RESEARCH ARTICLE

How does power technology innovation affect carbon productivity? A spatial perspective in China

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Abstract

Power technology innovation has been positioned as an effective way to contribute to China's carbon productivity. However, limited empirical evidence exists on the impact of power technology innovation on carbon productivity. Thus, based on the annual panel dataset of 30 China's provinces from 2001 to 2019, this study explored whether and how power technology innovation promotes or impedes the improvement of carbon productivity. First, carbon productivity in the framework of total factor was calculated based on the metafrontier Malmquist-Luenberger productivity index. Second, the effect of power technology innovation on carbon productivity was investigated using the spatial Durbin model. And we also examined whether heterogeneous power technology innovations have a synergistic effect on carbon productivity. Third, influence mechanism of power technology innovation affecting carbon productivity was identified. Results show that (1) there are notable differences in China's provincial carbon productivity, which is characterized by the spatial correlation. (2) Local power technology innovation has a promotion effect on carbon productivity in both local and neighboring provinces. Moreover, the promotion effect of breakthrough power technology innovation is stronger than that of incremental power technology innovation. (3) Catching-up Effect and Innovation Effect are important transmission channels through which power technology innovation improves carbon productivity. Finally, policy recommendations are provided.

Nomenclature

WTO	World Trade Organization
IPCC	Intergovernmental Panel on Climate Change
DEA	Data environment analysis
ML	Malmquist-Luenberger
MML	Metafrontier Malmquist-Luenberger
EC	Efficiency change
BPC	Best-practice gap change
TGC	Technology gap change
SLM	Spatial lag model
SEM	Spatial error model
SDM	Spatial Durbin model
IPC	International Patent Classification
ED	Economic development
FDI	Foreign direct investment
ER	Environmental regulation
FD	Fiscal decentralization
UL	Urbanization level
ISU	Industrial structure upgrading
PTI	Power technology innovation
CP	Carbon productivity
BPTI	Breakthrough power technology innovation
IPTI	Incremental power technology innovation

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Introduction

Since joining the World Trade Organization (WTO), China has enjoyed high-speed economic growth. To be specific, China's GDP has risen from sixth to second in the world during the past 20 years. However, the environmental issues derived from its extensive growth model have become

extremely severe. At present, China has been the leading energy consumer and carbon emitter in the world (Abbasi et al. 2022b). In 2020, China emitted 9,899.3 million tonnes of carbon dioxide, which accounted for 30.66% of the world's carbon emissions (BP 2021). To curb the increased carbon emissions, China proposed the "Dual carbon" goal in 2020, which makes a pledge to the international community that it will achieve a carbon peak by 2030 and carbon neutrality by 2060.

Different policies and measures aiming to reduce carbon emissions have been adopted to realize the ambitious goal as soon as possible in China. Among them, enhancing carbon productivity has been regarded as one of the most effective paths. Carbon productivity, which acts as an important comprehensive indicator of carbon emission performance, takes both the development of economy and carbon emissions into account in its definition and calculation (Wang et al. 2016). The World Bank and Intergovernmental Panel on Climate Change (IPCC) claimed that increasing carbon productivity is helpful to decrease carbon emissions while maintaining economic growth (Li et al. 2018b). Moreover, carbon productivity is also considered to be a significant determinant of national competitiveness (Long et al. 2020). In terms of China, its carbon productivity is still at a relatively low level (Li and Wang 2019), but has great room for improvement (Iftikhar et al. 2016). To know how to improve carbon productivity, the investigation on determinants of carbon productivity is one essential precondition, which facilitates the formulation of insightful carbon reduction policies. It is worth noting that technology innovation especially, green technology innovation, has been believed to be at the most central position in shaping carbon productivity (Xu et al. 2021).

Despite that many studies have investigated the effect of energy technology innovation on carbon productivity (Wang et al. 2012; Jordaan et al. 2017), the specific discussion on the effect of power technology innovation on carbon productivity is still absent. Power technology innovation involves not only the knowledge innovation with the purpose of developing electricity-related science and technology, but also the product innovation that could advance the commercial application of new electricity-related technologies. Compared to other categories of energy technology innovation, power technology innovation is characterized by more green attributes. Thus, we can speculate that the relationship between power technology innovation and carbon productivity theoretically tends to be positive. But no empirical evidence has been found.

In view of this, the following questions are of interest: Can power technology innovation effectively contribute to the advancement of China's carbon productivity? And whether different types of power technology innovation exert different influences on carbon productivity? Besides,

what are the influence mechanisms that power technology innovation affects carbon productivity? Moreover, given the spatial spillover effects, will local power technology innovation promotes/inhibits carbon productivity in the neighboring regions? To answer these questions, the spatial Durbin model is employed to explore the relationship between power technology innovation and carbon productivity. Figure 1 presents the analytical framework.

Our study makes the following contributions. First, little attention has been paid to the effect of energy technology innovation on carbon productivity at the industrial level. Hence, we will investigate the effect of energy technology innovation in the power industry, specifically, power technology innovation, on carbon productivity, thus identifying the role of power technology innovation in the low-carbon economy. This can inspire comprehensive policy decisions on the carbon abatement target from the industry perspective. Second, our study will take an in-depth look at the spatial characteristics of power technology innovation and carbon productivity. Using spatial econometric models, we will analyze both the direct and indirect effects of power technology innovation on carbon productivity. This would make up for the knowledge gap that most previous studies ignored the existence of spatial spillover effects in examining the environmental influences of energy technology innovation. Third, this study will depict a complete picture of how power technology innovation affects carbon productivity. More specifically, we will not only investigate the transmission channels through which power technology innovation influences carbon productivity but also examine the heterogeneous effects of different types of power technology innovation. Hence, the findings can provide insights for designing policies that enhance carbon productivity.

The remainder of the study is structured as follows: the "Literature review" section reviews the literature. The "Methodology and data" section outlines the econometric methodology and presents the data. The "Results and discussion" section discusses the obtained results. And the "Conclusions and policy implications" section concludes the study and provides policy implications.

Literature review

There have been plentiful studies on the measurement of carbon productivity, and these studies can fall into two categories: single factor indicator and total factor indicator. The former, proposed by Kaya and Yokobori (1997), is defined by the ratio of GDP to carbon emissions. Due to its ease of understanding and use, the single factor indicator has been extensively employed (Hu and Liu 2016; Liang et al. 2017; Li and Wang 2019). However, the single factor indicator only reflects a partial aspect of carbon productivity (Zhou

Fig. 1 Analytical framework
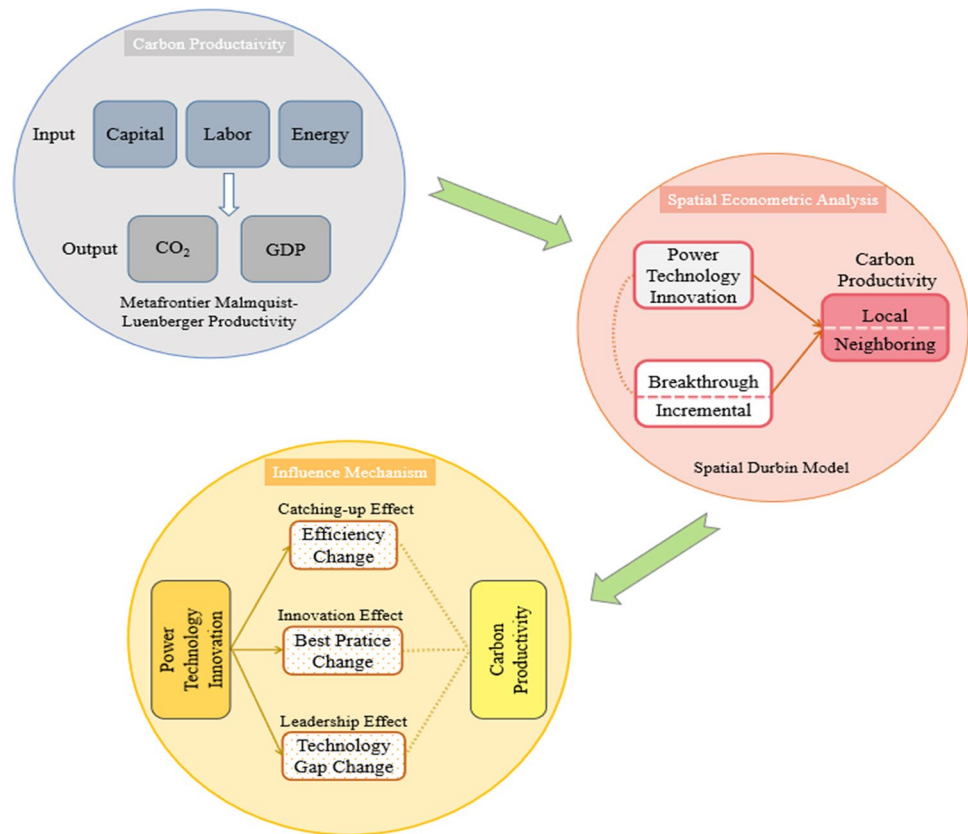
et al. 2010), while carbon productivity is the joint effect of energy consumption, economic development, and other factors (Li et al. 2018b). Given this, the total factor indicator that considers both multiple inputs and multiple outputs in the production technology was subsequently put forward, and it is more accurate and rational to represent carbon productivity. The total factor indicator, therefore, is currently drawing great attention to its development and application (Bai et al. 2019; Gao et al. 2021; Zhou and Tang 2021; Chen and Wu 2022).

As for the measuring methods of carbon productivity under the total factor framework, data environment analysis (DEA), which does not require specific function construction and can handle the problem characterized by multiple inputs and outputs, has been extensively adopted (Bai et al. 2019; Gao et al. 2021; Zhou and Tang 2021; Chen and Wu 2022). For example, Gao and Zhu (2016) assessed total factor carbon productivity in China's industrial sector by employing DEA. Li et al. (2021) developed a generalized equilibrium efficient frontier DEA model, which combines with the Malmquist productivity index to calculate China's regional carbon emission performance. Based on the measurement of carbon productivity, a growing group of literature focuses on exploring the determinants of carbon productivity. Technology innovation (Meng and Niu 2012; Han 2021), foreign direct investment (Pan et al. 2020), environmental regulation

(Ren et al. 2021), urbanization level (Zhao et al. 2020), and industrial structure (Guo et al. 2021) have been included as major factors that determine carbon productivity.

In recent decades, concerns over climate change have generated considerable discussion about the role of technology innovation in reducing carbon emissions or improving carbon productivity. For instance, Iqbal et al. (2021) explored the impact of environmental innovation on carbon emissions. They proposed that environmental-related technology innovation is beneficial to achieving the carbon neutrality target for 37 OECD economies. Han (2021) also examined the low-carbon effects of technology innovation and concluded that technology advancement positively affects China's regional industrial carbon productivity. However, Abbasi et al. (2022a) stated that technology innovation can aggravate carbon emissions in the short term because technology innovation in Pakistan is still in its early stage. In the long term, nevertheless, technology innovation can curb carbon emissions.

With the development of energy systems, the focus on the relationship between energy technology innovation and carbon productivity is increasing, but the consensus on whether energy technology innovation could improve carbon productivity has not been reached yet. For example, Jordaan et al. (2017) investigated the nexus between energy technology innovation and carbon emissions, and found that

energy technology innovation contributes to carbon emissions abatement. However, Wang et al. (2012) argued that energy technology patents have no significant promotion effect on carbon reductions. One possible explanation for this phenomenon is that these studies barely distinguished the categories of energy technology innovation. In other words, different categories of energy technology innovation may produce a distinctive effect on carbon productivity.

Now the gradual promotion of power's position in the energy system has pushed for power technology innovation to become the primary contributor to energy technology innovation. Brathwaite et al. (2010) believed that power technology innovation could speed up the transition of a coal-oriented economy and widen the feasible paths of declining the reliance on traditional fossil fuels. Additionally, He et al. (2021) demonstrated that power technology innovation is conducive to improving the efficiency of electricity use, thus promoting electricity saving.

Despite that the positive environmental effects of power technology innovation have been recognized, its role in shaping carbon productivity has not been fully revealed. In order to complement this subject, spatial econometric models are applied in this study to examine the relationship between power technology innovation and carbon productivity. More specifically, whether and how power technology innovation affects carbon productivity is examined by taking spatial effects into account.

Methodology and data

Measurement of carbon productivity

Malmquist productivity index that could be used to measure dynamic productivity index was proposed by Fare et al. (1994). On this basis, Chung et al. (1997) developed the Malmquist-Luenberger (ML) productivity index with the consideration of undesirable outputs to measure environmental productivity growth. After that, the ML index was widely applied in the field of environmental assessment (Fare et al. 2001; Nakano and Managi 2008; Aparicio et al. 2017). However, the ML productivity index does not take group heterogeneities into account, under which circumstance only biased results can be obtained because heterogeneity across groups might result in different production technology (Choi et al. 2015). To overcome this deficiency, Oh and Lee (2009) put forward the metafrontier Malmquist-Luenberger (MML)

productivity index, which incorporates group heterogeneities into the Malmquist productivity index. Besides considering group heterogeneities, this new index can also obtain better insights into productivity changes as it could decompose the productivity index in more detail. Therefore, the MML productivity index is applied to measure carbon productivity in this study.

Firstly, this study divides all provinces acting as the decision units into three groups: east regions, central regions, and west regions according to their geographical location (Cheng et al. 2018b). Then referring to Oh and Lee (2009), the three technologies, namely the contemporaneous benchmark technology $P_{R_j}^t$, the intertemporal benchmark technology $P_{R_j}^I$, and the global benchmark technology P^G, are set:

$$P_{R_j}^t = \left\{ (K^t, L^t, E^t, Y^t, C^t) \parallel (K, L, E) produce(Y, C) \right\}, \lambda P^t = P^t \tag{1}$$

$$P_{R_j}^I = conv \left\{ P_{R_j}^1 \cup P_{R_j}^2 \cup ... \cup P_{R_j}^T \right\} \tag{2}$$

$$P^G = conv \left\{ P_{R_1}^I \cup P_{R_2}^I \cup ... \cup P_{R_J}^I \right\} \tag{3}$$

where capital (K), labor (L), and energy (E) are the input of factors. GDP (Y) and carbon emissions (C) are treated as desirable output and undesirable output, respectively. P denotes technology set. t is time, $t = 1, ..., T$. And R_j refers to group j, $j = 1, 2, 3$. λ is the intensity vector.

Next, the following three output distance functions under the above technology sets are defined accordingly:

$$D^S(K, L, E, Y, C) = \inf \left\{ \phi > 0 \parallel (K, L, E, Y/\phi, C/\phi) \in P_{R_j}^S \right\}, S = t, t+1 \tag{4}$$

$$D^I(K, L, E, Y, C) = \inf \left\{ \phi > 0 \parallel (K, L, E, Y/\phi, C/\phi) \in P_{R_j}^I \right\} \tag{5}$$

$$D^G(K, L, E, Y, C) = \inf \left\{ \phi > 0 \parallel (K, L, E, Y/\phi, C/\phi) \in P^G \right\} \tag{6}$$

Then, the MML productivity index treated as carbon productivity is constructed as:

$$MML = \frac{D^G(K^{t+1}, L^{t+1}, E^{t+1}, Y^{t+1}, C^{t+1})}{D^G(K^t, L^t, E^t, Y^t, C^t)} \tag{7}$$

The index indicates the dynamic change of each province's carbon productivity. If MML > 1, it means carbon productivity increases compared to the last year, and vice versa.

Furthermore, the MML productivity index can be decomposed as:

$$
\begin{aligned}
MML &= \frac{D^{t+1}(K^{t+1},L^{t+1},E^{t+1},Y^{t+1},C^{t+1})}{D^t(K^t,L^t,E^t,Y^t,C^t)} \times \left\{ \frac{D^t(K^t,L^t,E^t,Y^t,C^t)}{D^{t+1}(K^{t+1},L^{t+1},E^{t+1},Y^{t+1},C^{t+1})} \times \frac{D^G(K^{t+1},L^{t+1},E^{t+1},Y^{t+1},C^{t+1})}{D^G(K^t,L^t,E^t,Y^t,C^t)} \right\} \\
&= \frac{D^{t+1}(K^{t+1},L^{t+1},E^{t+1},Y^{t+1},C^{t+1})}{D^t(K^t,L^t,E^t,Y^t,C^t)} \times \left\{ \frac{D^t(K^t,L^t,E^t,Y^t,C^t)}{D^{t+1}(K^{t+1},L^{t+1},E^{t+1},Y^{t+1},C^{t+1})} \times \frac{D^I(K^{t+1},L^{t+1},E^{t+1},Y^{t+1},C^{t+1})}{D^I(K^t,L^t,E^t,Y^t,C^t)} \right\} \times \\
&\quad \left\{ \frac{D^I(K^t,L^t,E^t,Y^t,C^t)}{D^I(K^{t+1},L^{t+1},E^{t+1},Y^{t+1},C^{t+1})} \times \frac{D^G(K^{t+1},L^{t+1},E^{t+1},Y^{t+1},C^{t+1})}{D^G(K^t,L^t,E^t,Y^t,C^t)} \right\} \\
&= EC \times BPC \times TGC
\end{aligned}
\tag{8}
$$

The efficiency change (EC) reflects technology efficiency change in carbon production between the two time periods (t, $t+1$), which is considered the Catching-up Effect. $EC > 1$ (<1) indicates efficiency improves (diminishes). The best-practice gap change (BPC) represents the change in the best-practice gap ratio between contemporaneous environmental technology and intertemporal environmental technology, being viewed as the Innovation Effect. Similarly, $BPC > 1$ (<1) implies technology increases (decreases). The technology gap change (TGC) is the change in technology gap between intertemporal environmental technology and global environmental technology, which measures the Leadership Effect. $TGC > 1$ (<1) reflects technology gap enlarges (narrows).

Spatial Durbin model

This study aims to adopt spatial econometric models to empirically analyze the effect of power technology innovation on carbon productivity. The main spatial econometric models are spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM). SDM that incorporates the spatial lag term of both the explanatory and explained variables can be viewed as a generalized form of SLM and SEM. Given that SDM can effectively eliminate parameter estimation bias of explanatory variables and error terms, which is resulted from the spatial dependence of the omitted variables (Lee and Yu 2016), SDM is employed as the baseline model in this study. Besides, the estimation results of SLM and SEM are also listed as references.

The constructed SDM is shown in Eq. (9):

$$
\begin{aligned}
CP_{it} &= \alpha + \rho \sum_{j=1}^{N} w_{ij} CP_{jt} + \beta PTI_{it} \\
&+ \theta \sum_{j=1}^{N} w_{ij} PTI_{ij} + \gamma Controls_{it} \\
&+ \lambda \sum_{j=1}^{N} w_{ij} Controls_{jt} + \varepsilon_{it}
\end{aligned}
\tag{9}
$$

where CP denotes carbon productivity for province i at year t; PTI stands for power technology innovation. Controls represents a series of control variables, including economic development, foreign direct investment, environmental regulation, fiscal decentralization, urbanization level, and industrial structure upgrading. w_{ij} is an element of spatial weight matrix W, which is based on the adjacency weights matrix. Specifically, if the two provinces are adjacent, w_{ij} equals to 1, otherwise 0. α, ρ, β, θ, γ, and λ are the parameters to be estimated. ε denotes the random error.

To further investigate the influence mechanism of power technology innovation affecting carbon productivity, the three decomposition components of carbon productivity are served as the explained variable in rotation for the following regression model based on SDM (Yang and Ni 2022):

$$
\begin{aligned}
X_{it} &= \alpha + \rho \sum_{j=1}^{N} w_{ij} X_{jt} + \beta PTI_{it} + \theta \sum_{j=1}^{N} w_{ij} PTI_{jt} \\
&+ \gamma Controls_{it} + \lambda \sum_{j=1}^{N} w_{ij} Controls_{jt} + \varepsilon_{it}
\end{aligned}
\tag{10}
$$

where X refers to efficiency change (EC) or best-practice change (BPC) or technology gap change (TGC). The other symbols have the same meaning as those in Eq. (9).

Variables

Explanatory variable

R&D expenditure and patent counts are widely adopted as the proxy of technology innovation in the literature. The former is commonly treated as the input of innovation activities, while the latter is taken as the output of innovation activities. The data of R&D expenditure of the power industry in each China's province are not available, but the data of patent counts are available in a relatively long timescale, providing specific and detailed information of technology innovation (Lindman and Soderholm 2016). Moreover, there is a broad consensus on patent classification and standard, which is beneficial to perform a comparative analysis (Albino et al. 2014). Hence, this study selects the number of patent counts to measure power technology innovation.

According to the International Patent Classification (IPC) codes, the classification code of the power industry is *H*. Thus, patents under *H* classification are selected to represent the power industry. Referring to Calel and Dechezlepretre (2016), here, the number of patent applications instead of the number of licensed patents is used. Considering that authorizing the patent often takes a considerably long time, the number of patent applications can reflect an enterprise's innovation effort more completely than the number of licensed patents (Zhu et al. 2019). In this study, we take the number of patent applications per 10,000 people to measure technology innovation.

Control variables

(1) Economic development (ED). Economic development is generally considered to be a crucial factor in determining carbon productivity. Achieving the decoupling between economic development and carbon emissions is an integrated aspect of improving carbon productivity. Du and Li (2019) demonstrated that one region would be more inclined to pay more attention to environmental quality when having a better economy. Here, GDP per capita is adopted as the proxy of economic development.

(2) Foreign direct investment (FDI). FDI could enhance productivity in the host country through technology and knowledge spillover effects (Yang et al. 2017). However, FDI may also bring about environmental pollution to the host as described by the "pollution heaven" theory. Here, the proportion of FDI to GDP is used to represent FDI utilization.

(3) Environmental regulation (ER). The influence of environmental regulation on carbon productivity has been extensively explored in previous studies (Hu and Wang 2020; Ren et al. 2021). Whether environmental regulation can facilitate carbon productivity, however, is under dispute. Here, the percentage of industrial pollution control investment to industrial output value is adopted to measure environmental regulation.

(4) Fiscal decentralization (FD). Under the background of decentralized administration in China, the institutional factor reflected by fiscal decentralization has been an indispensable factor in analyzing the environmental issues (Song et al. 2020). With the further fiscal decentralization, the local government has more ability to take measures to curb carbon emissions, while also having more freedom to pursue economic growth. This study takes the ratio of per capita of local fiscal expenditure to the sum of per capita of local and central fiscal expenditure to measure fiscal decentralization.

(5) Urbanization level (UL). Urbanization contributes to fixing the urban infrastructure, thus leading to an increase in energy consumption and carbon emissions (Abbasi and Adedoyin 2021). But on the other hand, the scale economy effect triggered by urbanization would help to curb energy consumption and carbon emissions (Lin and Zhu 2021). As the degree of population concentration in cities is a reflection of urbanization, the ratio of urban population to total population is employed to measure urbanization level.

(6) Industrial structure upgrading (ISU). To accomplish the goal of carbon reduction, it is of great significance to promote industrial upgrading (Cheng et al. 2018a). Here, industrial structure is measured based on the following equation:

$$ISU = \sum_{i=1}^{3} x_i * i \tag{11}$$

where $i = 1, 2, 3$; x_i means the proportion of the added values of industry i to total GDP. The larger the value of the index is, the better the industrial structure is.

Data

The dataset covers China's 30 provinces from 2001 to 2019. Due to the unavailability of the data for Taiwan, Hong Kong, Macau, and Tibet, these regions are excluded. The data used in this study mainly derives from the "China Statistical Yearbook," "China Energy Yearbook," and statistics of the yearbook (e.g., autonomous regions, municipalities). Besides, the data of power patent are from incoPat database that records detailed information on patent worldwide. In terms of the input factors in the measurement of carbon productivity, *K* denoting capital stock is measured by the perpetual
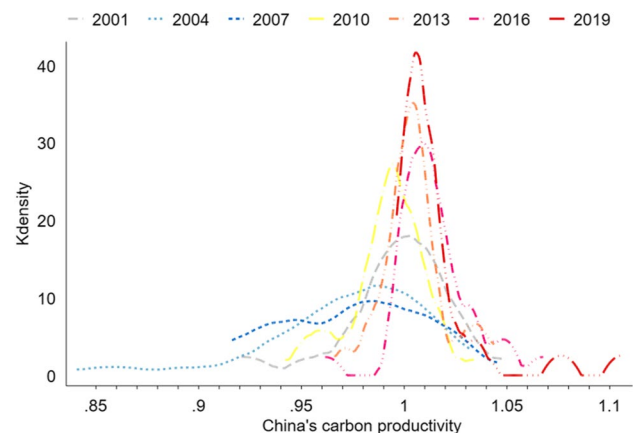
Fig. 2 Kernel density curves of China's carbon productivity

inventory method (Zhang et al. 2004), *L* referring to labor factor is represented by the actual employment at the end of the year, and *E* representing energy factor is measured by the energy consumption of the whole society. With regard to the outputs, desirable output *Y* is GDP, and undesirable output *C* denotes carbon dioxide emissions. All variables related to price are deflated to the constant price of 2000.

Results and discussion

Distribution dynamics in carbon productivity

The kernel density estimation approach is first adopted to examine the distribution characteristic and dynamic evolution of China's carbon productivity, where the Epanechnikov kernel density function is selected as the basic kernel function. On this basis, the kernel density curves of the representative years in the sample period are shown in Fig. 2. Obviously, all the kernel density curves of carbon productivity exhibit a single-peaked distribution, which indicates that the changes in carbon productivity are relatively concentrated. From the perspective of dynamic evolution, the kernel density curve in 1 year shifted first to the left in 2001–2010 and then to the right in 2010–2019, reflecting that China's carbon productivity experienced the process of

descending first and then ascending during the study period. For the decreasing trend, the possible reason may be that to pursue economic growth, environmental protection was taken a back seat and environmental issues became more and more serious, which posed a threat to the improvement of carbon productivity. Additionally, the increasing tendency after 2010 may be attributed to the government's continuous efforts on low-carbon development in recent years. For instance, during the "12th Five-Year Plan," China's government actively promoted the energy conservation and emission reduction, and strengthened ecological civilization.

Figure 3 draws the spatial distribution maps of China's carbon productivity in both 2001 and 2019. In 2001, close to 40 percent of the provinces had carbon productivity larger than 1, indicating that carbon productivity in these provinces increased compared to the last year. They were Tianjin, Shanxi, Heilongjiang, Shanghai, Jiangsu, Anhui, Shandong, Henan, Hainan, Chongqing, Sichuan, Shaanxi, and Xinjiang. In 2019, carbon productivity in almost all of the provinces enhanced. Only four provinces including Heilongjiang, Shaanxi, Ningxia and Xinjiang had carbon productivity less than 1. As a whole, China's carbon productivity improves a lot compared with the initial period of the study, which means that China's green low-carbon development has made a great achievement (Wang et al. 2021a). Moreover, in 2001, the spatial agglomeration feature of carbon productivity
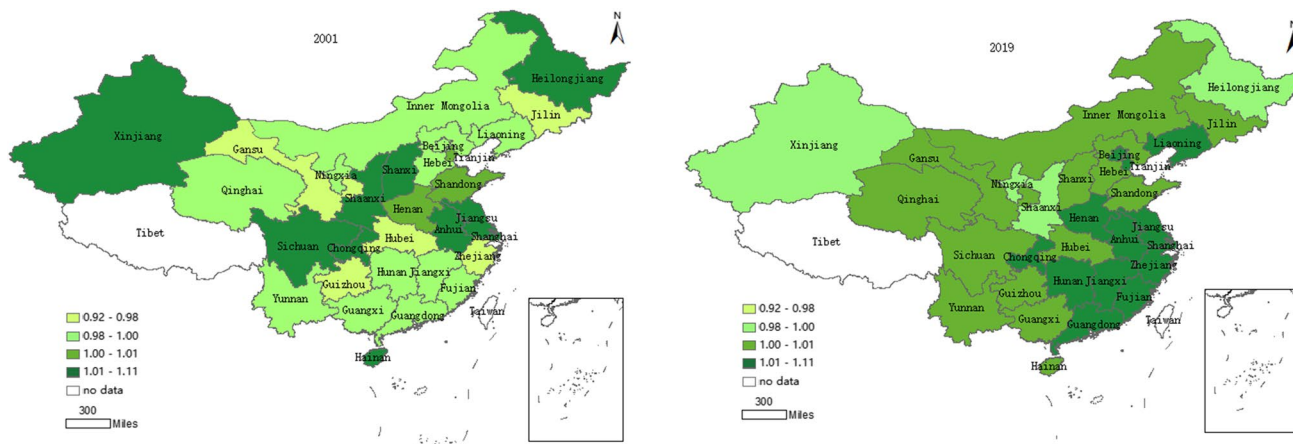

Fig. 3 Spatial distribution of carbon productivity in 2001 and 2019

Table 1 Global Moran's *I* of power technology innovation and carbon productivity

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
PTI	0.083[*]	0.102[*]	0.099[*]	0.098[*]	0.057	0.043	0.037	0.033	0.050	0.063
CP	−0.236[**]	−0.147	−0.045	−0.003	0.061	0.135[*]	0.194[**]	0.205[**]	0.210[**]	0.211[**]
Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean
PTI	0.080[*]	0.077[*]	0.094[*]	0.081[*]	0.100[**]	0.100[*]	0.082[*]	0.091[*]	0.076[*]	0.080[*]
CP	0.207[**]	0.205[**]	0.201[**]	0.202[**]	0.191[**]	0.202[**]	0.204[**]	0.233[**]	0.238[***]	0.189[**]

[*]$p < 0.1$, [**]$p < 0.05$, [***]$p < 0.01$

was not evident. However, by 2019, carbon productivity appeared clear spatial agglomeration characteristic and high level of carbon productivity were mainly located in the eastern coastal areas. This demonstrates that eastern local government made great efforts and accomplishments in the development of low-carbon economy,

Analysis of spatial autocorrelation

Both the global and local Moran's indexes for provincial power technology innovation and carbon productivity are calculated to test spatial autocorrelation in 2001–2019. Table 1 shows the annual values of global Moran's index during the study period. It can be seen that the annual value of the global Moran's index for power technology innovation and carbon productivity pass the significant test except for a few years. Coupled with the fact that their mean values of global Moran's index are also approved by the significant test, we can believe that both power technology innovation and carbon productivity present remarkably spatial agglomeration characteristics in 2001–2019. In terms of power technology innovation, its global Moran's index keeps positive in the whole study period. This means that the provinces with higher power technology innovation are inclined to gather, and so does the provinces with lower power technology innovation. In contrast, the global Moran's index for carbon productivity was negative from 2001 to 2004 and then positive from 2005 to 2019. That is, the spatial correlation of carbon productivity turned to be positive after 2004.

However, the above analysis is conducted on the whole, which cannot excavate their potential spatial heterogeneities. Thus, the local Moran's index is further calculated to explore local spatial relationships of power technology innovation and carbon productivity according to their mean values, and the corresponding results are presented by the visualization of Moran scatterplot in Fig. 4. It can be seen

Table 2 Test results for the form selection of spatial econometric models

Null hypothesis	Statistics	Value
Non-spatial effect	LM lag	371.513***
	Robust LM lag	14.824***
	LM error	414.762***
	Robust LM error	58.073***
Non-fixed effect	Hausman	36.09***
SLM model	LR lag	26.74***
	Wald lag	37.18***
SEM model	LR error	69.77***
	Wald error	60.79***

***$p < 0.01$

that High-High agglomeration areas in the first quadrant and Low-Low agglomeration areas in the third quadrant occupy the largest share of all provinces for both power technology innovation and carbon productivity, finally leading to positive spatial autocorrelation as revealed by the fitting lines. Hence, there exists positive spatial dependence of power technology innovation and carbon productivity in China's 30 provinces. Accordingly, it is essential to take the spatial location into account when investigating the effect of power technology innovation on carbon productivity.

Spatial econometric analysis

Effect of power technology innovation on carbon productivity

Wen et al.'s (2020) procedure is applied to determine the specific form of the spatial econometric model. First, we perform LM test and Robust LM test. The results presented in Table 2 show that the spatial effects should be considered
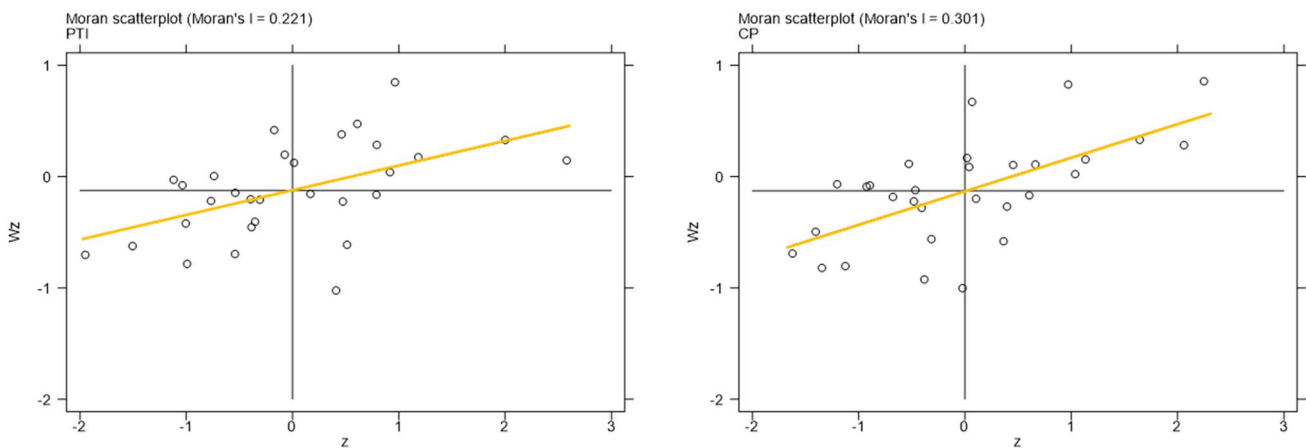

Fig. 4 Moran scatterplot of PTI and CP

Table 3 Estimation results of spatial econometric models

	(1) SDM	(2) SLM	(3) SEM
PTI	0.045***	0.041***	0.039***
	(12.288)	(13.160)	(11.355)
ED	−0.056	−0.038**	−0.069***
	(−1.445)	(−2.220)	(−2.963)
FDI	−0.007	−0.007	−0.010
	(−0.863)	(−0.906)	(−1.137)
ER	0.026**	0.017*	0.030***
	(2.532)	(1.734)	(2.830)
FD	−0.284**	−0.475***	−0.575***
	(−1.968)	(−4.263)	(−3.893)
UL	0.145***	0.122***	0.142***
	(3.027)	(2.695)	(2.978)
ISU	0.015**	0.017**	0.018**
	(2.190)	(2.460)	(2.441)
W* PTI	0.005		
	(0.768)		
ρ	0.459***	0.516***	
	(10.190)	(13.160)	
λ			0.511***
			(10.757)
N	570	570	570
Loglike	810.303	796.9308	775.4197
R^2	0.589	0.559	0.535

Z-statistics in parentheses, $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4 The decomposition results of SDM

	Direct effect	Indirect effect	Total effect
PTI	0.048***	0.043***	0.091***
	(12.915)	(4.280)	(8.209)
ED	−0.057	0.014	−0.043
	(−1.590)	(0.286)	(−0.910)
FDI	−0.002	0.069*	0.068
	(−0.231)	(1.722)	(1.547)
ER	0.017	−0.121***	−0.104**
	(1.522)	(−3.470)	(−2.555)
FD	−0.339**	−0.748***	−1.087***
	(−2.392)	(−3.084)	(−4.255)
UL	0.133***	−0.160	−0.027
	(2.671)	(−0.912)	(−0.138)
ISU	0.017**	0.007	0.023
	(2.218)	(0.205)	(0.629)

Z-statistics in parentheses, $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

reflecting that power technology innovation has a promoting effect on carbon productivity. Besides, the spatial lag term of power technology innovation is also positive, but it is not significant. Even if there are contain spatial lag terms, the regression coefficients of the SDM cannot directly reflect the marginal effect of explanatory variables. LeSage and Fischer (2008) figured out that the effects of explanatory variables based entirely on the point estimation results of the SDM might lead to a wrong conclusion. Therefore, the effects of explanatory variables on carbon productivity are further decomposed into direct effect and indirect effect, and results are shown in Table 4.

The direct effect of power technology innovation on carbon productivity is 0.048 and significant at the 1% level, which implies that local power technology innovation can improve its carbon productivity. More specifically, a 1% increase in power technology innovation could raise local carbon productivity by 0.048%. Similarly, Wang and Zhu (2020) proved that energy technology innovation exerts a positive influence on carbon reduction. As the main high energy consumption industry in China, power technology innovation is of great significance to promote green and low carbon development (Wang et al. 2021b). This may be due to that power technology innovation contributes to energy-saving technology and emission-reduction technology, thereby promoting the decoupling of economic growth and carbon emissions. And in terms of power, it plays a crucial role in alleviating energy poverty phenomenon in developing countries (Zhang et al. 2022). Thus, power technology innovation is conducive to increasing carbon productivity.

The indirect effect of power technology innovation on carbon productivity is 0.043 and significant at the 1% level, reflecting that power technology innovation in local

in exploring the relationship between power technology innovation and carbon productivity. Then, SDM is assumed to be the best choice to carry out this exploration. And on the premise of this assumption, the result of the Hausman test indicates that SDM with fixed effects is superior to that with random effects. Furthermore, both the LR test and Wald test are implemented to examine whether SDM needs to be degraded to SLM or SEM. It can be seen that their corresponding statistics pass the significance test at the 1% level, which implies that SDM, rather than SLM or SEM, is selected as the basic model in this study. For robustness, we also report the estimation results of SLM and SEM.

Table 3 shows the estimation results of the baseline regression results in Eq. (9). As can be seen in column 1, the estimated coefficient of spatially lag term of carbon productivity ρ is significantly positive at the 1% level, which exhibits a positive spatial correlation effect of China's carbon productivity. That is, a local province's carbon productivity exerted a demonstration effect on neighboring provinces, and this province also could enhance its carbon productivity by imitating and learning from the neighboring provinces. The coefficient of power technology innovation is significantly positive at the 1% level, preliminary

provinces can also advance carbon productivity in neighboring provinces. This result is consistent with Gu et al. (2020) who found that local energy technology progress can negatively decrease carbon intensity in neighboring provinces through technology spillover. There are two possible reasons for the positive effect of local power technology innovation on carbon productivity in neighboring regions. The one is that with the advancement of regional integration, the economic and political linkages between adjacent provinces would be more tightly. This would help create a more favorable environment for technology spillover and knowledge dissemination. In this case, local power technology innovation would be more likely to improve carbon productivity in the neighboring regions. The other one is that the local province would perform a demonstration function in terms of improving carbon productivity to motivate neighboring provinces because of regional competition and mutual imitation.

The total effect of power technology innovation on carbon productivity is 0.091, suggesting that a 1% increase in power technology innovation relates to a 0.091% increase in carbon productivity. It illustrates that by focusing on green technology development, China's innovation-driven low-carbon transition strategy has made a moderate accomplishment, laying a solid technology foundation for the goal of carbon peak and carbon neutralization (Lu et al. 2019). Importantly, what deserves more attention is how to bring the positive effect of power technology innovation into full play and further improve carbon productivity.

With regard to the control variables, the results are as follows. From the perspective of the direct effect, the coefficient of FD is significantly negative, indicating that fiscal decentralization inhibits carbon productivity. This is probably because under the GDP-oriented performance appraisal system, regional government generally puts economic growth first while giving inadequate attention to environmental protection (Luo and Wang 2017), thus weakening the institutional advantages of fiscal decentralization in enhancing carbon productivity. Both the coefficients of UL and ISU are remarkably positive, which reveals that supporting urbanization development and industrial structure upgrading is advantageous to the promotion of carbon productivity, and this was also confirmed by Lin and Zhu (2017).

Concerning the indirect effect, the coefficient of FDI is significantly positive, and it reflects that local FDI has a positive spatial spillover effect on the improvement of carbon productivity in neighboring provinces, which is consistent with Wang et al. (2021a). The coefficient of ER is negative at the 1% significance level, signifying that local environmental regulation exerts a downward influence on carbon productivity in neighboring regions, and this may be related to the transfer of carbon emissions to neighboring provinces induced by the stricter local environmental regulation. Moreover, local fiscal decentralization also acts as an inhibitor to the increase in carbon productivity of neighboring provinces. One possible explanation is that fiscal decentralization intensifies vicious competition among governments, thus promoting the development model at the expense of environment. The occurrence of this phenomenon in regional governments would produce a bad demonstration effect on each other (Luo and Wang 2017).

Effects of heterogeneous power technology innovations on carbon productivity

There are two types of technology innovation: incremental technology innovation and breakthrough technology innovation (Byun et al. 2021). Incremental innovation aims to deepen and expand the past research, while breakthrough innovation devotes to exploring the unknown knowledge. Since these two types of technology innovation have great differences in both the degree of innovation and the produced spillover effects, they may exert different impacts on carbon productivity. In view of this, power technology innovation here is divided into breakthrough power technology innovation (BPTI) and incremental power technology innovation (IPTI), and thus to figure out which type is more effective for the improvement of carbon productivity. Following Lu et al. (2019), the top 5% of cited patents are treated as breakthrough power technology innovation, and the remainder is incremental power technology innovation.

Table 5 reports the estimation results regarding the effects of different types of power technology innovation on carbon productivity. For breakthrough power technology innovation, its direct effect is 0.156, indirect effect is 0.242, and total effect is 0.397, which are all significant at the 1% level. In light of incremental power technology innovation, it has a direct effect of 0.006, an indirect effect of 0.012, and a total effect of 0.018, which all pass the 1% significance test. Obviously, heterogeneous power technology innovations have a quite different level of intensity in promoting carbon productivity. Moreover, both the direct and indirect promotion effects of breakthrough power technology innovation on carbon productivity are stronger than those of incremental power technology innovation. The underlying reason is that breakthrough power technology innovations can reset the technological trajectory of the power system, thereby causing the big shift in power technology that would have changed the original mode of production (Lu et al. 2019). However, incremental power technology innovation is generally the exploration of existing knowledge with the characteristics of gradualness and imitativeness. Therefore, if the power technology innovation relies on quantity accumulation without achieving deep development, it can only generate a limited effect on the improvement of carbon productivity.

Table 5 Estimation results of the heterogeneity analysis

		(1)	(2)
BPTI		0.135***	
		(6.318)	
W*BPTI		0.075***	
		(3.211)	
IPTI			0.005***
			(4.192)
W*IPTI			0.005***
			(4.192)
BPTI	Direct effect	0.156***	
		(6.780)	
	Indirect effect	0.242***	
		(5.297)	
	Total effect	0.397***	
		(6.840)	
IPTI	Direct effect		0.006***
			(5.082)
	Indirect effect		0.012***
			(5.636)
	Total effect		0.018***
			(6.522)
ρ		0.471***	0.464***
		(10.289)	(10.003)
N		570	570
Loglike		758.826	753.310
R^2		0.503	0.500

Z-statistics in parentheses, $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6 Influence mechanism analysis

		(1) EC	(2) BPC	(3) TGC
PTI		0.024***	0.034***	−0.009***
		(5.799)	(8.202)	(−2.656)
W* PTI		−0.025***	0.052***	0.007
		(−3.782)	(7.652)	(1.349)
PTI	Direct effect	0.024***	0.032***	−0.008**
		(5.582)	(7.651)	(−2.443)
	Indirect effect	−0.025***	0.043***	0.005
		(−3.339)	(6.848)	(0.590)
	Total effect	−0.001	0.076***	−0.003
		(−0.171)	(13.673)	(−0.357)
ρ		0.165***	−0.128**	0.466***
		(3.076)	(−2.087)	(10.548)
Controls		Yes	Yes	Yes
N		570	570	570
Loglike		740.478	763.052	852.091
R^2		0.304	0.341	0.315

Z-statistics in parentheses, $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Analysis of influence mechanism

Table 6 reports the estimation results regarding how power technology innovation affects carbon productivity. For the influence mechanism analysis, referring to Jia et al. (2021), this study mainly pays attention to the direct effect of power technology innovation on carbon productivity. In terms of efficiency change, the direct effect of power technology innovation is significantly positive, suggesting that power technology innovation can contribute to the advancement of technology efficiency in the local region. The finding is in line with Luo et al. (2022). This may be due to that power technology innovation directly optimizes resource distribution and utilization, which is conducive to improving technology efficiency.

From the perspective of best-practice change, there is also a significant promoting effect of power technology innovation. This manifests that power technology innovation helps increase production technology. In the study of Du and Li (2019), they also held that green technology innovation enhances carbon productivity through technological progress. The possible reason may be

related to technology spillover. With the strong spillover effect, power technology innovation contributes to the progress of technologies related to low-carbon production. Besides, boosting energy technology is beneficial to achieving optimum production (Abbasi et al. 2021), which can thus curb carbon emissions.

Regarding technology gap change, the direct effect of power technology innovation is −0.008, and significant at the 5% level, which illustrates that power technology innovation does not narrow the technology gap with production frontiers but widens it. This demonstrates that the Leading Effect fails to produce a positive effect. That is, the provinces located in the production frontier do not effectively play a demonstration role to drive the improvement of technology in other provinces.

Robustness test

To verify the above results, some additional robustness tests are further performed:

(1) To alleviate the possible reverse causality and endogenous problem in the econometric model, referring to Li et al. (2018a), this study lags the explanatory variables by 1 year and re-estimates the baseline model.
(2) For power technology innovation, the above study selects invention patents filling per million people in the power industry as the measurement. Here, the total number of invention patents and utility patents is taken

as the measurement of power technology innovation (Xu et al. 2021).

(3) In terms of carbon productivity, many scholars use the single factor index. That is, carbon productivity is calculated by the ratio of GDP to carbon emissions based on its basic definition (Hu and Wang 2020). Therefore, total factor carbon productivity is replaced with single factor carbon productivity.

The robustness test results are shown in Table 7. As can be seen, power technology innovation still has a positive effect on carbon productivity in both local and neighboring regions, and it is basically consistent with the baseline regression results. These results once again illustrate that power technology innovation can increase China's carbon

Table 7 Robustness test results

		(1) Lagged explanatory variables	(2) Alternative method of PTI	(3) Alternative method of CP
PTI		0.043***	0.025**	0.149***
		(11.291)	(2.498)	(12.332)
ED		−0.047	−0.084*	0.429***
		(−1.221)	(−1.868)	(3.325)
FDI		−0.006	−0.004	0.029
		(−0.767)	(−0.382)	(1.035)
ER		0.016	0.024**	0.181***
		(1.580)	(2.048)	(5.303)
FD		−0.342**	−1.013***	0.341
		(−2.417)	(−6.612)	(0.712)
UL		0.127***	0.067	−0.005
		(2.785)	(1.245)	(−0.032)
ISU		0.014**	0.015*	0.027
		(2.175)	(1.906)	(1.164)
W*PTI		0.006	0.039**	0.001
		(1.021)	(2.282)	(0.034)
PTI	Direct effect	0.047***	0.032***	0.150***
		(12.005)	(3.069)	(12.329)
	Indirect effect	0.046***	0.086***	0.023
		(4.405)	(3.194)	(1.076)
	Total effect	0.093***	0.118***	0.173***
		(8.059)	(3.795)	(8.179)
ρ		0.467***	0.465***	0.142**
		(10.517)	(9.448)	(2.044)
N		540	570	570
Loglike		797.617	739.665	139.008
R^2		0.553	0.487	0.379

Z-statistics in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

productivity, which is favorable to the achievement of green low-carbon development.

Conclusions and policy implications

Using the panel data covering China's 30 provinces from 2001 to 2019, this study provides new evidence for the effect of power technology innovation on carbon productivity. The metafrontier Malmquist-Luenberger productivity index was used to calculate China's carbon productivity. Considering the spatial spillover effects, SDM was adopted to investigate the impact of power technology innovation on carbon productivity.

The main conclusions of the study are as follows:

China's carbon productivity declined firstly and then increased over the period of 2001–2019. Compared with the beginning of 2001, China's carbon productivity had improved significantly in 2019. Besides, both power technology innovation and carbon productivity have a positive spatial autocorrelation. Power technology innovation has a positive effect on carbon productivity both in local and neighboring regions. Specifically, a 1% increase in power technology innovation could generate a 0.048% and 0.043% improvement in carbon productivity of local and neighboring regions, respectively. Moreover, the promoting effect of breakthrough power technology innovation is more obvious than that of incremental power technology innovation. Furthermore, the Catching-up Effect and Innovation Effect are important influence mechanisms where power technology innovation facilitates carbon productivity, while the Leadership Effect generates a negative effect, and it needs a breakthrough.

Based on these findings, the following policy implications are put forward:

First, given that carbon productivity and power technology are characterized by positive spatial autocorrelation, interregional cooperation in environmental protection should be set up. First, regular learning and exchange activities should be encouraged among local governments to share efficient experiences in low-carbon governance so as to promote demonstrating effect. In addition, it is crucial for the government to strengthen technology innovation cooperation among different regions by establishing technology innovation zones in the power industry to motivate the sharing of knowledge, information, and resources across regions. Moreover, the government should also consider the cross-regional transfer of carbon emissions induced by mandatory environmental regulations in neighboring regions. For instance, local governments should formulate clear regulations for enterprises reallocating from other areas and set up special teams to regularly assess these enterprises'

environmental performance. Accordingly, specific environmental goals should be proposed by these enterprises.

Second, the results of SDM reveal that accelerating power technology innovation is an effective way to contribute to carbon productivity. Thus, to achieve the transition to a low-carbon economy, the Chinese government should vigorously support power technology innovation. Firstly, a more detailed and specific technology innovation-driven strategy should be deployed in the power industry, and a dynamic adjustment directory of power technology innovation for enterprises should be enacted regularly. The government should also implement preferential policies for high-tech enterprises to motivate power technology innovation. Secondly, the government should provide more financial support for the R&D activities of the power industry. For instance, the government can set up a special fund for power innovation and guide the flow of credit resources to enterprises that actively carry out technology innovation by means of establishing guarantee funds. Thirdly, the government can encourage universities and research institutes to accelerate the establishment of public innovation support platforms and optimize the innovation education system by motivating innovation reform.

Third, the mechanism analysis shows that Catching-up Effect and Innovation Effect play a positive effect on the improvement of carbon productivity, while Leadership Effect exhibits a negative effect. Therefore, to spur the positive impact of Leadership Effect, a peer-to-peer technical assistance model within different regions can be established, that is, placing a technology-backward region as an assistance object for technology-developed regions. Technology-developed regions should provide targeted help for backward regions according to their problems in technology development, and the effect of assistance should be assessed, thus narrowing the technology gap. Besides, the Catching-up Effect and Innovation Effect can be further strengthened by carrying out some measures. For example, the government should strengthen the propaganda of advanced production processes by setting industry benchmarks and guiding enterprises to optimize production structures to increase efficiency. The government should also facilitate the industrialization of innovation activities that promote productivity through experiments in advanced enterprises.

This study can be further extended from the following aspects. Firstly, this study is based on panel data at the provincial level. Given that large disparities exist in socioeconomic situations among different cities within one province, empirical results could be more accurate when city-level data are available. And the utilization of city-level data can increase confidence in the role of power technology innovation in carbon productivity due to the significant increase in sample size. Secondly, this study focuses on the role of power technology innovation, while the influence of other types of energy technology innovation has not been analyzed. Future research can also explore the effects of renewable energy technology innovation and fossil energy technology innovation on carbon productivity, which can help formulate more targeted and comprehensive policies.

Declarations

Ethics approval This manuscript does not report on or involve the use of any animal or human data or issue.

Consent to participate All the authors agree to participate.

Consent for publication We consent to publish this manuscript in *Environmental Science and Pollution Research*. This manuscript has not been published in whole or in part nor is it being considered for publication elsewhere.

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