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RESEARCH ARTICLE

On green credits and carbon productivity in China

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Abstract
Based on panel data from 30 provinces over the period of 2003–2016, this study uses the spatial econometric model to examine the effect of green credits on carbon productivity. The research findings show that there is a significant positive correlation between green credits and carbon productivity among provinces during this period. Provinces with high levels of carbon productivity (green credits) are also geographically adjacent or economically close to provinces with high levels and vice versa. Regression results of the whole sample show that green credits not only promote carbon productivity, but also have a positive spatial spillover effect. Similar regression results using regional sub-samples indicate that the direct promotion effect and spatial spillover effect of green credits on carbon productivity are more obvious in the central and western regions than in the eastern parts of the country. The research findings have important and relevant policy implications as far as the relationship between green credits and carbon productivity is concerned.

Keywords Green credit · Carbon productivity · Spatial Durbin model

JEL Classification Q56 · Q52 · O51 · O16 · E51

Introduction

The serious impact of climate change on the economy and society has become a global issue of concern to all countries (Apergis et al. 2021). In fact, the main cause of climate change is the massive emission of carbon dioxide (CO_2) and other greenhouse gases (Alam et al. 2012). Over the past 40 years of reform and opening up, China's economy has grown rapidly, becoming the second largest after the USA in the world. However, the environmental problems behind this economic miracle cannot be ignored, as the amount of China's carbon emissions has overtaken that of the USA to be the largest in the world over the last decade.

To maintain sustainable economic growth, it is necessary to improve the quality of economic development. The Chinese government has proposed the visionary goals of "carbon emission peaking by 2030" and "carbon neutrality by 2060." In reality, China's current economic growth is highly dependent on energy consumption, and total carbon emissions are expected to continue to rise. It is a challenging task to achieve an absolute reduction in carbon emissions in a short period of time. To manage the relationship between economic growth and carbon emissions, it is imperative to improve the economic output per unit of carbon emissions, which is defined as carbon productivity in this paper (Ekins et al. 2012). In other words, improving carbon productivity is arguably the most important way that China will sustain its economic growth without emitting more CO_2 by 2030 and become carbon neutral by 2060 (Hu and Liu 2016; Shao et al. 2014).

In 2002, the World Bank introduced the Equator Principles, which were intended to require the banking sector to consider the environmental risks of projects in the financing process and to control environmental pollution at the source, and thus, green credits were born. For a long time, the lending activities of the financial sector have indirectly contributed to environmental degradation (White 1996; Chang et al. 2015; Sharpe 2015; Dong et al. 2019). In recent years, the rise of green finance has provided an opportunity to promote sustainable economic growth (Dikau and Volz 2021). China's 14th Five-Year Plan indicates that the establishment

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of a green financial system and the development of green credits are key areas to be promoted. In his report to the 19th National Congress of the Chinese Communist Party Central Committee in 2017, Xi Jinping pointed out that China would develop green finance, accelerate the reform of the ecological civilization development system, and build a beautiful China. In 2021, the People's Bank of China and the International Monetary Fund jointly convened a high-level seminar on "Green Finance and Climate Policy," emphasizing that green finance should play an "accelerator" role in carbon emission reduction. It is evident that China has been paying more and more attention to green finance in recent years.

China's green financial market currently consists of green credits, green bonds, green funds, and green insurance. Among them, green credits and green bonds are relatively more active in the green financial market. As of 2020, China's green credits exceeded 11 trillion yuan (ChinaIRN 2020). However, despite the rapid expansion of green credits, research on green credit policies is still in its infancy (Wang 2019). Against this backdrop, the development of green finance, represented by green credits, is an important direction for the future development of the financial sector. In the context of China's increasing emphasis on ecological protection and the pursuit of high-quality economic development, can the development of green credits effectively balance economic growth with the achievement of carbon emission reduction goals? In what ways do green credits affect carbon productivity? What are the specific directions of its impact? Is there significant spatial heterogeneity in the impact of green credit development on carbon productivity in different regions? This paper aims to answer these questions and provide some policy recommendations as to how to reduce carbon emission through green credit financing.

The main contributions of this paper are as follows. (1) Previous studies mainly considered the impact of green credits on carbon emission or economic growth from a single perspective and lacked research on the comprehensive indicator of carbon productivity. The key to increasing economic growth while reducing carbon emission is to increase carbon productivity. Therefore, this paper studies the relationship between green credits and carbon productivity to fill the literature gap in this field. (2) Few studies have considered the spatial distribution of green credits and carbon productivity. This paper uses Moran's index to test the spatial correlation between the two and draws Moran's scatter plots to demonstrate the spatial distribution features of green credits and carbon productivity. (3) We use a spatial Durbin model that is more realistic than the OLS regression and comprehensively analyzes the direct, indirect, and total effects of green credits on carbon productivity.

The rest of the paper is structured as follows. The second section reviews the relevant literature. The thirds section presents the econometric methods and data. The fourth section is the empirical analysis. The last section concludes with policy recommendations.

Literature review

Carbon productivity was originally proposed by Kaya and Yokobori (1997). The basic definition is the ratio of GDP to CO_2 emission over a certain period of time, which reflects the amount of GDP generated per unit of CO_2 in a country or region and is inversely proportional to the intensity of carbon emission in numerical terms.

Beinhocker et al. (2008) in a McKinsey study give the concept of carbon productivity, which is narrowly defined to reflect both controlling carbon emission and maintaining economic growth. The key to reducing carbon emission is to increase carbon productivity, which is the core of developing a low-carbon economy. The main factors affecting carbon productivity are technological progress (Du and Li 2019; Fan et al. 2021; Han 2021; Sun et al. 2021), industrial structure upgrading (You 2015), energy consumption (Laurent et al. 2010; Yao and Zhang 2021), economic growth, and the like.

With the promotion and improvement of green finance policies, the research on green finance has also been gradually enriched. In the early stage, scholars mainly discussed the connotation of green finance, the influencing factors of green finance, and the policy effects of green finance, while Salazar (1998) proposed the concept of green finance from the perspective of the integration and development of the financial industry and the green environment industry and defined green finance as the mutual promotion, integration, and development of economic development and environmental protection. In other words, green finance is an interdisciplinary approach that includes not only economics but also finance and environmental protection. This definition was later endorsed by Cowan (1998). Green finance needs to be protected by the rule of law in order to effectively serve economic entities (Duan and Meng 2011), and support and cooperation at the national level can effectively contribute to the continued development of green finance (Falcone et al. 2018). Financial institutions that engage in green finance have a greater sense of social responsibility and also gain higher social prestige and reputation for their green finance activities (Scholtens and Dam 2007). The development of green finance by financial institutions is not only beneficial to their own reputation, but also to their corporate risk management, making it easier for them to make management decisions that are beneficial to their long-term development goals (Fullenkamp 2002). With the development of green finance, scholars have gradually paid attention to the impact of green finance on the economy and the natural environment, but due to the limitation of data availability on green finance, existing studies mainly focus on green credits as a main form of green finance for empirical analysis, so does this paper.

Up to recently, few studies have directly focused on the relationship between green credits and carbon productivity. Therefore, the references of this paper mainly include two aspects: the impact of green credits on economic growth and the impact of green credits on the environment. Green credits are arguably the most common and dominant form of green finance, which promotes sustainable development by allocating more credit resources to green and low-carbon areas than traditional lending activities (Ba et al. 2018). The implementation of green finance or green credit policies may encourage more capital flows to green firms, make it more restrictive for non-green firms to raise finance (Liu et al. 2019; Zhou et al. 2021), and introduce tougher control over bank credit allocation to energy-intensive sectors (Wen et al. 2021; Wang et al. 2021). At the same time, green finance will also strengthen the risk connection with the new energy industry and reduce the risk connection with the traditional industry (Zhang et al. 2022). How green credit policies affect the economy after allocating more funds to the green sector has attracted serious academic debates. Some scholars have found that green finance has a negative impact on bank loan disbursement and inhibits the efficiency of investment in renewable energy enterprises (He et al. 2019a, b) and that green credit policies have a negative impact on economic development (Zhang et al. 2020). However, most scholars believe that green credit has a positive impact on economic growth. On the one hand, green credits can mobilize more capital to form green investment through differentiated currency-biased policies such as interest rate tilt and form capital elements for economic growth (Soundarrajan and Vivek 2016). On the other hand, the green credit policy requires commercial banks to fully consider the environmental risks of loan projects and exclude high-polluting and energy-intensive industries, so as to direct funds to green industries with high efficiency, energy conservation, and environmental protection, eliminate backward enterprises, and promote the upgrading of industrial structure to accelerate economic growth (Hu and Liu 2016). From the perspective of micro-enterprises, green credits can also improve micro-economic efficiency in three aspects: reducing transaction costs, diversifying or reducing innovation risks of enterprises, and supervising invested enterprises or projects (Liu 2019). In addition to the theoretical analysis, many scholars have proved that green credits can promote economic growth from the perspective of empirical analysis. Qiu (2017) used a spatial econometric approach to verify that green finance can promote economic growth using province level panel data in China. Pei et al. (2018) used Huzhou city as an example to analyze the relationship between green credits and regional economic growth by constructing a PVAR model. The research results show that green credits promote regional economic growth, but economic growth is a necessary condition for the continuing supply of green credits. Zhang et al. (2016) took Colombia as a research sample to explore the impact of green finance on economic growth, which found that green finance can promote the development of clean technology, clean energy, and economic growth effectively.

It can be seen that the impact of green credits on economic development is not unanimously conclusive. Likewise, the impact of green credits on the environment has two sides. Firstly, from the perspective of energy demand, while green credits promote economic growth, it will also increase energy demand and stimulate carbon emission (Zhang 2011). Secondly, from the perspective of technological progress, green credits provide R&D capital for green industries, which in turn promotes green technological progress and reduces carbon emission (Guo et al. 2019). Finally, considering the industrial structure, green credits crowd out industries with high energy consumption and high pollution, forcing enterprises to upgrade their industries and ultimately reduce carbon emission (Gu et al. 2021). The impact of green credits on the environment is so complex that many scholars have conducted empirical tests on this issue. Sun et al. (2019a, b) and Wang et al. (2021) used SO_2 emissions as an indicator of environmental pollution to demonstrate that green credits can effectively reduce environmental pollution in China. Tamazian et al. (2009) conducted an empirical test based on BRIC data in 1992–2004 and found that green credits are beneficial to reducing per capita CO_2 emission. At the micro-firm level, green credits can have a significant impact on firm performance. Government green credit policies can effectively improve environmental quality by reducing corporate energy consumption (Chen et al. 2019). Green credits can facilitate polluting firms to increase investment in environmental protection and green innovation, thereby reducing carbon emission at the firm level (Chintrakam 2008; Testa et al. 2011). Moreover, under the constraints of green credits, firms are more likely to treat pollution at source rather than dealing with pollution at the end of the production chains (Sun et al. 2019a, b).

Although existing papers lack a discussion on the relationship between green credits and carbon productivity, some scholars have studied the relationship between green finance and energy efficiency. Sadorsky (2010) found that financial development can promote energy efficiency by reducing information asymmetry between lenders and borrowers, reducing financial risks and borrowing costs, and enabling enterprises to obtain energy-efficient products and cutting-edge technologies. Islam et al. (2013) took Malaysia as a research sample and found that financial development affects energy consumption in both the short and long terms and financial development can reduce energy use by improving energy efficiency. Shen and Cao (2020) used China's provincial panel data to analyze the impact of green finance on carbon emission intensity using a double-difference model. The empirical results found that green finance can improve energy efficiency by improving the green transformation of industrial industries. As mentioned above, most scholars believe that green finance can improve energy efficiency.

In summary, although many scholars have studied the impact of green credits on the economy and the environment respectively, few have discussed the impact of green credits on carbon productivity, which is a composite indicator of the economy and the environment. Compared to carbon emissions or economic growth alone, carbon productivity is a dual consideration of economic growth and CO_2 emission reduction. Although the concepts of energy efficiency and carbon productivity are closely related, carbon productivity can directly reflect our goal of stabilizing CO_2 levels in the process of economic growth. However, energy efficiency does not imply new challenges faced by socio-economic development from the perspective of input factors, which can easily lead to one-sided pursuit of output quantity and neglect to control total carbon emissions (Liu et al. 2017). Consequently, studying the impact of green credits on carbon productivity is more in line with China's emission reduction requirements. Furthermore, traditional panel data regression models cannot effectively estimate the spatial spillover effect of green credits on carbon productivity, which is likely to be spatially dependent as a combined economic and environmental variable. In addition, China is a vast country. The economic development level, industrial structure, and urbanization process of the eastern region are significantly different from those of the central and western regions due to their location and policy advantages. Therefore, in order to effectively address and overcome the drawbacks of the traditional panel data regression models, this paper explores the direct, indirect, and total effects of green credit development on carbon productivity in China by constructing a spatial econometric model that takes spatial effects into account, using a panel data sample comprising 30 provinces, including 4 metropolitan cities and 5 autonomous regions which enjoy the provincial status in China, over the period 2003–2016. The sample is also divided into two subsamples by region (eastern, central, and western) to further investigate the potential spatial heterogeneity regarding the relationship between green credits and carbon productivity.

Methodology and data

The mechanism of green credits affecting carbon productivity

Theoretically, all factors that affect economic growth and carbon emission have an impact on carbon productivity (Liu and Hu 2016). According to the financial structure theory and the Equator Principle, green finance can play a role in optimizing the allocation of resources, which will inevitably lead to an increase in the level of factor productivity. More importantly, compared with traditional finance, green finance takes the negative externalities of the environment into account. Managers consider environmental risk factors in their business operations to innovate financial products, expand financing channels for green and low-carbon projects for new energy and other industries, solve financing problems for companies with significant environmental benefits, and encourage the development of start-up green industries. This ultimately leads to an increase in carbon productivity (Zhao 2021). Specifically, the main mechanisms through which green credits affect carbon productivity are as follows. Firstly, green credits are an important driving force for economic development, supporting and guiding the development of the real economy, and promoting the expansion of production and consumption activities, thus affecting economic growth and energy consumption (Sadorsky 2010), which in turn affect carbon productivity. Secondly, green credits are directed to green production, providing capital support for green technological progress. By restricting the loan amount for industries with high energy consumption, high pollution, and excess capacity, green credits increase R&D investment in industries with low energy consumption and high added value, which promotes technological innovation in corresponding industries, thereby promoting green economic growth and improving environment quality. King and Levine (1993) believed that by screening financing loan projects, banking financial institutions invest incremental funds for enterprise R&D, which can effectively promote enterprise technological innovation and improve productivity. And the technological progress of enterprises can improve the quality of the environment (Kumar and Managi 2010). Finally, green credits use financial tools to eliminate and exclude investment with high energy-consuming and high-polluting enterprises and projects and guide the funds flow to industries with low energy consumption, low emissions, and low pollution, support and cultivate environment-friendly industries, and ultimately realize the transformation of the industrial structure to be green and low-carbon oriented (Salazar 1998). The optimization and transformation of the industrial structure will further enhance carbon productivity (Liang and Zhao 2017).

The impact of green credits on carbon productivity can also be attributed to the scale effect, technology effect, and structural effect. In addition, carbon productivity is a variable with obvious spatial geographical attributes, and ignoring this characteristic to study the impact of green credits on carbon productivity will inevitably lead to biased results. The first law of geography states that "everything is connected to each other to some degree, and things that are closer together are more connected than things that are further away." Walheer et al. (2020) argue that technology spillovers have an inherent spatial correlation, with historical and geographic differences often leading to different technology creation capabilities and knowledge diffusion effects. The upgrading of industrial structures can serve as a demonstration effect for the neighboring regions. As a result, the addition of geospatial attributes can better reflect these effects. The systematic mechanisms of the impact of green credits on carbon productivity can be demonstrated in Fig. 1. It is worth mentioning that the direct effects and indirect effects in this paper are, respectively, referred to the influence of independent variables on the local region itself as well as the influence of the same variables on its neighboring areas. For the scale effect, the expansion of production scale in a particular region will inevitably affect its surrounding areas indirectly through business exchanges and/or any other form of inter-regional interactions. For the technical effect, knowledge can spread to the surrounding areas and indirectly affect their carbon productivity. For the structural effect, green credits facilitating industrial upgrading in a particular region will also lead to a demonstration effect on its surrounding areas, indirectly pushing them to optimize their industrial structure.

Spatial econometric model

Following Han's empirical model (Han 2021), this paper aims to identify the main determinants of carbon productivity with a focus on green credits in China. With appropriate modification, the basic empirical model is shown in Eq. (1):

$$\begin{aligned} lnCP_{it} &= \alpha + \beta_1 lnGC_{it} + \beta_2 lnY_{it} + \beta_3 lnES_{it} \\ &+ \beta_4 ln\mathrm{IS}_{it} + \beta_5 lnT_{it} + \beta_6 lnU_{it} + \beta_7 \mathrm{lnO}_{it} \\ &+ u_i + v_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where the dependent variable, carbon productivity (CP), is the ratio of GDP over CO_2 emission, with subscripts i and t, respectively, denoting province i and year t. GC denotes green credits, Y output, ES energy structure, IS industrial structure, T technology innovation, U urbanization, and O openness. u and v, respectively, control the area and time specific effects. ε is a white noise.

Currently, China does not have statistical yearbooks to directly publish CO_2 emission data. Therefore, how to accurately measure the total provincial carbon emission is the key to this paper. The paper refers to the "2006 IPCC National Greenhouse Gas Inventory Guidelines" compiled by the IPCC, using the methods provided in its second volume and combining the energy balance sheets of the provinces in the "China Energy Statistics Yearbook" to calculate the carbon emission of each province over the years. The specific calculation formulas are given in Eqs. (2) and (3):

$$CO_2 = \sum_{i=1}^{n} CO_2 = \sum_{i=1}^{n} E_i \times NCV_i \times CEF_i \times (44/12) \tag{2}$$

$$CEF_i = CC_i * COF_i(44/12) \tag{3}$$

where CO_2 indicates the total carbon emission calculated from various forms of energy consumption. i denotes the type of energy consumption. During 2003–2009, the following 11 energy sources were obtained: coal, coke, coke oven gas, other gas, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, and natural gas. During 2010–2016, there were 14 types of energy sources, adding

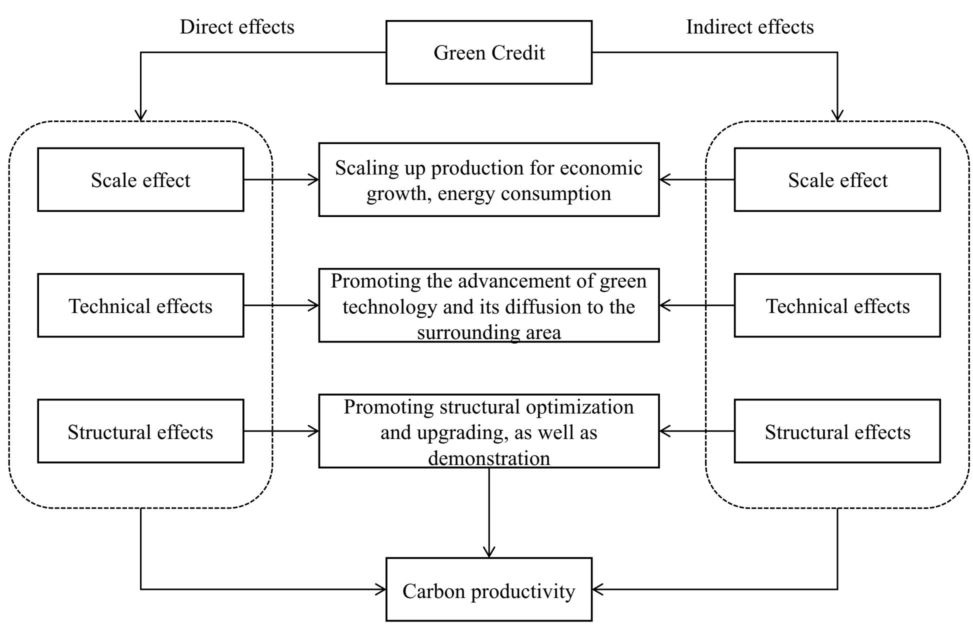


Fig. 1 Mechanisms of the impact of green credits on carbon productivity

Table 1 Descriptive statistics of variables

Variable (natural logarithm)	N	Mean	Std. Dev	Min	Max
lnCP	420	8.216	0.538	6.647	9.898
lnGC	420	3.743	0.375	1.254	4.356
lnY	420	9.990	0.629	8.216	11.322
lnES	420	4.154	0.398	2.163	5.020
lnIS	420	−0.103	0.349	−0.699	1.427
lnT	420	0.737	1.318	−2.041	3.835
lnU	420	4.037	0.842	3.222	9.210
lnO	420	2.945	0.975	0.296	5.234

blast furnace gas, converter gas, and liquefied natural gas to the original list. The various forms of energy consumption in each province are calculated on an annual basis to avoid secondary calculations and eliminate the input and loss in the process of energy processing and conversion as well as the part used as raw materials in industrial production, so as to obtain the net amount of energy consumption in each province. E_i is the physical consumption of the i-th energy; NCV_i, CC_i, and COF_i, respectively, represent the average low calorific value, carbon content, and carbon oxidation factor of the i-th energy; 44 and 12 are the molecular weights of CO_2 and carbon elements, respectively; and CEF_i represents the CO_2 emission factors of various energy sources.

The key independent variable in Eq. (1), green credit (*GC*), is a financial means used by the government as an economic leverage to facilitate environmental protection. The measurement indicators for green credits may include the share of green credits as a proportion of total credits, the share of loan expenditures for energy conservation and environmental protection projects as a proportion of total loan expenditures, and the share of six low energy-intensive industries interest expenditures as a proportion of all the industries interest expenditures. Due to data availability and for the principle of continuity, we use the share of the six low energy-intensive industry interest expenditures as a proportion of all the industries interest expenditures to represent the scale of green credits (Yin et al. 2019; Zhang and Zhao 2019; Jiang et al. 2020).

As for the control variables in Eq. (1), Y represents the level of economic development defined as real GDP per capita (Ren et al. 2021). Energy structure (ES) is defined as the ratio of coal consumption over total energy consumption (Zhang et al. 2013), industrial structure (IS) the ratio of the tertiary industry value-added over the manufacturing industry value-added (Gang et al. 2011), technological progress (T) the number of patents per 10,000 people (Zhao et al. 2019), urbanization (U) the share of urban population as a proportion of the total population (Khan and Su 2021), and openness (O) the ratio of foreign trade over GDP (Chen et al. 2020).

According to the First Law of Geography (Tobler 1970), we believe that all things are related to other things, but things that are closer are more related than things that are far away. Some scholars pointed out that when there is spatial dependence between regions, spatial econometric models must be considered to avoid biased results (Getis 2007). Therefore, the spatial econometric model is used to explore the relationship between green credits and carbon productivity. The commonly used spatial econometric models are the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM). When the dependent variable is spatially correlated, the SLM is used. Based on Eq. (1), the SLM model can be expressed as Eq. (4):

$$\begin{aligned} lnCP_{it} &= \rho \sum_{j=1}^{n} w_{ij} lnCP_{ij} + \beta_1 lnGC_{it} \\ &+ \beta_2 lnY + \beta_3 lnES + \beta_4 ln\mathrm{IS} \\ &+ \beta_5 lnT + \beta_6 lnU + \beta_7 \mathrm{lnO} + u_i + v_t + \varepsilon_{it} \end{aligned} \tag{4}$$

Table 2 Estimation results of benchmark measurement model

Variables	(1)	(2)	(3)	(4)
ln*GC*	0.414 (0.045)***	0.107 (0.034)***	0.427 (0.047)***	0.069 (0.040)*
ln*Y*	−0.054 (0.048)	0.246 (0.044)***	−0.086 (0.054)	0.418 (0.074)***
lnE*S*	−0.911 (0.041)***	−0.548 (0.040)***	−0.913 (0.041)***	−0.589 (0.041)***
ln*IS*	−0.123 (0.042)***	0.055 (0.038)	−0.108 (0.045)**	0.057 (0.053)
ln*T*	0.183 (0.024)***	0.022 (0.020)	0.179 (0.026)***	−0.016 (0.022)
ln*U*	−0.013 (0.016)	0.171 (0.060)***	−0.012 (0.016)	0.150 (0.061)**
ln*O*	−0.072 (0.017)***	−0.055 (0.020)***	−0.062 (0.024)**	−0.032 (0.021)
Constant	11.109 (0.512)***	7.260 (0.477)***	11.305 (0.537)***	5.905 (0.810)***
Individual FE	No	Yes	No	Yes
Time FE	No	No	Yes	Yes
Observations	420	420	420	420
R^2	0.786	0.961	0.782	0.964

numbers in parentheses represent standard errors, and ***, **, and * imply 1%, 5%, and 10% significance levels, respectively. *FE*, fixed effect where ρ represents the spatial regression coefficient of the dependent variable. w_{ij} stands for the i, j-th element of the spatial weight matrix. When the model concerns the spatial dependence reflected in the residuals, we have the SEM:

$$
\begin{aligned}
lnCP_{it} &= \lambda \sum_{j=1}^{n} w_{ij}\varphi_{ij} + \beta_1 lnGC_{it} \\
&+ \beta_2 lnY + \beta_3 lnES + \beta_4 ln\mathrm{IS} \\
&+ \beta_5 lnT + \beta_6 lnU + \beta_7 \mathrm{lnO} + u_i + v_t + \varepsilon_{it}
\end{aligned} \tag{5}
$$

where φ_{it} stands for the spatial autocorrelation error term and λ stands for the spatial autocorrelation coefficient of the error term. When the model concerns the spatial correlation of the independent as well as the dependent variables, we have the SDM:

$$
\begin{aligned}
\ln CP_{it} = \alpha + \rho \sum_{j=1}^{n} W_{ij} \ln CP_{it} + \beta_1 \ln GC_{it} + \beta_2 \ln Y_{it} + \beta_3 \ln ES_{it} + \beta_4 \ln IS_{it} + \beta_5 \ln T_{it} + \beta_6 \ln U_{it} + \beta_7 \mathrm{lnO}_{it} \\
+ \theta_1 W_{ij} \ln GC_{it} + \theta_2 W_{ij} \ln Y_{it} + \theta_3 W_{ij} \ln ES_{it} + \theta_4 W_{ij} \ln IS_{it} + \theta_5 W_{ij} \ln T_{it} + \theta_6 W_{ij} \ln U_{it} + \theta_7 W_{ij} \mathrm{lnO}_{it} \\
+ u_i + v_t + \varepsilon_{it}
\end{aligned} \tag{6}
$$

where θ*'s* represent the spatial regression coefficients of the independent variables. In order to test which model is more suitable, we applied the LR and Wald tests. We used two null hypothesis tests to explore which spatial model provides the best fit. When $\theta = 0$, the spatial Durbin model (SDM) is reduced to the spatial lag model (SLM). When $\theta + \rho\beta = 0$, it is reduced to the spatial error model (SEM) as discussed in Pan et al. (2020).

According to Li et al. (2018), the common three spatial weight matrixes are the geographic distance matrix, the geographic adjacency matrix, and the economic distance matrix. Among them, the geographic distance matrix is similar to the geographic adjacency matrix. In order to ensure the robustness of the results, this paper uses the geographic adjacency matrix as well as the economic distance matrix to construct the spatial measurement models. The description of these two matrixes is given below:

Geographic adjacency matrix (W_1): geographical adjacency spatial weight matrix w_{ij}. If province i and province j are geographically adjacent, then $w_{ij} = 1$. If province i and province j are not geographically adjacent, then $w_{ij} = 0$.

Economic distance matrix (W_2): economic distance spatial weight matrix w_{ij} stands for the reciprocal of the absolute value of the gap between the economic development levels of the two provinces. The specific definition is

$$w_{ij} = 1 / \left| Y_i - Y_j \right| \tag{7}$$

where Y_i and Y_j represent real per capita GDP in province i and j, respectively.

Data

This paper selects 30 provinces (metropolitan cities and autonomous regions) in China as the sample over the period 2003–2016. More recent data are not available due the fact the China Industrial Statistical Yearbook was only updated up to 2016. The original data comes from the previous China Statistical Yearbook, China Energy Statistical Yearbook, and China Industrial Statistics Yearbook. In order to eliminate the impact of prices, all the values are calculated based on the prices in 2003. At the same time, to mitigate the problem of heteroscedasticity in the data and facilitate the economic interpretation of the estimated coefficients, all the variables are taken natural logarithms. The descriptive statistics of all the variables are shown in Table 1.

Empirical results

Results from benchmark measurement models

The results of the benchmark OLS regression model and the estimated results after adding individual fixed effects and time fixed effects item by item are shown in Table 2. Model 1 represents simple OLS model. Model 2 adds individual fixed effects. Model 3 adds time fixed effects. Model 4 adds both the individual and time fixed effects. In all the models, the estimated coefficients of green credits on carbon productivity are positive and significant at the 5% level, showing that green credits improve carbon productivity. One possible explanation is that green credits, as a resource input, can promote regional economic growth, contain high-polluting industries, accelerate industrial transformation, and hence reduce carbon emission. Green credits also facilitate research and innovation toward clean technologies, providing a solid foundation for firms to sustain environmentally friendly business expansion.

As for the control variables, the coal-dominated energy structure will undoubtedly reduce carbon productivity. Economic growth and urbanization are found to have little impact on carbon productivity in model (1), but once the time and individual effects are considered in the other models, they are found to have a significantly positive effect. Industrial structure, technological progress, and openness are all found to have a negligible effect on carbon productivity.

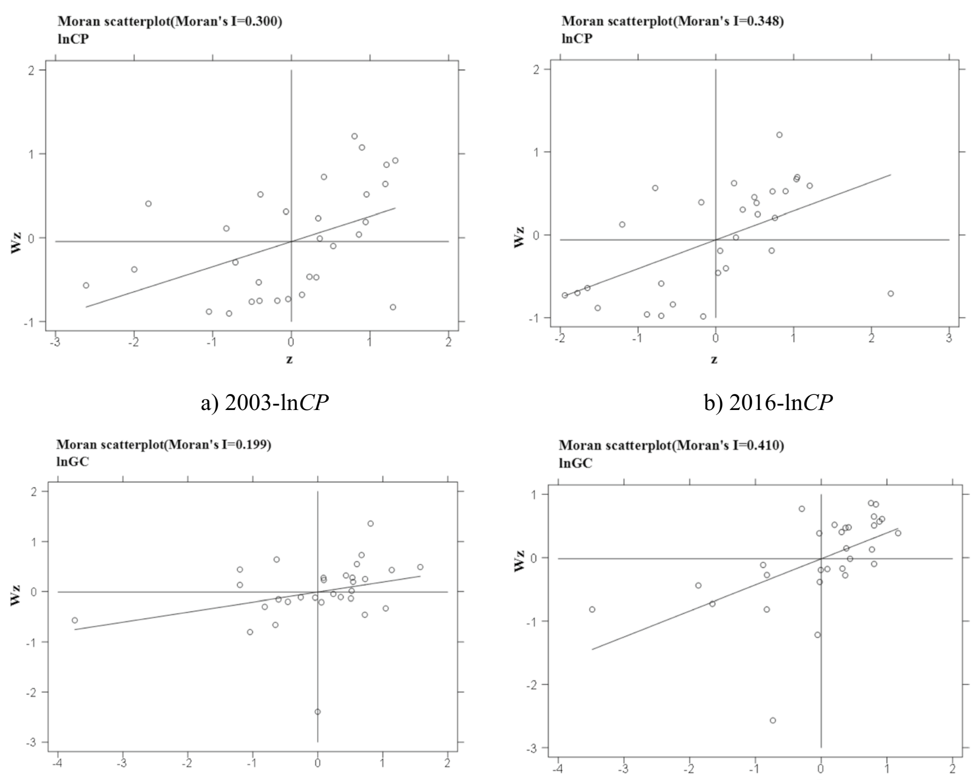
Table 3 Test results of global Moran's *I* indexes

	lnCP				lnGC			
Year	M(1)	P(1)	M(2)	P(2)	M(1)	P(1)	M(2)	P(2)
2003	0.333***	(0.001)	0.390***	0.007	0.199**	(0.016)	0.284**	(0.022)
2004	0.337***	(0.001)	0.392***	0.008	0.297***	(0.002)	0.340**	(0.014)
2005	0.356***	(0.001)	0.393***	0.008	0.323***	(0.002)	0.338**	(0.017)
2006	0.255***	(0.008)	0.343**	0.016	0.347***	(0.001)	0.321**	(0.019)
2007	0.359***	(0.001)	0.425***	0.005	0.338***	(0.001)	0.367***	(0.010)
2008	0.386***	(0.000)	0.464***	0.002	0.334***	(0.001)	0.433***	(0.003)
2009	0.351***	(0.001)	0.449***	0.003	0.361***	(0.000)	0.443***	(0.003)
2010	0.388***	(0.000)	0.506***	0.001	0.282***	(0.003)	0.272**	(0.035)
2011	0.335***	(0.001)	0.449***	0.003	0.218***	(0.004)	0.158*	(0.084)
2012	0.362***	(0.000)	0.478***	0.002	0.314***	(0.001)	0.273**	(0.033)
2013	0.300***	(0.003)	0.476***	0.002	0.356***	(0.000)	0.300**	(0.022)
2014	0.322***	(0.001)	0.487***	0.001	0.435***	(0.000)	0.343**	(0.012)
2015	0.330***	(0.001)	0.481***	0.002	0.403***	(0.000)	0.311**	(0.017)
2016	0.346***	(0.001)	0.477***	0.002	0.410***	(0.000)	0.403***	(0.004)

***, **, and * imply 1%, 5%, and 10% level of significance, respectively

Spatial autocorrelation test

Before performing spatial econometric analysis on the model, it is necessary to test whether there is spatial dependence between carbon productivity and green credits in each province. Methods to test spatial dependence include Moran's *I* index, Geary index, and Getis-Ord index, etc. The most widely used index, however, is Moran's *I* index. Therefore, this paper uses Moran's *I* index to test carbon productivity and green credits. The Moran's *I* index is defined in Eq. (8):



a) 2003-ln*CP* b) 2016-ln*CP*

c)2003-ln*GC* d)2016-ln*GC*

Fig. 2 Moran's I index scatter plots. **a** 2003-ln*CP*. **b** 2016-ln*CP*. **c** 2003-ln*GC*. **d** 2016-ln*GC*

Table 4 Spatial econometric model estimation results (DV = ln*CP*)

Variables	W1 SLM	W1 SEM	W1 SDM	W2 SLM	W2 SEM	W2 SDM
ln*GC*	0.044	0.074**	0.054*	0.105***	0.096***	0.073**
	(0.035)	(0.034)	(0.032)	(0.032)	(0.033)	(0.033)
ln*Y*	0.408***	0.287***	0.266***	0.227***	0.248***	0.279***
	(0.075)	(0.044)	(0.072)	(0.045)	(0.043)	(0.070)
ln*ES*	−0.624***	−0.585***	−0.477***	−0.533***	−0.545***	−0.529***
	(0.042)	(0.040)	(0.042)	(0.040)	(0.039)	(0.042)
ln*IS*	0.062	0.065*	0.066	0.046	0.068*	0.135***
	(0.054)	(0.038)	(0.047)	(0.037)	(0.037)	(0.043)
ln*T*	−0.020	−0.003	−0.023	0.019	0.013	−0.011
	(0.022)	(0.021)	(0.023)	(0.020)	(0.020)	(0.021)
ln*U*	0.175***	0.216***	0.132**	0.174***	0.198***	0.175***
	(0.062)	(0.059)	(0.062)	(0.057)	(0.056)	(0.057)
ln*O*	−0.055***	−0.076***	−0.075***	−0.055***	−0.067***	−0.071***
	(0.021)	(0.021)	(0.019)	(0.019)	(0.020)	(0.020)
W*ln*GC*			0.228***			0.093**
			(0.056)			(0.040)
ρ	0.001		0.173***	0.060		0.172***
	(0.049)		(0.064)	(0.046)		(0.051)
λ		0.106*			0.133**	
		(0.057)			(0.057)	
R^2	0.778	0.781	0803	0.777	0.778	0.794
obs	420	420	420	420	420	420
Regional effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Wald test spatial lag			15.10 [*P* = 0.000]			4.80 [*P* = 0.029]
LR test spatial lag			48.41 [*P* = 0.000]			43.14 [*P* = 0.000]
Wald test spatial error			17.20 [*P* = 0.000]			6.39 [*P* = 0.012]
LR test spatial error			46.54 [*P* = 0.000]			39.32 [*P* = 0.000]

numbers in parentheses represent standard errors, and ***, **, and * imply 1%, 5%, and 10% significance levels, respectively

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(lnY_i - ln\overline{Y}\right)\left(lnY_j - ln\overline{Y}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{8}$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(lnY_i - ln\overline{Y}\right)^2 \tag{9}$$

where $\ln Y_i$ represents the observed value of carbon productivity or green credits in the i-th province, n the number of provinces, and w_{ij} the spatial weight matrix. The value of Moran's I index is generally between [− 1, 1]. Moran's I index greater than 0 indicates a positive spatial correlation. Moran's I index less than 0 indicates a negative spatial correlation. Moran's I index equal to 0 indicates no spatial correlation. To ensure the robustness of the results, this paper considers two spatial weight matrixes: the spatial adjacency weight matrix (W_1) and the economic distance weight matrix (W_2). Since Hainan Province is an island, to ensure that each province has neighbors, Hainan's neighbor is assumed to be Guangdong Province and vice versa, as both provinces are close to each other. The results of the Moran's I index test are shown in Table 3, where M(1) represents the global Moran I index under the spatial adjacency weight matrix, and P(1) represents the corresponding P value. M(2) represents the global Moran I index under the economic distance weight matrix, and P(2) represents the corresponding P value. From the test results, it can be seen that the global Moran I indexes of carbon productivity and green credits were significantly greater than 0 in the sample period, and the corresponding P values were close to 0. It can be preliminarily concluded that China's carbon productivity and green credits are both spatially correlated.

The results of the global Moran's I index test in Table 3 show that green credits and carbon productivity in each province are spatially correlated as a whole, but the global Moran's I index cannot describe the local spatial correlation

Table 5 Estimation results of direct, indirect, and total effects in the full sample (DV = ln*CP*)

Variables	Direct effects		Indirect effects		Total effects	
	W1	W2	W1	W2	W1	W2
lnGC	0.065 (0.032)**	0.083 (0.034)**	0.277 (0.066)***	0.118 (0.043)***	0.343 (0.072)***	0.201 (0.054)***
lnY	0.269 (0.068)***	0.276 (0.065)***	0.153 (0.112)	−0.000 (0.082)	0.422 (0.102)***	0.276 (0.074)***
lnES	−0.473 (0.039)***	−0.521 (0.040)***	−0.015 (0.091)	0.045 (0.064)	−0.488 (0.092)***	−0.477 (0.067)***
lnIS	0.066 (0.045)	0.129 (0.041)***	0.039 (0.086)	−0.073 (0.057)	0.105 (0.091)	0.056 (0.064)
lnT	−0.022 (0.021)	−0.007 (0.019)	0.023 (0.038)	0.051 (0.026)*	0.001 (0.037)	0.044 (0.030)
lnU	0.124 (0.063)**	0.166 (0.058)***	−0.301 (0.140)**	−0.161 (0.063)***	−0.177 (0.176)	0.005 (0.101)
lnO	−0.071 (0.020)***	−0.065 (0.021)***	0.130 (0.039)***	0.090 (0.029)***	0.059 (0.045)	0.025 (0.039)

numbers in parentheses represent standard errors, and ***, **, and * imply 1%, 5%, and 10% significance levels, respectively

of provincial green credits and carbon productivity. To further explore the agglomeration and local spatial correlation characteristics of neighboring provinces, a local Moran's *I* index scatter plot is used to reflect the characteristics of spatial agglomeration. To save space, this paper only selects two representative years 2003 and 2016 to create the scatter plots of Moran's *I* index reflecting the local spatial relationship between carbon productivity and green credits under the geographic adjacency matrix (Fig. 2).

The abscissa of the Moran's *I* index scatter plot is *z*, which represents the observation value of the space unit itself after standardization. The ordinate is *W*z, which represents the average value of the observation value of the adjacent unit after standardization. Most of the scattered points in Fig. 2 are located in the first quadrant (high-high) and the third quadrant (low-low), and only a small number of the scattered points fall in the second quadrant (high-low) and the fourth quadrant (low–high). The local Moran's *I* index in the first and third quadrants is greater than 0, indicating that there is a positive correlation between carbon productivity and green credits in the provinces and their neighboring regions. It can be seen that carbon productivity in each province in China is positively correlated with that in the neighborhood. The typical characteristics and clustering are very significant, further supporting the above conclusion. Combining the slope of the correlation curve of the Moran's *I* index scatter plot in 2003 and 2016, it is not difficult to find that whether it is carbon productivity or green credits, the positive spatial correlation became higher over time. In other words, the geographical distribution of China's carbon productivity and green credits has become more and more obvious over time.

Spatial econometric model estimation results

Spatial econometric models include the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM). The estimation results of the three spatial econometric models under the geographic neighborhood spatial weight matrix (W_1) and the economic distance spatial weight matrix (W_2) are given in Table 4.

Based on the uniqueness principle of model selection, the WALD and LR tests were used to test whether the spatial Durbin model could be simplified to a spatial lag models or a spatial error model. The results rejected the original hypothesis at the 10% significance level, indicating that the spatial Durbin model was the most appropriate. Therefore, the subsequent analysis in this paper will use this as the baseline model controlling for the time and spatial double fixed effects.

Table 6 Estimation results of direct, indirect, and total effects in the eastern region (DV = ln*CP*)

Variables	Direct effects		Indirect effects		Total effects	
	W_1	W_2	W_1	W_2	W_1	W_2
lnGC	0.109 (0.045)**	0.132 (0.044)***	0.076 (0.082)	0.002 (0.055)	0.185 (0.086)**	0.133 (0.066)**
lnY	0.128 (0.076)*	0.127 (0.077)*	0.321 (0.110)***	0.398 (0.147)***	0.449 (0.115)***	0.526 (0.120)***
lnES	−0.387 (0.040)***	−0.327 (0.047)***	0.079 (0.079)	0.114 (0.059)*	−0.308 (0.086)***	−0.213 (0.083)**
lnIS	0.133 (0.063)**	0.065 (0.060)	−0.273 (0.149)*	−0.183 (0.098)*	−0.140 (0.147)	−0.118 (0.100)
lnT	0.061 (0.025)**	0.045 (0.023)*	−0.036 (0.039)	0.010 (0.038)	0.025 (0.041)	0.055 (0.037)
lnU	−0.445 (0.179)**	−0.496 (0.165)***	−0.223 (0.247)	−0.881 (0.340)***	−0.668 (0.328)**	−1.377 (0.401)***
lnO	−0.214 (0.042)***	−0.208(0.043)***	−0.088 (0.068)	−0.136 (0.062)**	−0.303 (0.086)***	−0.343 (0.072)***

numbers in parentheses represent standard errors, and ***, **, and * imply 1%, 5%, and 10% significance levels, respectively

Table 7 Estimation results of direct, indirect, and total effects in central and western regions (DV = lnCP)

Variables	Direct effects		Indirect effects		Total effects	
	W_1	W_2	W_1	W_2	W_1	W_2
lnGC	0.083 (0.039)**	0.056 (0.042)	0.242 (0.072)***	0.087 (0.049)*	0.325 (0.080)***	0.143 (0.066)**
lnY	0.571 (0.098)***	0.571 (0.090)***	−0.012 (0.152)	−0.279 (0.113)**	0.559 (0.140)***	0.292 (0.091)***
lnES	−0.454 (0.061)***	−0.506 (0.063)***	−0.011 (0.121)	0.158 (0.104)	−0.465 (0.125)***	−0.348 (0.109)***
lnIS	0.179 (0.061)***	0.179 (0.054)***	0.040 (0.103)	−0.003 (0.067)	0.219 (0.111)**	0.177 (0.078)**
lnT	−0.005 (0.027)	0.016 (0.025)	−0.028 (0.051)	0.041 (0.032)	−0.032 (0.049)	0.057 (0.038)
lnU	0.158 (0.081)*	0.152 (0.080)*	−0.466 (0.195)**	−0.168 (0.089)*	−0.308 (0.248)	−0.016 (0.135)
lnO	−0.027 (0.024)	−0.001 (0.024)	0.138 (0.045)***	0.113 (0.033)***	0.111 (0.053)**	0.111 (0.044)**

numbers in parentheses represent standard errors, and ***, **, and * imply 1%, 5%, and 10% significance levels, respectively

From the empirical results in Table 4, it can be seen that the spatial lag coefficients ρ of the explained variables under the two spatial weight matrixes are 0.173 and 0.172, respectively, which are significant at the 1% level. This once again shows that China's carbon productivity has a significant spatial dependence. The carbon productivity of neighboring regions has a positive effect on the carbon productivity of the region under study. The coefficients of green credits are 0.054 and 0.073, respectively, which are significant at the 5% level, indicating that green credits can improve regional carbon productivity. The spatial lags of green credits are all positive at the 5% significance level, indicating that green credits can also promote carbon productivity in the surrounding areas.

Spatial Durbin model effect decomposition

As discussed earlier, the spatial Durbin model incorporating the spatial lag terms cannot directly reflect its marginal effect, and its regression coefficient cannot be directly used to measure the degree of influence of the independent variables on the dependent variable. Therefore, according to Lesage (2008), the partial differential method decomposes the effect of explanatory variables on the explained variables. Table 5 shows the direct, indirect, and total effects of the independent variables on the dependent variable under the two weight matrixes. The direct effect represents the influence of the explanatory variable on the explained variable in the region, the indirect effect represents the influence of the explanatory variable in the neighboring provinces on the local explained variable, and the total effect is the sum of the direct and indirect effects (Lv and Li 2021).

From the decomposition results in Table 5, it can be seen that the direct effects of green credits under the two spatial weight matrixes are both positive and significant at the 5% level, showing that green credits can promote regional carbon productivity. Moreover, the indirect effect of green credits is significantly positive, exceeding the direct effect, implying that the level of green credits in neighboring areas also significantly promotes the level of carbon productivity in the region. From the total effect, green credits are significantly positive under the two weight matrixes, which mean that the level of green credits can effectively improve the overall carbon productivity. Specifically, green credits enhance regional carbon productivity through scale, structure, and technical changes. Green credits restrain industries with high energy consumption and high pollution, invest more in high-tech and clean enterprises, promote green technological progress, and force high-polluting firms to upgrade production structure, resulting in carbon productivity growth. The demonstration effect of structural upgrading and optimization as well as green technological progress will spread to the surrounding areas, raising their carbon productivity. The results in Table 5 show that the indirect impact of green credits on carbon productivity is greater than the direct impact. One possible explanation is that the surrounding areas can improve their own carbon productivity by following the production practices and adopting similar green technologies used by the local region under concern to improve their industrial structure at low cost. In addition, the production scale expansion effect brought about by green credits in the neighboring regions may have a more potent effect on the local region under concern than on the neighboring regions themselves, which explains why the indirect (neighboring) effect is more powerful than the direct (local) one (Lv and Li 2021).

As for the control variables, the direct and overall effects of economic growth on carbon productivity are both significantly positive, but the indirect effects are insignificant. This shows that carbon emission under the same level of development is decreasing and the quality of the country's economic development is improving. However, the increase in the level of economic development has little spatial spillover effect on carbon productivity as the improvement is confined to the same region. The coal-based energy structure will significantly reduce carbon productivity, while the regional energy structure only has an impact on regional carbon productivity, which is basically in line with theoretical expectation.

Table 8 Full sample robustness test results (DV = ln*CP*; ln*GC* is lagged by one period)

Variables	Direct effects		Indirect effects		Total effects	
	W_1	W_2	W_1	W_2	W_1	W_2
lnGC	0.042 (0.031)	0.063 (0.032)*	0.284 (0.062)***	0.167 (0.041)***	0.326 (0.070)***	0.230 (0.054)***
lnY	0.437 (0.066)***	0.430 (0.064)***	0.115 (0.109)	0.048 (0.082)	0.551 (0.100)***	0.478 (0.080)***
lnES	−0.523 (0.037)***	−0.563 (0.037)***	−0.025 (0.085)	0.024 (0.063)	−0.548 (0.085)***	−0.539 (0.066)***
lnIS	0.068 (0.042)	0.129 (0.039)***	0.059 (0.079)	−0.033 (0.055)	0.127 (0.084)	0.097 (0.063)
lnT	−0.055 (0.020)***	−0.039 (0.019)**	0.033 (0.037)	0.026 (0.027)	−0.022 (0.036)	−0.013 (0.031)
lnU	0.119 (0.060)**	0.139 (0.057)**	−0.339 (0.132)**	−0.233 (0.064)***	−0.220 (0.165)	−0.094 (0.102)
lnO	−0.039 (0.019)**	−0.029 (0.020)	0.180 (0.038)***	0.112 (0.030)***	0.140 (0.044)***	0.084 (0.039)**

numbers in parentheses represent standard errors, and ***, **, and * imply 1%, 5%, and 10% significance levels, respectively

The impact of industrial structure upgrading on carbon productivity is positive but insignificant. China's industrial structure is in a predicament of "third advances and second retreats," which means that the service industry (the so-called third industry in China) has become more dominant in the national economy at the expenses of the manufacturing industry (the second industry). In this process, continuous exploration is required. Therefore, it is difficult for the upgrading of industrial structure to improve carbon productivity immediately. The impact of technological progress on carbon productivity is also uncertain. Because of the limited data sources, technological progress defined in this paper is the total number of patents divided by the population. Some technological advances are to expand the scale of production. Others are to promote energy conservation and emission reduction. Therefore, technological progress in a broad sense may not necessarily affect carbon productivity.

The development of urbanization will significantly increase regional carbon productivity and reduce carbon productivity of the surrounding areas. The possible reason for this is that as the level of urbanization increases, the level of infrastructure will improve, thereby increasing local carbon productivity. However, the region under study will increase its resource consumption in the surrounding areas during the development process, and the final overall effect will not be significant. The opposite of the impact of urbanization on carbon productivity is the degree of openness. The level of openness will significantly reduce carbon productivity of the region and increase carbon productivity of the surrounding areas. This phenomenon is consistent with the so-called "pollution haven" hypothesis, meaning that more advanced countries (regions) tend to relocate the more polluting industries to the less developed economies (regions). As China is still a developing country, it tends to play the role of processing and manufacturing and the export of raw materials in the process of globalization; the increase in the level of openness will reduce the country's carbon productivity. However, in the course of trade exchanges, progress in green technology may spread to the surrounding areas, thereby promoting the increase in the level of carbon productivity in the surrounding areas, leading to an inconclusive result of the final overall effect.

Robustness test by region

Because of China's vast territory, there are significant differences in economic development levels, infrastructure, resource endowments, etc., across different regions. This paper divides the whole sample into two regional sub-samples to examine whether regional heterogeneity affects the

Table 9 Robustness test results in the eastern region (DV = ln*CP*; ln*GC* is lagged by one period)

Variables	Direct effects		Indirect effects		Total effects	
	W_1	W_2	W_1	W_2	W_1	W_2
lnGC	0.088 (0.049)*	0.103 (0.049)**	0.074 (0.080)	−0.001 (0.060)	0.162 (0.080)**	0.102 (0.071)
lnY	0.189 (0.075)**	0.163 (0.081)**	0.372 (0.103)***	0.416 (0.152)***	0.561 (0.100)***	0.579 (0.121)***
lnES	−0.386 (0.041)***	−0.344 (0.050)***	0.046 (0.077)	0.061 (0.058)	−0.340 (0.072)***	−0.283 (0.077)***
lnIS	0.086 (0.065)	0.046 (0.062)	−0.219 (0.133)*	−0.176 (0.094)*	−0.133 (0.119)	−0.130 (0.093)
lnT	0.059 (0.028)**	0.055 (0.026)**	−0.030 (0.037)	−0.002 (0.040)	0.029 (0.034)	0.052 (0.037)
lnU	−0.577 (0.185)***	−0.529 (0.178)***	−0.332 (0.246)	−0.727 (0.375)*	−0.909 (0.308)***	−1.256 (0.431)***
lnO	−0.197 (0.040)***	−0.205 (0.042)***	−0.026 (0.060)	−0.041 (0.069)	−0.223 (0.072)***	−0.246 (0.076)***

numbers in parentheses represent standard errors, and ***, **, and * imply 1%, 5%, and 10% significance levels, respectively

Table 10 Robustness test results in the central and western regions (DV = ln*CP*; ln*GC* is lagged by one period)

Variables	Direct effects		Indirect effects		Total effects	
	W_1	W_2	W_1	W_2	W_1	W_2
lnGC	0.077 (0.037)**	0.065 (0.039)*	0.261 (0.074)***	0.156 (0.048)***	0.338 (0.086)***	0.221 (0.068)***
lnY	0.802 (0.095)***	0.734 (0.084)***	−0.127 (0.157)	−0.257 (0.111)**	0.675 (0.148)***	0.477 (0.100)***
lnES	−0.526 (0.056)***	−0.556 (0.058)***	0.053 (0.119)	0.164 (0.102)	−0.473 (0.125)***	−0.392 (0.110)***
lnIS	0.154 (0.056)***	0.176 (0.050)***	0.049 (0.101)	−0.012 (0.065)	0.202 (0.111)*	0.164 (0.078)**
lnT	−0.032 (0.025)	−0.008 (0.024)	−0.037 (0.052)	0.004 (0.032)	−0.069 (0.054)	−0.004 (0.041)
lnU	0.166 (0.078)**	0.164 (0.080)**	−0.437 (0.203)**	−0.264 (0.093)***	−0.271 (0.255)	−0.101 (0.142)
lnO	−0.006 (0.023)	0.012 (0.023)	0.157 (0.046)***	0.107 (0.032)***	0.151 (0.055)***	0.119 (0.044)***

numbers in parentheses represent standard errors, and ***, **, and * imply 1%, 5%, and 10% significance levels, respectively

impact of green credits on carbon productivity. According to the classification of the National Bureau of Statistics, the eastern (coastal) region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan, and the remaining provinces belong to the central-western (inland) regions. Tables 6 and 7, respectively, show the spatial regression results of the eastern region as well as the central and western regions.

Through comparison, it is found that green credits have an overall promotion effect on carbon productivity in both the subsample regions, but the effect is more significant in the central and western regions as compared to that of the eastern region. From a spatial comparison, the spatial spillover effect of green credits in the central and western regions is more obvious. The reason for this result may be related to the differences in China's regional development. The economic development level, industrial structure, and industrialization process of the eastern region have entered a relatively mature state, and the advantages of green credits in improving carbon productivity are relatively more difficult to be fully realized. The development of the central and western regions is lagging behind so that the marginal effect of green credits to improve carbon productivity is higher. Secondly, the development level of the provinces in the eastern region is relatively more balanced, and the competition between them is fiercer, so it is more difficult to obtain a higher spatial spillover effect from the neighboring provinces.

Further robustness tests

In this paper, two spatial weight matrixes are used to ensure the robustness of the regression results to a certain extent. To further solve the endogenous problems caused by missing variables or measurement errors, the first-order lag of green credits is selected as an instrumental variable for the core explanatory variable. The spatial Durbin model is re-estimated replacing the original variables with instrumental variables using the full sample and the subsamples. The regression results are shown in Tables 8, 9, and 10. From the regression results, it can be seen that the coefficient of lagged green credits is basically the same as in the original regression results. The instrumental variable method overcomes the possible endogeneity problem of the core explanatory variables, but the final results show little difference, implying that the basic regression results are robust.

Conclusions and policy recommendations

Under the pressure of carbon emission reduction, the development of green finance represented by green credits is an important direction for the future development of China's financial industry. This paper constructs a spatial Durbin model using the geographical adjacency matrix and the economic distance matrix to empirically analyze the impact of green credits on China's carbon productivity. The key research findings are summarized as follows. Firstly, there is a high degree of spatial correlation between carbon productivity and green credits in China at the national as well as the regional levels, with a clear tendency of regional aggregation in geographical distribution. The results of the national-level estimation show that green credits have a significant effect on carbon productivity of a particular province and the neighboring areas. The spatial spillover effect is larger than the direct effect, with the total effect of green credits being significantly positive. Secondly, at the regional level, the direct and total effects of green credits are positive in the east and central-west regions, but the indirect effect is only positive in the central-west regions. The total effect in the central-west region is larger than that in the east region, implying that the carbon productivity improvement effect and the spatial spillover effect of green credits in China mainly come from the central-west region. Finally, the results of the other control variables show that the level of economic development can increase carbon productivity, the coal-based energy structure can hinder the increase of carbon productivity, and industrial structure as well as technological progress does not significantly increase carbon productivity.

Based on the above findings, to promote the early realization of a low-carbon economy and improve carbon productivity in China, this paper puts forward the following policy recommendations.

Firstly, based on the fact that green credits have a positive promotion effect on carbon productivity and the spatial spillover effect of green credits is significant, China can promote carbon productivity by increasing the scale of green credits, and local governments should choose to move from competition to cooperation in the development process, strengthen technology exchange, improve the market mobility of high-end human resources, and form high-value carbon productivity agglomerations as soon as possible.

Secondly, based on the fact that the enhancement effect is stronger in the central and western regions and the spatial effect is more significant, the government may focus more on increasing the scale of green credits in the central and western regions while strengthening technology exchanges in the eastern regions to create a better environment for the synergistic development of the eastern provinces.

Finally, general technological progress did not improve carbon productivity, but the essence of improving carbon productivity is to improve green technology. As a result, provincial governments should guide enterprises to invest more in green technology research and strengthen their ability to absorb green technologies.

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Data availability The datasets used during the current study are available from the corresponding author on reasonable request.

Declarations

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