Environmental Science and Pollution Research (2021) 28:65776–65790
https://doi.org/10.1007/s11356-021-15419-8

RESEARCH ARTICLE

The local-neighborhood effect of green credit on green economy: a spatial econometric investigation

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Received: 10 May 2021 / Accepted: 8 July 2021 / Published online: 28 July 2021

Abstract

Green credit is one of the most important financial instruments to promote sustainable development. Taking the provincial panel dataset of China as the research sample, this paper investigates the spatial impacts of green credit on the green economy. The super slack-based measure (Sup-SBM) model with undesirable outputs is employed to calculate the level of green economy within China. On this basis, we establish spatial Durbin models to study the impact of green credit on green economy and its transmission mechanisms. The results show that green credit exhibits a local-neighborhood effect on green economy; that is, the green credit can not only improve the local green economy but also generate spatial spillover effect to promote the development of green economy in surrounding areas. The above conclusion still holds after the robustness test by replacing spatial weight matrices and alternative measurement for the explained variable. Furthermore, enhancing innovation efficiency and optimizing energy structure are important ways for green credit to promote green economy. The findings of this study not only provide a new perspective for understanding the economic consequences of green credit policy but also provide empirical evidence for the important role of green finance in achieving the win-win goals of economic growth and environmental protection.

Keywords Green credit · Green economy · Local-neighborhood effect · Innovation efficiency · Energy structure · Spatial Durbin model · China

Introduction

The novel coronavirus disease (COVID-19) has caused the tragic loss of life and threatened the sustainable economic growth. To build a greener, more sustainable, and inclusive post-pandemic world, countries all over the world should put in place policies and practices for green recovery (United Nations Environment Programme 2021). To this end, China has promoted the development of green finance to cope with eco-environmental challenges (Pan et al. 2021). In 2021, the State Council of China (SCC) issued the *Guidance on Accelerating the Establishment and Improvement of Green, Low-carbon and Circular System for Economic Development* and proposed to develop green finance to promote green transformation, emphasizing the important role of green finance in modern environmental governance system (SCC 2021).

According to the G20 Green Finance Study Group (2016), green finance refers to investment and financing activities that can produce environmental benefits. The ultimate goal of green finance is to promote sustainable development (An et al. 2021). The green credit is one of the most important green financial instruments in China (Yang et al. 2020). It incorporates environment-related risks into credit management and allocates more funds to low-carbon and environmentally friendly industries (China Banking Regulatory Commission 2012). The green credit in China has developed rapidly. By the end of June 2020, the balance of green credit has exceeded 11 trillion yuan, which is one of the highest in the world (People's Bank of China 2020). The existing literature has contributed to the discussion on the effects of green credit policy, but the results are mixed. On the one hand, there

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are two opposite opinions on the implementation efficiency of green lending. Some scholars argued that financial institutions, as the main body of green credit, strived to maximize profits and did not fully implement green credit due to the lack of economic incentives (Biswas 2011). However, several studies demonstrated that financial institutions actively followed the principle of green credit because of capital security (Zhang et al. 2011), compliance cost, and differentiated competition (Hu and Cao 2011; Gao and Gao 2018). Moreover, financial supervision (Lu and Fang 2018), peer pressure (Contreras et al. 2019), and financial innovation such as order financing (Wang et al. 2021a) can solve the problem of insufficient incentives. On the other hand, the prior literature has mixed views on the impacts of green credit policy. One strand of literature believed that green credit policy promoted industrial upgrading (Hu et al. 2020) and improved environmental quality (Cai et al. 2019; Sun et al. 2019); instead, other strands argued that green credit was not conducive to economic performance and the positive effect on environment was not significant (Liu et al. 2017).

Taken together, the existing studies are insufficient to shed light on the effects and influencing mechanisms of green credit policy. First, most of the literature examines the impacts of green credit policy from a single perspective, without considering the dual goals of green credit on environment and economy, and thus lacks comprehensive evaluation systems for green credit policy. Second, most of the mainstream literature ignores the spatial effect of green credit policy. According to the first law of geography proposed by Tobler (1970), near things are more related to each other. Therefore, the spatial distance is an important factor affecting the relationship between variables. Previous studies have also found that there exists interaction and correlation between environmental behaviors and economic activities within different regions (see Shao et al. 2020; Yuan et al. 2020; Zhang et al. 2020). It is therefore necessary to incorporate spatial factors into the research framework of green credit policy. What is more, the influencing mechanisms of green credit policy on economy and environmental still need further in-depth analysis.

To fill aforementioned research gaps, this study establishes spatial econometric models to explore the local-neighborhood effect of green credit policy. With China's provincial panel dataset as the research sample, we apply the Sup-SBM data envelopment analysis (DEA) model considering undesirable outputs to calculate the green economy, which is used as the proxy to comprehensively measure the dual objectives of green credit policy on economy and environment. Furthermore, we construct the spatial Durbin model to investigate the local-neighborhood effect of green credit policy, which not only studies the impacts of green credit on local region's green economy but also explores the spatial effect on surrounding areas' green development. In addition, in order to clarify the influencing mechanisms of green credit policy, we discuss how green credit policy can promote green economy through improving innovation efficiency and reducing the share of fossil energy consumption.

The marginal contributions of this study are threefold. First, this paper illustrates the effects of green credit policy from both economic and environmental perspectives. The results show that green credit policy helps promote the development of green economy, which not only enriches the literature on green credit policy but also provides empirical evidence for achieving the win-win situation between economic development and environmental protection. Second, most of the existing literature on green credit focuses on the local effect and ignores the spatial correlation. This paper extends the application of spatial econometrics to green financial research and finds that green credit policy has positive effects on the green economy in the surrounding areas, verifying the existence of spatial spillover effects of green credit. Third, based on the green lending principles, this paper clarifies the transmission mechanisms of green credit on green development. Our study emphasizes the importance of innovation efficiency and energy structure optimization in the practice of green credit policy, which not only deepens the understanding of green credit but also enriches the research on its transmission mechanisms.

The remainder of this paper is organized as follows. The "Institutional background and literature review" section presents the institutional background and literature review. The "Research method and data" section describes the method and data. The empirical results and discussion follow in the "Results and discussion" section, and the "Conclusion and policy implications" section concludes and makes policy implications.

Institutional background and literature review

Institutional background of China's green finance

The term green finance originated from the Equator Principles (EPs)[1] proposed by the International Finance Corporation (IFC) in 2003, which called for financial institutions to consider environmental and social factors in their investment and financing activities (Scholtens and Dam 2007). Looking back on the development of green finance in China, it is typical of Chinese characteristics. Different from the voluntary characteristics of EPs, China's green financial system combines the stringent government supervision and flexible market incentives. The government plays a significant role in guiding and supervising the promotion of green finance. Table 1 shows some important green finance policies of China, and it can

[1] Available at the official website of Equator Principles Association. https://equator-principles.com

Table 1 Overview of major green financial policies in China

Year	Policy	Institution	Contents
1995	Notice on Implementing Credit Policy and Strengthening Environmental Protection	PBC	Credit policy should consider environmental protection and resource conservation
2007	Opinions on Implementing Environmental Protection Policies and Preventing Credit Risk	PBC, SEPA, and CBRC	For the first time, green credit was taken as an important market-based means of environmental protection, energy conservation, and emission reduction
2007	Guidance on Environmental Pollution Liability Insurance	SEPA and CIRC	Carry out the research and pilot demonstration of environmental pollution liability insurance system
2012	Green Credit Guidelines	CBRC	Put forward clear requirements for financial institutions to carry out green credit and thus promote energy conservation and emission reduction
2015	Energy Efficiency Credit Guidelines	CBRC and NDRC	Provide credit funds for energy users to improve energy efficiency and reduce energy consumption
2016	Opinions on the Construction of Green Financial System	PBC, MFC, and NDRC	Develop green finance, enrich green financial products, promote international cooperation in green finance, and prevent financial risks
2017	Green Finance Reform Pilot Zone Scheme (Zhejiang, Jiangxi, Guangdong, Guizhou, and Xinjiang)	PBC, NDRC, MFC, MEEC, CBRC, CSBC, and CIRC	Establish green finance reform pilot zone to promote the green transformation and upgrading of the economy
2021	Guidance on Accelerating the Establishment and Improvement of Green, Low-carbon and Circular System for Economic Development	SCC	Promote the convergence of international green finance standards, the two-way opening of green finance market, and climate investment and financing

Notes: PBC is the People's Bank of China, SEPA is the State of Environmental Protection Administration of China, CBRC is China Banking Regulatory Commission, CIRC is China Insurance Regulatory Commission, NDRC is the National Development and Reform Commission of China, MFC is the Ministry of Finance of China, MEEC is the Ministry of Ecology and Environment of China, CSRC is China Securities Regulatory Commission, and SCC is the State Council of China

be seen that China's emphasis on green finance is increasing and gradually moving from advocacy recommendations to specific provisions. At present, China's green financial system is under continuous improvement, with green standards, environmental information disclosure, incentive mechanisms, product innovation, and international cooperation as its five core pillars.[2] China's green financial market has developed rapidly, and the function of optimizing resource allocation has been continuously strengthened. The scales of green credit and green bonds have continued to expand. By the end of 2020, their stocks are among the highest in the world.[3] Besides, the construction of emission trading market has accelerated (Zhang and Zhang 2020), and other innovative products such as green funds, green insurance, green trust, green public-private partnership (PPP), and green leasing have been emerging. In particular, China has proposed the goal of carbon neutrality, which provides an opportunity for green finance to take a new step forward. As one of the major advocates and practitioners of green finance, China has played great roles in the green recovery of the world economy. However, China's green finance is still in its infancy (Dong et al. 2021), and there are many theoretical and practical issues to be explored. The studies of green finance from the perspective of China can help provide Chinese solutions and contribute to the global sustainable development.

Green credit policy, economic development, and environmental pollution

Green credit is the earliest and fastest growing green financial product in China. In 2007, China formally introduced the green credit policy. However, it was not until the promulgation of the *Green Credit Guidelines* in 2012 that comprehensive and specific requirements for the implementation of green credit were put in place. As a financial innovation, green credit has dual objectives. It emphasizes not only environmental benefits but also economic benefits, aiming to improve the ability to serve the real economy. Therefore, the green credit has a profound impact on green development. However, the real effect of green credit is highly uncertain. In practice, the implementation of green credit can be influenced by many factors (Huang et al. 2021b; Yin et al. 2021). Therefore, in-depth and extensive studies are particularly necessary to accurately evaluate the true effects of green credit. This has motivated a large number of scholars to investigate the effects of green credit policy on the economy and environment (see Fig.1).

[2] Available at the official website of the People's Bank of China. http://www.pbc.gov.cn/goutongjiaoliu/113456/113469/4201524/index.html

[3] Data source: http://www.pbc.gov.cn/goutongjiaoliu/113456/113469/4211212/index.html

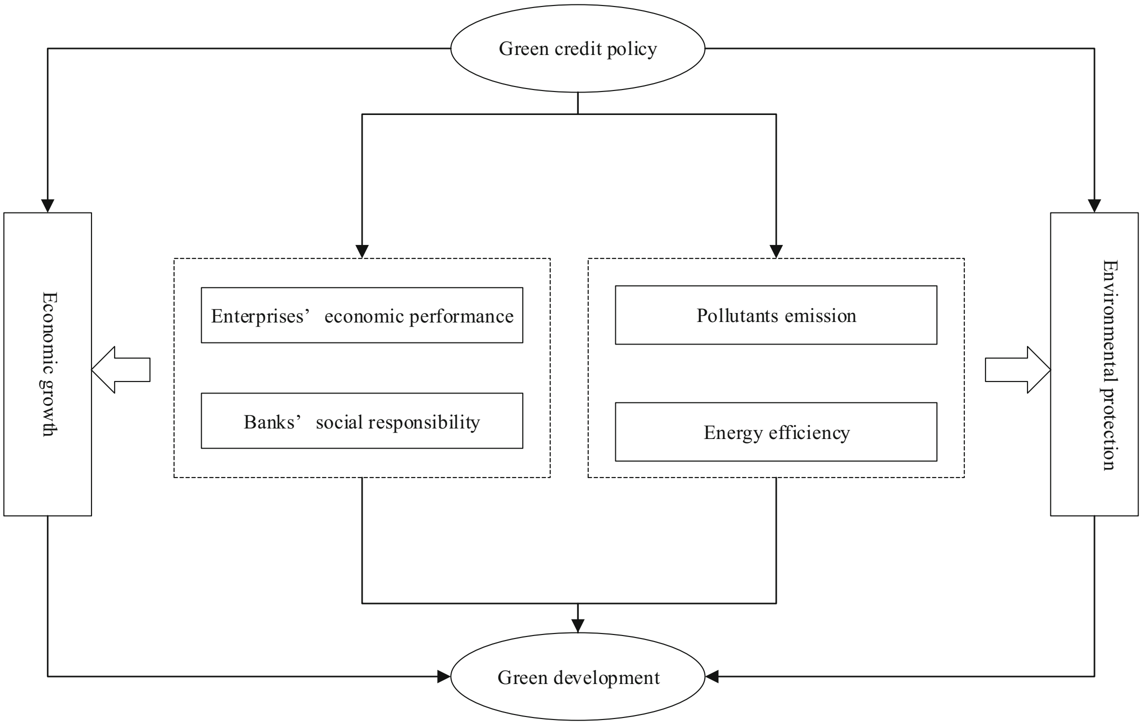

Fig. 1 The impacts of green credit policy on the economy and environment

On the one hand, some studies have found that green credit policy is highly correlated with the economic performance of firms. Green credit policy can directly influence the innovation activities of enterprises. Hu et al. (2021) revealed that the *Green Credit Guidelines* (GCG) of China stimulated green innovation in highly polluting firms, leading to a green transition. Furthermore, the environment-related innovation induced by green credit policy can promote green total factor productivity (Zhang 2021). However, Wen et al. (2021a) found the opposite results within energy-intensive industries; that is, the GCG reduced allocation efficiency of bank credit and negatively affected the total factor productivity of firms, while Zhang and Vigne (2021) argued that the negative effects of green credit policy on firm performance were weakened in a dynamic process. In addition, the green credit can be an important factor in moderating the relationship between different activities of enterprises. For example, Zhou et al. (2021) found that green credit mitigated the negative impact of social responsibility on banks' financial performance.

On the other hand, many scholars have discussed the impacts of green credit policy on environmental pollution. Andersen (2017) argued through theoretical derivation and empirical analysis that capital distortion caused by credit constraints increased pollution emissions. Therefore, it is necessary to rationally reallocate credit resources through green credit policy in the process of environmental abatement. Sun et al. (2019) found that China's green credit policy effectively encouraged enterprises to reduce water pollution. Zhang and Vigne (2021) found similar results that green credit significantly reduced pollution emissions in China. Dong et al. (2020a) took China's provincial panel data as research sample, finding that green lending helped developing countries address environmental pollution problems. Considering the environmental constraints, Song et al. (2021) found that green credit improved the efficiency of energy utilization, which was important for promoting green development.

Although previous studies have contributed significantly to the research and discussion of green credit policy, there are still some gaps that need to be filled. First, to the best knowledge of us, few studies have included both environmental and economic factors in the research framework of green credit policy (Liu and He 2021). Therefore, this paper adopts the concept of green economy to measure the dual goals of green credit for economy and environment in a more integrated manner. The green economy is defined as one that is low-carbon, resource-efficient, and socially inclusive (UNEP 2011). How to promote green economy has drawn attention of researchers and policy-makers. Many studies have explored the factors influencing the green economy (Zhao et al. 2020). For example, Zhuo and Deng (2020) used synthetic control method to find that China's Western Development Strategy (WDS) positively affected the green economy. Yuan et al. (2020) investigated the nonlinear impacts of manufacturing agglomeration (MA) on the green economy in China and found a significant positive U-shaped relationship between MA and the green economy. Based on a dataset from the member countries of the

Belt and Road Initiative (BRI), Zhang et al. (2021) showed that public spending contributed to the green economy. However, few studies have explored the impact of green credit policy on the green economy.

Second, most of the studies ignore the spatial spillover effects of green credit policy. Generally, there are strong spatial correlations between economic and environmental activities in different regions (see Shao et al. 2020; Yuan et al. 2020; Zhang et al. 2020). Dong et al. (2020b) showed that environmental regulation not only affected the green technology progress in the local regions but also changed the innovation of green technology in the neighboring regions. From the perspective of green finance, Li and Gan (2021) showed that the development of green finance improved the ecological environment in the surrounding areas. However, few literatures explore the spatial effects of green credit policy. As an important environmental policy, it is necessary to study the local-neighborhood impacts of green credit policy, and the present study is based on this consideration.

Research method and data

Model specification

Benchmark model

First, without considering spatial factors, we establish the following econometric model to study the impact of green credit policy on the green economy.

$$GE_{it} = \alpha_0 + \alpha_1 GC_{it} + \alpha_2 Controls^1_{it} + \mu^1_i + \nu^1_t + \varepsilon^1_{it} \quad (1)$$

where i is province, t is time, and GE_{it} represents the green economy. GC_{it} represents the green credit, and $Controls^1_{it}$ denotes control variables in Equation (1). μ^1_i and ν^1_t represent the fixed effects. ε^1_{it} is the random error term, with $\varepsilon^1_{it} \sim iid(0, \sigma^2)$.

Spatial econometric model

Furthermore, the spatial econometric model is established to test the local-neighborhood effect of green credit policy. It is recognized that the Durbin model (SDM) is a more general form of spatial models (Elhorst 2014), which can be degenerated into the spatial autoregression model (SAR) and spatial error model (SEM). We refer to Shao et al. (2020) and thus set the SDM as follows:

$$\begin{aligned} GE_{it} = {} & \beta_0 + \beta_1 GC_{it} + \beta_2 Controls^2_{it} + \beta_3 \textstyle\sum_{j=1}^{N} W_{ij} GE_{jt} \\ & + \beta_4 \textstyle\sum_{j=1}^{N} W_{ij} GC_{jt} + \beta_5 \textstyle\sum_{j=1}^{N} W_{ij} Controls^2_{jt} + \mu^2_i \\ & + \nu^2_t + \varepsilon^2_{it} \end{aligned} \quad (2)$$

where $i(j)$ is the space unit and $Controls^2_{it}$ refers to control variables in Equation (2). W_{ij} is the spatial weight matrix, reflecting the interdependence and correlation among different spatial units. $\sum_{j=1}^{N} W_{ij} GE_{jt}$ denotes the spatial lag term of the explained variable, $\sum_{j=1}^{N} W_{ij} GC^2_{jt}$ denotes the spatial lag term of the explanatory variable, and $\sum_{j=1}^{N} W_{ij} Controls^2_{jt}$ represents the spatial lag terms of control variables.

It is worth noting that the coefficients of spatial econometric models by point estimation method can lead to bias. With reference to the existing studies, we decompose the impacts of green credit policy into direct and indirect effects. The direct effect reflects the impact of green credit on the local green economy; the indirect effect shows the impact of green credit on the surrounding areas' green economy, which is known as the spatial spillover effect. The sum of these two effects measures the total effects of green credit policy.

Spatial weight matrix

The spatial weight matrix is critical to the spatial economic analysis, which is an important tool to quantify the spatial dependence among observations. There is no unified standard for the selection of spatial weight matrix, and most of the existing studies set weight matrices based on geographical distance (d_{ij}). Referring to Huang et al. (2021a), we set the following geographical distance spatial weight matrix.

$$W_{ij} = \begin{cases} 1/d_{ij}, i \neq j \\ 0 \quad\quad , i = j \end{cases} \quad (3)$$

Considering that different settings of matrix may have impacts on the estimation results, we also set alternative weight matrices for robustness test. First, we use the discrete matrix, which is the simplest binary 0-1 spatial weight matrix (W^{0-1}_{ij}) and often be used in previous studies of spatial economics (Radmehr et al. 2021).

$$W^{0-1}_{ij} = \begin{cases} 1, i \ adjoins \ j \\ 0, else \end{cases} \quad (4)$$

Second, with the development of spatial econometrics, the economic factors are gradually incorporated into the spatial weight matrix, which is widely used in the field of environmental economics. Referring to Shao et al. (2020), this paper embeds the gross domestic production (GDP) into the geographical distance matrix to establish the following asymmetric spatial weight matrix ($W^{geo-eco}_{ij}$).

$$W^{geo-eco}_{ij} = \begin{cases} (GDP_j/GDP_i)/d_{ij}, i \neq j \\ 0 \quad\quad\quad\quad\quad\quad\quad , i = j \end{cases} \quad (5)$$

Definition of variables

Explained variable

In previous literature, the stochastic frontier analysis (SFA) method (Chen et al. 2021) and DEA technique (Ma et al. 2019; Wu et al. 2020) are mainly used to measure the level of green economy. The latter does not need to set specific function forms to determine the efficiency frontier, nor does it require subjectively giving the weight of the index, and thus has stronger objectivity. Referring to the ideas of Zhao et al. (2020), we measure the green economy of each province in China, and the definitions of input-output factors are shown in Table 2.

Explanatory variable

The core explanatory variable is the scale of green credit. There are two widely used methods to measure green credit in previous literature: dummy variable (Su and Lian 2018) and the amount of loan for energy saving and environmental protection (Wen et al. 2021b). Referring to Wen et al. (2021b), the proportion of loans obtained by energy-efficient and environmental protection enterprises to total loans in each province is taken as the proxy variable for green credit.

Control variables

Referring to Yuan et al. (2020), we include the following control variables in the model to mitigate the bias caused by missing variables: (1) economic development (*ECO*), expressed by the real GDP per capita; (2) infrastructure (*INF*), expressed by the road area per capita; (3) opening degree (*OPE*), expressed by the ratio of real foreign direct investment to GDP; (4) population density (*PEO*), expressed by the logarithm of the total number of people per square kilometer; (5) employment rate (*EMP*), expressed by the percentage of urban employment in the total number of people; (6) industrial structure (*IND*), expressed by the proportion of the secondary industry; and (7) the intensity of environmental regulation (*REG*), calculated by the proportion of investment related to environment protection in GDP.

Sample and data source

The research sample of this paper is Chinese provincial panel dataset from 2007 to 2017, including 30 provinces (municipalities) in China. Considering the availability and completeness of the dataset, Tibet, Hong Kong, Macao, and Taiwan are excluded. The data of innovation inputs and patent are from the *China Science and Technology Yearbook*, the data of energy consumption are from the *China Energy Statistical Yearbook*, the data of pollution emission and environmental investment are from the *China Environmental Statistical Yearbook*, the financial data of enterprises are from the *China Stock Market and Accounting Research* database, and other data are from the *China Statistical Yearbook*. With regard to missing data, the linear interpolation is employed to supplement. In order to avoid the adverse effect of extreme values, all continuous variables are subjected to 1% winsorization process. Moreover, with 2007 as the base year, the price-related indicators are converted to the real price levels to enhance the comparability. Table 3 shows the descriptive statistics of variables.

Results and discussion

Benchmark regression

Table 4 shows the benchmark regression results of green credit on green economy without considering spatial factors. The estimated coefficient of green credit (*GC*) in column (1) is 0.149, which is positive at the 1% significance level. To avoid missing important variables and multicollinearity problems, this paper adds control variables stepwise in columns (2)–(8). The regression results show that the estimated coefficients of green credit (*GC*) are all positive at the 1% significance level, indicating that green credit policy can significantly contribute to the development of green economy within

Table 2 Definition of input-output factors

Type	Index	Definition	Unit
Inputs	Capital stock	The total investment in fixed assets	10^8 yuan
	Labor input	The number of employees at the end of a year	10^4 people
	Energy consumption	Electricity consumption of the whole society	10^8 kilowatt-hour
Desirable output	Economic output	Real gross domestic product	10^8 yuan
Undesirable outputs	Environmental pollution	Industrial sulfur dioxide	10^4 tons
		Industrial wastewater	10^4 tons
		Industrial solid waste	10^4 tons

China. In column (8), the regression coefficient of green credit (*GC*) is 0.168, and it means that as the size of green credit increases 1 unit, the level of green economy can increase by approximately 0.168 units. The findings are consistent with prior studies by scholars (Wang et al. 2019; Wang et al. 2021b), suggesting that green credit plays important roles in the win-win situation between environmental protection and economic development.

The local-neighborhood effect of green credit policy

Next, we turn to the spatial econometric analysis. First, the global Moran's index is calculated to test the spatial correlation with the following equations:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(GE_i - \overline{GE}\right)\left(GE_j - \overline{GE}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{6}$$

$$I^* \equiv \frac{I - E(I)}{\sqrt{Var(I)}} \tag{7}$$

where I is the global Moran's index, n is the number of space units, and W_{ij} is the spatial weight matrix. GE_i and GE_j refer to the green economy of regions i and j, respectively. $\overline{GE}$ measures the average level of the green economy. S^2 is the sample variance, with $S^2 = \sum_{i}^{n} \left(GE_i - \overline{GE}\right)^2/n$). I^* is the standardized Moran's index, $E(I)$ is the mean value of I, and $Var(I)$ represents the variance. Table 5 shows the results of Moran's index from 2007 to 2017. It can be seen that values of Moran's index are significantly positive for all years, indicating that the green economy within China presents a significant and positive spatial correlation.

The results of Moran's index test described above support the rationality of using the spatial models. On this basis, Table 6 reports the regression results of the spatial Durbin model (SDM). The results of LR test show that the SDM is reasonable. In column (8), which contains all the control variables, the spatial lag term of the explained variable is negative and significant at the 1% level ($W * GE = 0.418$, $z = 6.044$), indicating that the positive spatial correlation within China's green economy exists. The spatial lag term of green credit is significantly positive at the level of 1% ($W * GC = 0.564$, $z = 3.052$), which indicates that green credit has a positive impact on the green economy in the surrounding areas. The direct effect of green credit is 0.176, which indicates the positive and significant impact of green credit on local green economy; the indirect effect is 1.039, reflecting that green credit has positive impact on the green economy in surrounding areas. The above regression results show that, the green credit has a local-neighborhood effect on the green economy. Green credit not only promotes the development of green economy in the local but also plays a positive demonstration role in effectively driving the development of green economy in the surrounding areas.

Table 3 Descriptive statistics

Variables	Obs.	Mean	Median	Std. dev.	Min.	Max.
GEE	330	0.484	0.402	0.208	0.285	1.105
GC	330	0.445	0.395	0.267	0.022	0.968
ECO	330	9.341	9.452	0.916	6.897	11.096
INF	330	2.582	2.610	0.358	1.413	3.234
OPE	330	5.210	5.567	1.623	1.124	7.565
PEO	330	5.210	5.567	1.623	1.124	7.565
EMP	330	7.837	7.849	0.443	6.733	8.669
IND	330	0.962	0.965	0.032	0.680	0.986
REG	330	0.463	0.480	0.081	0.213	0.582

Robustness test

In order to enhance the robustness of the above results, we repeat above regression using different spatial weight matrices. In addition, we also examine whether the local-neighborhood effect of green credit still holds when the explained variable is replaced.

Replacing the spatial weight matrix

The selection of spatial weight matrix has important impacts on the studies, and different settings may lead to large differences in the results or even reversal of the conclusions. In this subsection, we take W_{ij}^{0-1} and $W_{ij}^{geo-eco}$ as the spatial weight matrices into Equation (2) for estimation; the results are shown in Tables 7 and 8, respectively. The statistics of LR spatial lag (LR _ lag) and LR spatial error (LR _ error) are all significant, which once again validate the reasonableness of spatial Durbin model. The spatial lag terms $W * GE$ and $W * GC$ are both positive and statistically significant, supporting the spatial correlation of green economy and the spatial spillover effect of green credit. The direct, indirect, and total effects of green credit are all significantly positive, which suggest the local-neighborhood effect of green credit on green economy.

Alternative explained variable

The ratio of economic output to environmental pollution emission is used as an alternative index for the explained variable, with $GE_{it}^* = Ln(RGDP_{it}/EPI_{it})$, where GE_{it}^* is a proxy variable for the green economy and $RGDP_{it}$ denotes the real GDP. EPI_{it} is the environmental pollution index, which is calculated by the entropy method following to Zhou and Wu (2018), and

Table 4 Benchmark regression results of green credit on green economy

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GC	0.149***	0.128**	0.135***	0.142***	0.152***	0.151***	0.159***	0.168***
	(2.854)	(2.571)	(2.602)	(2.638)	(2.662)	(2.695)	(2.753)	(2.760)
ECO		− 0.366***	− 0.289***	− 0.269**	− 0.244**	− 0.244**	− 0.139	− 0.147
		(− 3.262)	(− 2.768)	(− 2.199)	(− 2.066)	(− 2.068)	(− 0.964)	(− 1.015)
INF			− 0.184***	− 0.185***	− 0.159***	− 0.158***	− 0.163***	− 0.140**
			(− 3.064)	(− 3.170)	(− 2.823)	(− 2.803)	(− 2.850)	(− 2.257)
OPE				− 0.008	− 0.008	− 0.008	− 0.007	− 0.005
				(− 0.621)	(− 0.696)	(− 0.703)	(− 0.562)	(− 0.448)
PEO					0.101***	0.102***	0.107***	0.099***
					(3.617)	(3.646)	(3.968)	(3.814)
EMP						− 0.170***	− 0.179***	− 0.172**
						(− 2.803)	(− 2.637)	(− 2.482)
IND							− 0.363*	− 0.343*
							(− 1.813)	(− 1.733)
REG								− 0.016
								(− 1.111)
Constant	0.491***	3.823***	3.430***	3.296***	2.305**	2.463**	1.571	1.669
	(12.671)	(3.771)	(3.503)	(2.986)	(2.365)	(2.547)	(1.326)	(1.398)
Obs.	330	330	330	330	330	330	330	330
R^2	0.834	0.840	0.844	0.844	0.849	0.849	0.851	0.852

Notes: (1) t-values are in parentheses; (2) ∗, ∗∗, and ∗∗∗ represent significance levels at the 10%, 5%, and 1%, respectively

the calculation process is shown in the Appendix. The regression results with GE_{it}^{*} as the explained variable are shown in Table 9. From the results in columns (1)–(8), the local-neighborhood effect of green credit on green economy is verified once again, which enhances the robustness of the aforementioned findings.

Analysis of transmission mechanisms

In order to clarify the transmission channels of the local-neighborhood effect of green credit, this paper establishes the following model to explore the ways of green credit affecting green economy:

$$M_{it} = \gamma_0 + \gamma_1 GC_{it} + \gamma_2 Controls_{it}^{k} + \gamma_3 \sum_{j=1}^{N} W_{ij} M_{jt} + \gamma_4 \sum_{j=1}^{N} W_{ij} GC_{jt} + \gamma_5 \sum_{j=1}^{N} W_{ij} Controls_{jt}^{k} + \mu_i^k + \nu_t^k + \varepsilon_{it}^k \quad (8)$$

where M_{it} is the variable representing transmission mechanism and the superscript k is used to distinguish different equations ($k = 3, 4, \ldots$). On the basis of the principles and practice of green credit in China, we consider the following two influencing ways (see Fig.2).

The driving effect of green credit on innovation

Considering that innovation is an important engine for the green and low-carbon development, we first explore the innovation-driven effect of green credit. In 2012, China issued the *Green Credit Guidelines* (GCG), stating that financial institutions should implement differentiate and dynamic credit policies to promote the transformation and restructuring of economy. Under the guidance of green principles, it requires all industries to increase technological innovation, update and renovate traditional and backward production equipment, eliminate the previous heavily polluting and energy-intensive

Table 5 Results of spatial correlation test

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Moran index	0.279	0.285	0.263	0.262	0.265	0.228	0.224	0.323	0.328	0.312	0.278
Z value	3.338	3.394	3.170	3.160	3.183	2.776	2.727	3.876	3.932	3.788	3.385
P value	0.000	0.000	0.001	0.001	0.001	0.003	0.003	0.000	0.000	0.000	0.000

Table 6 Spatial effect of green credit on green economy

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GC	0.161**	0.111*	0.115*	0.122*	0.133**	0.129*	0.128*	0.121*
	(2.479)	(1.651)	(1.721)	(1.851)	(2.001)	(1.955)	(1.930)	(1.814)
*W*GE*	0.473***	0.449***	0.443***	0.448***	0.440***	0.437***	0.433***	0.418***
	(7.243)	(6.583)	(6.491)	(6.638)	(6.557)	(6.480)	(6.315)	(6.044)
*W*GC*	0.545***	0.708***	0.686***	0.576***	0.637***	0.622***	0.588***	0.564***
	(4.195)	(4.359)	(4.231)	(3.492)	(3.900)	(3.806)	(3.172)	(3.052)
Controls	NO	YES (1)	YES (2)	YES (3)	YES (4)	YES (5)	YES (6)	YES (7)
W Controls*	NO	YES (1)	YES (2)	YES (3)	YES (4)	YES (5)	YES (6)	YES (7)
Obs.	330	330	330	330	330	330	330	330
LR-lag	17.60***	19.00***	17.90***	12.20***	15.21***	14.48***	10.06***	9.32***
LR-error	25.12***	21.74***	20.59***	14.56***	18.01***	17.08***	11.60***	10.68***
Log-likelihood	352.729	358.650	363.644	368.323	374.640	376.112	377.748	380.607
Direct, indirect, and total effects of GC								
Direct effect	0.225***	0.185**	0.183***	0.184**	0.197***	0.191***	0.187**	0.176**
	(3.413)	(2.525)	(2.577)	(2.538)	(2.717)	(2.652)	(2.550)	(2.387)
Indirect effect	1.123***	1.341***	1.262***	1.107***	1.190***	1.144***	1.080***	1.039***
	(6.156)	(4.968)	(4.637)	(3.830)	(4.339)	(4.151)	(3.391)	(3.303)
Total effect	1.348***	1.526***	1.445***	1.291***	1.388***	1.336***	1.268***	1.216***
	(6.750)	(5.010)	(4.784)	(3.958)	(4.447)	(4.272)	(3.557)	(3.432)

Notes: (1) *z* values are in parentheses; (2) *, **, and *** represent significance levels at the 10%, 5%, and 1%, respectively; (3) NO denotes no control variables, and YES(k) (k = 1,2, 3, …, 7) means the number of control variables is *k*

Table 7 Robustness test with discrete (0-1) weight matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GC	0.266***	0.171**	0.167**	0.192***	0.200***	0.200***	0.186***	0.177**
	(3.984)	(2.427)	(2.375)	(2.734)	(2.883)	(2.878)	(2.690)	(2.535)
*W*GE*	0.308***	0.269***	0.270***	0.296***	0.275***	0.274***	0.264***	0.255***
	(5.832)	(4.829)	(4.873)	(5.338)	(4.823)	(4.808)	(4.596)	(4.350)
*W*GC*	0.491***	0.449***	0.391***	0.319**	0.380***	0.379***	0.329**	0.304**
	(4.304)	(3.613)	(3.129)	(2.505)	(2.983)	(2.966)	(2.529)	(2.281)
Controls	NO	YES (1)	YES (2)	YES (3)	YES (4)	YES (5)	YES (6)	YES (7)
W Controls*	NO	YES (1)	YES (2)	YES (3)	YES (4)	YES (5)	YES (6)	YES (7)
Obs.	330	330	330	330	330	330	330	330
LR-lag	18.52***	13.05***	9.79***	6.27**	8.90***	8.80***	6.39**	5.20**
LR-error	29.20***	16.33***	12.42***	9.02***	12.15***	11.99***	8.63***	6.94***
Log-likelihood	335.464	343.220	347.522	350.882	356.994	357.059	360.539	361.301
Direct, indirect, and total effects of GC								
Direct effect	0.314***	0.208***	0.199***	0.224***	0.233***	0.232***	0.213***	0.203***
	(4.646)	(2.795)	(2.699)	(3.007)	(3.168)	(3.170)	(2.944)	(2.759)
Indirect effect	0.783***	0.662***	0.568***	0.513***	0.579***	0.567***	0.486***	0.464***
	(6.078)	(4.388)	(3.678)	(3.145)	(3.678)	(3.523)	(3.148)	(2.836)
Total effect	1.098***	0.870***	0.767***	0.737***	0.812***	0.799***	0.699***	0.666***
	(7.486)	(4.746)	(4.163)	(3.718)	(4.233)	(4.107)	(3.790)	(3.404)

Notes: (1) *z* values are in parentheses; (2) *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively; (3) NO denotes no control variables, and YES(k) (k = 1,2, 3, …, 7) means the number of control variables is *k*

Table 8 Robustness test with asymmetric geography-economy weight matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GC	0.314***	0.168**	0.167**	0.167**	0.156**	0.156**	0.140*	0.144**
	(4.799)	(2.381)	(2.408)	(2.377)	(2.146)	(2.153)	(1.945)	(1.995)
*W*GE*	0.364***	0.433***	0.432***	0.430***	0.439***	0.431***	0.413***	0.280**
	(3.323)	(4.081)	(4.090)	(4.087)	(4.225)	(3.925)	(3.640)	(2.183)
*W*GC*	1.713***	1.043***	0.977***	0.888***	0.873***	0.879***	0.673**	0.668**
	(6.915)	(3.428)	(3.230)	(2.883)	(2.846)	(2.867)	(2.119)	(2.099)
Controls	NO	YES (1)	YES (2)	YES (3)	YES (4)	YES (5)	YES (6)	YES (7)
W Controls*	NO	YES (1)	YES (2)	YES (3)	YES (4)	YES (5)	YES (6)	YES (7)
Obs.	330	330	330	330	330	330	330	330
LR-lag	47.82***	11.75***	10.43***	8.31***	8.10***	8.22***	4.49**	4.41**
LR-error	62.88***	13.67***	12.25***	9.82***	9.39***	9.52***	5.23**	5.02**
Log-likelihood	337.950	349.405	353.673	356.088	361.258	361.951	365.253	371.080
Direct, indirect, and total effects of GC								
Direct effect	0.368***	0.209***	0.206***	0.203***	0.191**	0.189**	0.166**	0.160**
	(5.491)	(2.798)	(2.799)	(2.714)	(2.457)	(2.461)	(2.179)	(2.131)
Indirect effect	2.923***	1.996***	1.839***	1.700***	1.664***	1.618***	1.226**	1.011**
	(5.781)	(3.974)	(3.681)	(3.281)	(3.371)	(3.132)	(2.396)	(2.492)
Total effect	3.291***	2.205***	2.045***	1.903***	1.854***	1.808***	1.393**	1.171***
	(6.380)	(4.139)	(3.877)	(3.442)	(3.482)	(3.268)	(2.557)	(2.679)

Notes: (1) *z* values are in parentheses; (2) *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively; (3) NO denotes no control variables, and YES(k) (k = 1,2, 3, …, 7) means the number of control variables is *k*

Table 9 Robustness test with alternative explained variable

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GC	0.324**	0.368**	0.357**	0.334**	0.250*	0.249*	0.231	0.266*
	(2.217)	(2.512)	(2.454)	(2.279)	(1.720)	(1.713)	(1.576)	(1.852)
*W*GE*	0.544***	0.429***	0.423***	0.436***	0.426***	0.425***	0.409***	0.351***
	(11.115)	(6.235)	(6.136)	(6.314)	(6.209)	(6.152)	(5.741)	(4.811)
*W*GC*	2.579***	1.845***	1.705***	1.574***	1.605***	1.601***	1.401***	1.254***
	(8.137)	(5.314)	(4.866)	(4.321)	(4.490)	(4.459)	(3.455)	(3.168)
Controls	NO	YES (1)	YES (2)	YES (3)	YES (4)	YES (5)	YES (6)	YES (7)
W Controls*	NO	YES (1)	YES (2)	YES (3)	YES (4)	YES (5)	YES (6)	YES (7)
Obs.	330	330	330	330	330	330	330	330
LR-lag	66.21***	28.24***	23.68***	18.67***	20.16***	19.88***	11.94***	10.04***
LR-error	74.66***	33.58***	28.21***	22.24***	22.63***	22.26***	13.09***	11.30***
Log-likelihood	96.559	107.894	110.417	111.365	119.223	119.273	120.096	130.968
Direct, indirect, and total effects of GC								
Direct effect	0.667***	0.549***	0.519***	0.493***	0.402**	0.398**	0.357**	0.364**
	(4.570)	(3.515)	(3.429)	(3.157)	(2.561)	(2.549)	(2.233)	(2.358)
Indirect effect	5.747***	3.412***	3.067***	2.939***	2.869***	2.819***	2.407***	2.045***
	(12.416)	(5.965)	(5.318)	(4.715)	(4.833)	(4.864)	(3.630)	(3.436)
Total effect	6.414***	3.961***	3.586***	3.432***	3.271***	3.217***	2.764***	2.409***
	(12.905)	(6.183)	(5.676)	(4.932)	(4.867)	(4.900)	(3.721)	(3.599)

Notes: (1) *z* values are in parentheses; (2) *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively; (3) NO denotes no control variables, and YES(k) (k = 1,2, 3, …, 7) means the number of control variables is *k* production modes, and design environmentally friendly production processes to achieve the green development. The Porter effect points out that reasonable environmental policies can enable enterprises to increase their innovation efforts, thereby increasing economic performance and compensating for the increased production costs (Porter and Linde 1995). China's green credit policy combines the dual advantages of economic incentives and government supervision, making it easier to achieve the innovation compensation effect described above. Therefore, green credit may stimulate the technological innovation to promote the development of green economy within China. On this basis, this paper adopts innovation efficiency to test the innovation-driven effect of green credit. According to the study of Battese and Coelli (1992), the stochastic frontier analysis method (SFA) is used to calculate the innovation efficiency. Accordingly, the trans-log function is defined as follows:

$$LnY_{it} = \lambda_0 + \lambda_1 LnK_{it} + \lambda_2 LnL_{it} + \lambda_3 t + \lambda_4 LnK_{it} \times LnL_{it} + \lambda_5 LnK_{it} \times t + \lambda_6 LnL_{it} \times t + \frac{1}{2}\lambda_7 (LnK_{it})^2 + \frac{1}{2}\lambda_8 (LnL_{it})^2 + \frac{1}{2}\lambda_9 t^2 + \nu_{it} - \mu_{it} \quad (9)$$

where Y_{it} is the output factor, expressed by the number of patent applications in current year (Jin et al. 2019). K_{it} and L_{it} represent the scale of capital for research and development (R&D) and the number of R&D personnel, respectively. ν_{it} and μ_{it} represent the random error and inefficiency terms, respectively. The innovation efficiency can be measured by the following equation:

$$TE_{it} = exp(-\mu_{it}) \quad (10)$$

Then, take innovation efficiency into Equation (8) to get the following equation:

$$TE_{it} = \gamma_0 + \gamma_1 GC_{it} + \gamma_2 Controls^3_{it} + \gamma_3 \sum_{j=1}^{N} W_{ij} TE_{jt} + \gamma_4 \sum_{j=1}^{N} W_{ij} GC_{jt} + \gamma_5 \sum_{j=1}^{N} W_{ij} Controls^3_{jt} + \mu^3_i + \nu^3_t + \varepsilon^3_{it} \quad (11)$$

where $Controls^3_{it}$ represents control variables, including the level of economic development (ECO_{it}), infrastructure construction (INF_{it}), the degree of opening(OPE_{it}), the population density (PEO_{it}) and the level of education (EDU_{it}).

Table 10 reports the regression results of green credit on innovation efficiency. According to the results in column (6), the spatial lag terms of innovation efficiency and green credit are statistically significant and positive ($W * TE = 0.277$, $z = 3.650$; $W * GC = 0.008$, $z = 2.340$). Regarding the effect of green credit on innovation efficiency, the direct effect is 0.009, which indicates that green credit has a positive role in promoting the local innovation efficiency; and the indirect effect is 0.014, indicating that green credit has a positive spillover effect on the innovation efficiency in the surrounding areas. Considering the local-neighborhood effect of green credit on innovation efficiency, an increase of one unit of green credit can promote the overall innovation efficiency by 0.024 units. The above findings support the innovation-driven effect of green credit. Through this mechanism, green credit can contribute to the development of China's green economy.

The optimization effect of green credit on energy structure

In addition, another question of concern is the impact of green credit on energy structure. China is one of the world's major

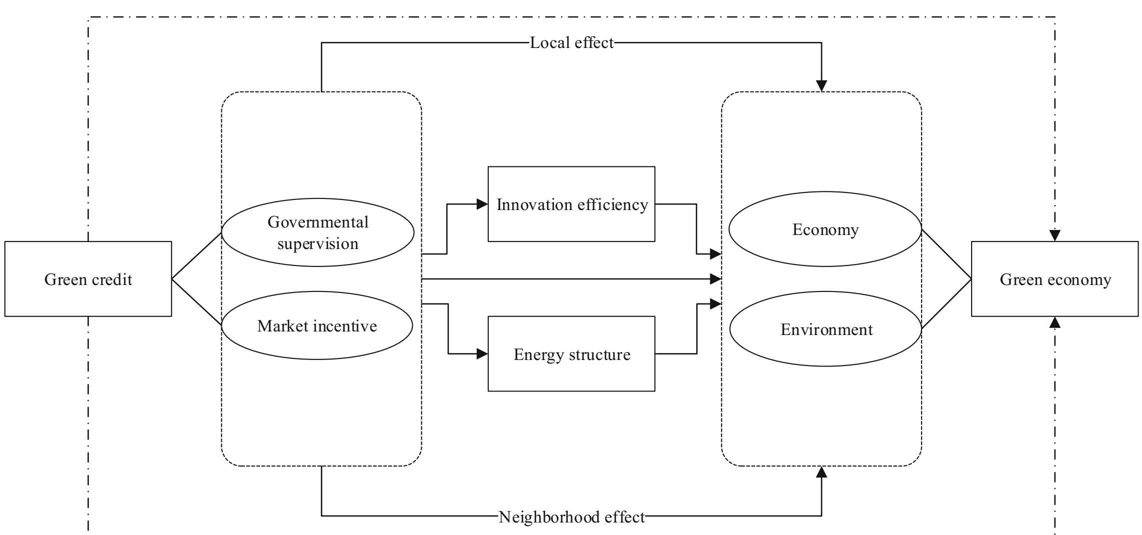

Fig. 2 The local-neighborhood effect of green credit on green economy

Table 10 Results of innovation-driven effect

Variables	(1)	(2)	(3)	(4)	(5)	(6)
GC	0.009***	0.010***	0.010***	0.009***	0.010***	0.009***
	(6.818)	(7.426)	(7.458)	(7.083)	(7.138)	(6.116)
*W*TE*	0.840***	0.279***	0.270***	0.273***	0.288***	0.277***
	(38.560)	(3.706)	(3.545)	(3.619)	(3.833)	(3.650)
*W*GC*	0.013***	0.012***	0.012***	0.011***	0.010***	0.008**
	(4.185)	(3.471)	(3.571)	(3.217)	(2.955)	(2.340)
Controls	NO	YES (1)	YES (2)	YES (3)	YES (4)	YES (5)
*W*Controls*	NO	YES (1)	YES (2)	YES (3)	YES (4)	YES (5)
Obs.	330	330	330	330	330	330
LR-lag	17.51***	12.05***	12.75***	10.35***	8.73***	5.47**
LR-error	43.19***	21.31***	21.98***	17.83***	16.02***	9.91***
Log-likelihood	1606.353	1656.270	1656.663	1662.443	1666.333	1669.003
Direct, indirect, and total effects of GC						
Direct effect	0.017***	0.011***	0.011***	0.010***	0.010***	0.009***
	(9.745)	(7.646)	(7.855)	(7.401)	(7.346)	(6.174)
Indirect effect	0.126***	0.020***	0.020***	0.018***	0.018***	0.014***
	(9.584)	(5.010)	(4.848)	(4.431)	(4.052)	(3.328)
Total effect	0.143***	0.030***	0.031***	0.029***	0.028***	0.024***
	(10.173)	(6.815)	(6.844)	(6.114)	(5.627)	(4.655)

Notes: (1) z values are in parentheses; (2) $*$, $**$, and $***$ represent the significance levels at 10%,5%, and1%, respectively; (3) NO denotes no control variables, and YES(k) (k = 1,2, 3,4, 5) means the number of control variables is k

carbon emission countries (International Energy Agency 2019); promoting clean energy and eliminating backward capacity is one of the most important measures for China to realize green and low-carbon transformation. Since China issued the *Energy Efficiency Credit Guidelines* in 2015, financial institutions have been required to provide credit support for reducing energy consumption and improving energy efficiency. To a certain extent, it can encourage enterprises to improve energy efficiency, reduce fossil energy consumption, and increase the use of clean energy. Therefore, the green credit may have positive impact on energy structure optimization. Through credit reallocation, it reduces fossil energy consumption and the resulting pollution emissions on the basis of meeting the energy demand necessary for economic development, which is beneficial to the green economy in China.

Referring to Yang et al. (2018), the share of fossil energy consumption is used to measure the energy structure, which is brought into Equation (8) to get the following equation:

$$ES_{it} = \gamma_0 + \gamma_1 GC_{it} + \gamma_2 Controls_{it}^4 + \gamma_3 \sum_{j=1}^{N} W_{ij} ES_{jt} + \gamma_4 \sum_{j=1}^{N} W_{ij} GC_{jt} + \gamma_5 \sum_{j=1}^{N} W_{ij} Controls_{jt}^4 + \mu_i^4 + \nu_t^4 + \varepsilon_{it}^4 \quad (12)$$

where $Controls_{it}^4$ represents control variables, including the level of economic development (ECO_{it}), infrastructure construction (INF_{it}), the degree of opening(OPE_{it}), the structure of industry (IND_{it}), and the intensity of environmental regulation (REG_{it}).

Table 11 shows the optimization effect of green credit on energy structure. According to the results in column (6), the spatial lag term of energy structure ($W*ES$) is 0.217, which is statistically significant and positive at the 5% level, indicating a positive spatial correlation of energy structure within China. The spatial lag term of green credit ($W*GC$) is − 0.221, indicating a significant and negative spatial spillover effect of green credit on fossil energy consumption in the surrounding areas. Furthermore, the direct effect of green credit on energy structure is − 0.217, which indicates that green credit can optimize the local energy structure; and the indirect effect is − 0.331, which indicates that green credit has spillover effect on energy structure in the surrounding areas. According to the total effect of green credit on energy structure, the increase of green credit can reduce the share of the fossil energy consumption and thus promote the green economy through the energy structure optimization effect.

Conclusions and policy implications

Taking the provincial panel dataset of China from 2007 to 2017 as the research sample, this study applies the Sup-SBM data envelopment analysis (DEA) with undesirable outputs to calculate the level of green economy within China.

Table 11 Results of energy structure optimization effect

Variables	(1)	(2)	(3)	(4)	(5)	(6)
GC	− 0.163***	− 0.185***	− 0.189***	− 0.200***	− 0.202***	− 0.208***
	(− 5.688)	(− 6.125)	(− 6.482)	(− 6.837)	(− 6.879)	(− 7.133)
*W*ES*	0.274***	0.305***	0.258***	0.234**	0.250**	0.217**
	(2.817)	(3.174)	(2.619)	(2.326)	(2.453)	(2.094)
*W*GC*	− 0.090*	− 0.223***	− 0.206***	− 0.216***	− 0.245***	− 0.221***
	(− 1.661)	(− 3.116)	(− 2.962)	(− 2.985)	(− 3.018)	(− 2.750)
Controls	NO	YES (1)	YES (2)	YES (3)	YES (4)	YES (5)
*W*Controls*	NO	YES (1)	YES (2)	YES (3)	YES (4)	YES (5)
Obs.	330	330	330	330	330	330
LR-lag	2.76*	9.71***	8.77***	8.91***	9.11***	7.56***
LR-error	8.10***	16.58***	14.41***	14.46***	13.36***	11.02***
Log-likelihood	623.819	628.049	642.247	645.661	645.973	652.125
Direct, indirect, and total effects of GC						
Direct effect	− 0.169***	− 0.200***	− 0.200***	− 0.210***	− 0.215***	− 0.217***
	(− 5.863)	(− 6.461)	(− 6.799)	(− 7.073)	(− 7.113)	(− 7.094)
Indirect effect	− 0.185***	− 0.383***	− 0.339***	− 0.340***	− 0.381***	− 0.331***
	(− 3.039)	(− 3.779)	(− 3.308)	(− 3.558)	(− 3.128)	(− 3.040)
Total effect	− -0.354***	− 0.584***	− 0.539***	− 0.550***	− 0.595***	− 0.548***
	(− 5.478)	(− 5.266)	(− 4.925)	(− 5.227)	(− 4.489)	(− 4.503)

Notes: (1) *z* values are in parentheses; (2) *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively; (3) NO denotes no control variables, and YES(k) (k = 1,2,3,4,5) means the number of control variables is *k*

On this basis, the spatial panel Durbin models are established to study the local-neighborhood effect of green credit on green economy and its influencing mechanisms. The results show that there exists significant spatial correlation of green economy in different regions. The green credit has local-neighborhood effect on green economy; that is, the green credit can not only improve the local green economy but also generate spatial spillover effect to promote the green development in the surrounding areas. The above conclusion still holds after the robustness test by replacing spatial weight matrix and alternative explained variables. Furthermore, innovation efficiency and energy structure are important channels for green credit to improve the green economy. The green credit matters in the green transformation of economy through innovation-driven effect and energy structure optimization effect. The research of this study not only provides a new perspective for understanding the economic consequences of green credit but also provides empirical evidence for the important role of green finance in achieving the win-win situation between economic growth and environmental protection.

The above findings have significant policy implications for promoting green finance and sustainable development. First, we should pay more attention to the important role of financial policies (Zhang et al. 2019) such as green credit in economic development and environmental protection and promote green development by constructing a sound green financial market. Specifically, the government departments, as the supervisor and promoter of green finance, should increase government subsidies to build green financial infrastructure and design a reasonable and effective green incentive mechanism. What is more, it is necessary to guide and urge banks and enterprises to practice green principles. Financial institutions, as the main implementers of green finance, should advocate the Equator Principles (EPs), fully consider environmental risks in their financial activities, cultivate a green financial culture, and cooperate with relevant official departments to support the development of green and low-carbon industries. Enterprises are the main force of green development and should actively change their business philosophy, raise their awareness of environmental risks, and actively fulfill social responsibilities.

Second, we should consider the spatial spillover effect of green credit policy, strengthen inter-regional exchanges and cooperation, and enhance the driving effect of green credit on local green development and the demonstration effect on neighboring areas through joint implementation of green credit principles. Ultimately, the overall improvement of the green economy within China can be achieved. Third, it is necessary to clarify the transmission mechanisms of green credit on the environment and economy and thus adjust the policy according to the actual situation in a timely manner. This paper finds that green credit policy contributes to the development of green economy by improving innovation efficiency and optimizing energy structure, which contributes to the development of green economy. Therefore, it is important to increase support for green innovation and encourage enterprises to actively participate in greening production and operation. In addition, we should continue to promote clean energy, increase credit support for the clean energy sectors, and provide stable and sustainable energy security for economic and social development through optimizing the energy structure and thus contribute to the green economy.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11356-021-15419-8.

Availability of data and materials The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Authors' contributions Conceptualization: Xiaodong Lei, Yanli Wang. Methodology: Xiaodong Lei. Formal analysis and investigation: Xiaodong Lei, Qi Chen. Writing, original draft preparation: Xiaodong Lei. Writing, review and editing: Yanli Wang, Dongxiao Zhao. Funding acquisition: Yanli Wang. Supervision: Yanli Wang. All authors read and approved the final manuscript.

Funding This work was supported by the Project of National Social Science Foundation of China (No. 20BJY079) and the project of Humanity and Social Science of Ministry of Education of China (No. 19YJA790086).

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare that they have no competing interests.

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