local and surrounding areas.

As for control variables, PD and EDL both contribute to an overall increase in CE. The possible reason for this is that population expansion and economic development can cause consumption and production expansion effects, leading to an increase in household consumption, an expansion of enterprise production scale, stimulating economic development and generating more carbon dioxide, resulting in an overall increase in CE. OPL can effectively reduce CE in the local and surrounding areas. The possible reason for this is that OPL has promoted international trade and technological exchanges, allowing domestic enterprises to introduce and absorb advanced foreign technologies, including clean energy technology, energy conservation and emission reduction technology, and so on. The introduction and application of these technologies can help reduce CE in the production process. In addition, with the increasing awareness of environmental protection, green consumption and low-carbon living have gradually become new trends in society. OPL enables domestic consumers to access more green products and services, thereby promoting the popularization of green consumption and low-carbon living, thus helping to reduce CE in surrounding areas.

4.6 The Results of Endogeneity Test

In regression analysis, if there is a certain relationship between the dependent variables and the disturbance term, it can lead to endogeneity issues, which in turn can render statistical results inaccurate. Common endogeneity problems mainly include omitted variable bias, selection bias, measurement error, and bidirectional causality. Given that this study has selected a sufficient and representative set of variables that can influence CE, it can, to some extent, mitigate the endogeneity problem caused by omitting relevant variables. However, it cannot resolve the endogeneity issue stemming from the bidirectional causality between GC and CE. The instrumental variable method can effectively address endogeneity issues. Compared to the two-stage least squares method, the Generalized Method of Moments (GMM) can provide robust estimation under conditions of heteroscedasticity. Therefore, this study draws on the research of Halleck Vega and Elhorst (2017) to estimate the SDM under the 0-1 spatial weight matrix and employs the System GMM method within the instrumental variable framework to tackle the endogeneity problem. Additionally, following the approach of Han and Yang (2020), the

Table 9. The Moran's I of GC and CE of China from 2008 to 2022.

Years	GC	Years	CEs
2008	0.410*** [0.000]	2008	0.303*** [0.000]
2009	0.426*** [0.000]	2009	0.314*** [0.000]
2010	0.475*** [0.000]	2010	0.292*** [0.000]
2011	0.406*** [0.000]	2011	0.297*** [0.000]
2012	0.428*** [0.000]	2012	0.286*** [0.000]
2013	0.415*** [0.000]	2013	0.279*** [0.000]
2014	0.458*** [0.000]	2014	0.273*** [0.000]
2015	0.496*** [0.000]	2015	0.261*** [0.000]
2016	0.485*** [0.000]	2016	0.266*** [0.000]
2017	0.522*** [0.000]	2017	0.253*** [0.000]
2018	0.561*** [0.000]	2018	0.240*** [0.000]
2019	0.513*** [0.000]	2019	0.243*** [0.000]
2020	0.437*** [0.000]	2020	0.238*** [0.000]
2021	0.385*** [0.000]	2021	0.247*** [0.000]
2022	0.332*** [0.000]	2022	0.252*** [0.000]

Notes: *, **, *** indicate significant at 10%, 5%, 1% confidence levels respectively, and *p*-value is in square brackets.

Table 10. The results of LM test.

Models	LM tests	(1)
SEM	Lagrange multiplier	70.079*** [0.000]
	Robust Lagrange multiplier	46.614*** [0.000]
SLM	Lagrange multiplier	123.322*** [0.000]
	Robust Lagrange multiplier	53.858*** [0.000]

Notes: *, **, *** indicate significant at 10%, 5%, 1% confidence levels respectively, and *p*-value is in square brackets. LM, Lagrange Multiplier; SEM, Spatial Error Model; SLM, Spatial Lag Model.

Table 11. The results of spatial spillover effects.

Variables	Direct effect	Indirect effect	Total effect
lnGC	–0.130*** (–2.65)	–0.287*** (–3.11)	–0.417*** (–3.13)
lnPD	–0.165* (–1.71)	0.436*** (3.39)	0.271** (2.41)
lnOPL	–0.021 (–1.45)	–0.215*** (–2.58)	–0.236*** (–2.64)
lnEDL	0.298*** (3.82)	–0.032 (–1.63)	0.266*** (3.69)

Notes: *, **, *** indicate significant at 10%, 5%, 1% confidence levels respectively, and *t*-value is in parentheses.

study selects the first and second lags of CE and GC as instrumental variables for estimation.

From the perspective of instrumental variable exogeneity, the lagged terms of CE and GC satisfy the fundamental conditions for instrumental variables. According to economic theory, lagged variables are uncorrelated with contemporaneous disturbance terms because they occur prior to the disturbances, thus ensuring exogeneity. Simultaneously, lagged variables exhibit strong correlations with contemporaneous variables, effectively capturing the dynamic characteristics of the variables. Specifically, the lagged terms of CE and GC reflect historical carbon emission levels and the implementation of green credit policies, demonstrating significant time-series correlations with contemporaneous CE and GC, thereby serving as valid instrumental variables. From a theoretical standpoint, the selection of lagged terms as instrumental variables aligns with the fundamental assumptions of dynamic panel data models. The GMM estimation method proposed by Arellano and Bond is based on this principle, utilizing lagged variables as instrumental variables to address endogeneity issues. This approach not only handles endogeneity within the model but also effectively controls for individual heterogeneity and time effects. Furthermore, Hansen's overidentification test theory provides a statistical basis for validating the effectiveness of instrumental variables, ensuring the rationality of their selection. Therefore, choosing the first- and second-order lagged terms of CE and GC as instrumental variables not only meets the basic requirements of exogeneity and relevance but also has a solid theoretical foundation, effectively resolving endogeneity issues in the model and enhancing the reliability and robustness of the estimation results.

The estimation results are shown in Table 12. The *p*-value of the Autocorrelation (AR) (1) statistic is less than 0.1, while the *p*-value of the AR(2) statistic is greater than 0.1. Therefore, at the 10% significance level, we do not reject the null hypothesis that there is no autocorrelation in the second-order differences of the disturbance terms. The *p*-value of the Sargan test statistic is greater than 0.1, so at the 10% significance level, we do not reject the null hypothesis that the selected instrumental variables are jointly valid. Moreover, by comparing with the results of the benchmark

Table 12. The results of endogeneity test.

Variables/Statistics	(1)
lnGC	–0.602***
	(–4.131)
lnPD	0.115**
	(2.382)
lnOPL	–0.156***
	(–3.390)
lnEDL	0.124*
	(1.379)
Wald Test	3843.811***
	[0.000]
AR(1)	–1.337**
	[0.039]
AR(2)	–0.632
	[0.684]
Sargen Test	52.169
	[0.726]

Notes: *, **, *** indicate significant at 10%, 5%, 1% confidence levels respectively. AR, Autocorrelation.

regression, the signs and significance levels of all variables remain largely unchanged. This demonstrates that the System GMM method adopted in this study to address endogeneity issues is reasonable, and the estimation results are robust.

4.7 The Results of Robustness Tests

4.7.1 Replacing Dependent Variable

To further validate the robustness of the empirical results, this study used dummy variables as replacement indicators for GC variables. Starting from the official implementation of GC in 2012, the value of GC indicators before 2012 is 0, and the value of GC indicators after 2012 is 1. Table 13 shows the estimation results for replacing the GC variable with a dummy variable. Compared with the benchmark regression data, although the coefficient size of GC has changed, it still has a significant negative impact on CE at the 1% level. Therefore, the results of the benchmark regression are valid and robust.

4.7.2 Replacing Sample Time

To verify the robustness of the empirical results again, this paper adopted the method of changing the sample time from 2003–2022 to 2013–2022. Table 14 shows the estimation results for replacing the sample period. Compared with the benchmark regression data, although the coefficient size of GC has changed, it still has a significant negative impact on CE at the 1% level. Therefore, the results of the benchmark regression are also valid and robust.

Table 13. The results of replacing dependent variable.

Variables/Statistics	(1)
lnGC	–0.856***
	(–5.909)
lnPD	0.072**
	(2.081)
lnOPL	–0.221***
	(–4.358)
lnEDL	0.179*
	(2.412)
Constant	5.941***
	(7.280)
Observations	450
R-squared	0.719

Notes: *, **, *** indicate significant at 10%, 5%, 1% confidence levels respectively, and *t*-value is in parentheses.

Table 14. The results of replacing sample time.

Variables/Statistics	(1)
lnGC	–0.879***
	(–5.47)
lnPD	0.095**
	(2.232)
lnOPL	–0.132***
	(–3.708)
lnEDL	0.126**
	(2.022)
Constant	6.027***
	(8.193)
Observations	300
R-squared	0.742

Notes: *, **, *** indicate significant at 10%, 5%, 1% confidence levels respectively, and *t*-value is in parentheses.

4.7.3 Replacing Spatial Weight Matrix

To verify the robustness of the spatial effects, we replaced the spatial weight matrix. Therefore, we replaced the spatial weight matrix with the economically and geographically nested spatial weight matrix, which can comprehensively consider the impact of geographical distance and economic development level. The formula for this matrix is as follows:

$$\mathrm{w}_{\mathrm{i,j}}^{\mathrm{eg}} \begin{cases} \frac{1}{\mathrm{d_{i,j}}\left|\mathrm{G_i}-\mathrm{G_j}\right|}, & \text{if } \mathrm{i} \neq \mathrm{j} \\ 0, & \text{if } \mathrm{i} = \mathrm{j} \end{cases} \tag{14}$$

Where $\mathrm{d_{i,j}}$ denotes the distance between i-th and j-th province. Moreover, $\mathrm{G_i}$ and $\mathrm{G_j}$ refer to the real GDP of i-th and j-th province. Table 15 presents the estimation results for replacing the spatial weight matrix. Compared with Table 11, the signs and significance levels of all variables re-

Table 15. The results of replacing spatial weight matrix.

Variables	Direct effect	Indirect effect	Total effect
lnGC	–0.173***	–0.309***	–0.482***
	(–2.618)	(–3.241)	(–3.707)
lnPD	–0.148*	0.385***	0.237**
	(–1.672)	(3.463)	(2.178)
lnOPL	–0.058	–0.246***	–0.304***
	(–1.573)	(–2.822)	(–2.971)
lnEDL	0.368***	–0.082*	0.286***
	(4.049)	(–1.741)	(3.922)

Notes: *, **, *** indicate significant at 10%, 5%, 1% confidence levels respectively, and *t*-value is in parentheses.

main largely unchanged. Therefore, the results of the spatial effects are valid and robust.

5. Conclusions and Suggestions

5.1 Conclusions

This study shows that: (1) The benchmark regression results indicate that China's GC has a suppressive effect on CE. (2) The development of GC in the eastern and central regions significantly promotes the reduction of CE. (3) The results of the mediating effect show that IS, TA, and EE are all intermediary transmission pathways for GC to suppress CE. (4) The results of spatial effects show that GC has significant spatial spillover characteristics for CE. GC has negative spatial spillover effects on CE, contributing to the reduction of CE.

The carbon emission reduction mechanisms of green credit policy through three pathways—industrial structure upgrading, technological innovation incentives, and energy efficiency optimization—exhibit potential universal applicability in their theoretical framework for emerging economies undergoing industrial transformation. Although this study empirically employs Chinese provincial data, the core mechanism whereby financial institutions guide production factors toward low-carbon sectors through differentiated credit allocation essentially reflects the general logic of the synergistic interaction between financial instruments and environmental regulation. In economies at the mid to late industrialization stages with dominant high-energy-consumption industries, the capital constraint's inhibitory effects on polluting industries and its positive incentive effects on green technological innovation may demonstrate similar policy response patterns. Variations in policy effectiveness across institutional environments primarily stem from heterogeneities in financial market maturity and regulatory frameworks. Taking emerging markets with relatively underdeveloped financial infrastructure but urgent environmental regulation needs as examples, green credit policy implementation requires localized incentive designs, such as developing risk-sharing instruments or facilitating cross-border green capital flows.

The validated mediated pathways provide empirical foundations for constructing multi-level policy coordination frameworks, particularly manifested in how targeted credit allocation drives the green transformation of traditional industries and how technology diffusion effects strengthen regional low-carbon collaboration networks. The identified spatial spillover effects further reveal possibilities for environmental policy coordination among geographically adjacent or economically interconnected regions. The mechanisms of green technology spillover and industrial collaborative emission reduction suggest that cross-administrative green financial cooperation mechanisms could amplify policy effectiveness. For economies undergoing regional integration, establishing credit information-sharing platforms or joint carbon markets based on environmental performance could effectively promote the spatial reallocation of green capital. From a global green finance perspective, the revealed transmission chain of "financial resource allocation→industrial structure adjustment→technological innovation iteration→energy efficiency improvement" provides transferable policy toolkits for balancing the dual objectives of economic growth and ecological constraints. Subsequent research could further investigate how institutional environments (e.g., carbon pricing mechanism sophistication, environmental information disclosure transparency) moderate pathway intensity, thereby deepening the theoretical understanding of green finance policies' universal applicability boundaries.

The study's contributions to international management and policy literature lie in providing empirical evidence for the effectiveness of financial regulatory policies (green credit) in steering economic transition toward sustainability, offering referential value for numerous emerging markets and even developed countries implementing green finance initiatives. The findings resonate with sustainable development theory and institutional policy effectiveness theory, emphasizing financial instruments' pivotal role in environmental governance. Within a globalization context, green credit policy not only serves as China's key instrument for achieving dual-carbon goals but also provides replicable policy frameworks for other economies. Through financial institutions' credit resource allocation, green credit policy can direct capital flows toward low-carbon environmental projects while constraining high-pollution energy-intensive industries, thereby promoting industrial structure optimization and energy efficiency enhancement. This mechanism demonstrates universal applicability globally, particularly in emerging economies facing similar environmental challenges, where green credit policy could function as an effective tool for achieving win-win outcomes in economic growth and environmental protection.

5.2 Suggestions

As the most economically developed region in China, the eastern region possesses robust technological innovation capabilities and industrial foundations, and thus should further deepen green technology innovation and industrial upgrading through green credit policies. Firstly, the government should increase support for green technology research and development by establishing special funds and providing tax incentives to encourage enterprises to engage in green technology innovation. For instance, special funds for green technology research and development could be established in fields such as new energy and energy conservation, supporting enterprises in conducting cutting-edge technology research. Secondly, the eastern region should accelerate the green transformation of traditional high-carbon industries by guiding capital flows toward low-carbon and environmentally friendly projects through green credit policies, promoting the green transformation of energy-intensive industries such as steel and chemicals. Specifically, differentiated green credit interest rate policies could be formulated to provide low-interest loans to enterprises implementing green technology upgrades, thereby reducing their transformation costs. Additionally, the eastern region should strengthen the construction of green industrial chains, promoting coordinated development among upstream and downstream enterprises to form green industrial clusters. For example, the development of green supply chain finance could be supported through green credit policies, encouraging core enterprises to drive green transformation among upstream and downstream small and medium-sized enterprises. Finally, the eastern region should enhance international exchanges and cooperation in green technology by introducing advanced foreign technologies and management expertise to improve the green innovation capabilities of local enterprises. For instance, a green technology international cooperation platform could be established to facilitate in-depth collaboration between domestic and foreign enterprises in green technology research, development, and application.

As a significant industrial base in China, the central region features a relatively singular industrial structure and high energy consumption, and thus should prioritize industrial structure optimization and energy efficiency improvement through green credit policies. Firstly, the government should guide capital flows toward low-carbon and environmentally friendly industries through green credit policies, promoting the transformation and upgrading of traditional energy-intensive industries. For instance, differentiated green credit policies could be formulated to provide low-interest loans to enterprises implementing energy-saving and emission-reduction technological upgrades, supporting their green transformation. Secondly, the central region should accelerate the development of emerging green industries by supporting the rapid growth of sectors such as new energy and energy conservation through green credit policies. Specifically, special funds for green industries could be established to support enterprises in green technology research, development, and industrial application. Additionally, the central region should enhance energy efficiency by supporting enterprises in optimizing energy management systems and applying energy-saving technologies through green credit policies. For example, specialized green loans could be provided for energy efficiency improvement projects, supporting enterprises in upgrading energy-saving technologies and equipment. Finally, the central region should strengthen the innovation of green financial products by developing diversified green financial instruments to meet the financing needs of different enterprises. For instance, financial products such as green bonds and green insurance could be introduced to provide enterprises with diversified financing channels, thereby driving the development of green industries.

The western region of China, characterized by its fragile ecological environment yet abundant renewable energy resources, should prioritize ecological conservation and renewable energy development through green credit policies. Firstly, the government should support ecological conservation projects through green credit policies, promoting initiatives such as returning farmland to forests and soil and water conservation. For instance, a special fund for ecological protection could be established to support enterprises in implementing ecological restoration and environmental protection projects. Secondly, the western region should accelerate the development and utilization of renewable energy by supporting the construction of clean energy projects such as wind and solar power through green credit policies. Specifically, low-interest loans could be provided for renewable energy projects to reduce their financing costs and facilitate the rapid development of clean energy. Additionally, the western region should enhance the development of green agriculture by supporting projects in ecological and organic agriculture through green credit policies. For example, a special fund for green agriculture could be established to support enterprises in the research, development, and promotion of green agricultural technologies. Finally, the western region should strengthen the accessibility of green financial services by establishing green financial service centers to provide enterprises with professional green financial consultation and services, thereby enhancing their green financing capabilities. For instance, efforts could be made to extend green financial services to grassroots levels, offering convenient green financing channels for small and medium-sized enterprises and farmers to support their green production and operations.

China's regional economic development levels and resource endowments vary significantly, necessitating enhanced regional coordination and cross-regional green financial cooperation through green credit policies. Firstly, the government should establish a cross-regional green financial cooperation mechanism to promote the coordinated implementation of green credit policies across regions through policy alignment and information sharing. For instance, a cross-regional green financial cooperation platform could be established to facilitate coordination and collaboration among regions in the formulation and implementation of green credit policies. Secondly, the eastern regions should strengthen the transfer of green technologies and financial support to the central and western regions, guiding the flow of capital and technology to these areas through green credit policies to foster the development of their green industries. Specifically, a cross-regional green technology transfer fund could be established to support the transfer and application of green technologies from the eastern regions to the central and western regions. Additionally, regions should enhance the cross-regional circulation of green financial products by developing cross-regional green financial products to meet the financing needs of enterprises in different regions. For example, cross-regional green bonds and green funds could be introduced to provide diversified financing channels for enterprises and promote the development of green industries. Finally, regions should strengthen cross-regional exchanges and cooperation in green financial talent by establishing a green financial talent exchange platform to facilitate the mobility and collaboration of green financial professionals across regions, thereby enhancing the specialization of green financial services. For instance, cross-regional training and exchanges for green financial talent could be promoted to improve the quality and efficiency of green financial services in various regions.

6. Limitations and Area of Future Research Studies

This research has some limitations despite achieving its intended objectives, and future research can further deepen the analysis based on this research. Firstly, our study selected provincial panel data, and in fact, there may be significant differences within individual provincial administrative regions in China. Therefore, future research can select panel data from prefecture-level cities and use methods such as city size and regional classification in heterogeneity analysis. Secondly, this study adopted a spatial econometric model, which can effectively analyze the spatial correlation between variables, but does not involve the effectiveness evaluation of policies such as GC and GF. Finally, the measurement of Green Credit (GC) exhibits certain limitations: (1) this indicator primarily reflects credit constraints in high-energy-consuming industries and may not comprehensively capture the implementation details of green credit policies, such as the direct support for green projects; (2) the indicator does not differentiate the contributions of various types of green credit (e.g., green bonds, green funds), potentially underestimating the overall effectiveness of green finance; (3) the indicator fails to account for regional disparities in policy enforcement, which may lead to misinterpretations of the effectiveness of green credit policies. Therefore, future research could employ methods such as the Propensity Score Matching-Difference-in-Differences (PSM-DID) model to evaluate the contributions and effectiveness of relevant policies, and consider introducing multidimensional indicators, such as the scale of green credit and the proportion of green project financing, to more comprehensively assess the impact of green credit policies.

Abbreviations

GC, Green Credit; CE, Carbon Emissions; IS, Industrial Structure; TA, Technological Advance; EE, Energy Efficiency; PD, Population Density; OPL, Openness Level; EDL, Economic Development Level.

Availability of Data and Materials

All data reported in this paper will be shared by the correspondence author upon resonable request.

Author Contributions

TL: analyzed the data, wrote the manuscript. ZC: Data curation, Methodology, Project administration, Resources. LX: Software, Supervision, Validation, Visualization, Writing—original draft, Writing—review & editing. All authors contributed to editorial changes in the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

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Conflict of Interest

The authors declare no conflict of interest. Li Xu is from Zhong'an United Investment Group Co., Ltd., this company had no role in the study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Declaration of AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work the authors used ChatGpt-3.5 in order to check spell and grammar. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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