Was Chinese Green-Credit Policy Driving the Transformation or Transfer of High-Polluting Enterprises?

Yancheng Zhang[1] Yu Zhang[2]

June, 2020

Abstract

This paper investigates the regional differences and spatial effects of Chinese green credit policy. Our research is based on the transmission mechanisms of green credit in promoting industrial structural upgrading. And a number of conclusions are drawn. First of all, green credit could promote the regional industrial structure through two major mechanisms, namely, the financial orientation approach and the technological incentive approach. What is more, this effect however differed in the Eastern, Central and Western regions of China. Furthermore, the impact of green credit on the regional industrial structure had a two-way spatial spillover effect. On one hand, green credit directly promote the upgrading of Chinese industrial structures in both local and surrounding regions, on the other hand, it inhibited the upgrading of industrial structures in the surrounding areas due to the increasing cost to high-polluting enterprises brought by green credit policy. Therefore, it is crucial to be vigilant in either the simultaneous promotion and suppression of green credit within the surrounding areas. Due to our conclusion, this paper suggests government to set higher entry standards for the transfer of high-polluting enterprises between provinces.

Keywords: green credit; industrial structure upgrading; two-way spatial spillover effect; spatial Durbin model

[1] Sophomore of Nankai University, xzhang2373@wisc.edu

[2] Sophomore of Nankai University, 1814122@mail.nankai.edu.cn

We are deeply indebted toward Xin Geng, Jia He from Nankai University. We also thank Yue Hu as the referee from the 9th SIIFC Conference for her brilliant comments.

I. Introduction

Green credit is also known as sustainable and environmental financing. This concept is originated from the combination of green civilization and the financial industry, which advocates for the transformation of high-polluting enterprises through the influence of finance. The goal of green credit policy in China is to embrace the economic growth and environmental protection at the same time. Currently, environmental challenges in China have been escalating at an alarming rate, and the Chinese government is responding with increasing urgency. On July 12, 2007, China issued *Opinions on Implementing Environmental Protection Policies and Regulations to Prevent Credit Risks.* This was the first time the government put forward the policy objective of "promoting industrial upgrading through the development of green credit". In 2012, the former CBRC issued *Green Credit Guidelines*. They specifically requested financial institutions to increase their efforts in implementing green credit. They also set out a goal of guiding green credit into a period of steady development. In 2016, the outline of the 13th Five-Year Plan explicitly proposed to "establish a green financial system, develop green credit, green bonds and establish green development funds", providing further support to the development concept of "innovation, green, openness and sharing". Under the guidance of the government's policies, the scale of green credit in China has been steadily increasing. As of the end of the first quarter of 2019, the balance of green loans in domestic and foreign currencies had reached 9.23 trillion Yuan in China.

The fundamental measure of Chinese commercial banks' green credit policy lies in the guidelines for their credit allocation operations [1]. According to these guidelines, financial institutions represented by commercial banks should provide preferential interest rates and quota support to environmental protection agencies and clean energy enterprises. They should also take measures such as implementing restrictive finance or punitive high interest rates for highly polluting and high energy-consuming businesses. These policies on green credit aim to lead funds flow from highly polluting industries to energy-saving and environmental-friendly industries, through the guidance of commercial banks. Such endeavor will promote the transformation of economic development towards a high-quality environment-friendly one. Eventually, it promotes the upgrading of the industrial structure. The effectiveness of this policy is supported by the findings of Chen Qi (2019) [2], who argues that green credit has a significant impact on restricting the loan sizes of "two highs and one over" (high pollution, high energy consumption and overcapacity) enterprises. What is more, this inhibiting effect is more pronounced among non-state owned "two highs and one over" businesses.

Therefore, under the active guidance of foresighted government policies and the resource allocation brought about by green credit, it is considered to act as a booster towards achieving significant upgrades in China's industrial structure. Nowadays, many scholars have studied the interaction between green credit and the upgrading of industrial structure. Li Bin and Su Jiaxuan (2016) [3] concluded that the correlation between the green credit ratio (the amount of loans for energy-saving and environmental protection projects/total loans) and the share of secondary and tertiary industries in GDP is considerable. Xu Sheng, Zhao Xinxin and Yao Shuang (2018) [4] made efforts in exploring the influential mechanism of green credit on industrial structural upgrades and proposed three possible strategies: capital formation, signaling, and feedback/credit rating assessment. Building upon the research done by Xu Sheng et al., Qian Shuitu, Wang Wenzhong and Fang Haiguang (2019) [5] analyzed the impact of green credit on industrial structure from five aspects: capital formation, capital orientation, information transmission, industrial integration and risk allocation mechanisms. As evidenced above, there are many studies describing the correlation between green credit and industrial upgrading, and various articles exploring potential influencing mechanisms.

Furthermore, due to cultural differences and differences in policy between China's eastern, central and western regions, many scholars have begun to conduct regional studies on green credit. One common approach is shown in a study by Song Qinqige et al. [6], where data from particular regions (e.g. Qinghai and Hebei) were chosen and studied separately. These data were then compared in order to elucidate the differences between different cities. This approach has the advantage of being specific and provides didactic suggestions for policy formation in a particular city. However, it is limited by the amount of data available, so it is difficult to produce empirically valid results using this method. Li Yu, Hu Haiya and Li Hao (2020) [7] broke free from the limitations of studying a particular region and turned instead to a cross-sectional comparative analysis of regions across provinces and cities in China. They found that the promoting effect of green credit on industrial structure upgrading is more pronounced in the eastern parts of China, and less evident in China's central and western regions. Meanwhile, in terms of cross-regional research on green credit's spatial effects, Han Kezhen [8] suggested that the level of green financial development in a given region would positively promote the efficiency of green technological innovation in its surrounding regions. Wu Jiahui et al. [9] also pointed out that green credit has a direct effect on promoting the improvement of environmental quality in the surrounding regions.

In this paper, we use used panel data of 31 provinces and cities in China (excluding Hong Kong, Macao and Taiwan) from 2007-2018, and found that green credit policy have had a inhibiting effect on industrial upgrading in neighboring areas. Based on the fact that green credit can increase the financial costs of "two highs and one over" businesses, we point out that some enterprises, whose development is constrained by green credit, may be driven to relocate their businesses into the surrounding provinces in order to avoid the costs of transformation. This might also have an indirect negative impact on the industrial upgrading of the surrounding regions.

The remainder of the paper proceeds as follows. Section 2 provides a theoretical framework. Section 3 describes the various data sources used in the analysis, while Section 4 report the empirical results. Section 5 concludes.

II. Theoretical analysis and research mechanisms

Green credit is one of the most powerful tools in the sphere of green finance. Combining the dual functions of micro-funding and macro-policy regulation, the influencing mechanism on the upgrading of regional industrialized structure is relatively complex. Reviewing the existing literature along with China's green credit policy, this paper argues that the process of green credit promoting industrial structure optimization mainly consists of two mechanisms. The first one is the direct mechanism, the capital orientation approach. This is when the measures of green credit policy are reflected in commercial banks, incorporating the level of environmental pollution control into the credit granting criteria, controlling the flow of credit funds from their source. On one hand, they directly increase the credit costs of enterprises in the "two highs and one over" industries and encourage some high polluting businesses to withdraw from the market. On the other hand, they provide direct financial support to environmental protection agencies and clean energy enterprises and promote the expansion of green enterprises. The second one is the indirect mechanism, the technology incentive approach. Differentiated loan policies are adopted indirectly to promote the technological progress of existing enterprises. In the first place, restrictions on the scale of the flow of capital force "two highs and one over" style businesses to internally transform in order to broaden their financing channels. For example, it will encourage them to invest more into the research and development of environmental protection and energy-saving technologies, to increase their own production capacity and improve their environmental management levels. Moreover, original environmental protection agencies and energy-saving enterprises will expand the scale of their green projects more than they did before.

Based on the aforementioned two mechanisms, the first hypothesis proposed in this paper is this:

H1: Green credit can promote the upgrading of regional industrial structure through capital orientation **and technology incentive.**

In addition, due to the regional heterogeneity of green credit policies and economic development levels in various regions, there may be regional differences in the potential mechanism and its effects. Accordingly, this paper proposes a second hypothesis:

H2: There is regional heterogeneity in the promoting effect of green credit on regional industrial structure optimization and upgrading.

In addition, a differentiated credit policy may promote the increase of the proportion of tertiary industries in the neighboring regions through the following two mechanisms. Firstly, it will encourage the industrial structural upgrading in neighboring provinces and cities due to the demand of forming supporting facilities within these neighboring regions. Ultimately, this may promote the formation of greener industry clusters. Secondly, due to factors of information asymmetry, the division and location of human resources in urban clusters and unbalanced regional economic development, the direct transmission mechanism will indirectly lead to negative effects. Considering multiple factors such as the original consumer market and transportation costs, some businesses with low levels of environmental management may choose to enter the neighboring regions to avoid the cost of technological innovation. Some neighboring regions may relax their green credit policies and take over the "two highs and one over" businesses in order to boost their own economic development. This will eventually hinder the upgrading of industrial structure in that area. Based on the above theoretical analysis, a third hypothesis in this paper is proposed.

H3: There is a two-way spatial spillover effect of green credit on the promotion of regional industrial structure optimization and upgrading

III. Empirical Model Setting and Variable Description

3.1 Data sources and variables

Based on data availability and the actual situation of green credit policy implementation, this paper selects 31 provinces and cities in China(excluding Hong Kong, Macao and Taiwan) from 2007-2018 as its research sample. It takes industrial structure and green credit levels as its core explanatory variables.

(1) Explanatory variables

According to the theory of industrial structural evolution, the upgrading of an industry's structure is generally brought about by a shift in the economic center of gravity, from a primary industry to a secondary industry and then to a tertiary industry, at a macrocosmic level. In order to exclude the endogenous influence of economic growth on the development of tertiary industries, this paper adopts the ratio of the scale of tertiary industry to the total GDP (SGR) of each province to measure the level of local industrial structure.

(2) Core explanatory variables

The current domestic data on green credit has a lack of direct indicators. Therefore, most scholars choose to adopt indirect indicators to estimate the amount of green credit available. For example, Liu Chuanzhe and Ren Yi (2019) [10] use the ratio of energy-saving and environmental protection project loans versus total bank loan size. On the other hand, Chen and Liu (2019) [11] use the credit data of local listed environmental protection agencies as an indirect indicator of local green credit volume. Nowadays, many scholars, such as Xu Sheng et al. (2018) [4] and Li Yu et al. (2018) [7] use the interest expenses of six high-energy-consuming industries as a reverse proxy indicator of green credit. Based on the consideration that only national-level data are available for loans for energy conservation and environmental protection projects, this paper ultimately refers to this method, which is the one most often used by scholars.[3] This is a logarithm of interest expenditures of the six major energy-consuming industries in each province (municipality or region) used as a reverse indicator, which are then normalized to measure the level of green credit.

(3) Intermediary variables

This paper proposes two transmission mechanisms, a direct mechanism (capital orientation) and an indirect mechanism (technology incentive) for the intermediate process of green credit to promote industrial structural upgrading. The direct mechanism is based on the definition of green credit. It emphasizes the provision of additional interest rate preferences and quota support by financial institutions represented by commercial banks, to support environmental protection agencies. Therefore, this paper uses green credit as the core explanatory variable in the empirical design to test its role in promoting industrial structural upgrading. This explains the existence of capital orientation. Therefore, this paper adopts R&D expenditures by provinces and cities (lnRDexp) to quantify the level of technological progress they make and uses it as a mediating variable to test the existence of technological incentives by adopting a step-by-step method of regression.

(4) Control variables

The control variables in this paper are selected from three levels: economic development, energy prices and foreign investment. (1) The economic development level of a region is measured by per capita GDP (pGDP). Generally speaking, the higher the level of economic development in a region, the faster and more effective its industrial structure upgrading will be. (2) The energy price level is measured by the industrial producer purchase price index. In order to eliminate heteroskedasticity and inflation factors, this paper analyzes data from the year 2007 as its base period to calculate the logarithmic industrial producer real purchase price index (lnrEPI). Theoretically, higher energy prices will, to a certain extent, suppress the production activities of industrial enterprises in the region, thus promoting the upgrading of the region’s industrial structure. (3) The level of foreign investment is measured by the share of foreign direct investment in a region’s GDP (lnFDIR).

In this paper, the data of the added value of tertiary industries in each province and city were drawn from the *China Tertiary Industry Statistical Yearbook*. The regional GDP per capita and GDP index were taken from the *China Statistical Yearbook*. The purchase price index of industrial producers in each region was sourced from the *China Price Statistical Yearbook*. Regional R&D expenditure, foreign direct investment and the number of industrial enterprises above the set scale were taken from the provincial statistical yearbooks.. Interest expenditure data of the six high-energy-consuming industries in the areas analyzed were from the *China Industrial Statistical Yearbook*. The descriptive statistical analysis of each variable is shown in Table 1:

[3] The fourth part of this paper will use the expenditure of accredited environmental firms as explanatory variables to test models’ robustness.

Table 1 Descriptive statistics of variables

Level	Variable measurement	Acronym	Mean	Std	Min	Max
Industrial structure	Tertiary industry accounts for total GDP	SGR	43.87	9.481	28.6	80.980
Green Credit	Interest Expenditures of the Six High Energy-Consuming Industries	lnPGL	5.852	1.804	-.266	9.246
Level of technological progress	R&D expenditure	lnRDexp	12.124	1.504	8.064	15.93
Economic Development	GDP per capita	pGDP	4.390	2.510	0.692	140.211
Energy Price Level	Industrial Producer Real Purchase Price Index	lnrEPI	4.664	0.191	4.388	6.954
Foreign Investment Level	Foreign direct investment as a proportion of GDP	lnFDIR	-6.108	1.054	-11.194	-4.36

3.2 Model Setting

(1) Mediating effect model

In this paper, a mediating effect model was used to test hypothesis 1 and hypothesis 2, and the test method was the step-by-step methodology proposed by Judd and Kenny (1981)[13]. The specific model is shown as follows:

$$SGR_{it} = \beta_{11} lnPGL_{it} + \beta_{12} lnpGDP_{it} + \beta_{13} lnrEPI_{it} + \beta_{14} FDIR_{it} + \lambda_{1i} + \epsilon_{1it} \quad (1)$$

$$RDexp_{it} = \beta_{21} lnPGL_{it} + \beta_{22} lnpGDP_{it} + \beta_{23} lnrEPI_{it} + \beta_{24} FDIR_{it} + \lambda_{2i} + \epsilon_{2it} \quad (2)$$

$$SGR_{it} = \beta_{31} lnPGL_{it} + \beta_{32} lnpGDP_{it} + \beta_{33} lnrEPI_{it} + \beta_{34} RDexp_{it} + \beta_{35} FDIR_{it} + \lambda_{3i} + \epsilon_{3it} \quad (3)$$

While SGR_{it} is the share of tertiary sector in GDP of region i in year t, $lnPGL_{it}$ is the amount of green credit measured by the interest expenditure of the six energy-intensive industries in region i in year t. $lnRDexp_{it}$ signifies the R&D expenditure of region i in year t. $lnpGDP_{it}$ denotes the GDP per capita of region i in year t. $lnrEPI_{it}$ is the real purchase price index of industrial producers in region i in year t. $lnFDIR_{it}$ expresses the share of direct foreign investment in GDP of region i in year t. λ_{ji} is the individual fixed effect and ϵ_{jit} is the random disturbance term.

If the coefficients of the core explanatory variables and mediating variables of the above three equations are more significant, hypothesis 1 will be considered valid. This paper then tested hypothesis 2 further, by dividing the regional sample on this basis.

(2) $Moran's\ I$

According to the first law of geography[4] proposed by Waldo R. Tobler, this paper argued that there are also spatial correlations and spatial spillover effects of green credit on the promoting of regional industrial structural upgrading processes. Firstly, to test spatial

[4] Waldo R. Tobler, a Swiss-American geographer and cartographer, who proposed the first law of geography in 1970: "Everything is related, and things that are close together are more closely related".

correlation, the global $Moran's\ I$ statistic and the local $Moran$ index were chosen to conduct a two-sided test of spatial autocorrelation (a global spatial autocorrelation test and a local spatial autocorrelation test). The global $Moran's\ I$ formula reflects the degree in similarity of spatially adjacent, spatially neighboring cells. Its formula is calculated as:

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(\frac{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}{n}\right)} \tag{4}$$

The local $Moran$ index, which measures local spatial autocorrelation, reflects the correlation between the industrial structure optimization level of the ith region and the average level of the whole region. It also expresses the correlation between the industrial structure optimization level of the surrounding areas of the ith region and the level of the region as a whole. The local $Moran$ index is defined as:

$$I_i = \frac{\sum_{j=1}^{n} w_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{\frac{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}{n}} \tag{5}$$

$Y_i = SGR_i$, $\bar{Y} = \frac{lnDSGR_i}{n}$, n represents the total number of regions (n = 31 in this model), while w_{ij} represents the spatial weight matrix.

(3) Spatial Durbin model

If the l $Moran$ index of industrial structure optimization rate of 31 provinces and cities in China during 2007-2018 is greater than 0 and passes a significance test, it indicates that there was a significant spatial positive autocorrelation between industrial structures during the years 2007-2018. Consequently, the spatial Durbin model (SDM) with broader adaptability will be selected in this paper to further examine the spatial spillover effects between green credit and industrial structure. Factoring in endogeneity, the spatial Durbin model with fixed effects was developed in this paper as follows:

$$lnSGR_{it} = \rho\sum_{j=1}^{n} W_{ij} lnSGR_{it} + \beta X_{it} + \psi\sum_{j=1}^{n} W_{jt}X_{jt} + \lambda W u_i + \epsilon_t \tag{6}$$

$$(\boldsymbol{I}_n - \rho\boldsymbol{W})\boldsymbol{lnSGR} = \boldsymbol{X\beta} + \boldsymbol{WX\psi} + \boldsymbol{\lambda W u} + \boldsymbol{\varepsilon}$$
$$\boldsymbol{lnSGR} = \sum_{r=1}^{n_x} \boldsymbol{S}_r(\boldsymbol{W})\boldsymbol{x}_r + \boldsymbol{B}(\boldsymbol{W})^{-1}\boldsymbol{\mu} + \boldsymbol{A}(\boldsymbol{W})^{-1}\boldsymbol{\varepsilon}$$
$$\begin{pmatrix} E(lnSGR_1) \\ E(lnSGR_2) \\ \vdots \\ E(lnSGR_n) \end{pmatrix} = \sum_{r=1}^{n_x} \begin{pmatrix} S_r(W)_{11} & S_r(W)_{12}\cdots & S_r(W)_{1n} \\ S_r(W)_{21} & S_r(W)_{22}\cdots & S_r(W)_{2n} \\ \vdots & \vdots \ddots & \vdots \\ S_r(W)_{n1} & S_r(W)_{n2}\cdots & S_r(W)_{nn} \end{pmatrix} \begin{pmatrix} x_{1r} \\ x_{2r} \\ \vdots \\ x_{nr} \end{pmatrix} \tag{7}$$

$$W = \begin{bmatrix} w_{1,1} & w_{2,1} & \cdots & w_{1,31} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,31} \\ \vdots & \vdots & \ddots & \vdots \\ w_{31,1} & w_{31,2} & \cdots & w_{31,31} \end{bmatrix} \quad (8)$$

While ρ is the spatial autoregressive coefficient of the dependent variable, ψ is the spatial regression coefficient of the independent variable. $W_{ij}$is the spatial weight matrix - indicating the degree of contiguity among the 31 provinces (W_{ij}=1 means that provinces i, j are contiguous with each other; $W_{ij} = 0$ means that provinces i, j are not contiguous with each other), λ is the spatial error coefficient, X_{it}, X_{jt} contain the level of green credit, GDP per capita, real purchase price index of industrial producers, R&D expenditure, and the proportion of direct foreign investment in the GDP of the year for regions i, j and in year t, respectively.

The direct and indirect effect is defined as:

$$\text{Total Effect}_t = \frac{1}{n}\mathbf{1}'S_r(W)\mathbf{1} \quad (9)$$

$$\text{Direct Effect}_t = \frac{1}{n}tr\big(S_r(W)\big) \quad (10)$$

$$\text{Indirect Effect}_\text{t} = \text{Total Effect}_\text{t} - \text{Direct Effect}_\text{t} \quad (11)$$

IV. Analysis of empirical results

The order of empirical tests in this paper is as follows. Firstly, a mediating effect model was established to verify the transmission mechanism of green credit to promote the upgrading of industrial structure. Regional differences were examined according to their different geographical locations. After that, the spatial correlation of industrial structure, which is the explanatory variable, was checked through visualization and a Moran index test. Finally, a fixed-effects spatial Durbin model was developed to further investigate the two-way spatial spillover effects of green credit levels on the upgrading of industrial structure between regions, and the results were analyzed in terms of mechanism and policy recommendations.

4.1 Analysis of the empirical results of the intermediate effects model

In order to investigate the existence of two major transmission mechanisms, the indirect and direct approaches, this paper tests hypothesis 1 through a step-by-step test.

Table 2 Regression results of the intermediate effects model

Variables	(1)	(2)	(3)
	SGR	lnRDexp	SGR
lnPGL	1.422***	0.261***	1.303***
	(31.39)	(13.78)	(23.40)
lnRDexp	—	—	0.455***
	—	—	(3.55)
Pgdp	0.477***	0.109***	0.427***
	(13.71)	(7.49)	(11.57)
lnrEPI	0.367***	0.064	0.338**
	(2.56)	(1.07)	(2.40)
lnFDIR	-0.234***	-0.083***	-0.197***
	(-4.13)	(-3.49)	(-3.47)
Constant	56.389***	9.319***	52.147***
	(74.52)	(29.49)	(37.04)
R-squared	0.962	0.851	0.963

Note: t-values are shown in parenthesis, ***, **, * represent the 1%, 5%, 10% mark respectively.

In model (1), the regression coefficient of green credit on industrial structure had significantly positive results, indicating that green credit has a positive promotional effect on industrial establishments. The coefficient of green credit on R&D expenditure in model (2) also had significantly positive results, confirming that an increase in green credit can promote more local investment and research efforts. Model (3) indicates that both green credit and R&D expenditure make a significant contribution to industrial structure. Combining the results of the three models, green credit not only contributes directly to the optimization of industrial structure, but it also promotes the upgrading of local industrial structure by driving an increase in regional R&D investment and promoting the level of technological progress. This finding confirms hypothesis 1 that the existence of direct "financial orientation" and indirect "technological incentives" makes green credit a booster of industrial upgrading.

However, MacKinnon et al. (2002)[13] suggest that step-by-step tests of regression coefficients are difficult to test for their significant mediating effects when these mediating effects are negligible. Therefore, the efficacy of step-by-step tests is low. However, Wen Zhonglin et al. (2014)[14] argue that if a step-by-step test yielded significant results, the premise that such tests' efficacy being low cannot be valid. Accordingly, the above study further validates the results of this paper.

4.2 Empirical testing of the fixed-effects model by region

In order to investigate the impact of green credit on the upgrading of industrial structure in different regions, this paper divides its sample data into East, Central and West according to their state of economic development, based on the guidelines proposed by the National Development and Reform Commission.[5] A fixed-effect regression analysis for

[5] The eastern part is the area which contains the first provinces and cities in China to adopt the coastal opening policy and that have a high level of economic development. This part includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan, etc. The central part is the less economically developed region, including Shanxi, Inner Mongolia, Jilin,

the whole and each region was adopted.

Table 3 Results for fixed-effect regression analysis by region

Variables	The whole region	East	Central	West
lnPGL	1.303***	1.021***	0.912***	1.100***
	(23.40)	(9.77)	(7.38)	(7.61)
lnRDexp	0.455***	0.870***	0.273	0.237
	(3.55)	(4.76)	(1.29)	(0.97)
pGDP	0.427***	0.389***	0.933***	0.858***
	(11.57)	(8.64)	(8.39)	(6.27)
lnrEPI	0.338**	0.672	0.253	0.538
	(2.40)	(1.55)	(1.56)	(1.18)
lnFDIR	-0.197***	-0.308	0.195	-0.170***
	(-3.47)	(1.05)	(1.09)	(-2.69)
Constant	52.147***	47.991***	58.084***	51.485***
	(37.04)	(18.03)	(25.78)	(16.07)
R-squared	0.963	0.970	0.964	0.975
Number of provinces	31	11	10	10

Note: t-values are shown in parenthesis, ***, **, * represent the 1%, 5%, 10% mark respectively.

Table 3 shows the regression results for the impact of green credit on industrial structure upgrading in the whole region, and in the East, Central and West. Firstly, from the whole sample, the regression coefficient of the core explanatory variable green credit level on the explanatory variable industrial structure is 1.303 and is at the 1% mark. In general, the suitability of the model shows that it fits well, so the positive association between the two in hypothesis 1 is confirmed. At the same time, the results indicate that GDP per capita and industrial structure upgrading also show a positive correlation, and this is in line with most of the findings from previous studies undertaken. When the overall level of regional economic development is low, economic growth and production expansion are often accompanied by an increase in pollution. The negative effects of this pollution will eventually outweigh economic growth in terms of social welfare, and people will seek to control environmental pollution while developing the economy, which ultimately promotes industrial structure optimization and upgrading. Secondly, energy prices, as measured by the Industrial Producer Purchase Price Index, show a positive relationship with the upgrading of industrial structure. This is also consistent with reality; the higher the energy prices, the fewer local high-polluting enterprises there will be. As a result, it will potentially promote the upgrading and adjustment of industrial structure indirectly. More investment in R&D can also promote the upgrading of industrial structure. Based on experiences in real life, investment in R&D indicates importance the government and businesses attach to R&D. The increase of investment in R&D also suggests that the enterprises themselves are promoting innovation from the cost perspective, thus promoting the upgrading of industrial structure. Furthermore, the proportion of direct foreign investment has a certain inhibiting effect on the upgrading of industrial structure.

Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan and Guangxi, etc. The western part is the least economically developed region, including Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang, etc.

This is partly in line with the "pollution paradise" hypothesis, which states that foreign investors prefer to invest in areas with lower environmental standards and a less sustainable industrial structure. As such, environmental issues merit attention.

The promoting effect of green credit on industrial structure optimization is also validated in the different regional samples examined in this study. The regression coefficients are all at the 1% mark, but show some regional variations. Among them, the regression coefficients are smaller in China's central region when compared to its eastern region, indicating that the effect of green credit on the upgrading of industrial structure is less pronounced in its central region. With an industrial cluster of secondary sector enterprises, China's central region is overly reliant on its own resource advantage for development. Therefore, the concentration of highly polluting businesses is more evident in China's central region. As a result, China's central region is less receptive to the upgrading of industrial structure and increasing the level of green credit. Thus the upgrading of industrial structure there is comparatively slow. At the same time, the regression coefficient is noticeably larger in China's western region compared to its eastern region, indicating that the promotion of green credit on industrial structure is more pronounced in its western part. This also verifies hypothesis 2, to a certain extent, indicating that as environmental awareness and government intervention increase in the western region [4], increased investment in green credit is more likely to be a driving force behind the optimization of industrial structure. On the other hand, due to the fact that the development of industry happened earlier in the eastern region, with a better developed economy and a well adjusted environmental protection facilities and industrial structure (Li Yu et al., 2018) [7], the driving force of green credit there is relatively low. Looking at the data from China's central and western regions combined, the promoting effect of R&D investment on local industrial upgrading in these two regions is negligible. This is because the economic foundations of China's central and western regions are starkly different from those in its eastern areas. The innovation gap is too vast, and there is a lack of education, making the uptake and potential to introduce advanced technologies generally slower. This in turn affects the implementation of new technologies in China's central and western regions and makes it difficult to spur effective innovation and economic growth there (Nie Yanhua and Zhang Yuming, 2009)[15].

4.3 Spatial correlation test of industrial structure optimization and upgrading

Based on the above conclusions, this paper adopts the spatial Durbin model in order to verify hypothesis 3. Firstly, this paper visualized the industrial structure level of these regions based on an industrial structure optimization rate of 31 provinces in China. Evidently, there is a certain degree of correlation between these regions, such as the provinces in China's developed eastern coastal region generally having better industrial structure upgrading efficacy.

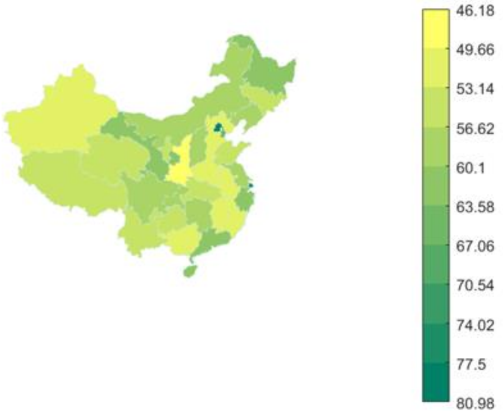

Figure 1: Visualization of the SGR share in 31 Chinese provinces[6]

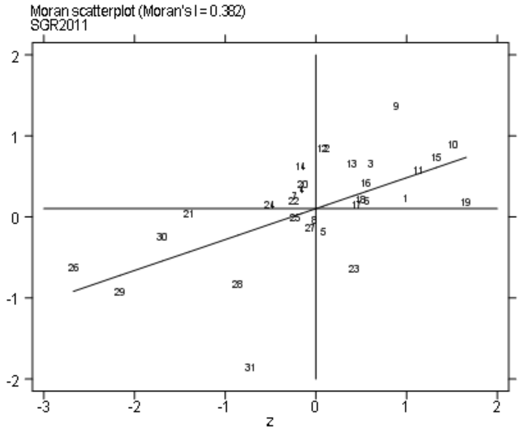

Figure 2: Local $Moran's\ I$ scatter plot of the tertiary sector's share[7]

Secondly, this paper measures the $Moran's\ I$ value and local $Moran$index's level of industrial structure optimization based on the panel data of industrial structure and green credit development level of 31 provinces and cities from 2007-2018. There is clearly a noticeable spatial correlation of industrial structure: the results of the global correlation are shown in Table 4, and the results of the local correlation (taking 2011 as an example) are shown in Figure 2.

Table 4 Global $Moran's\ I$ index for the level of industrial structure (SGR)

Year	Global $Moran's\ I$	Year	Global $Moran's\ I$	Year	Global $Moran's\ I$
2007	0.369***	2011	0.394***	2015	0.368***
2008	0.372***	2012	0.386***	2016	0.383***
2009	0.383***	2013	0.380***	2017	0.382***
2010	0.398***	2014	0.368***	2018	0.383***

Note: ***, **, * represent the 1%, 5%, 10% mark respectively.

In Figure 2, there are significantly more points in quadrants one and three than in quadrants two and four, indicating that more provinces and cities are clustered in the "low-low" and "high-high" types than in the "high-low" and "low-high" types. Therefore, provinces and cities with a lower (or indeed higher) level of industrial structure optimization are more likely to group together, and the spatial differences between them are smaller.

[6] Limited by the availability of data, the sample in this paper only includes 31 provincial capitals in China and does not include Hong Kong, Macao and Taiwan, so the data for these cities are not shown in Figure 1.

[7] 1 - Beijing, 2 - Tianjin, 3 - Hebei, 4 - Shanxi, 5 - Inner Mongolia, 6 - Liaoning, 7 - Jilin, 8 - Heilongjiang, 9 - Shanghai, 10 - Jiangsu, 11 - Zhejiang, 12 - Anhui, 13 - Fujian, 14 - Jiangxi, 15 - Shandong, 16 - Henan, 17 - Hubei, 18 - Hunan, 19 - Guangdong, 20 - Guangxi, 21 - Hainan, 22 - Chongqing, 23 - Sichuan, 24 - Guizhou, 25 - Yunnan, 26 - Tibet, 27 - Shaanxi, 28 - Gansu, 29 - Qinghai, 30 - Ningxia, and 31 - Xinjiang.

4.4 Analysis of the empirical results of the spatial Durbin model

On the basis of the above tests, this paper uses a spatial Durbin model examining fixed effects, and investigates the spatial effects of the level of green credit on the effect of industrial structure upgrading between different regions by dividing the direct spatial effects from the indirect spatial effects.

According to the statistical results of the spatial Durbin model, the coefficient of the spatially lagged explanatory variable W*SGR is 0.535 and passes the 1% significance test, indicating that the industrial structure levels of different provinces have a mutually beneficial influence on each other, and the industrial structure upgrading of one province (city) also plays a positive role on the industrial structure of its neighboring provinces (cities). The coefficient of green credit level (lnPGL) is 1.505 and passes the 1% significance test, indicating that the level of green credit positively contributes to the level of local industrial structure. In addition, comparing the fixed-effects model with the SDM model with spatial fixed effects, we find that R^2 rises to 0.969. This indicates that the fit of the spatial Durbin model has further increased, which justifies the spatial econometric model.

Table 5 Spatial Durbin model regression results considering fixed effects

Variable	Variable coefficient	Variable	Variable coefficient
lnPGL	1.505***	W*lnPGL	-1.086***
	(16.84)		(-9.27)
pGDP	0.313***	W*pGDP	-0.067
	(8.29)		(-1.05)
lnrEPI	0.071	W*lnrEPI	0.070
	(0.63)		(0.32)
lnRDexp	0.277***	W*lnRDexp	0.335
	(2.80)		(1.44)
lnFDIR	-0.164***	W*lnFDIR	0.194**
	(-3.62)		(2.27)
W*SGR	0.535***		
	(10.69)		
R-squared	0.969		

Note: t-values are shown in parenthesis, ***, **, * represent the 1%, 5%, 10% mark respectively.

Since a change in an independent variable not only affects the level of industrial structure in the province (city), but may also feed the resulting effect back to the level of industrial structure in neighboring areas, the estimated values of the coefficients are broken down into direct and indirect effects (i.e. spatial spillover effects). The results of this breakdown are shown in Table 6.

Table 6 SDM break down of spatial fixed effects

Variable	Direct effect	Indirect effect	Total effect
lnPGL	1.466***	-0.540***	0.926***
pGDP	0.326***	0.191*	0.052***
lnrEPI	0.098	-0.204	0.302
lnRDexp	0.350***	0.936**	1.285***
lnFDIR	-0.147***	0.215	0.067

Note: t-values are shown in parenthesis, ***, **, * represent the 1%, 5%, 10% mark respectively.

The direct effect of the core explanatory variable level of green credit on the industrial structure is 1.466, which is significant the 1% mark. This indicates that the level of green credit has a significant positive effect on the upgrading of the local industrial structure. Through the mechanisms of capital orientation and technology incentive, green credit controls the flow of credit funds at source, raises the cost of credit for “two highs and one over” businesses, and expands the scale of environmental protection and clean energy enterprises. It increases investment in R&D of environmental protection and energy-saving technologies, and thus achieves an upgrading of its regional industrial structure. Among the direct effects of the control variables, the explanation of energy consumption prices decreased compared to the fixed-effects model. The indications of all the other variables did not change significantly, and will not be explained further.

In terms of indirect effects, this paper shows that the indirect effect of the main explanatory variable level of green credit on industrial structure is -0.540, which is highly significant at the 1% mark. In their study of green credit and environmental quality, Wu Jiahui et al. (2019) also showed a negative coefficient result, but did not emphasize this in their explanation. The results of this paper suggest that the development of local green credit can have a significantly negative effect on the upgrading of industrial structure in the surrounding areas, which seems to deviate from the aggregation effect of the level of industrial structure. On the one hand, according to the results of the spatial autocorrelation coefficient, the upgrading of the industrial structure in one province will lead to the upgrading of the industrial structure in the surrounding areas, through a demand for supporting industries, forming a benign industrial structure cluster. On the other hand, green credit, through a capital-led mechanism, significantly raises the cost of credit for “two highs and one over” businesses, which are driven to move into neighboring provinces to avoid the costs of technological innovation, thus inhibiting the upgrading of the industrial structure of neighboring provinces. The above two effects overlap with each other, creating a two-way spatial effect.

This two-way mechanism is already reflected in China’s Beijing-Tianjin-Hebei region. Tianjin, driven by Beijing, has vigorously developed green credit, which has facilitated the upgrading of the local industrial structure, and has implemented the *Tianjin Ecological Protection Regulations* since March 2019, effectively stopping the relocation and increase of highly polluting enterprises in the city. At the same time, highly polluting enterprises in Beijing and Tianjin have moved into Hebei, which has a more relaxed policy. Hebei has taken on a large number of similar enterprises for its own economic development as well as for the development of regional cooperation, leading to the much-needed local industrial upgrading challenges of today. Regarding the transformation and upgrading of the local industrial structure in Beijing, a large number of businesses have been drawn to move to Hebei by two factors: low production costs and the relaxed industrial policy there. As shown in Figure 4 (the blue arrows indicate direct migration and red arrows indicate brief migration), this is achieved through direct migration and indirect migration. Direct migration is carried out in the form of the relocation of local Beijing industrial businesses from the city, to the Hebei region. For example, the relocation of Beijing Shougang to

Caofeidian in Hebei has alleviated many of Beijing's environmental problems such as air and water pollution, but has had a significantly negative impact on the area in which these businesses have relocated. In addition, the main plants of dozens of enterprises, including Beijing Coking Chemical Company, have also moved to Tangshan [17]. Although these enterprises have made comprehensive changes to their technology and equipment, and the local government has provided financial support to help them reduce pollutant emissions, they have still caused some environmental pollution overall. Indirect relocation means that industrial enterprises located in Hebei produce industrial products for Beijing to meet the energy consumption required by Beijing in its development process. A typical example is the Sanhe thermal power plant in Hebei, which has been supplying heat to Beijing since 2011. According to Zhao Yuming et al. (2013) [18], the Sanhe thermal power plant requires a total of 800,000 tonnes of coal to be burned and emits up to 3,000 tonnes of sulphur dioxide.

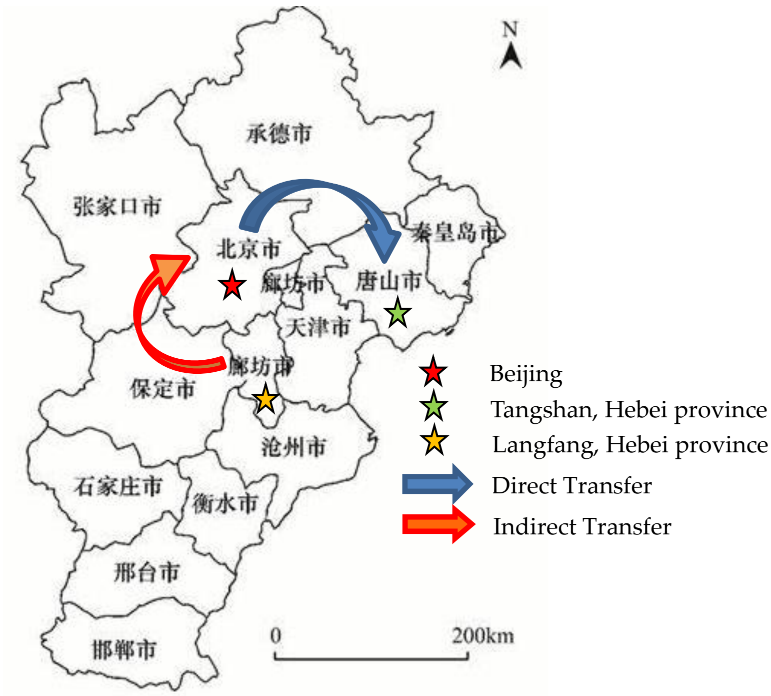

Figure 3: transfer of highly polluting enterprises in the Beijing-Tianjin-Hebei area

Apart from the Beijing-Tianjin-Hebei area, the transfer is also seen in the form of polluting businesses moving from eastern regions to central and western regions. For example, the national demonstrative zones were set up in central and western regions such as Anhui and Guangxi to undertake an industrial transfer, facilitating the policy of moving high energy-consuming enterprises away from the east. In short, the two-way spatial effect of green credit between regions inhibits the positive effects of green credit on the one hand, and creates negative external factors on the other, causing unnecessary losses to society.

In addition, R&D investments show a significant positive spillover effect, indicating that local technological progress can lead to the upgrading of industrial structures in neighboring regions, which is consistent with the findings of previous studies (Sun Zhao et al., 2014)[16]. This is also in line with the original design of China's regional synergistic development process. At the same time, energy prices as measured by the industrial producer purchase price index have a negative spillover effect, indicating that high local energy prices force some enterprises with high energy demands to move to other regions. Most of these businesses rely on energy for development, which to a certain extent inhibits the upgrading of industrial structure in the regions these enterprises have moved to.

4.5 Robustness tests

In order to ensure the robustness and reliability of the above empirical findings, this paper conducts robustness tests by substituting its core explanatory variables. Considering that the total amount of green credit is only available at the national level, this paper reconstructs a measure of the level of regional green credit by replacing the interest expenditure of the original six high energy-consuming industries with the amount of credit of local listed environmental enterprises (lnPGAL). The main findings of this paper are not affected by bringing the new core explanatory variables into the model for testing. Therefore, the model developed is considered to be robust. Due to length of the paper, the specific robustness test results are presented in the Appendix at the end of the paper.

V. Conclusions and policy implications

Firstly, green credit can significantly contribute to the upgrading of industrial structure through the direct financial orientation approach and the indirect technological incentives approach. But there are significant regional variations to this contribution. Green credit is more effective in China's western region than in its eastern region, while it is least effective in its central region. China should make plans according to the situation in different regions. Formulating green credit policies which are tailored to the current state of development in each region, and balancing the development of green finance across regions are essential. In the east, it is important to focus on strengthening public awareness and governmental control. In the west, deeper financial investment and liberalization should be promoted. In the central region, it is more effective to implement both these policies in parallel. The relatively weak financial sector in the west should be recognized. The difficulties in transforming the environmental protection of businesses due to pre-existing economic problems, the weak ability of enterprises to transform and innovate on their own, and the slow development of the local green finance and credit industry should be continually borne in mind. In contrast, the financial market mechanism in the eastern region is better established, so the role of the government in the formulation of industrial policies and public awareness is more important there. The promotion mechanism of green credit in the central region is the weakest, so the government needs to carry out measures of both controlling/guiding and deepening financial investment.

Secondly, as green credit promotes the upgrading of the local industrial structure, it in turn creates a larger cluster of high-quality industries to drive the upgrading of the industrial structure of the surrounding areas. Therefore, China should improve the coordination mechanism between green financial credit and industrial structure upgrading, and strive to establish a corresponding mechanism which is coherent, scientific and strategic. We should make full use of the positive spillover effects of economically developed regions to enrich and benefit the surrounding areas, to promote the formation of well-defined and mutually reinforcing industrial clusters, the establishment of a proportional governance framework and an overall improvement in efficiency. We should take advantage of the connection between financial institutions, environmental protection agencies and government policies to introduce clearly oriented preferential policies and regulatory requirements. For areas which are relatively less well developed, we should provide targeted assistance while stimulating environmental protection businesses' own regeneration of funds and improving their own sense of social responsibility, so as to gradually reduce their dependence on government assistance.

Finally, the development of green credit has a negative spatial spillover effect by inhibiting the optimization of industrial structure in neighboring regions. This phenomenon can be explained as follows. The transfer of polluting enterprises from some developed regions is causing difficulties in industrial upgrading in the surrounding areas. Some environmental enterprises have failed to fulfill their environmental commitments. There is a lack of comprehensive assessment by financial institutions of the business conditions and future risks of environmental enterprises,. There is also a high risk of default on some green loans. Therefore, China should promote relevant legislation and supervision, timely data disclosure, timely supervision of environmental protection agencies to disclose their operating conditions, increase control over transferred industries, and effectively increase the proportion of polluting industries to be transformed locally. At the same time, the government needs to promptly unblock the information communication channels between local environmental protection agencies and financial institutions to reduce the impact of information asymmetry.

Reference

[1] Zhang Guangping, Dong Honglei, Shen Shu, Zhang Guangping. Green credit supports financial innovation and industrial structure transformation [J]. Financial Regulatory Research,2016(05):98-108.

[2] Chen Qi. Is China's Green Credit Policy Implementing -- Based on the Analysis of the Loan Scale and Cost of "Two High and Surplus Enterprises" [J]. Contemporary Finance and Economics,2019(03):118-129.

[3] Li Bin, Su Jiaxuan. Is industrial restructuring beneficial to the development of green economy? -- An empirical study based on spatial econometric model [J]. Ecological Economy,2016,32(06):32-37.

[4] Xu Sheng, Zhao Xinxin, Yao Shuang. Impact of green credit on industrial structure upgrading [J]. Journal of Shanghai University of Finance and Economics,2018,20(02):59-72

[5] Qian Shu-shu, Wang Wenzhong, Fang Hai-guang. An empirical analysis of the effect of green credit on the optimization of China's industrial structure [J]. Finance Theory & Practice,2019(01):1-8.

[6] Song Qinge, Li Yang, Jing Gang. Research on the promotion of green finance to industrial upgrading in Qinghai Province [J]. Statistics and Management,2020,35(09):8-14.

[7] LI Yu, HU Haiya, LI Hao. An Empirical Analysis of the Impact of Green Credit on the Upgrading of Industrial Structure in China: Based on the Panel Data of China's Province [J]. Economic Problems,2020(01):37-43.

[8] Han Kezhen. The relationship between green finance development and green technology innovation efficiency: An empirical analysis based on spatial spillover perspective [J]. Price Theory & Practice,2020(04):144-147+178.

[9] Wu Jiahui, Wang Lu, Qu Jiahui, Zhang Jing. Will green credit help improve environmental quality? -- An empirical study based on spatial Dupin model [J]. Gansu Finance,2020(06):39-46.

[10] Liu Chuanzhe, Ren Yi. Research on the impact of green credit on low-carbon energy consumption structure [J]. Wuhan Finance,2019(11):66-70.

[11] Chen H, Liu C, Xie F, Zhang T, Guan, F. Green Credit and Company R&D Level: Empirical Research Based on Threshold Effects[J].Sustainability,2019,11(07): 1-14.

[12] Judd CM, Kenny DA. Process Analysis: Estimating Mediation in Treatment arthroplasty [J].Evaluation Review,1981,5(5):602-619.

[13] MacKinnon DP, Lockwood CM, Hoffman JM, West SG, Sheets V. A comparison of methods to test mediation and other intervening variable effects[J].Psychol The Methods, 2002, 7 (1) : 83-104.

[14] Wen Zhonglin; Advances in Psychological Science,2014,22(5): 731-745. DOI: 10.1016 / j.cjj.2016.01.002

[15] Nie Yanhua, Zhang Yuming. Economic Research Guide,2009(03):135-136. (in Chinese)

[16] Sun Zao, Liu Lihua, Sun Yazheng. The effect of market orientation, local protectionism and R&D spillover effect: Evidence from China's industry [J]. Management World,2014(08):78-89.

[17] Ling Qiu, Yuming Shen, Wangbing Ren, Tingting Yan. Regional differentiation and influencing factors of energy use efficiency in China [J]. Journal of Natural Resources,2008(05):920-928.

[18] Zhao Yuming, Sun Gennian. Measurement of tons of soot gas emission and pollution dynamic prediction of thermal power enterprises in Hebei Province [J]. China Environmental Monitoring,2013,29(04):142-146.

Appendix

Table 7 Regression results for the intermediate effects model

Variables	(1)	(2)	(3)
	SGR	lnRDexp	SGR
lnPGAL	1.499***	0.293***	1.368***
	(28.44)	(14.60)	(20.59)
lnRDexp			0.446***
			(3.15)
Pgdp	0.000***	0.000***	0.000***
	(11.94)	(6.43)	(10.37)
lnrEPI	0.383**	0.076	0.349**
	(2.49)	(1.30)	(2.29)
lnFDIR	-0.194***	-0.074***	-0.161***
	(-3.18)	(-3.20)	(-2.63)
Constant	63.747***	10.667***	58.993***
	(82.65)	(36.36)	(34.93)
R-squared	0.956	0.857	0.957

Note: t-values are shown in parenthesis, ***, **, * represent the 1%, 5%, 10% mark respectively.

Table 8 Fixed effects model robustness tests

Variables	Overall	Eastern Regions	Central Regions	Western Regions
lnPGAL	1.368***	1.120***	0.944***	0.892***
	(20.59)	(10.16)	(7.42)	(6.36)
pGDP	0.418***	0.352***	1.004***	1.103***
	(10.37)	(7.68)	(9.69)	(8.59)
lnrEPI	0.349**	0.896**	0.292*	0.137
	(2.29)	(2.06)	(1.80)	(0.29)
lnRDexp	0.446***	0.815***	0.185	0.181
	(3.15)	(4.50)	(0.86)	(1.13)
lnFDIR	-0.016***	-2.37	0.352**	-0.174***
	(-2.63)	(0.60)	(2.05)	(-2.59)
Constant	58.99***	52.835***	64.678***	61.044***
	(34.93)	(20.12)	(26.00)	(16.06)
R-squared	0.957	0.971	0.963	0.971
Number of provinces	31	11	10	10

Note: t-values are shown in parenthesis, ***, **, * represent the 1%, 5%, 10% mark respectively.

Table 9 SDM robustness tests

Variables	Coefficients	Variables	Coefficients
lnPGAL	1.823***	W*lnPGAL	-1.474***
	(17.06)		(-11.36)
pGDP	0.199***	W*pGDP	0.064
	(5.48)		(0.97)
lnrEPI	-0.027	W*lnrEPI	0.096
	(-1.42)		(0.44)
lnRDexp	0.120	W*lnRDexp	0.553**
	(1.14)		(2.36)
lnFDIR	-0.115**	W*lnFDIR	0.135
	(-2.21)		(1.61)
W*SGR	0.551***		
	（11.45）		
R-squared	0.969		

Note: t-values are shown in parenthesis, ***, **, * represent the 1%, 5%, 10% mark respectively.

Table 10 Robustness tests for spatial effects decomposition

Variables	Direct effects	Indirect effects	Total effects
lnPGAL	1.754***	-0.935***	0.819***
	(16.64)	(-5.09)	(4.41)
pGDP	0.224***	0.344***	0.569***
	(6.12)	(3.36)	(5.38)
lnrEPI	-0.035	-0.160	0.156
	(-0.03)	(0.39)	(0.33)
lnRDexp	0.217*	1.236***	1.453***
	(1.88)	(2.87)	(2.90)
lnFDIR	-0.103**	0.153	0.050
	(-2.21)	(0.92)	(0.27)

Note: t-values are shown in parenthesis, ***, **, * represent the 1%, 5%, 10% mark respectively.