



Research on the influence of technological innovation on carbon productivity and countermeasures in China

Bing Han¹

Received: 4 October 2020 / Accepted: 30 November 2020 / Published online: 4 January 2021
© The Author(s), under exclusive licence to Springer-Verlag GmbH, DE part of Springer Nature 2021

Abstract

Increasing carbon productivity is an important measure taken by China to deal with global climate change, and technological innovation is the fundamental way to promote industrial carbon productivity. To explore the low-carbon effects of technological innovation, based on the panel data of 30 provinces in China from 2009 to 2017, this paper established a spatial panel measurement model and a panel threshold regression model to explore the spatial spillover effects and threshold characteristics of technological innovation on industrial carbon productivity. The research shows the following: on the one hand, technological innovation and industrial carbon productivity each has obvious spatial correlation, and technological innovation has a significant spatial spillover effect on the improvement of industrial carbon productivity, and the indirect spillover between regions is greater than the direct spillover effect within the area. On the other hand, the impact of technological innovation on industrial carbon productivity has a double threshold effect. With the continuous improvement of technological innovation capabilities, the promotion of industrial carbon productivity has become increasingly more influential. Through the division of threshold values, the technological innovation capabilities of various regions in China are significantly heterogeneous, and the overall level is low. Although technological innovation capabilities have improved in recent years, there is still much room for improvement. Finally, this article puts forward relevant suggestions from the construction of regional technological innovation system, economical green circular development, and the establishment of a green technological innovation system.

Keywords Technological innovation · Industrial carbon productivity · Spatial spillover effects · Threshold model

Introduction

The continuous increase in greenhouse gas emissions and environmental pollution has caused severe impacts on natural ecosystems and socio-economic systems. According to data from the World Health Organization, air pollution has become the fifth leading cause of death in the world. Approximately 7 million people die from air pollution every year. As the world's largest carbon dioxide emitter, about 656,000 people in China lose their lives every year due to indoor or outdoor air pollution (Han et al. 2020). Controlling greenhouse gas

emissions and exploring a sustainable low-carbon development method have become the core requirements of China's economic construction (Lo and Broto 2019). Research on the necessity, possibility, and reality of the low-carbon economy has also become one of the focuses of the academic community. The low-carbon growth of the global economy needs to control greenhouse gas emissions while ensuring stable economic growth, and it is "industrial carbon productivity" that can combine these two goals (Iftikhar et al. 2016). Although the composition of industrial carbon productivity is simple (the economic output per unit of carbon dioxide emissions), it gives new constraints on social and economic development from the perspective of input factors (Long et al. 2020). Industrial carbon productivity strips out the carbon hidden in energy and material products and becomes a new indicator that can be compared with traditional labor productivity and capital productivity (He and Su 2009).

So how to increase industrial carbon productivity? Fundamentally speaking, technological innovation is the core driving force for long-term stable economic growth and the

Responsible Editor: Philippe Garrigues

✉ Bing Han
skd996327@sdust.edu.cn

¹ College of Humanity and Law, Shandong University of Science and Technology, No. 579, Qianwangang Road, Huangdao District, Qingdao City, Shandong Province, China

fundamental way to promote the transformation of the traditional economy to a low-carbon economy (Peng and Tao, 2018; Buijtenlijk et al. 2018). First, technological innovation can increase economic output while reducing the input of factor resources by improving production processes, thereby improving production efficiency and promoting low-carbon economic development (Murphy, 2015). Second, technological innovation can encourage the transformation of industries from low value-added to high value-added, accelerate the adjustment of industrial structure, and promote the development of a low-carbon economy as a whole (Yu, 2020). Third, technological innovation can also strengthen regional exchanges and enhance the overall local innovation capacity through technological diffusion and digestion, absorption, and re-innovation, thereby promoting the development of a low-carbon economy (Yin et al. 2019).

However, it is worth noting that due to the existence of the spatial effect of technological innovation, its impact on the low-carbon economy will be “strengthened” or “weakened” (Oliveira, 2019; Binz et al. 2014). Therefore, the influence path of technological innovation on industrial carbon productivity is not like the simple linear influence we intuitively assume. Some regional technological innovation efforts only provide conditions for “free-riding” in other regions, but their industrial carbon productivity has stagnated or even declined (Gay and Szostak, 2020). Besides, the low-carbon effect of technological innovation may not be a purely linear relationship, but non-linear. This is because technological innovation is a long-term activity that requires a large amount of capital and human resources. At different stages, there may be significant differences in the low-carbon effects of technological innovation (Bolli et al. 2020). For regions with weak technological innovation capabilities, the initial innovation investment may have little impact, and it has little impact on economic growth and environmental protection. For areas with strong technological innovation capabilities, due to factors such as a solid innovation foundation and complete supporting infrastructure, the low-carbon effect is more obvious (Tojeiro-Rivero and Moreno 2019; Jo et al. 2016). Unfortunately, in the existing literature about technological innovation on economic growth and carbon emissions, this spatial effect and non-linear impact are often ignored. Therefore, this article uses spatial measurement analysis and threshold analysis methods to study the low-carbon impacts of technological innovation and profoundly explores the significance of technological innovation for the development of China’s low-carbon economy.

The possible contributions of this article are as follows: first, this paper has calculated the technological innovation capabilities and industrial carbon productivity levels of various regions in China and analyzed their spatial characteristics; second, this article explores the low-carbon driving effect of technological innovation on industrial carbon productivity

from the perspective of spatial heterogeneity; and third, based on the threshold regression model, this paper studies the non-linear relationship between technological innovation and industrial carbon productivity. In theory, this article expands the related theoretical research on technological innovation and industrial carbon productivity. In practice, this article provides experience and reference for China’s low-carbon development during the transition period. At the same time, it can also provide a reference for other developing countries to rely on technological innovation to promote sustainable development.

Literature review

In the context of global economic transformation and low-carbon development, technological innovation has increasingly become a key measure to promote the sustainable development of the national economy. Hence, scholars are paying attention to the development of technological innovation. Judging from the current literature results, it mainly includes the following aspects:

Research on the relationship between technological innovation and carbon emissions

Regarding the impact of technological innovation on carbon emissions, scholars have different views. Some scholars believe that technological innovation can reduce carbon emissions through the use of alternative clean energy, carbon capture and storage technologies, and energy efficiency improvements. For example, using data from 30 provinces in China from 2005 to 2010, Feng and Yuan (2016) proposed that both technological innovation and R&D investment have significant technical spillover effects, which can significantly promote carbon emission reduction. Similarly, by analyzing the panel data of OECD member countries from 2000 to 2014, Ganda (2019) proposed that patent output can significantly affect carbon emissions. Although innovation and technology investment have different impacts on carbon emissions in various countries, there is still evidence that improving technological innovation capabilities can effectively promote carbon emission reduction. Taking 13 countries, including Canada and Japan, as samples, Nguyen et al. (2020) pointed out that innovation is one of the five critical factors that promote carbon emission reduction. Increasing investment in technological innovation is a crucial measure to reduce carbon intensity. Based on global patent data analysis, Yan et al. (2017) measured the technological innovation and carbon intensity of 15 economies around the world. Through empirical analysis, they believe that the inhibitory effect of technological innovation on carbon intensity is not only a direct and significant direct impact. Besides, by improving the intermediary variable of energy consumption

structure, technological innovation can also play an indirect inhibitory effect on carbon intensity.

However, some scholars have suggested that technological innovation may bring more energy consumption and carbon emissions while promoting economic growth. For example, based on the empirical data analysis of 35 industrial sectors in China, Jin et al. (2014) found that although technological innovation has promoted economic growth through means such as increasing labor productivity, its carbon emission effects have become more significant. Also, some scholars believe that the impact of technological innovation on carbon emissions is not just a pure inhibition or promotion. For example, Wang and Wang (2013) used an impulse response function and variance decomposition method to measure the dynamic response of environmental regulations, technological innovation, and carbon emissions under the impact of external factors. The results showed that the mutual response curve between technological innovation capability and carbon emissions is N-shaped and inverted U-shaped. Fisher and Wing (2008) believe that advanced technology can reduce energy consumption intensity; however, due to the existence of the “rebound effect,” a large-scale increase in output will lead to a rise in energy consumption and total carbon emissions, making the relationship between technological innovation and environmental pollution uncertain.

Research on the relationship between technological innovation and economic growth

Since the establishment of innovation economics, a large number of scholars have conducted in-depth study on the causal relationship between technological innovation and economic growth from theoretical and empirical aspects and have achieved some research results. Kuznets emphasized the role of technological innovation in promoting economic growth in both “Modern Economic Growth” and “National Economic Growth.” Economists represented by Romer and Lucas have demonstrated the long-term promotion effect of technological innovation on economic growth based on the endogenous growth model. In terms of empirical research, most studies show that technological innovation mainly promotes economic growth by increasing R&D investment and increasing productivity. For example, Hall et al. (2005) verified that the increase of R&D investment in a particular industry could not only improve the technological progress of the industry but also contribute to the increase of labor productivity in other related industries and thus can improve the overall economic output level of a region. Studies by Bravo-Ortega and Marín (2011) show that for every 10% increase in R&D per capita, an economy’s long-term productivity will increase by an average of 1.6%. Chinese scholars have also conducted systematic research on the relationship between technological innovation and economic growth.

Based on panel data analysis of 30 provinces in China, Lu and Jin (2011) found that R&D investment has a significant role in promoting economic growth. The role of technological innovation in promoting economic growth is unquestionable. Still, in the process of China’s economic transformation, there are significant differences in the driving role of technological innovation in economic growth. For example, Yan and Xu (2019) pointed out that the impact of technological innovation on economic growth is not stable. Specifically, with the continuous improvement of technological innovation capabilities, the impact on economic development has gradually changed from negative to positive. This is because in the early stage of technological innovation, a large amount of R&D cost investment is required, and innovation results must undergo a certain period of transformation to promote economic growth.

Industrial carbon productivity and low-carbon economy development

Kaya and Yokobori (1997) put forward the concept of industrial carbon productivity for the first time. They pointed out that industrial carbon productivity is a core indicator to measure the level of sustainable development of a country. Moreover, they proposed that the measurement method of industrial carbon productivity is GDP per unit of carbon dioxide. Since then, industrial carbon productivity has been widely used by scholars as a representative variable of low-carbon economic growth (Lu et al. 2018). Beinhocker et al. (2008) believe that industrial carbon productivity represents the level of sustainable economic development. It not only measures the degree of economic development but more importantly, it measures the degree of coordination between economic development and the reduction of carbon emissions. Wang et al. (2016) proposed that the measurement and evaluation of industrial carbon productivity in various countries is of great significance for mitigating global climate change.

Similarly, taking China and other developing countries as examples, Li and Wang (2019) proposed that increasing industrial carbon productivity is the core method to alleviate the contradiction between economic development and ecological protection in these countries. Based on the realistic requirements of low-carbon development and high-quality development of the Chinese economy, Zhan et al. (2010) and Han et al. (2020) also affirmed the importance of improving industrial carbon productivity for China’s economic construction. Some scholars also regard the improvement of industrial carbon productivity and the level of social and humanistic development as the two main characteristics of a low-carbon economy (Liu and Geng, 2010); increasing industrial carbon productivity is of considerable significance to the realization of the welfare performance of the entire society (Liu and Cao, 2011).

Existing literatures have essential reference value for this article. Still, considering the pressure of global climate change and the reality of China’s economic transformation and development, the research on technological innovation and industrial carbon productivity has the following expansion space: first, most existing literature mainly focuses on unilateral research on the economic effects, environmental effects, or industrial structure adjustment effects of technological innovation. However, for China at this stage, whether it is to promote GDP growth, improve the level of rationalization of the industrial structure, or reduce greenhouse gas emissions, in the end, China is looking for a sustainable development path. This requires us to coordinate the relationship between ecological security and economic development reasonably. Therefore, this paper believes that exploring the relationship between technological innovation and industrial carbon productivity is in line with the realistic requirements of China and other developing countries to promote low-carbon economic growth. The analysis of this issue can more effectively provide policy-makers with theoretical explanations and decision-making suggestions. Second, the existing literature mainly uses linear analysis methods to explore the impact of technological innovation on the socio-economic system but ignores the analysis of the effect of technological innovation from a non-linear perspective, especially the lack of research on industrial carbon productivity. Third, due to the significant differences in the technological innovation capabilities and industrial carbon productivity levels of various regions in China, the traditional spatial homogeneity hypotheses studied in the past have defects in explaining the effects of technological innovation. Therefore, based on the current research results, this article attempts to use the spatial panel regression model and the threshold panel regression model to analyze the impact of technological innovation on industrial carbon productivity and provide empirical evidence for in-depth exploration of the low-carbon effects of technological innovation.

Model construction and variable selection

Model construction

This article focuses on the impact of technological innovation on the improvement of industrial carbon productivity while considering that industrial carbon productivity may also be affected by other non-technical factors. Therefore, the economic development level (GDP_{it}), urbanization level (UR_{it}), energy intensity (EI_{it}), and industrial structure (IS_{it}) are introduced to establish the following measurement model

$$CP_{it} = \beta_0 + \beta_1 TI_{it} + \beta_2 GDP_{it} + \beta_3 UR_{it} + \beta_4 EI_{it} + \beta_5 IS_{it} + \varepsilon_{it} \tag{1}$$

Variable selection

(1) Industrial carbon productivity (CP). The connotation of industrial carbon productivity is to promote high-quality economic development, which includes two aspects, more total economic output, and fewer pollutant emissions. For China’s current environmental protection work, the most important thing is to control carbon dioxide emissions. Therefore, this article uses the ratio of GDP to carbon dioxide emissions to indicate the degree of industrial carbon productivity. The larger the value, the higher the level of industrial carbon productivity.

(2) Technological innovation (TI). This article uses the number of patent applications granted to characterize technological innovations, including invention patents; use model patents; and design patents. Due to the significant differences in the economic value and degree of innovation and technological importance of these three types of patents, this article draws on the practice of Bai and Wang (2016); respectively assigns the rights of 0.2, 0.3, and 0.5 to the three kinds of patents; and uses the weighted average value as the measure of technological innovation.

(3) In this paper, the following four variables are selected to control the unobservable regional characteristic effects. Economic development level (GDP) is measured by the actual GDP of each region; to eliminate the influence of inflation factors, the data are deflated based on the 2009 base period. Urbanization (UR) is measured by the proportion of the urban population in the total population. Energy intensity (EI) is measured by energy consumption per unit of GDP. Industrial structure (IS) is measured by the ratio of the added value of the tertiary industry to the regional GDP.

Descriptive statistical analysis

The data used in this article all come from the “China Statistical Yearbook,” “China Environmental Statistical Yearbook,” “China Energy Statistical Yearbook,” statistical yearbooks of various regions, and open data platforms. To improve the accuracy and credibility of the estimation and for the possible impact of price fluctuations, this article uses GDP index, consumer price index, and fixed asset investment price index to deflate all currency quantities and adjust them to compare prices. At the same time, to avoid heteroscedasticity and multicollinearity, this paper takes the logarithm of related variables.

Table 1 shows the correlation matrix and descriptive statistics of the variables, it can be seen from the test results that most variables are correlated at the 1% significance level, and the correlation coefficient between core variables is significant. For example, the correlation coefficient between technological innovation and industrial carbon productivity is 0.6202 at the 1% significance level, indicating that a high level

Table 1 Correlation matrix and summary statistics of variables

Variable	<i>CP</i>	<i>TI</i>	<i>GDP</i>	<i>EI</i>	<i>UR</i>	<i>IS</i>
<i>CP</i>	1.000					
<i>TI</i>	0.6202***	1.000				
<i>GDP</i>	0.5771***	0.6172***	1.000			
<i>EI</i>	0.6802***	0.7377***	0.5158***	1.000		
<i>UR</i>	0.5986***	0.5301***	0.9422***	0.4979***	1.000	
<i>IS</i>	0.6598***	0.3623***	0.6008***	0.3517***	0.6734***	1.000
Mean	0.553	8.461	1.309	0.983	3.988	0.456
SD	0.374	1.475	0.480	0.502	0.222	0.100
Min	0.074	4.363	0.101	0.324	3.398	0.293
Max	2.802	11.484	2.442	2.507	4.495	0.885

of technological innovation can help increase industrial carbon productivity.

Quantitative analysis of low-carbon effects of technological innovation model

The spatial characteristics of low-carbon effects of technological innovation

Spatial correlation analysis

To test whether the spatial effect of technological innovation and industrial carbon productivity exists, this article uses the global Moran I index and Moran scatter plot to analyze the spatial correlation and the degree of regional correlation between technological innovation and industrial carbon productivity.

First, construct a spatial weight matrix w_{ij} that satisfies the following conditions. The matrix elements are determined using the “economic distance” matrix standard:

$$W^* = W \times E \quad (2)$$

$$E_{ij} = \frac{1}{|\bar{Y}_i - \bar{Y}_j|} (i \neq j) \quad (3)$$

The Moran I test was conducted on the spatial correlation of China’s technological innovation and industrial carbon productivity from 2009 to 2017. The results are shown in Table 2. Moran I’s normal statistic Z value of technological innovation and industrial carbon productivity is higher than the critical value of 0.01 level (1.96) in 2009–2017. This shows that technological innovation and industrial carbon productivity between provinces in China are greatly affected by spatial distribution, which has apparent spatial agglomeration characteristics. This paper mainly probes into the mechanism of Internet development affecting high-quality growth, and in view of

this research topic, this paper adopts the panel data regression method for empirical research. The econometric model is constructed as follows:

During the sample period, according to the partial scatter plots of technological innovation and industrial carbon productivity (as shown in Fig. 1 and Fig. 2), combined with the LISA clustering diagram (as shown in Fig. 3 and Fig. 4), it can be seen that each point represents a province. Most of the points fall in the first and third quadrants, which show that the technological innovation and industrial carbon productivity of various provinces in China show visible characteristics of “high-high” and “low-low” agglomeration, and there is a robust spatial similarity within provinces.

The above analysis shows that technological innovation and industrial carbon productivity each has obvious spatial correlation, which is characterized by the fact that provinces with higher technological innovation (industrial carbon productivity) levels are adjacent to each other. Provinces with lower technological innovation (industrial carbon productivity) levels are adjacent to each other. Therefore, it is necessary to use spatial measurement models further to analyze the low-carbon effects of technological innovation.

Construction of spatial panel regression model

When the observed individuals are interdependent in space, the geospatial factors are mainly manifested as the model containing the dependent variable spatial lag or spatial error term. Among them, the first model is called the spatial autoregressive model (SLM), and the second model is called the spatial error model (SEM). LeSage (2008) built a Spatial Durbin Model (SDM) that includes both endogenous explanatory variables and exogenous explanatory variables.

If it is assumed that the spatial autocorrelation relationship between variables is reflected by the spatial lag of the dependent variable, the spatial autoregressive model used to investigate the low-carbon effect of technological innovation is:

Table 2 Moran I of China’s technological innovation and industrial carbon productivity

		2009	2010	2011	2012	2013	2014	2015	2016	2017
Technological innovation	Moran I	0.202	0.192	0.181	0.162	0.165	0.159	0.163	0.178	0.171
	Critical value Z	2.599	2.496	2.371	2.173	2.205	2.146	2.183	2.342	2.271
Industrial carbon productivity	Moran I	0.235	0.207	0.228	0.234	0.199	0.230	0.225	0.242	0.223
	Critical value Z	3.009	2.771	3.041	3.094	2.75	3.089	3.116	3.411	3.242

$$CP_{it} = \beta_0 + \beta_1 TI_{it} + \beta_2 GDP_{it} + \beta_3 UR_{it} + \beta_4 EI_{it} + \beta_5 IS_{it} + \rho \sum_j \omega_{ij} CP_{it} + s_i + \varepsilon_{it} \tag{4}$$

where s_i is the spatial fixed effect, ε_{it} is the random error term, and ω_{ij} is the spatial weight matrix. $\sum_j \omega_{ij} CP_{it}$ is the spatial lag variable, and ρ is the spatial autoregressive coefficient, which measures the direction and extent of the influence of explanatory variables such as the level of adjacent technological innovation on the industrial carbon productivity of the central area.

If it is assumed that the error interference term reflects the spatial autocorrelation between variables, the spatial error model used to investigate the low-carbon effect of technological innovation is:

$$CP_{it} = \beta_0 + \beta_1 TI_{it} + \beta_2 GDP_{it} + \beta_3 UR_{it} + \beta_4 EI_{it} + \beta_5 IS_{it} + \lambda \sum_j \omega_{ij} \varepsilon_{it} + s_i + \mu_{it} \tag{5}$$

where $\sum_j \omega_{ij} \varepsilon_{it}$ is the spatial lag error term and λ is the spatial error autocorrelation coefficient, which measures the direction and extent of the impact of the error in the adjacent area on the industrial carbon productivity level in the central area.

If it is assumed that the spatial autocorrelation between variables is reflected by the explanatory variable spatial lag, the spatial Dubin model used to investigate the low-carbon effects of technological innovation is:

$$CP_{it} = \beta_0 + \beta_1 TI_{it} + \beta_2 GDP_{it} + \beta_3 UR_{it} + \beta_4 EI_{it} + \beta_5 IS_{it} + \beta_7 W(TI_{it}) + \beta_8 W(GDP_{it}) + \beta_9 W(UR_{it}) + \beta_{10} W(EI_{it}) + \beta_{11} W(IS_{it}) + \rho \sum_j \omega_{ij} CP_{it} + s_i + \varepsilon_{it} \tag{6}$$

where $W(TI_{it}), W(GDP_{it}), W(UR_{it}), W(EI_{it})$, and $W(IS_{it})$ represent the spatial variables of regional technological innovation level, economic development level, urbanization level, energy intensity, and industrial structure, respectively.

Spatial panel regression model selection

Before conducting a formal spatial measurement model analysis, it is necessary to perform model estimation and statistical testing on the non-spatial panel measurement model and

Fig. 1 Moran scatter plot of the mean value of technological innovation from 2009 to 2017

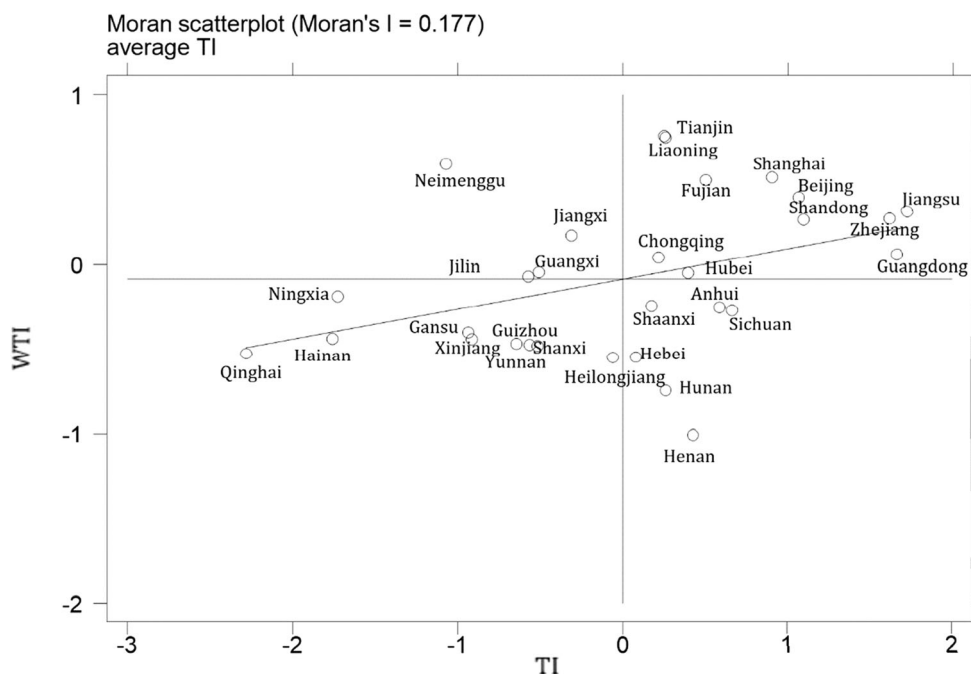
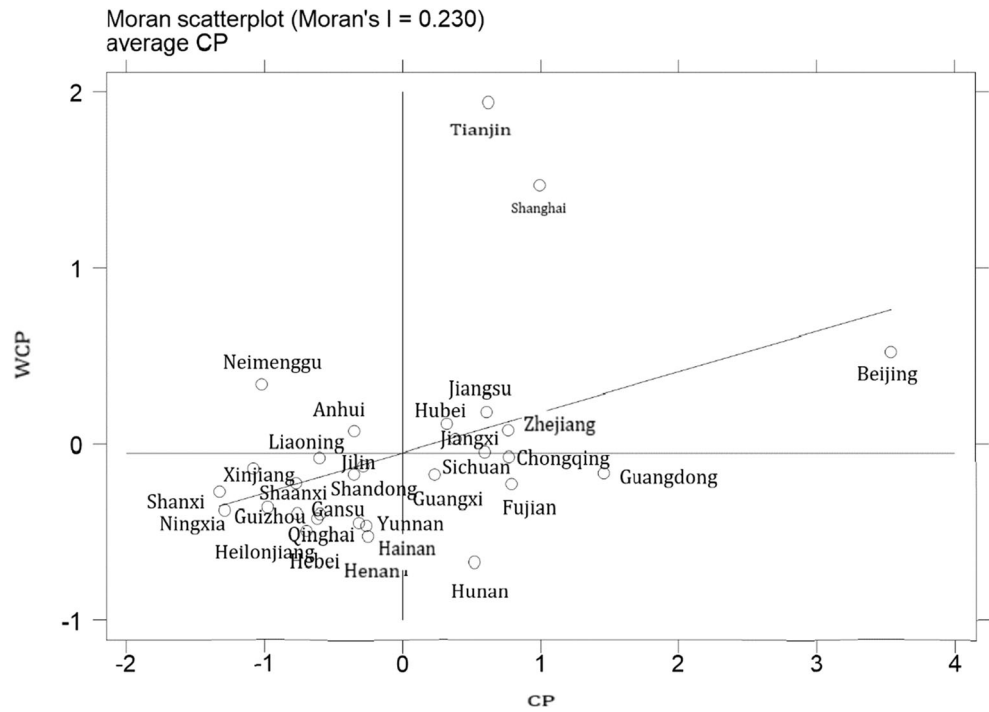


Fig. 2 Moran scatter plot of the mean value of carbon production from 2009 to 2017



further judge the existence of spatial correlation through the LM test. This paper selects the combined OLS model, space fixed-effect model, time fixed-effect model, and time-space fixed-effect model for model estimation. The results are shown in Table 3.

Combining the two L.R. spatiotemporal effect tests and the log-likelihood function value Log-L, it can be seen that it is more appropriate to select the individual and time double fixed-effect model. The Log-L value is 239.6467, which shows that the double fixed effects model has a better fit,

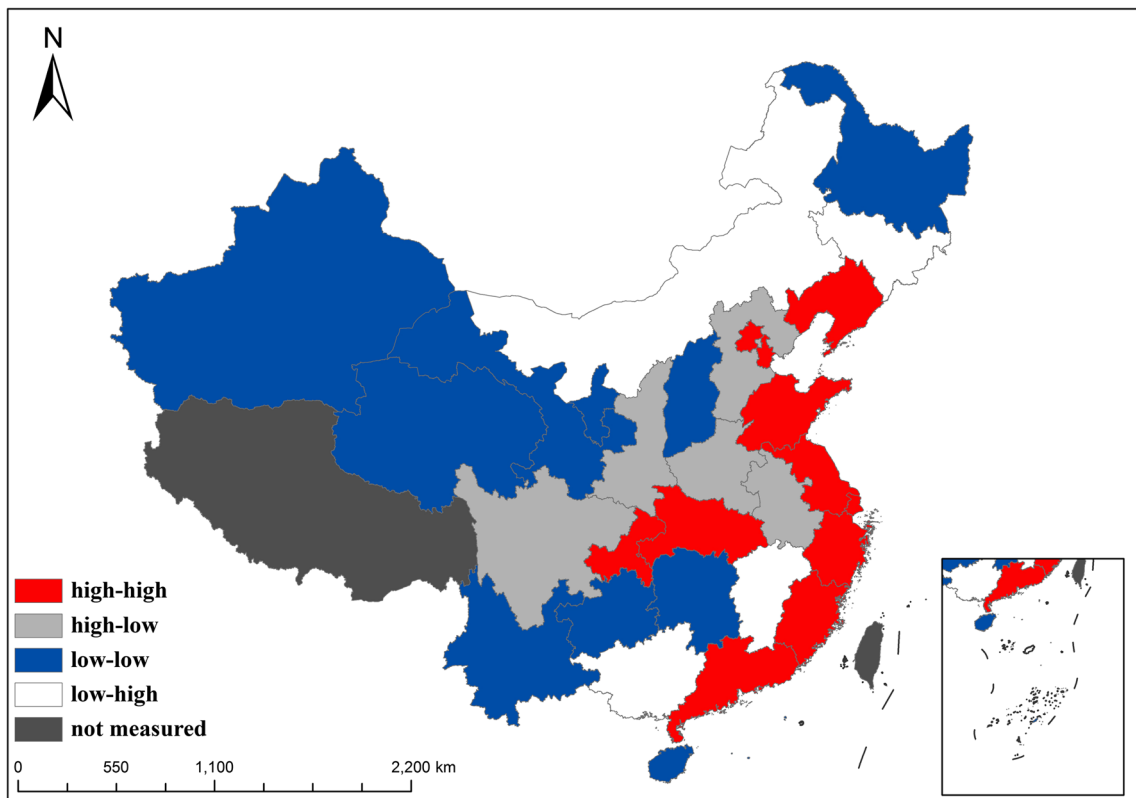


Fig. 3 Technological innovation average LISA Map

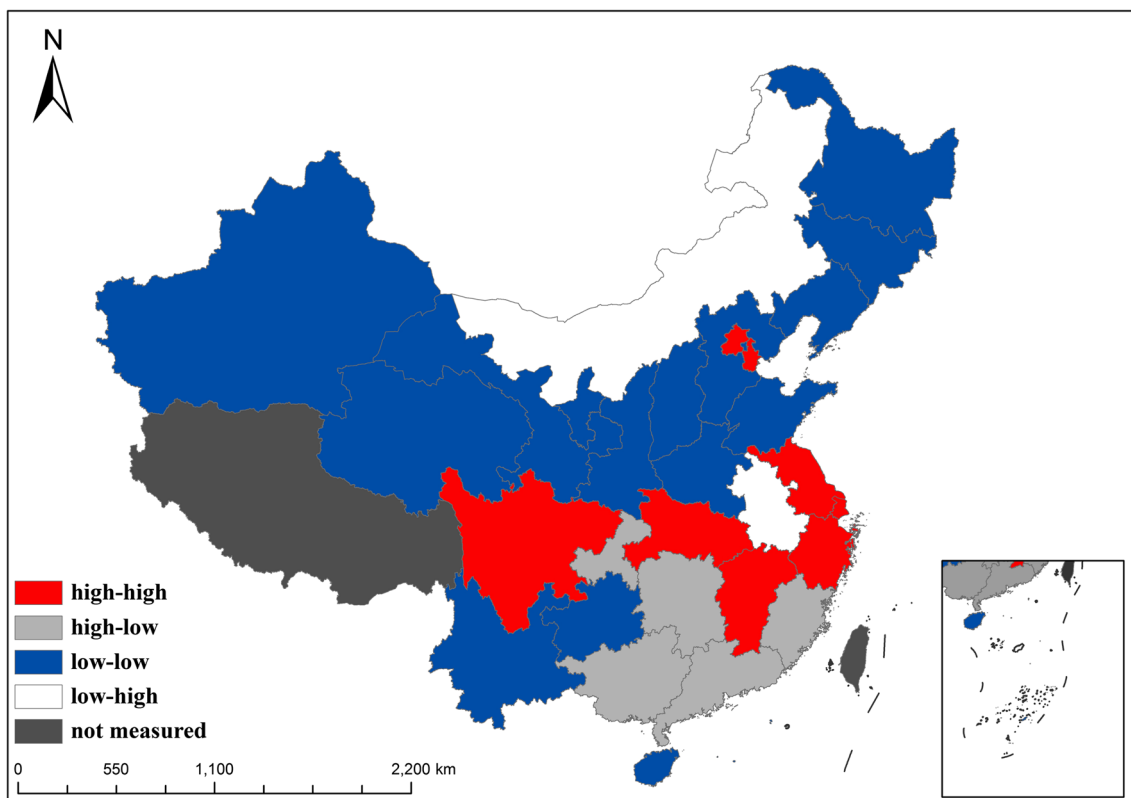


Fig 4 Carbon production average LISA Map

and both types of LR tests pass the significance test, indicating that rejection degenerates into a special effect and time effect model. Besides, this paper performs a classic LM test and a robust LM test on various models to judge further the existence of spatial correlation and the choice of SEM and SLM models. Table 3 shows that under the spatial and temporal effects, the panel data passed the significance test, indicating that there is a spatial lag correlation. According to the selection

rules of SLM and SEM, the spatial lag model (SLM) should be considered.

Before the specific model is determined, it is necessary to pass the Wald test and L.R. test to determine whether the SDM model can degenerate into SLM or SEM. Among them, the Wald test is used to judge whether SDM can degenerate into SLM, and L.R. test is used to judge whether SDM can degenerate into

Table 3 Non-spatial panel model estimation results

Variable	Pooled OLS	Spatial fixed effects	Time period fixed effects	Spatial and time period fixed effects
Intercept	-0.687716 (-1.107141)			
TI	0.04270*** (2.8810)	0.0692* (1.6605)	0.0416*** (2.8244)	0.0487 (1.1400)
GDP	-0.0532 (-0.6750)	0.6287*** (4.6405)	0.0399 (0.4204)	0.0787 (0.3243)
EI	-0.2961*** (-7.4638)	-0.1850**(-2.0368)	-0.2999*** (-7.5887)	-0.1060 (-1.1696)
UR	0.1170 (0.6794)	-1.9179***(-7.3589)	-0.0893 (-0.4367)	-1.7495*** (-6.4444)
IS	1.6931*** (9.5283)	0.6742*** (3.3025)	1.8869*** (9.3738)	-0.7351** (-2.2568)
R ²	0.6759	0.5433	0.6505	0.1854
Log-L	34.6855	222.8066	37.0938	239.6467
LM-lag	0.0343	15.5543***	0.226	4.1726**
(Robust)	0.5868	72.8608***	0.0021	41.0398***
LM-error	0.8135	0.4764	0.333	0.0051
(Robust)	1.366	57.7828***	0.1091	36.8723***
LR-test joint significance spatial fixed effects			405.1059***	
LR-test joint significance time period fixed effects			33.6803***	

Table 4 Test results

Test	Statistics
Wald test	147.28***
Ratio test	146.19***
Hausman test	83.76***
LM1 test	58.44***
LM2 test	504.66***

SEM. It can be seen from Table 4 that the two types of test statistics both pass the 1% significance test, indicating that the null hypothesis that can be degenerated into SLM or SEM is rejected. At the same time, using the Hausman test and L.R. test to select specific effect models, the three types of test statistics are all significant at the 1% level, and the null hypothesis is also rejected.

Therefore, this article finally chooses the classic double fixed effect spatial Dubin model for conducting spatial econometric analysis on the low-carbon effects of technological innovation.

Spatial measurement estimation results

The estimated results of the spatial Durbin model under different effects are shown in Table 5. Among them, the spatial effect and the space-time effect are substantial in Log-L, and the number of significant variables is large, indicating that the spatial panel data has visible spatial effects. Whether it is from Spatial tho significance level, Log-L or significant variable analysis, double fixed effects are a more appropriate model choice. From the displayed results, technological innovation has a significant positive impact on regional industrial carbon

Table 6 SDM affect decomposition

Effect	Variable	Spatial and time period fixed effects		
		Coefficients	z Values	Std. Err.
LR-Direct	TI	0.1185***	3.37	0.0351
	GDP	0.0467	0.24	0.1955
	EI	-0.1109	-1.59	0.0699
	UR	-0.4586	-1.62	0.2824
LR-Indirect	IS	0.2538	0.92	0.2771
	TI	0.3065***	4.18	0.0732
	GDP	2.9341***	6.3	0.4656
	EI	-0.3478*	-1.94	0.1797
LR-Total	UR	-6.5905***	-12.43	0.5300
	IS	1.2061*	1.89	0.6383
	TI	0.4251***	5.48	0.0775
	GDP	2.9809***	6.56	0.4545
	EI	-0.4588**	-2.55	0.1798
	UR	-7.0492***	-14.94	0.4719
	IS	1.4599**	2.17	0.6725

productivity. For every 1% increase in technological innovation, regional industrial carbon productivity will rise by 0.1383%. Among the control variables, urbanization and energy intensity both have an adverse effect on industrial carbon productivity. Besides, all spatial lag variables have passed the significance test, and the coefficients are the same as the original variables, indicating that the industrial carbon productivity of a specific geographic space unit depends on various explanatory variables in other geographic spaces and has significant exogenous interaction effects.

Table 5 SDM estimation results

Variable	Spatial fixed effects		Time period fixed effects		Spatial and time period fixed effects	
	Coefficients	z Values	Coefficients	z Values	Coefficients	z Values
TI	0.0733**	2.02	0.0123	0.79	0.1383***	3.99
GDP	-0.0622	-0.29	0.0554	0.34	0.2528	1.26
EI	-0.1483*	-1.93	-0.3620***	-8.79	-0.1418**	-1.97
UR	-0.6074**	-2.1	-0.1616	-0.81	-0.9150***	-3.46
IS	0.0532	0.19	1.7471***	7.02	0.3329	1.20
W*TI	0.1152	1.53	-0.2286***	-3.68	0.4366***	4.26
W*GDP	1.1809***	3.89	0.5861*	1.65	3.8169***	7.38
W*EI	-0.3999**	-2.2	-0.6485***	-4.08	-0.4849**	-2.03
W*UR	-5.1462***	-8.23	-0.6521	-1.17	-8.7311***	-11.95
W*IS	1.8122***	5.41	-0.9924**	-1.99	1.6123**	2.04
Spatial rho	-0.1305	-1.32	0.0662	0.63	-0.3697***	-3.59
R ²	0.6776		0.4480		0.5496	
Log-L	270.9560		47.8468		300.1758	

Furthermore, the more critical application of spatial measurement model estimation is to explore the various spatial effects of each variable of spatial panel data on regional industrial carbon productivity, including direct effects, indirect effects, and total effects. The estimated results are shown in Table 6. The direct effect refers to the cumulative effect of spatial feedback on the impact of this province on neighboring provinces, including the internal impact of its province and the feedback effect of neighboring provinces after being affected by the province. The indirect effect is the spillover effect, which means the indirect influence of one’s province on neighboring provinces. The total effect represents the sum of the direct and indirect effects of a variable.

It can be seen from Table 6 that technological innovation has significant direct, indirect, and total effects, and the impact coefficients are all positive, indicating that technological innovation not only promotes the province’s green economy but also has apparent spatial spillover effects on neighboring provinces. This shows that technological innovation is an essential means to improve industrial carbon productivity within and around the region and promote a low-carbon economy. Compared with technological innovation, the four types of control variables set in this article do not have significant direct effects, because the feedback effects they contain are not noticeable. However, their spatial spillover effects are significant, indicating that the spillover effects of the control variables on neighboring provinces are more prominent. The level of economic development and the upgrading of industrial structure can significantly promote the industrial carbon productivity of the provinces around the region, while energy intensity and urbanization significantly reduce the level of industrial carbon productivity. In the comparison of the coefficient values, the driving effect of economic development is more substantial, indicating that increasing the level of economic development can provide material support for the development of green economy and is an effective measure to promote industrial carbon productivity. The urbanization has a more substantial inhibitory effect, indicating that the environmental pollution caused by urbanization poses specific challenges to the development of low-carbon economy.

Table 7 Test results of threshold significance

Threshold	F-value	p value	Critical value		
			1%	5%	10%
Single threshold	60.88**	0.0200	40.7969	48.6203	80.0511
Double threshold	42.04*	0.0600	34.9514	45.5822	72.9351
Triple threshold	35.31	0.5567	85.5358	95.3846	124.6822

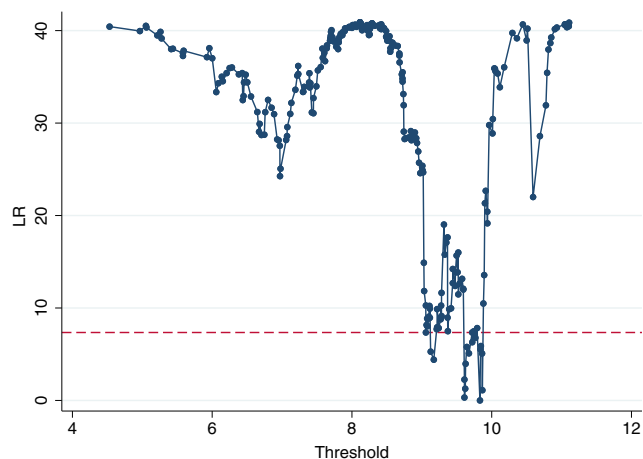


Fig. 5 The first threshold value

Panel threshold model analysis

Model construction

The previous article has verified the existence of the spatial effect of technological innovation on industrial carbon productivity. However, due to the significant differences in the technological innovation capabilities and industrial carbon productivity of various regions in China, the level of technological innovation may have a positive impact on the technological spillover effect. In other words, the impact of technological innovation on industrial carbon productivity may not be a mere promotion. Still, it may show a complicated non-linear relationship due to different levels of regional technological innovation. To verify the above relationship, this paper uses the non-dynamic panel threshold regression model proposed by Hansen (1999) to test the threshold effect between technological innovation and industrial carbon productivity and then analyze the optimal scenario of technological innovation to promote the development of the low-carbon economy. Based on this, this article builds the following model:

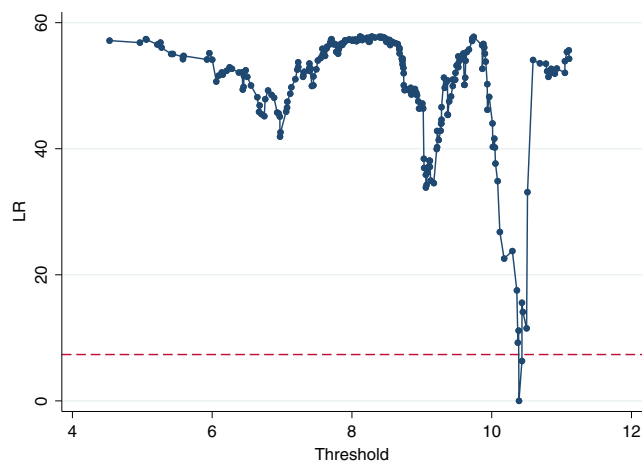


Fig. 6 The second threshold value

Table 8 Threshold values and confidence intervals

Model	Threshold estimators	95% confidence intervals
Single threshold	9.8315	[9.7672, 9.8403]
Double threshold	10.3900	[10.3849, 10.4328]

The threshold value under the single threshold model is γ ; for the two cases of $TI_{it} \leq \gamma$ and $TI_{it} > \gamma$, the impact of technological innovation on industrial carbon productivity shows significant differences. This paper constructs a single threshold model with technological innovation as the threshold:

$$CP_{it} = \mu_i + \beta_1 TI_{it} \times I(TI_{it} \leq \gamma) + \beta_2 TI_{it} \times I(TI_{it} > \gamma) + \beta X_{it} + \varepsilon_{it} \tag{7}$$

where γ is the threshold value, $I(\bullet)$ is the index function, and the value is 1 when the corresponding conditions are satisfied. Otherwise, it is 0, $\varepsilon_{it} \sim \text{idd}(0, \delta^2)$ is random interference, and the other variables are the same as above.

The above model assumes that there is only one threshold, and when there is a double threshold or multiple thresholds, the model can be expanded on this basis. Take the double threshold as an example ($\gamma_1 < \gamma_2$); the model is as follows:

$$CP_{it} = \theta + \alpha_1 GDP_{it} + \alpha_2 UR_{it} + \alpha_3 EI_{it} + \alpha_4 IS_{it} + \beta_1 TI_{it} \times I(TI_{it} \leq \gamma_1) + \beta_2 TI_{it} \times I(\gamma_1 < TI_{it} \leq \gamma_2) + \beta_3 TI_{it} \times I(TI_{it} > \gamma_2) + \varepsilon_{it} \tag{8}$$

(2) Hypothesis testing

Test 1: Whether the threshold effect is significant. Taking a single threshold model as an example, the original hypothesis is $H_0 : \beta_1 = \beta_2$, which means that there is no threshold effect. The corresponding alternative hypothesis is $H_1 : \beta_1 \neq \beta_2$, indicating that there is a threshold effect. Construct LM statistics to perform statistical verification on the null hypothesis, and the test statistic is $F(\gamma) = [SSE_0 - SSE_1(\hat{\gamma})] / \hat{\sigma}^2$. $SSE_0(\gamma)$ and

$SSE_1(\hat{\gamma})$ are the residual sum of squares obtained under the assumption of H_0 and H_1 , respectively. Since $F(\gamma)$ is a non-standard distribution under the null hypothesis H_0 , Hansen (1999) proposed to use Bootstrap self-sampling to obtain an asymptotic distribution and then calculate the P value that accepts the null hypothesis.

Test 2: Whether the threshold estimate is equal to the actual value. The original hypothesis is $H_0 : \hat{\gamma} = \gamma_0$, the alternative hypothesis is $H_1 : \hat{\gamma} \neq \gamma_0$, and the corresponding likelihood ratio statistic is $LR_1(\gamma) = [SSE_1(\gamma) - SSE_1(\hat{\gamma})] / \hat{\sigma}^2$. $SSE_1(\gamma)$ and $SSE_1(\hat{\gamma})$ are the residual sum of squares obtained under the assumption of H_0 and H_1 , respectively, $LR_1(\gamma)$ is non-standard distribution. When $LR_1(\gamma_0) > c(\alpha)$, the null hypothesis should be rejected, where $c(\alpha) = -2\log(1 - \sqrt{1 - \alpha})$, and α represents the significance level.

Results and analysis of the panel threshold model

Based on the panel threshold measurement method, this paper conducts an empirical study on the complex mechanism between the technology innovation level and industrial carbon productivity in each region. The F -value obtained after 300 repeated sampling and the corresponding self-sampling P -value are shown in Table 7. Both the single threshold and double threshold effects of the model have passed the test; that is, there is a significant double threshold effect. The threshold values are 9.8315 and 10.3900, respectively. Therefore, this article analyzes the dual-threshold effect in detail.

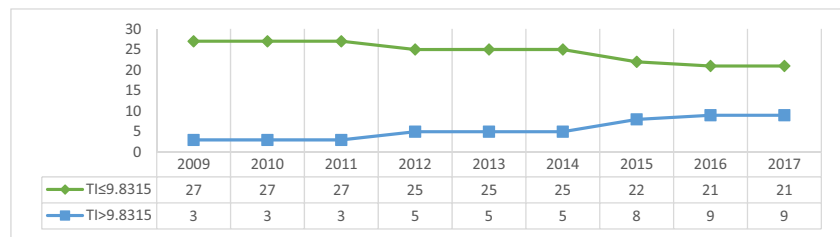
To observe the threshold value estimation and confidence interval more clearly, this paper uses the least square likelihood ratio statistic L.R. to identify the threshold value, and the threshold estimate is the value of γ when L.R. is zero. Next, this article draws the likelihood ratio function diagrams of the two threshold values, as shown in Fig 5 and Fig 6.

Table 8 reports two threshold estimates and 95% confidence intervals. In combination with Fig 5 and Fig 6, it can be seen that the 95% confidence intervals of the two threshold values γ_1 and γ_2 are [9.7672, 9.8403] and [10.3849, 10.4328],

Table 9 Distribution of relative thresholds of technology innovation levels in 30 provinces of China from 2009 to 2017

	9.8315 < TI ≤ 10.3900	TI > 10.3900
2009	Jiangsu, Zhejiang, Guangdong	
2010	Zhejiang, Guangdong	Jiangsu
2011		Jiangsu, Zhejiang, Guangdong
2012-2014	Beijing, Shandong	Jiangsu, Zhejiang, Guangdong
2015	Shanghai, Anhui, Shandong, Sichuan	Beijing, Jiangsu, Zhejiang, Guangdong
2016	Shanghai, Anhui, Fujian, Shandong, Sichuan	Beijing, Jiangsu, Zhejiang, Guangdong
2017	Shanghai, Anhui, Fujian, Sichuan	Beijing, Jiangsu, Zhejiang, Guangdong, Shandong

Fig. 7 Change trend of technological innovation threshold



respectively, and all L.R. values are less than 7.35, which is the critical value at the 5% significance level.

The above analysis shows that the impact of technological innovation on industrial carbon productivity is non-linear. According to the threshold effect test, two threshold variables can be obtained, and the estimated values are 9.8315 and 10.3900. To further analyze the relative threshold distribution of the technological innovation level of my country’s 30 provinces from 2009 to 2017, the samples can be divided into three groups, namely “low level,” “medium level,” and “high level”; the grouping results are shown in Table 9 and Fig. 7.

The threshold regression results show that technological innovation has a positive effect on industrial carbon productivity (as shown in Table 10), but there are individual differences. When the level of technological innovation is lower than 9.8315, every 1% increase in innovation capability will promote a 0.0573% increase in industrial carbon productivity, but it fails the significance test. When the level of technological innovation crosses the first threshold, which is between 9.8315 and 10.3900, the positive impact of technological innovation on industrial carbon productivity is enhanced, and the coefficient of elasticity is 0.0756 at a significant level of 0.05. As the level of technological innovation crosses the second threshold, technological innovation has the most effective promotion of industrial carbon productivity, and the coefficient of elasticity is 0.0991 at a significant level of 0.01. This shows that the high-tech innovation level range is the optimal range; at this time, technological innovation can effectively promote regional industrial carbon productivity.

From the above analysis results, it is not difficult to see that when discussing the relationship between technological

innovation and industrial carbon productivity, it is necessary to consider the innovation foundation of each region fully. The specific analysis is as follows.

In areas with medium and high technological innovation levels, not only are the accumulation levels of technological innovation relatively high, but also their modern ecological concepts, energy-saving technologies, and green production capabilities are strong. Technological innovation is more significant in driving economic low-carbon growth. The main reason is that in regions with a high level of technological innovation, the level of energy-saving technologies such as technology integration and process optimization can effectively save resources, thereby improving energy efficiency, promoting the decoupling of energy consumption and economic development, and reducing pollutant emissions. This in turn improves industrial carbon productivity. Besides, technological innovation has a clustering effect. In areas with a high level of technological innovation, the industrial chain has been improved and optimized, which has changed the traditional resource allocation structure of production factors and optimized the input-output structure. Industrial labor production efficiency and resource and environmental output efficiency are both high. In turn, it can promote the transformation of the regional economy to low-carbon development and increase industrial carbon productivity.

In areas with low technological innovation levels, although the coefficient of interaction between technological innovation and industrial carbon productivity is positive, it is not significant. The main reason is that in the early stage of technological innovation activities of enterprises, the improvement of production technology and the update of supporting

Table 10 Estimation results of model parameters.

CP	Coef.	Std. Err	t	$p > t $	95% Conf. Interval	
GDP	0.4174	0.1255	3.33	0.001	0.1701	0.6647
UR	-0.2568	0.0832	-3.09	0.002	-0.4207	-0.0929
EI	-1.4571	0.2426	-6.01	0.000	-1.9350	-0.9792
IS	0.4378	0.1879	2.33	0.021	0.0675	0.8080
TI(TI ≤ 9.8315)	0.0573	0.0380	1.51	0.133	-0.0176	0.1321
TI(9.8315 < TI ≤ 10.3900)	0.0756	0.0381	1.98	0.049	0.0004	0.1508
TI(TI > 10.3900)	0.0991	0.0381	2.60	0.010	0.0240	0.1741
cons	5.3260	0.9206	5.79	0.000	3.5121	7.1398

facilities require a large number of scientific research funds. However, technological innovation is a complex process involving many aspects such as industrial structure transformation and upgrading and input and output of innovative elements. In the short term, it is challenging to produce noticeable innovation spillover effects. On the other hand, the sustainable development ideas of governments, enterprises, and the public in low-tech innovation areas are not mature, and the penetration and popularity of ecological civilization construction are not high. These factors have weakened the low-carbon development effect of technological innovation.

In terms of control variables, the level of economic development and industrial structure is significantly positive at the 5% level, indicating that the level of economic development and the essential influencing factors of the industrial structure have a significant positive effect on low-carbon economic growth. Energy intensity and urbanization have a significant negative impact on carbon productivity, indicating that China's current urbanization development is unsustainable and is not conducive to improving regional industrial carbon productivity. This is consistent with the conclusion drawn above.

Conclusions

In the context of economic transformation, relying on technological innovation to promote industrial carbon productivity is a crucial measure for China and other developing countries to promote low-carbon sustainable development. Based on the possible spatial spillovers and threshold effects of technological innovation on the improvement of industrial carbon productivity, this paper uses relevant data from 30 provinces in China from 2009 to 2017 to study the spatial and non-linear relationship between technological innovation and industrial carbon productivity. This article has achieved the following research conclusions.

First, China's technological innovation and industrial carbon productivity both have strong spatial spillover effects. Technological innovation not only responds to the promotion of the green economy in the region but also has apparent spatial spillover effects on neighboring provinces. At the same time, regional industrial carbon productivity is not only affected by related indicators in the region but also affected by related indicators in surrounding areas. Second, technological innovation plays an essential role in improving industrial carbon productivity. The direct effects, spillover effects, and total effects tests all verify the existence of low-carbon effects of technological innovation. Third, technological innovation has a noticeable threshold effect on the improvement of industrial carbon productivity. As technological innovation continues to cross the threshold, the low-carbon effect of technological innovation has become more and more prominent, and the coefficient of action has gradually increased. When

technological innovation crosses the second threshold of 10.39, every 1% increase in technological innovation will promote a 0.0991% increase in industrial carbon productivity, and the promotion effect is the most obvious.

Based on the above research conclusions, to promote China to improve the level of technological innovation better, and effectively promote the increase of industrial carbon productivity, this paper proposes the following recommendations:

First, because of the regional imbalance in China's technological innovation capabilities, the construction of a regional technological innovation system should be further strengthened to narrow the technological innovation gap. For regions with a low level of technological innovation, it is necessary to increase R&D investment and promote technological innovation cooperation between regions by introducing high-end technological innovation elements, thereby enhancing technological innovation capabilities. Regions with a high level of technological innovation should pay more attention to independent innovation, seek innovation and accumulation of original theories and original technologies, focus on endogenous innovation in economic development, and optimize and improve technological innovation capabilities.

Second, promote regional green technological innovation and realize green and low-carbon circular development. Compared with traditional technological innovation, green technological innovation can effectively use advanced cutting-edge production technology, useless factor input, achieve maximum economic effects, and reduce damage to the ecological environment. As green technology innovation requires more innovation and accumulation, regional governments should try their best to realize the coordinated optimization of green technology R&D systems, application systems, intermediary systems, and security systems.

Third, establish a green technology innovation system and implement the national innovation transformation strategy. The government should promote horizontal coordination between departments and vertical cooperation between regions, optimize the technology and financial system, establish and improve talent collaboration and innovation mechanisms, and use technological innovation as an essential strategy to promote the transformation of regional economic development patterns.

Acknowledgments I am very grateful to the editors and anonymous reviews for reviewing this paper.

Author's contributions Conceptualization: [Han Bing]; Methodology: [Han Bing]; Software: [Han Bing]; Writing-original draft: [Han Bing]; Writing-review and editing: [Han Bing]; Supervision: [Han Bing].

Funding This work was supported in part by the Soft Science Project of Shandong Province under Grant 2019RKB01250, and in part by Shandong Province higher education "Green innovation Science and Technology Plan" project under Grant 2020RWB003.

Data availability The datasets generated during the current study are available in the repository of the National Bureau of Statistics of China, <http://www.stats.gov.cn/>.

Compliance with ethical standards

Ethics approval Not applicable

Consent for participate Not applicable

Consent for publication Not applicable

Conflict of interest I declared that I have no conflicts of interest in this work.

References

- Bai JH, Wang LD (2016) Does the innovation driven promote the improvement of economic growth quality? *Studies in Science of Science* 34:1725–1735
- Beinhocker E, Oppenheim J, Taylor M (2008) The carbon productivity challenge curbing climate change and sustaining economic growth. *McKinsey global institute* 23:45–69
- Binz C, Truffer B, Coenen L (2014) Why space matters in technological innovation systems—mapping global knowledge dynamics of membrane bioreactor technology. *Research Policy* 43:138–155
- Bolli T, Seliger F, Woertel M (2020) Technological diversity, uncertainty and innovation performance. *Applied Economics* 2020:52
- Bravo-Ortega C, Marín ÁG (2011) R&D and productivity: a two-way avenue? *World Development* 39:1090–1107
- Buijtdendijk H, Blom J, Vermeer J (2018) Eco-innovation for sustainable tourism transitions as a process of collaborative co-production: the case of a carbon management calculator for the Dutch travel industry. *Journal of Sustainable Tourism* 26:1222–1240
- Feng JF, Yuan JH (2016) Effect of technology innovation and spillovers on the carbon intensity of human well-being. *SPRINGERPLUS* 5: 346
- Fisher VK, Wing IS (2008) Accounting for quality: issues with modeling the impact of R&D on economic growth and carbon emissions in developing economies. *Energy economics* 30:2771–2784
- Ganda F (2019) The impact of innovation and technology investments on carbon emissions in selected organization for economic co-operation and development countries. *Journal of Cleaner Production* 217:469–483
- Gay C, Szostak BL (2020) From territorialised innovation to collaborative innovation space: what are the issues for contemporary organizations? *JOURNAL OF INNOVATION ECONOMICS & MANAGEMENT*. 32:135–137
- Hall BH, Jaffe AB, Trajtenberg M (2005) Market value and patent citations: a first look. *Social Science Electronic Publishing* 36:16–38
- Han DR, Li TC, Feng SS, Shi ZY (2020) Application of threshold regression analysis to study the impact of clean energy development on China's carbon productivity. *INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH*. 17:1060
- Hansen BE (1999) Threshold effects in non-dynamic panels: Estimation, testing, and inference. *J. Econom.* 93:345–368
- He JK, Su MS (2009) Carbon productivity analysis to address global climate change. *China Soft Science*. 10:42–47
- Iftikhar Y, He WJ, Wang ZH (2016) Energy and CO₂ emissions efficiency of major economies: a non-parametric analysis. *Journal of Cleaner Production*. 139:779–787
- Jin PZ, Zhang YB, Peng X (2014) The double-edged effect of technological progress in carbon dioxide emissions reduction: empirical evidence from 35 sub-industrial sectors in China. *Studies in Science of Science* 32:706–716
- Jo GS, Park G, Kang J (2016) Unravelling the link between technological M&A and innovation performance using the concept of relative absorptive capacity. *Asian Journal of Technology Innovation* 24: 1–22
- Kaya Y, Yokobori K (1997) *Environment, energy and economy: strategies for sustainability*. United Nations University Press, Tokyo, Japan
- Lesage JP (2008) An Introduction to Spatial Econometrics. *Revue D Économie Industrielle* 123:513–514
- Liu GP, Cao LP (2011) Research on carbon productivity based on welfare performance. *Soft Science* 25:71–74
- Li SJ, Wang SJ (2019) Examining the effects of socioeconomic development on China's carbon productivity: a panel data analysis. *Science of total environment* 659:681–690
- Liu Y, Geng Y (2010) An overview on low carbon economy. *China Population, Resources and Environment*. 20:123–128
- Lo K, Broto VC (2019) Co-benefits, contradictions, and multi-level governance of low-carbon experimentation: Leveraging solar energy for sustainable development in China. *GLOBAL ENVIRONMENTAL CHANGE-HUMAN AND POLICY DIMENSIONS*. 59:101993
- Long RY, Gan X, Chen H, Wang JQ, Li QW (2020) Spatial econometric analysis of foreign direct investment and carbon productivity in China: two-tier moderating roles of industrialization development. *RESOURCES CONSERVATION AND RECYCLING*. 155: 104677
- Lu FY, Jin DD (2011) An empirical analysis on the effect of R&D input to economic growth based on panel data. *China Industrial Economics* 3:149–157
- Lu M, Wang X, Cang Y (2018) Carbon productivity: findings from industry case studies in Beijing. *Energies* 11(10)
- Murphy R (2015) The emerging hyper carbon reality, technological and post-carbon utopias, and social innovation to low-carbon societies. *Current Sociology* 63:317–338
- Nguyen TT, Pham TAT, Tram HTX (2020) Role of information and communication technologies and innovation in driving carbon emissions and economic growth in selected G-20 countries. *Journal of Environmental Management* 261:110162
- Oliveira, A.B. The space importance of geographical proximity in scientific research and technological innovation processes. *BOLETIN GOIANO DE GEOGRAFIA*, 2019, 39, UNSP54379.
- Peng X, Tao X (2018) Decomposition of carbon intensity in electricity production: Technological innovation and structural adjustment in China's power sector. *Journal of Cleaner Production* 172:805–818
- Tojeiro-Rivero D, Moreno R (2019) Technological co-operation, R&D outsourcing, and innovation performance at the firm level: the role of the regional context. *Research Policy* 48:1798–1808
- Wang K, Xian YJ, Wei YM, Huang ZM (2016) Sources of carbon productivity change: A decomposition and disaggregation analysis based on global Luenberger productivity indicator and endogenous directional distance function. *ECOLOGICAL INDICATORS* 66: 545–555
- Wang Y, Wang YQ (2013) Dynamic research on environmental regulation, technology innovation and carbon emissions in China—based on impulse response function and variance decomposition method. *Economy and Management* 27:5–10
- Yan SY, Xu XJ (2019) Financial industry agglomeration, technology innovation and regional economic growth—an Analysis based on PVAR model of panel data at provincial level. *Journal of Beijing Institute of Technology (Social Sciences Edition)* 21, 103–109
- Yan ZM, Yang ZM, Du KR (2017) Impact of low-carbon technological innovation on carbon intensity. *Finance & Trade Economics* 38: 112–128

- Yin H, Zhao J, Xi X, Zhang Y (2019) Evolution of regional low-carbon innovation systems with sustainable development: An empirical study with big-data. *Journal of Cleaner Production* 209:1545–1563
- Yu BB (2020) Industrial structure, technological innovation, and total-factor energy efficiency in China. *Environmental Science And Pollution Research* 27:8371–8385
- Zhan W, Zhu DJ, Bai ZL (2010) Research on relationship between industrial carbon emissions and carbon productivity in shanghai. *China Population, Resources and Environment*. 20:24–29

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.