



Carbon emission reduction effect of renewable energy technology innovation: a nonlinear investigation from China's city level

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Abstract

There has always been controversy over how renewable energy technologies can play a role in reducing carbon emissions. Based on the energy patent data and the economic data of 244 prefecture-level cities from 2007 to 2017 in China, we explore the carbon reduction effect of renewable energy technology and its mechanism from the perspective of energy production, conservation, and management. The two-way fixed effect, instrumental variable, spatial Durbin, and mediation effect models are employed to explore empirical results. We found that (1) the impact of renewable energy technologies on carbon emissions is nonlinear, with an inverted U shape. However, this inverted U-shaped relationship only exists locally in cities and there are uncertainties in adjacent cities, which indicates that cross-regional cooperation in renewable energy technology needs to be improved. (2) The mechanism analysis shows that industrial agglomeration and energy consumption scale are the channels that renewable energy technologies affect carbon emissions. Thus, the implicit carbon emissions generated by industrial agglomeration and the failure to green upgrade energy consumption are the main reasons for the inverted U-shaped relationship. (3) The carbon reduction effect of renewable energy technologies of conservation type takes effect first, and renewable energy technologies of production type do not reduce carbon emissions in non-eastern cities, which means that non-eastern cities are likely to become pollution havens. This study provides evidence for renewable energy technologies to achieve efficient carbon emission reduction and cross-regional technical cooperation.

Keywords Renewable energy technology innovation · Carbon emission · Energy patent · Spatial econometric model · Nonlinear effect

Introduction

Technological innovation plays a vital role in affecting pollution and carbon emissions (Wahab 2021). In particular, technological innovations in the energy sector have greatly contributed to reconciling the potential contradiction between economic growth and carbon emission (Zhang and Cheng 2009; Khan et al. 2023a; Khan et al. 2023b). It is noteworthy that the impact of energy technology innovation on carbon emissions is uncertain (Álvarez-herránz et al. 2017; Zhu et al. 2020). The main reason is that different from green technology innovation, energy technology

innovation is not beneficial to the environment entirely. In other words, although non-green energy technology innovation has improved energy intensity, it will increase non-green energy consumption (Qu et al. 2023), which will not decrease carbon emission. This is the earliest inference about the energy rebound effect from the Jevons paradox. Consequently, because of the intervention of the energy rebound effect, it is necessary to determine whether technological innovation can reduce carbon emissions (Yang and Li 2017). However, the innovation of energy technology in Jevons paradox period mainly focused on coal, oil, and other traditional fossil energy, and the concept of renewable energy was still in its infancy. The emission reduction effect of the current renewable energy technology innovation has always been controversial and needs to be discussed (Qu et al. 2022; Su and Fan 2022; Yang et al. 2019).

Renewable energy sources and their technologies are considered clean compared to fossil energy sources (Wang et al. 2023). However, renewable energy technology

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can play a role in carbon emission reduction only when it is applied in practice (Wang and Zhu 2020), some areas do not have the appropriate natural resources for renewable energy generation. In other words, the renewable energy technology developed in place A does not have to be effective only in place A (Zhu et al. 2020). For instance, cities in Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta in China are regions with high carbon emissions and are also the regions with the strongest innovation vitality and the most patent applications. Most of the renewable energy technologies are applied in cities with relatively abundant renewable energy resources. In these cities, carbon emission reduction effect is generated by the application of renewable energy technologies to replace fossil energy. The carbon emission reduction effect of renewable energy technology will be affected in neighboring cities with relatively scarce renewable energy resources. Consequently, the impact of renewable technology innovation on carbon emissions may have a spatial spillover effect (Chen et al. 2018a; Jiang et al. 2022; Lin and Ma 2022; Yang et al. 2019).

In addition, we need to further explain the mechanism by which renewable energy technology reduces carbon emissions. Specifically, renewable energy technology innovation will positively promote industrial structure green transformation and energy structure optimization (Su and Fan 2022; Wang and Zhu 2020). As a matter of fact, renewable energy technology is generally considered clean, so the development of renewable energy technology is a sign of green transformation of industrial structure. On the other hand, innovation in renewable energy technologies can help energy transformation by encouraging the substitution of fossil fuels, in order to obtain its effect of reducing carbon emissions (Dilanchiev et al. 2023). However, economic development creates a rigid demand for energy resources, and while there is a transition towards a greener energy consumption structure, the energy consumption scale is also gradually expanding. It is only through the coordination and synchronization of the energy consumption structure and scale that renewable energy technologies can effectively reduce carbon emissions. A similar situation exists at the industrial level. Consequently, mechanism analysis is carried out from the energy and industry levels to explain the impact of renewable energy technologies on carbon emissions. The production process and management process of energy and the new technology and method of energy application are considered as technological innovation. Different types of renewable energy technology innovation may have different impacts on carbon emissions. This paper divides renewable energy technologies from the perspectives of energy production, conservation, and management, and discusses the carbon emission reduction effects of different types of renewable energy technologies.

Generally, the potential contributions of this paper are as follows. (1) We have provided new evidence for the non-linear impact of renewable energy technology innovation on carbon emissions and from the perspective of energy production, conservation, and management. (2) The mediation effect model is employed to comprehensively analyze the mechanisms of renewable energy technology innovation affecting carbon emissions, including energy-related and industrial channels, to explain the causes of nonlinearity. (3) Considering the spatial spillover effect of carbon emissions and renewable energy technologies, and based on the geographic and economic composite weight matrix, the impact of renewable energy technology innovation on carbon emissions is investigated from a spatial perspective.

This paper is organized as follows. The literature review and research hypothesis are presented in the “Literature review” section. The methodology is shown in the “Methodology” section. The “Data and variables” section shows data and variables. The “Empirical results and discussion” section includes the empirical results and discussion. The conclusions are in the “Conclusion and policy implications” section.

Literature review

Although many studies have recognized the irreplaceable impact of technology on pollutants, the pollution emission of the previous studies focuses on SO₂, nitrogen oxide (NO_x), and biological oxygen demand (BOD), and less on carbon emission, the main factor causing climate change. In the context of increasingly serious climate change, we need to pay attention not only to the emissions of pollutants such as sulfur dioxide, wastewater, solid waste, and PM_{2.5} involved in traditional fields, but also to greenhouse gases represented by carbon, which is consistent with the goal of carbon peak and carbon neutralization in China.

Nonlinear impact of renewable energy technology innovation on carbon emissions

Numerous studies have found that the impact of technology innovation on carbon emissions is not immutable. The typical theoretical explanation is the rebound effect or backfires effect in the energy sector, which is an old issue that comes from the Jevons paradox. For instance, Yang and Li (2017) believe that although technology innovation is the greatest contributor to carbon emission mitigation, however, due to the rebound effect, the carbon emission reduction effect of technology innovation needed further study. Chang et al. (2018) found that when the technology level in clean-good production is higher, the rebound effect is more pronounced, and there are more pollutants, which leads to the unstable

impact of technology innovation on the environment. Berner et al. (2022) support the conclusion of the rebound effect that the improvement of energy efficiency brought about by technological innovation will not reduce carbon emissions immediately. Moreover, Sun et al. (2019) believe that the current green innovation realizes energy conservation and emission reduction through improving energy efficiency, which depends on the support of the government. Due to the cost effect, it is difficult for green innovation to reduce carbon emissions in the short term only by relying on the role of the market-oriented. The study from Álvarez-herránz et al. (2017) suggests that the carbon reduction effects of energy technology innovation may not be achieved overnight. Dauda et al. (2021) used panel data from 1990 to 2016 in Africa to explore the impact of innovation on carbon emissions and found that there was a nonlinear inverse U-shaped relationship between innovation and carbon emissions. Lin and Zhu (2019) focus on China and discussed the impact of renewable energy technology innovation on carbon emissions, which is a study specifically aimed at energy technology. They believed it necessary to consider the nonlinear impact of renewable energy technology on carbon emissions. Obobisa et al. (2022)'s research believes that although green innovation and the increase of renewable energy consumption benefit reduced carbon emissions, its carbon emission reduction effect is based on economic growth and institutions. Based on these viewpoints, we believe that the impact of renewable energy technology innovation on carbon emissions may show a nonlinear characteristic.

Hypothesis 1. Renewable energy technology innovation has a nonlinear impact on carbon emissions.

Spatial spillover effects of renewable energy technology innovation on carbon emissions

Then, why is the impact of renewable energy technology innovation on carbon emissions nonlinear? Many scholars tried to explore this issue from the perspective of the spatial spillover effect of carbon emissions and technology innovation. One potential fact is that pollutants such as carbon emissions have significant spatial autocorrelation features. Balado-Naves et al. (2018) believe that considering the spatial spillover effect of carbon emissions is helpful to further explore the EKC hypothesis's assertion about pollutants and economic growth. Subsequently, Fernández et al. (2022) and Peng et al. (2021) believe that energy technology and green technology also have the spatial diffusion effect, and it is impossible to accurately consider their impact on the economy and environment without considering the diffusion of technology innovation. Yang et al. (2020) also considered the spatial effect of environment-biased technological progress and carbon emissions and found that

environment-biased technological progress would increase fossil energy consumption, thereby increasing carbon emissions. This is the main reason why green technologies cannot directly achieve carbon reduction effects. The above discussions on green innovation and environment-biased technological progress have laid a solid foundation for the research of energy technology. Wang and Zhu (2020) studied the impact of energy technology innovation on carbon emissions by employing spatial econometrics and believed that renewable energy technology innovation can achieve a carbon emission reduction effect, and this effect still has spatial heterogeneity. Zhu et al. (2020) discuss the impact of renewable energy technology innovation on air pollution and believe that after considering the spatial spillover effect, different pollutants are significantly changed from each other in terms of the impact of renewable energy technology innovation. It is not difficult to find that the impact of renewable energy technology innovation on carbon emissions can be accurately discussed only when the potential space spillover effect is considered.

Hypothesis 2. The impact of renewable energy technology innovation on carbon emissions has a spatial spillover effect.

Carbon reduction channels for renewable energy technology innovation

When discussing the spatial spillover effect, some studies have pointed out that technology innovation will have an impact on carbon emissions through energy and industry channels (Yang et al. 2020; Wang and Zhu 2020). Lin and Ma (2022) analyzed the channels through which green technology innovation affects carbon emissions, and found that energy efficiency, energy structure, and industrial upgrading are the main factors. Su and Fan (2022) believe that the joint action of renewable energy technology innovation and industrial structure upgrading can promote green economic development. Its research shows that renewable energy technology innovation can further affect the economy and the environment through industrial upgrading. Xu et al. (2021) pointed out that green technology innovation will affect carbon emission performance through industrial structure and energy consumption structure. Meanwhile, industrial agglomeration is also considered to be an important factor affecting air pollutants and carbon emissions (Chen et al. 2022a).

Moreover, as renewable energy technology innovation is closely related to the energy sector, it is an indisputable fact that renewable energy technology innovation can affect energy consumption structure, energy efficiency, and other energy factors (Obobisa et al. 2022). Yang et al. (2019) pointed out the potential impact of energy structure when

discussing the influencing factors of energy technology innovation. Lin and Zhu (2019) also believe that attention must be paid to the energy structure when exploring renewable energy technologies, including fossil energy consumption and renewable energy consumption. Therefore, we indicate the energy effects of renewable energy technology innovation on carbon emissions in terms of energy consumption scale, energy consumption structure, and energy intensity. Regarding the industrial effect, we rely on industrial structure and industrial agglomeration to measure it. The research hypothesis is as follows:

Hypothesis 3. Renewable energy technology innovation can affect carbon emissions through energy and industry factors.

Methodology

The empirical analysis method is expanded from the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model. The STIRPAT model is a classical method to discuss pollution emission and its impact factors, and it is widely employed to analyze the environmental impact of technology (Chen et al. 2022a; Huang et al. 2021; Sadorsky 2014; Shao et al. 2011; Xu and Lin 2015; Zhu et al. 2020).

Firstly, we extend the STIRPAT model to obtain a baseline model of this paper in nonlinear formation:

$$\ln CO2_{it} = \alpha + \alpha_1 \ln RETI_{it} + \alpha_2 (\ln RETI_{it})^2 + \sum X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{1}$$

In Eq. (1), we employ renewable energy technology innovation (*RETI*) to replace the technology (*T*) in the STIRPAT model to explore its impact on carbon emissions and mechanism. The quadratic term of renewable energy technology innovation (*RETI*²) is used to explore the potential nonlinear impact of renewable energy technology innovation on carbon emissions.

The dependent variable is the carbon emissions (*CO2*) of the city *i* in year *t*. *X* represents a set of control variables, including population (*POP*), affluence (*pGDP* and *pGDP*²), foreign direct investment (*FDI*), government intervention (*GOV*), financial development (*FD*), urbanization (*URB*), transportation infrastructure (*TI*), and green space (*GS*). γ_i and μ_t denote city fixed effect and year fixed effect, respectively. ε_{it} indicates the error term. This paper clusters to the city level.

In addition, to decrease potential endogeneity caused by reverse causality (Habiba et al. 2022), the impact of renewable energy technology innovation on carbon emissions

was discussed based on the two-stage least square (2SLS) method and instrumental variables (IV) as follows:

$$\ln \overline{RETI}_{it} = \alpha + \alpha_1 \ln IV_{it} + \beta_1 \ln POP_{it} + \beta_2 \ln pGDP_{it} + \beta_3 (\ln pGDP_{it})^2 + \sum X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{2}$$

$$\ln CO2_{it} = \alpha + \theta_1 \ln \overline{RETI}_{it} + \beta_1 \ln POP_{it} + \beta_2 \ln pGDP_{it} + \beta_3 (\ln pGDP_{it})^2 + \sum X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{3}$$

Eq. (2) and Eq. (3) constitute the first stage and the second stage regressions. *IV* is an instrumental variable for renewable energy technology innovation of city *i* in year *t*. The instrumental variables in this paper are environmental concerns (*EV*), environmental regulation (*ER*), and the lag term of *RETI*, respectively. The interpretation of other variables was consistent with Eq. (1).

Secondly, we extend Eq. (1) to the spatial econometric model to analyze the potential spatial spillover effect of renewable energy technology innovation on carbon emissions. Some studies believe that there is a spatial spillover effect of carbon emissions (Chen et al. 2022a; Wang and Zhu 2020; Yang et al. 2020; Dong et al. 2022), so we can consider that the dependent variable in Eq. (1) has spatial effects. In addition, the spatial spillover effect of technological innovation has also been confirmed to some extent (Fernández et al. 2022; Peng et al. 2021; Zhu et al. 2020), so the independent variable and its quadratic term also have the spatial spillover effect. Consequently, the spatial Durbin model (SDM) is considered. The SDM model of Eq. (4) is as follows:

$$\ln CO2_{it} = \alpha + \alpha_1 \ln RETI_{it} + \alpha_2 (\ln RETI_{it})^2 + \rho W \ln CO2_{it} + \rho_1 W \ln RETI_{it} + \rho_2 W (\ln RETI_{it})^2 + \sum \beta_j X_{it} + \sum \theta_j WX_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{4}$$

where ρ is the coefficient of spatial effect with the dependent variable, and *W* is the spatial weight matrix. Other variables have the same meaning as Eq. (1). Regarding the spatial weight matrix (*W*), economic distance weight matrix (*W*^{GDP}), geographic distance weight matrix (*W*^{GEO}), and composite spatial weight matrix (*W*¹ and *W*²) are considered, where the geographic distance matrix (*W*^{GEO}) is gotten by calculating the latitude and longitude distance (*d*) between city *i* and city *j*, which is expressed as follows:

$$W^{GEO} = \begin{cases} \frac{1}{d_{ij}^2} & (i \neq j) \\ 0 & (i = j) \end{cases} \tag{5}$$

The economic distance matrix (*W*^{GDP}) is gotten by calculating the difference between the average value of per capita GDP (*Y*) in the sample period of city *i* and city *j*.

$$W^{GDP} = \begin{cases} \frac{1}{|Y_i - Y_j|} & (i \neq j) \\ 0 & (i = j) \end{cases} \quad (6)$$

The composite spatial weight matrix of W^l is composed of a W^{GDP} and a W^{GEO} as follows:

$$W^l = \phi W^{GEO} + (1 - \phi) W^{GDP} \quad (7)$$

where ϕ represents the weight of W^{GEO} and W^{GDP} in W^l , and $\phi \in (0, 1)$. We assume that $\phi = 0.5$ which shows that the power of geographical distance and economic distance on spatial spillover effect is similar.

The composite spatial weight matrix of W^2 is used for the robustness test, as follows:

$$W^2 = W^{GEO} \times W^{GDP} \quad (8)$$

The index of Moran's I is employed to test the spatial effect, which is a typical practice (Yang et al. 2020; Zhu et al. 2020).

Thirdly, the mediation effect models employed for mechanism analysis are as follows:

$$\ln CO2_{it} = \theta_0 + \theta_1 \ln RETI_{it} + \sum Y_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (9)$$

$$M_{it} = \beta_0 + \beta_1 \ln RETI_{it} + \sum Y_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (10)$$

$$\ln CO2_{it} = \lambda_0 + \lambda_1 \ln RETI_{it} + \lambda_2 M_{it} + \sum Y_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (11)$$

M is the mediation variable, including the industrial structure (IS), industrial agglomeration (AGG), energy consumption scale (EC), energy consumption structure (ES), and energy intensity (EI). Y is a set of control variables except for the mediation variable. The meanings of γ_i , μ_t , and ε_{it} are consistent with Eq. (1). If coefficients θ_1 , β_1 , and λ_2 in Eq. (9), Eq. (10), and Eq. (11) are significant, and the coefficient of λ_1 compared θ_1 in Eq. (11) and Eq. (9) becomes smaller or decreased significantly, which indicates that there is a mediation effect.

Data and variables

We employ the data of 244 prefecture-level cities in China as the research sample and the period of 2007 to 2017. Since there are various missing observations in prefecture-level cities before 2006, the research sample of this paper starts from 2007. Due to the lack of data on the environment and energy consumption, prefecture-level cities in Tibet, Hong Kong, Macao, and Taiwan are not included. We have retained prefecture-level cities with relatively complete data on foreign direct investment in the areas

of Xinjiang, Qinghai, Gansu, Ningxia, and Inner Mongolia. In addition, for the consistency of the sample period, prefecture-level cities with short establishment time are excluded from the research sample (e.g., cities named Sansha, Suizhou, and Danzhou). Taking 2007 as the base year, we employed the GDP price index to deflate the per capita GDP data to eliminate the impact of price fluctuations. The GDP price index is collected on the website of the development research center of the State Council¹.

Dependent variable

This paper takes the carbon emissions ($CO2$) and their per capita form ($pCO2$) of prefecture-level cities in China as the dependent variables (Chen et al. 2022b; Lin and Ma 2022; Wang and Zhu 2020). The data on carbon emissions are mainly collected from China Emission Accounts and Datasets (CEADs)² and populated using energy data from the China Urban Statistical Yearbook and the research from Chen et al. (2021).

Main independent variables

The main independent variables are renewable energy technology innovation ($RETI$) and its quadratic term ($RETI^2$). This paper measures the level of $RETI$ in an area based on the number of renewable energy technology patent applications (Noailly and Smeets 2015; Noailly and Smeets 2021). Measuring the energy technology innovation by energy patents has been widely used (Fernández et al. 2022; Huang et al. 2021; Johnstone et al. 2010; Noailly and Shestalova 2017; Qu et al. 2022, 2023; Wang and Zhu 2020). It is noteworthy that the technologies related to the application of energy cover many fields. Therefore, from the perspective of production, conservation, and management of energy, we divide the above renewable energy technology patents into three types: energy production ($RETI_{EP}$), energy conservation ($RETI_{EC}$), and energy management ($RETI_{EM}$).

Specifically, the renewable energy technology innovation of the energy production type includes solar energy, wind energy, geothermal energy, hydro energy, marine (ocean) energy, biomass energy, and waste-to-energy. Renewable energy technology innovation of the energy conservation type includes storage of electricity energy, storage of thermal energy, and measurement of electricity consumption. The renewable energy technology innovation of the energy management type includes treatment of energy waste, reuse of energy waste materials, pollution control, and so on.

¹ <http://www.drcnet.com.cn/www/int/>

² <https://www.ceads.net.cn/>

The patent data representing innovation comes from the China National Intellectual Property Administration (CNIPA) and is matched to the prefecture-level city through the address and zip code of the renewable energy technology patent. The international patent classification (IPC) of relevant renewable energy technology patents is provided in Table 16 of Appendix 1.

Instrumental variables

To alleviate the endogeneity caused by the reverse causality between carbon emissions and renewable energy technology innovation, this paper uses the following instrumental variables for 2SLS:

- (1) According to Xu et al. (2021), we believe that environmental concerns (*EV*) can be used as an instrumental variable for renewable energy technology innovation. The improvement of public environmental concerns will have a positive impact on renewable energy technology innovation. Environmental concern is mostly the choice of public opinion or individuals, and the level of environmental concern will not affect carbon emissions (Li et al. 2021). This paper uses the Baidu Index to measure environmental concern, which is considered to be an effective indicator to measure public environmental concern in the context of the information time (Du et al. 2019; Li et al. 2021; Liu et al. 2019). Similar schemes refer to the Google Index (Kahn and Kotchen 2011; Zheng et al. 2012). Specifically, haze, environmental pollution, air pollution, and climate change were selected as the search keywords of the Baidu Index. The reason for selecting these keywords is that they have high public perception and can represent the public's concern about the environment, that is, environmental concern (Li et al. 2021).
- (2) Another instrumental variable of renewable energy technology innovation is environmental regulation (*ER*). Numerous studies have revealed that environmental regulation can have an impact on technological innovation, and green innovation, including renewable energy technology innovation (Shao et al. 2020). Although the environmental regulation shows the reduction of pollution emissions (Du et al. 2019), however, according to the Porter hypothesis, the compliance cost effect and innovation offset effect jointly determine the impact of environmental regulation on enterprise innovation (Shao et al. 2020). Renewable energy technology innovation can reduce pollution emissions and thus reduce compliance costs with environmental regulations. Referring to Chen et al. (2018b), this paper adopts the proportion of the frequency of words related to the word “environmental protection”

in the local government work report in the number of words in the full text of the report as the proxy variable of environmental regulation.

In addition, the first-order lag of renewable energy technology innovation will also be regarded as an instrumental variable for comparative analysis.

Control variables

The baseline and spatial econometric models in this paper are extended by the STIRPAT model, so other variables affecting carbon emissions need to be controlled.

- (1) Population density (*POP*): The population of a region is an important factor affecting carbon emissions (Chen et al. 2018a), which is prominent in developing countries. The population density is expressed by the population per unit area of each prefecture-level city in this paper.
- (2) Economic development (*pGDP* and *pGDP*²): The environmental Kuznets curve (EKC) hypothesis shows that there is a nonlinear relationship between economic development and carbon emissions (Balado-Naves et al. 2018). Per capita GDP is a typical indicator to measure the economic development of a city. Concurrently, the nonlinear relationship described in the EKC hypothesis is investigated with the support of the quadratic term of per capita GDP (*pGDP*²).
- (3) Foreign direct investment (*FDI*): The direction of the impact of foreign direct investment on carbon emissions is uncertain. Some studies believe that FDI helps to control carbon emissions (Zhang and Zhou 2016), but there are also opposite conclusions (Yang et al. 2020). In this paper, the *FDI* is expressed as the proportion of foreign direct investment in GDP.
- (4) Government intervention (*GOV*): As the macroeconomic actors, government intervention will certainly have an impact on pollution emissions (Wang et al. 2021b). However, the impact of government intervention on pollution emissions may show nonlinear features. We describe government intervention in terms of the proportion of expenditure in the local fiscal budget in GDP (Peng et al. 2021).
- (5) Financial development (*FD*): The impact of financial development on carbon emissions has always been a concern (Acheampong et al. 2020; Shahbaz et al. 2021). This paper employs the proportion of the cash surplus of various loans of financial institutions in GDP at the end of the year as the proxy variable of financial development.
- (6) Urbanization (*URB*): The carbon emission caused by urbanization is also a hot issue of academic con-

cern (Sadorsky 2014; Wang et al. 2021a). Meanwhile, the time-varying and U-shaped relationship between urbanization and carbon emissions have been partially discussed (Sufyanullah et al. 2022; Xu and Lin 2015). Therefore, the proxy variable of urbanization is constructed by the digital number (DN) of the grayscale value by employing the nighttime light data provided by the National Geophysical Data Center (NGDC) with unstable light sources removed (Liu et al. 2012; Xu et al. 2021). In addition, the nighttime stable light data in the meteorological satellite program's operational linescan system (DMSP-OLS)³ format and the national polar-orbiting partnership satellite's visible infrared imaging radiometer suite (NPP-VIIRS)⁴ format are calibrated concerning Chen et al. (2021) and Hu et al. (2022) methods.

- (7) Transportation infrastructure (*TI*): The development of infrastructure in a city will promote energy consumption and generate carbon emissions (Chen et al. 2022b), especially transportation infrastructure (Xie et al. 2017). In this paper, the transportation infrastructure is represented by the actual paved per capita road area at the end of the year.
- (8) Green space (*GS*): Urban afforestation, forest, and vegetation are considered an early classical carbon storage scheme, which can inhibit carbon emissions (Jo 2002; Zhao et al. 2010). The per capita public green area is the proxy variable of green space in this paper.

Mechanism variables

Mechanism analysis is divided into energy factors and industrial factors.

(1) Industrial factor mechanism variables include industrial structure (*IS*) and industrial agglomeration (*AGG*). Industrial structure has always been regarded as a key factor causing air pollution and affecting carbon emissions (Yang et al. 2020). Generally, the manufacturing industry (a secondary sector of the economy in China) is an important source of increasing carbon emissions (Chen et al. 2019; Zhu et al. 2020). We regard the industrial structure as the proportion of the secondary sector of the economy in GDP because it is the main energy-consuming sector. Industrial agglomeration will also have an impact on air pollutants or carbon emissions (Chen et al. 2022c; Yang et al. 2020), which may be an important reason for the spatial spillover effect of carbon emissions. Therefore, we employ a standardized location quotient to measure the level of industrial

agglomeration concerning the O'Donoghue and Gleave (2004) method as follows:

$$AGG = \left(e_{ir} / \sum e_{ir} \right) / \left(\sum e_{ir} / \sum_i \sum_r e_{ir} \right) \quad (12)$$

where e_{ir} represents the employment of r industry in city i . We measure the standardized location quotient by the employment of the secondary sector of the economy.

(2) Energy factor mechanism variables include energy consumption scale (*EC*), energy consumption structure (*ES*), and energy intensity (*EI*). There is no doubt that factors related to energy consumption are important reasons for carbon emissions, especially fossil energy (Zhang and Cheng 2009). Employing renewable energy is an important way to reduce carbon emissions (Huang et al. 2021; Wang et al. 2016). The energy consumption scale is measured in per capita form of standard coal. Due to the lack of data on renewable energy consumption in the prefecture-level city in China, this paper employs the proportion of electricity consumption in total energy consumption to represent the energy consumption structure (Xu et al. 2021). The energy intensity is measured by energy consumption scale per unit GDP (10,000 tons of standard coal).

Empirical results and discussion

This section includes the descriptive statistics; the second part is analysis of the baseline model; the third part is to eliminate potential endogeneity problems; the fourth part is considering the potential spatial spillover effect of *CO2* and *RETI*; the fifth part is the robustness test; the sixth part is the mechanism analysis based on the mediation effect model; and the seventh part is the analysis of the potential heterogeneity.

Descriptive statistics

All variables are presented in natural logarithms, and the logarithmic transformation with renewable energy technology patents of $(1 + X)$ to avoid missing values. The datasets of this paper come from the China City Statistical Yearbook, the China National Intellectual Property Administration (CNIPA), the National Geophysical Data Center (NGDC), and the government work reports of prefecture-level cities in China. Table 1 shows the descriptive statistics of variables.

Descriptive statistics make some facts emerge: (1) Not all cities in China have carried out renewable energy technology innovations. (2) The economic indicators show that there is a huge break in city development in China. (3) The gaps

³ <http://www.ngdc.noaa.gov/eog/dmsp.html>

⁴ <https://eogdata.mines.edu/products/vnl/>

Table 1 Descriptive statistics of variables

	Variables	Mean	Std. dev	Min	Max	Obs
Dependent variables	<i>lnCO2</i>	3.104	0.749	0.738	5.441	2684
	<i>lnpCO2</i>	-2.846	0.654	-6.479	-0.355	2684
Main independent variables	<i>lnRETI</i>	4.827	1.695	0	10.271	2684
	<i>lnRETI_EP</i>	3.924	1.607	0	9.285	2684
	<i>lnRETI_EC</i>	3.391	1.840	0	9.228	2684
	<i>lnRETI_EM</i>	3.723	1.740	0	9.073	2684
Control variables	<i>lnpGDP</i>	10.728	0.643	8.327	15.675	2684
	<i>lnPOP</i>	-3.349	0.872	-7.637	0.774	2684
	<i>lnGS</i>	0.840	0.961	-5.877	4.328	2684
	<i>lnTI</i>	1.053	0.889	-2.921	4.291	2684
	<i>lnFDI</i>	-5.396	1.349	-14.848	0.713	2684
	<i>lnGOV</i>	-0.989	0.754	-3.835	1.798	2684
	<i>lnFD</i>	0.987	0.630	-2.043	3.247	2684
	<i>lnURB</i>	-1.204	1.472	-5.464	2.876	2684
Mechanism variables	<i>lnIS</i>	3.875	0.263	2.276	4.477	2684
	<i>lnAGG</i>	-5.246	0.945	-8.198	-2.196	2684
	<i>lnES</i>	-0.277	0.784	-3.712	2.495	2684
	<i>lnEC</i>	4.403	1.184	0.952	8.183	2684
	<i>lnEI</i>	-11.907	0.829	-14.709	-8.069	2684

Table 2 The estimation results of carbon emission in the baseline model

Variables	<i>lnCO2</i>				
	(1)	(2)	(3)	(4)	(5)
<i>lnRETI</i>	0.0191*** (5.45)	0.0644*** (8.58)			
<i>lnRETI</i> ²		-0.0056*** (-7.32)			
<i>lnRETI_EP</i>			0.0460*** (7.28)		
<i>lnRETI_EP</i> ²			-0.0050*** (-5.95)		
<i>lnRETI_EC</i>				0.0264*** (5.88)	
<i>lnRETI_EC</i> ²				-0.0039*** (-5.98)	
<i>lnRETI_EM</i>					0.0406*** (7.96)
<i>lnRETI_EM</i> ²					-0.0052*** (-7.88)
Control variables	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes
Constant	1.9127*** (5.21)	2.9797*** (9.17)	2.6387*** (7.76)	2.7041*** (7.77)	3.1090*** (9.65)
Adj <i>R</i> ²	0.9917	0.9920	0.9919	0.9918	0.9920
Obs	2684	2684	2684	2684	2684

*, **, ***Significance at the 10%, 5%, and 1% level. *T* statistics in parentheses. Clustering to the city level

between per capita public green area, foreign direct investment, and urbanization are prominent

Analysis of baseline model

Table 2 reports the baseline model based on Eq. (2). The dependent variable in columns (1) to (5) is carbon emissions, and the independent variable in column (1) only contains the primary term of $RETI$. The empirical results in column (1) show that renewable energy technology innovation has not played a role in reducing carbon emissions, which is contrary to intuition. Column (2) reports the empirical results considering the quadratic term of renewable energy technology innovation. The coefficients of the primary ($RETI$) and quadratic terms ($RETI^2$) of the renewable energy technology innovation are significant at 1%, and the primary term is positive and the quadratic term is negative; that is, there is an important inverse U-shaped relationship between renewable energy technology innovation and carbon emissions. Based on column (2), the inflection point of the inverse U-shaped curve is further calculated (5.75), and it is found that only when the renewable energy technology innovation develops to the established scale, its carbon emission reduction effect can be highlighted. Due to space constraints, the coefficients of the control variables are reported in Table 17 of Appendix 1.

The reason for the above stylized facts may be due to the high cost of renewable energy technology and the different application purposes of renewable energy technology. It is not difficult to find that there are various types of renewable energy technologies. For example, the carbon emission reduction effect of renewable energy technologies such as solar energy, wind energy, and hydro energy is indirectly highlighted by replacing the application of traditional fossil energy in electric power production. Therefore, the renewable energy technology of energy production type often has a long construction cycle and high investment cost, which makes it difficult to immediately show the effect of carbon emission reduction. The renewable energy technologies of energy management and energy conservation type are directly related to pollution treatment, pollutant recovery, and even carbon capture, utilization, and storage (CCUS). Although such technologies also have cost problems, their carbon emission reduction effects may be more prominent. We must also note that in the long run, renewable energy technology of energy production type can produce significant economic benefits, while other types of renewable energy technologies can improve utilization by reducing pollutants.

We further consider different types of renewable energy technologies with energy production ($RETI_{EP}$), energy conservation ($RETI_{EC}$), and energy management ($RETI_{EM}$). The empirical results in columns (3), (4), and

Table 3 The first stage of the two-stage least square

Variables	$\ln RETI$		
	(1)	(2)	(3)
$\ln EV$	0.0763*** (4.95)		
$\ln ER$		0.0394*** (2.91)	
$L \ln RETI$			0.0454** (2.35)
Control variables	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes
Constant	-4.6830** (-2.26)	-13.810*** (-4.09)	-11.6618*** (-3.40)
F test (p)	900.80 (0.000)	626.31 (0.000)	652.50 (0.000)
Adj R^2	0.9922	0.9823	0.9848
Obs	1708	2684	2440

*, **, ***Significance at the 10%, 5%, and 1% level. T statistics in parentheses. Clustering to the city level

(5) also show a similar inverse U shape, which indicates that the impact of different types of renewable energy technologies on carbon emissions may be analogous. However, in column (4), the inflection point between renewable energy technology of energy conservation type and carbon emission is earlier than column (2) ($3.38 < 5.75$). The results show that renewable energy technology of energy conservation type can achieve carbon emission reduction faster than the other two technologies ($3.38 < 4.60$, $3.38 < 3.91$). This kind of renewable energy technology is related to storage of electricity energy, storage of thermal energy, measurement of electricity consumption, low energy lighting, etc., in the modern society dominated by electrical appliances; these patents have greatly improved energy efficiency and played a direct role in reducing carbon emissions.

Analysis of endogeneity

Reverse causality is an easily discovered source of endogeneity problems. Cities with fewer carbon emissions may not be interested in renewable energy technology innovation, and the level of renewable energy technology innovation will have an impact on carbon emissions, which is a typical situation of reverse causality. The endogeneity problem caused by the reverse causality between carbon emissions and renewable energy technology innovation is addressed by the instrumental variable method and 2SLS. It should be noted that the Baidu Index started in 2011, so the sample period with environmental concern as the instrumental variable is from 2011 to 2017.

Table 4 The second stage of the two-stage least square

Variables	$\ln CO_2$		
	(1)	(2)	(3)
	$\ln EV$	$\ln ER$	$L \ln RETI$
$\ln RETI$	0.1450*** (4.01)	0.2313** (2.00)	0.3084** (2.32)
$\ln RETI^2$	-0.0131*** (-4.10)	-0.0195** (-2.02)	-0.0265** (-2.33)
Control variables	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes
Constant	3.8970*** (11.13)	5.3357*** (3.01)	5.9274*** (3.40)
Adj R^2	0.9958	0.9905	0.9893
Obs	1708	2684	2440

*, **, ***Significance at the 10%, 5%, and 1% level. T statistics in parentheses. Clustering to the city level

The instrumental variables are environmental concerns, environmental regulation, and the first-order lag of renewable energy technology innovation. We can find the results of the first stage regression in Table 3. In columns (1) to (3), the coefficient between each instrumental variable and renewable energy technology innovation is significantly positive, and the F -statistic test is significantly greater than 10 at 1%, indicating that there are no weak instruments. Therefore, environmental concern is conducive to renewable energy technology innovation, and environmental regulation will also promote renewable energy technology innovation. According to column (3), renewable energy technology innovation also has the features of technology dependence. The level of technological innovation in the early period will have an impact on the current period. Table 4 shows the results of the second stage of the 2SLS method. After considering the endogeneity problem, the causality between renewable energy technology innovation and carbon emissions is still significantly inverse U-shaped at 1% and 5% levels. Therefore, the impact of renewable energy technology on carbon emissions shows the first increase and then a decrease.

Analysis of spatial spillover effect

We further analyzed the potential spatial spillover effects of carbon emissions and renewable energy technology innovation under the spatial weight matrix of W^1 . The index of Moran's I is used for the spatial effect test with the variables of $\ln CO_2$ and $\ln RETI$. The test results of the spatial effect are shown in Table 18 of Appendix 2. The Moran's I scatter diagram (2007, 2012, and 2017) are presented in Fig. 1 and Fig. 2 of Appendix 2. To simplify the table, the coefficients

of the control variables and their spatial lag terms are not reported in Table 5.

According to Table 5, the Wald-statistic test shows that the SDM model cannot degenerate into SEM or SAR models. The coefficient of the spatial lag term of the dependent variables ($W * \ln CO_2$) in columns (1) to (4) is significantly positive at the 1% level, which verifies that there is a significant spatial spillover effect of carbon emissions. The reasons for this effect relate to the carbon pollution cycle and the carbon footprint formed by economic activities, which is consistent with the spatial effect test of Appendix 2. This result implies that the governance of carbon emissions needs the coordination of various cities.

After considering the spatial effects of dependent variables and main independent variables, the relationship between renewable energy technology innovation and carbon emissions still presents an inverse U shape. However, this inverse U-shaped relationship is effective for local renewable energy technologies, while the inverse U shape between renewable energy technologies and carbon emissions in adjacent cities is not reliable. Specifically, we further consider renewable energy technology innovation from the types of energy production, energy conservation, and energy management. The empirical results show that the variations in spatial lag terms in columns (2) to (3) are not significant. There is an inverse U-shaped relationship between renewable energy technology of energy production type and carbon emissions, only locally, not in adjacent cities.

It should be noted that the spatial effect item in column (4) shows that the renewable energy technology of energy management type also has an inverse U-shaped relationship with adjacent cities ($W * \ln RETI_{EM}$ and $W * \ln RETI_{EM}^2$). Generally, renewable energy technology of energy management type is employed to treat the pollutants generated by energy application, including energy technology patents such as treatment of waste, reuse of waste materials, and pollution control. Most of the pollutants must be treated in fixed regions, which requires cross-urban coordination and cooperation so this type of renewable energy technology has a significant spatial spillover effect.

Robustness tests

The robustness tests are as follows: First, we employ the per capita carbon emissions to re-estimate the baseline and spatial model to eliminate the scale effect. Second, considering the spatial weight matrix of W^2 , the results of the spatial econometric model are verified again. Third, the samples of the municipalities and low-carbon cities pilot were excluded. Fourth, the winsorize (replace sample value less than 1% and more than 99%) is used to limit the

Fig. 1 Moran's I scatter diagram of $\ln CO_2$ with W^l in 2007, 2012, and 2017

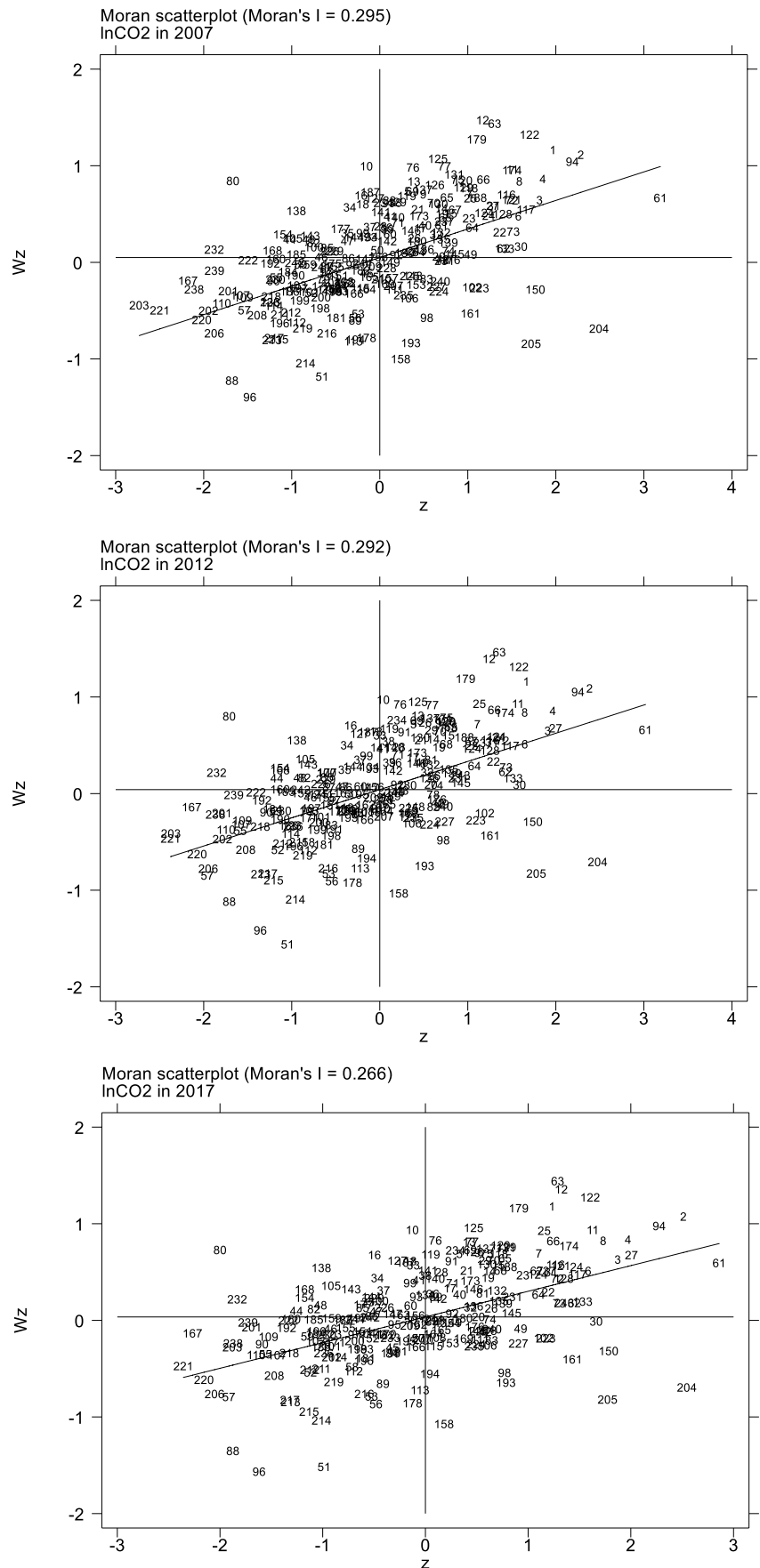


Fig. 2 Moran's I scatter diagram of $\ln RETI$ with W^l in 2007, 2012, and 2017

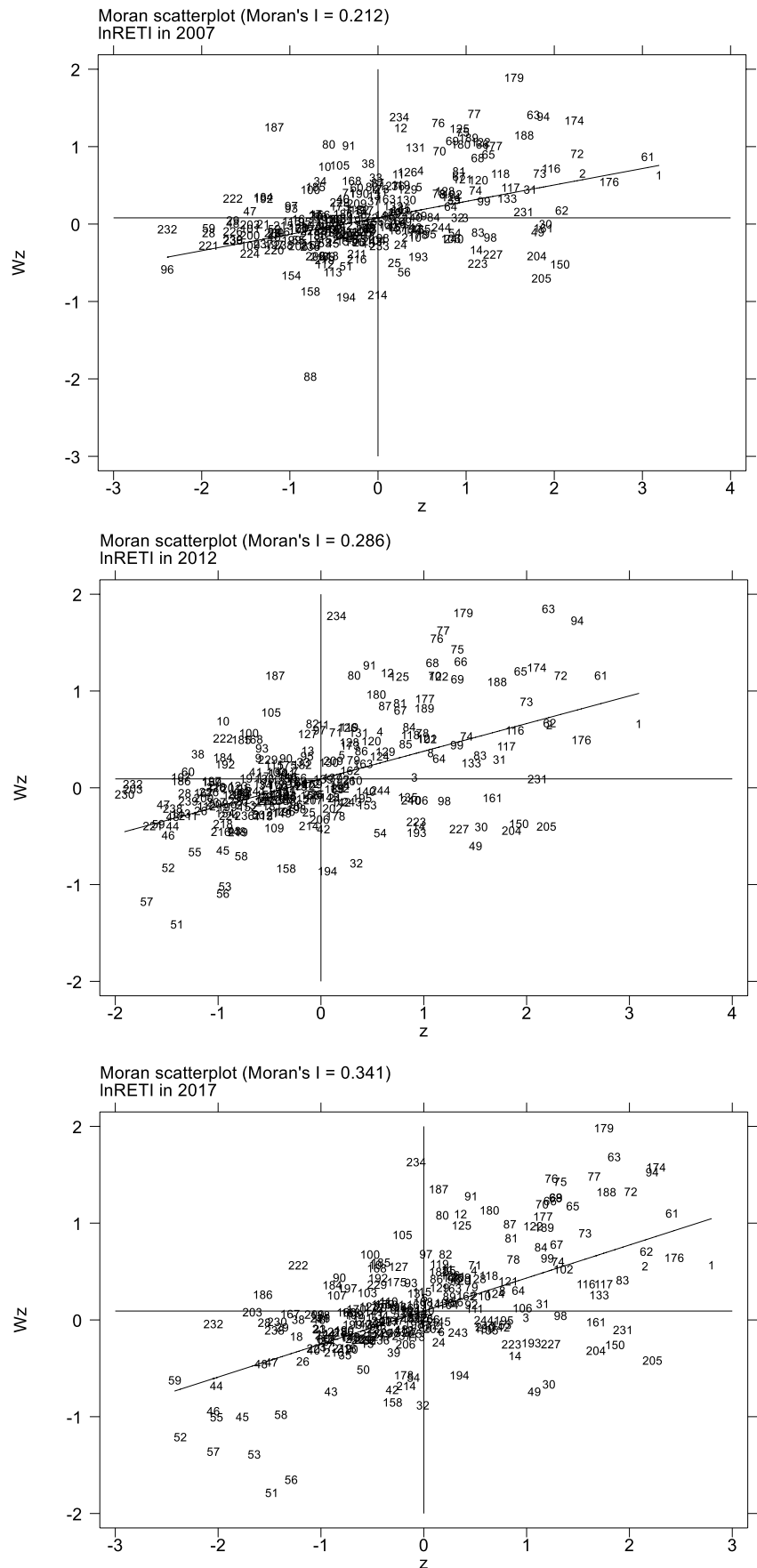


Table 5 Empirical results of carbon emission in the spatial econometric model

Variables	<i>lnCO2</i>			
	(1)	(2)	(3)	(4)
	FE	FE	FE	FE
<i>W*lnCO2</i> (ρ)	0.8417*** (54.45)	0.8460*** (55.25)	0.8449*** (55.04)	0.8398*** (53.89)
<i>lnRETI</i>	0.0330*** (6.71)	-	-	-
<i>lnRETI</i> ²	-0.0031*** (-5.85)	-	-	-
<i>lnRETI_EP</i>	-	0.0233*** (5.47)	-	-
<i>lnRETI_EP</i> ²	-	-0.0024*** (-4.13)	-	-
<i>lnRETI_EC</i>	-	-	0.0132*** (4.49)	-
<i>lnRETI_EC</i> ²	-	-	-0.0021*** (-4.62)	-
<i>lnRETI_EM</i>	-	-	-	0.0188*** (5.35)
<i>lnRETI_EM</i> ²	-	-	-	-0.0028*** (-5.80)
<i>W*lnRETI</i>	0.0248** (2.21)			
<i>W*lnRETI</i> ²	-0.0020** (-2.02)			
<i>W*lnRETI_EP</i>		0.0145 (1.49)		
<i>W*lnRETI_EP</i> ²		-0.0020* (-1.75)		
<i>W*lnRETI_EC</i>			0.0157 (1.07)	
<i>W*lnRETI_EC</i> ²			-0.0017* (-1.93)	
<i>W*lnRETI_EM</i>				0.0278*** (3.26)
<i>W*lnRETI_EM</i> ²				-0.0024*** (-2.59)
Control variables	Yes	Yes	Yes	Yes
Space item of control variables	Yes	Yes	Yes	Yes
Wald test (p)	170.13 (0.000)	32.65 (0.005)	39.38 (0.001)	185.27 (0.000)
Obs	2684	2684	2684	2684

*, **, ***Significance at the 10%, 5%, and 1% level. *T* statistics in parentheses. *W* is the spatial weight matrix

impact of extreme values of the empirical results. Moreover, the coefficients of the control variables and the space item of control variables are not reported in the robustness test for simplification.

Table 6 Robustness test for scale effect (baseline model)

Variables	<i>lnpCO2</i>			
	(1)	(2)	(3)	(4)
<i>lnRETI</i>	0.0667*** (7.64)			
<i>lnRETI</i> ²	-0.0076*** (-8.52)			
<i>lnRETI_EP</i>		0.0483*** (6.21)		
<i>lnRETI_EP</i> ²		-0.0068*** (-6.56)		
<i>lnRETI_EC</i>			0.0260*** (4.63)	
<i>lnRETI_EC</i> ²			-0.0057*** (-7.66)	
<i>lnRETI_EM</i>				0.0419*** (6.87)
<i>lnRETI_EM</i> ²				-0.0071*** (-8.96)
Control variable	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Constant	-6.7357*** (-15.05)	-7.1607*** (-15.69)	-6.9921*** (-14.74)	-6.6691*** (-14.98)
Adj <i>R</i> ²	0.9807	0.9805	0.9806	0.9808
Obs	2684	2684	2684	2684

*, **, ***Significance at the 10%, 5%, and 1% level. *T* statistics in parentheses. Clustering to the city level

Robustness test for scale effect

Table 6 shows the scale effect test results of the baseline model. Compared with columns (2) to (5) in Table 2, the empirical results are maintained except for the coefficient values of the baseline model. The inverse U-shaped relationship between renewable energy technology innovation and carbon emissions still exists, and the inflection point of renewable energy technology of energy conservation type is still the earliest, and its carbon emission reduction effect is the most prominent. Therefore, after the scale effect is eliminated by employing per capita carbon emissions (*lnpCO2*), the empirical results of this paper are believable.

Table 7 shows the scale effect test results of the spatial model. Per capita carbon emissions (ρ) still have a significant spatial spillover effect. The inverse U shape between renewable energy technology innovation and carbon emissions is not stable in adjacent cities. Only renewable energy technology of energy management type has produced a spatial spillover effect, which once again shows that the co-processing of carbon emissions and pollutants between

Table 7 Robustness test for scale effect (spatial econometric model with the matrix of W^1)

Variables	$lnpCO2$			
	(1)	(2)	(3)	(4)
	FE	FE	FE	FE
$W*lnpCO2 (\rho)$	0.6714*** (29.69)	0.6798*** (30.47)	0.6764*** (30.31)	0.6584*** (28.40)
$lnRETI$	0.0427*** (5.71)			
$lnRETI^2$	-0.0047*** (-5.78)			
$lnRETI_{EP}$		0.0300*** (4.62)		
$lnRETI_{EP}^2$		-0.0039*** (-4.36)		
$lnRETI_{EC}$			0.0159*** (3.56)	
$lnRETI_{EC}^2$			-0.0034*** (-5.05)	
$lnRETI_{EM}$				0.0241*** (4.51)
$lnRETI_{EM}^2$				-0.0039*** (-5.30)
$W*lnRETI$	0.0057 (0.33)			
$W*lnRETI^2$	-0.0011 (-0.69)			
$W*lnRETI_{EP}$		0.0020 (0.14)		
$W*lnRETI_{EP}^2$		-0.0012 (-0.68)		
$W*lnRETI_{EC}$			0.0079 (0.69)	
$W*lnRETI_{EC}^2$			-0.0012 (-0.85)	
$W*lnRETI_{EM}$				0.0136 (1.05)
$W*lnRETI_{EM}^2$				-0.0023* (-1.66)
Control variables	Yes	Yes	Yes	Yes
Space item of control variables	Yes	Yes	Yes	Yes
Wald test (p)	147.48 (0.000)	137.06 (0.000)	147.08 (0.000)	165.05 (0.000)
Obs	2684	2684	2684	2684

*, **, ***Significance at the 10%, 5%, and 1% level. t statistics in parentheses. W is the spatial weight matrix

different cities already has the foundation. Therefore, after the potential scale effect is eliminated by per capita carbon emissions, the empirical results of this paper are robust.

Robustness test for spatial spillover effect

We further use another composite spatial weight matrix (W^2) to test the robustness of the spatial spillover effect.

The empirical results in columns (1) to (4) show that the relationship between renewable energy technologies and local urban carbon emissions is still inverted U-shaped. Although the constitution of the spatial weight matrix is changed, the results of the spatial spillover effect are not affected essentially (Table 8). Therefore, as long as the same spatial factors (geographic distance and economic distance) are considered, the spatial effect between

Table 8 Robustness test with different spatial weight matrix (W^2)

Variables	$lnCO2$			
	(1)	(2)	(3)	(4)
	FE	FE	FE	FE
$W*lnCO2 (\rho)$	0.6781*** (40.15)	0.6779*** (40.08)	0.6795*** (40.09)	0.6820*** (40.64)
$lnRETI$	0.0400*** (6.85)			
$lnRETI^2$	-0.0039*** (-6.08)			
$lnRETI_{EP}$		0.0241*** (4.87)		
$lnRETI_{EP}^2$		-0.0024*** (-3.52)		
$lnRETI_{EC}$			0.0182*** (5.32)	
$lnRETI_{EC}^2$			-0.0028*** (-5.37)	
$lnRETI_{EM}$				0.0242*** (5.87)
$lnRETI_{EM}^2$				-0.0037*** (-6.43)
$W*lnRETI$	0.0063 (0.57)			
$W*lnRETI^2$	0.0008 (0.82)			
$W*lnRETI_{EP}$		0.0112 (1.23)		
$W*lnRETI_{EP}^2$		-0.0004 (-0.34)		
$W*lnRETI_{EC}$			-0.0026 (-0.38)	
$W*lnRETI_{EC}^2$			0.0020** (2.40)	
$W*lnRETI_{EM}$				0.0033 (0.43)
$W*lnRETI_{EM}^2$				0.0012 (1.38)
Control variables	Yes	Yes	Yes	Yes
Space item of control variables	Yes	Yes	Yes	Yes
Wald test (p)	248.41 (0.000)	251.31 (0.000)	234.93 (0.000)	265.95 (0.000)
Obs	2684	2684	2684	2684

*, **, ***Significance at the 10%, 5%, and 1% level. T statistics in parentheses. W is the spatial weight matrix

renewable energy technology innovation and carbon emissions will be maintained.

Robustness test for locational advantage and low-carbon cities pilot

First, the locational advantages brought by municipalities directly under the central government (Beijing,

Shanghai, Tianjing, and Chongqing) need to be eliminated. Table 9 shows the empirical results after excluding the municipalities. We still compare these empirical results with the detection in columns (2) to (5) of Table 2. The inverse U-shaped relationship between renewable energy technology innovation and carbon emissions is maintained. The inflection point of column (3) in Table 9 is 2.770, which shows that renewable

Table 9 Robustness test for excluding samples of locational advantages

Variables	<i>lnCO2</i>			
	(1)	(2)	(3)	(4)
<i>lnRETI</i>	0.0552*** (7.64)			
<i>lnRETI</i> ²	-0.0046*** (-6.27)			
<i>lnRETI</i> _EP		0.0387*** (6.43)		
<i>lnRETI</i> _EP ²		-0.0039*** (-4.98)		
<i>lnRETI</i> _EC			0.0205*** (4.77)	
<i>lnRETI</i> _EC ²			-0.0037*** (-4.51)	
<i>lnRETI</i> _EM				0.0349*** (7.06)
<i>lnRETI</i> _EM ²				-0.0044*** (-6.94)
Control variable	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Constant	3.1181*** (9.71)	2.8320*** (8.55)	2.8133*** (8.20)	3.2651*** (10.18)
Adj <i>R</i> ²	0.9916	0.9915	0.9914	0.9916
Obs	2640	2640	2640	2640

*, **, ***Significance at the 10%, 5%, and 1% level. *T* statistics in parentheses. Clustering to the city level

energy technology of energy conservation type still shows carbon emission reduction effects prominently.

Second, the empirical results in Table 10 exclude the impact of the low-carbon cities pilot. The low-carbon cities pilot will reduce the carbon emissions of a region in other aspects, but the inverse U-shaped curve still exists after the impact of the low-carbon cities pilot is released.

Robustness test for extreme value

Table 11 shows the empirical results after excluding extreme values, with the causality maintained except for the value of the coefficients. In general, the empirical result of the baseline model and the spatial model in this paper is robust.

Analysis of mechanism

Table 12 reports the mechanism analysis results of the industrial factor. When industrial structure (IS) is regarded as a mediation variable, the coefficient of renewable energy technology innovation in columns (1) to (2) is not significant.

Table 10 Robustness test for excluding samples of low-carbon cities pilot

Variables	<i>lnCO2</i>			
	(1)	(2)	(3)	(4)
<i>lnRETI</i>	0.0551*** (6.93)			
<i>lnRETI</i> ²	-0.0046*** (-5.55)			
<i>lnRETI</i> _EP		0.0372*** (5.78)		
<i>lnRETI</i> _EP ²		-0.0037*** (-4.29)		
<i>lnRETI</i> _EC			0.0176*** (3.81)	
<i>lnRETI</i> _EC ²			-0.0023*** (-3.45)	
<i>lnRETI</i> _EM				0.0348*** (6.49)
<i>lnRETI</i> _EM ²				-0.0044*** (-6.31)
Control variable	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Constant	3.2029*** (9.44)	2.9585*** (8.65)	2.8941*** (8.10)	3.3621*** (9.79)
Adj <i>R</i> ²	0.9909	0.9908	0.9907	0.9908
Obs	2376	2376	2376	2376

*, **, ***Significance at the 10%, 5%, and 1% level. *T* statistics in parentheses. Clustering to the city level

Consequently, the industrial structure is not a mediation variable of renewable energy technology innovation affecting carbon emissions. The empirical results in columns (3) to (4) show that industrial agglomeration is the channel which renewable energy technologies affect carbon emissions.

Table 13 reports the mechanism analysis results of the energy factor. The results in columns (1) to (2) show that energy consumption (*EC*) scale is a mediation variable between renewable energy technologies and carbon emissions by acting on energy consumption scale. The mediation effects of energy consumption structure (*ES*) and energy intensity (*EI*) are not valid. Therefore, only industrial agglomeration (*AGG*) and energy consumption scale (*EC*) meet the mediation effect. Specifically, the renewable energy technology innovation increases carbon emissions by inducing the industrial agglomeration and increasing the energy consumption scale, which indicates that the carbon emissions generated by the application cost of renewable energy technology are larger than the carbon emission reduction effect in the short term.

Table 11 Robustness test for excluding samples of extreme value

Variables	lnCO2			
	(1)	(2)	(3)	(4)
lnRETI	0.0673*** (8.87)			
lnRETI ²	-0.0059*** (-7.40)			
lnRETI_ EP		0.0482*** (7.34)		
lnRETI_ EP ²		-0.0051*** (-5.83)		
lnRETI_ EC			0.0255*** (5.86)	
lnRETI_ EC ²			-0.0037*** (-5.82)	
lnRETI_ EM				0.0422*** (8.30)
lnRETI_ EM ²				-0.0057*** (-8.26)
Control variable	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Constant	1.6890*** (2.94)	1.0159* (1.77)	1.1095* (1.92)	2.0490*** (3.66)
Adj R ²	0.9931	0.9930	0.9929	0.9931
Obs	2684	2684	2684	2684

*, **, ***Significance at the 10%, 5%, and 1% level. *T* statistics in parentheses. Clustering to the city level

Table 12 Empirical results of the mediation effect model of industrial factor

Variables	M=lnIS	lnCO2	M=lnAGG	lnCO2
	(1)	(2)	(3)	(4)
lnRETI	0.0019 (0.35)	0.0191*** (5.43)	0.0447*** (3.37)	0.0184*** (5.25)
M		0.0278 (1.48)		0.0149** (2.44)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Constant	-4.3117*** (-4.56)	2.0326*** (5.49)	-6.6815*** (-7.02)	2.0122*** (5.46)
Adj R ²	0.8736	0.9917	0.9345	0.9917
Obs	2684	2684	2684	2684

*, **, ***Significance at the 10%, 5%, and 1% level. *T* statistics in parentheses. Clustering to the city level

In general, to develop renewable energy technologies, related industries are highly concentrated in specific areas, leading to the repeated construction of industrial agglomeration areas related to renewable energy technologies, which increases carbon emissions. In addition, the spread of renewable energy technologies has unlocked the energy consumption potential constrained by fossil energy, which is related to the energy rebound effect. It can be seen that although renewable energy technologies are highly expected to reduce carbon emissions, the repeated construction caused by industrial agglomeration and the blind expansion of energy consumption scale are the important reasons for their failure to reduce carbon emissions immediately. In addition, renewable energy technologies have not promoted the effective green upgrading of energy consumption structure, which has also become a key factor in the rise of carbon emissions in the short term. Both the improvement of renewable energy consumption and the clean transformation of energy structure should be based on the application of renewable energy technology, which requires a large amount of technology application costs (new technics, new equipment, new construction, etc.). Therefore, the application cost of renewable energy technology and its implied carbon emission are the main factors restricting its carbon reduction effect, which is also easy to be forgotten.

Analysis of heterogeneity

Heterogeneity analysis includes four aspects: geographic region, patent type, resource-based city, and key city for environmental protection. Table 14 and Table 15 show the empirical results of heterogeneity. To simplify the analysis, each column contains four regression results, so the constants and R² are not reported. In Table 14, the impact of resource-based (RB) cities and key cities for environmental protection (EP) is mainly reflected in the value of the coefficient, that is, the impact of intensity. By calculating the inflection point (RB 5.489 > 5.139, EP 5.773 > 4.309), it is found that resource-based cities and key cities for environmental protection are more dependent on renewable energy technologies, and renewable energy technology innovation can achieve carbon emission reduction effects faster in these cities.

In Table 15, in China’s non-eastern cities, renewable energy technology innovation of the energy production type and energy management type cannot achieve carbon emission reduction effects. Only renewable energy technologies of energy conservation type that related to the treatment of pollutants have achieved carbon emission reduction in non-eastern cities. Therefore, the phenomenon of pollution haven may exist in China’s central and western cities. Finally, patent types do not have a special impact, and both invention patents and utility model patents can play a role in reducing carbon emissions.

Table 13 Empirical results of the mediation effect model of energy factor

Variables	$M=lnEC$ (1)	$lnCO2$ (2)	$M=lnES$ (3)	$lnCO2$ (4)	$M=lnEI$ (5)	$lnCO2$ (6)
$lnRETI$	0.0802*** (4.42)	0.0184*** (5.27)	-0.0008 (-0.06)	0.0191*** (5.46)	0.0698*** (3.12)	0.0195*** (5.52)
M		0.0091* (1.73)		0.0060 (1.03)		-0.0053 (-1.15)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.3916 (0.22)	1.9091*** (5.30)	-0.8049 (-0.76)	1.9175*** (5.23)	-15.5865*** (-5.43)	1.8303*** (4.78)
Adj R^2	0.9347	0.9917	0.8865	0.9917	0.7602	0.9917
Obs	2684	2684	2684	2684	2684	2684

*, **, ***Significance at the 10%, 5%, and 1% level. T statistics in parentheses. Clustering to the city level

Table 14 Heterogeneity with resource-based cities and environmental protection cities

Variables	$lnCO2$			
	RB cities (1)	Non-RB cities (2)	EP cities (3)	Non-EP cities (4)
$lnRETI$	0.0505*** (4.91)	0.0925*** (8.90)	0.0762*** (7.26)	0.0767*** (7.22)
$lnRETI^2$	-0.0046*** (-4.10)	-0.0090*** (-8.59)	-0.0066*** (-6.43)	-0.0089*** (-7.45)
$lnRETI_{EP}$	0.0364*** (3.92)	0.0641*** (7.47)	0.0570*** (6.48)	0.0502*** (5.68)
$lnRETI_{EP}^2$	-0.0041*** (-3.10)	-0.0077*** (-7.12)	-0.0060*** (-5.38)	-0.0076*** (-6.07)
$lnRETI_{EC}$	0.0175*** (3.02)	0.0462*** (6.78)	0.0319*** (5.46)	0.0316*** (4.80)
$lnRETI_{EC}^2$	-0.0037*** (-3.73)	-0.0067*** (-7.57)	-0.0050*** (-6.03)	-0.0061*** (-5.77)
$lnRETI_{EM}$	0.0299*** (4.30)	0.0558*** (7.91)	0.0497*** (7.01)	0.0453*** (6.26)
$lnRETI_{EM}^2$	-0.0037*** (-3.72)	-0.0080*** (-8.93)	-0.0063*** (-7.13)	-0.0077*** (-7.17)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Obs	1001	1683	1804	880

*, **, ***Significance at the 10%, 5%, and 1% level. T statistics in parentheses. RB is a resource-based city. EP is a key city for environmental protection

Conclusion and policy implications

Based on the economic data and energy technology patent data of prefecture-level cities in China from 2007 to 2017, the impact of renewable energy technology innovation on carbon emissions and its mechanisms are discussed. This investigation into renewable energy technology innovation is conducted with the perspective of energy production, conservation, and management.

The instrumental variable method alleviates the endogeneity problem between renewable energy technology innovation and carbon emissions, and the spatial econometric model eliminates the spatial spillover effects of renewable energy technology innovation and carbon emissions. Subsequently, we also employed the mediation effect model to analyze the mechanism.

We found that (1) renewable energy technology innovation has a nonlinear inverted U-shaped impact on carbon emissions. It is important to note that spatial spillovers

Table 15 Heterogeneity with geographic region and patent type

Variables	<i>lnCO2</i>			
	Eastern cities (1)	Non-East cities (2)	Invention (3)	Utility model (4)
<i>lnRETI</i>	0.0896*** (5.67)	0.0323*** (4.16)	0.0398*** (7.17)	0.0574*** (8.23)
<i>lnRETI</i> ²	−0.0093*** (−6.57)	−0.0018** (−2.05)	−0.0050*** (−7.37)	−0.0071*** (−8.61)
<i>lnRETI_EP</i>	0.0656*** (4.89)	0.0213*** (3.30)	0.0291*** (6.15)	0.0434*** (7.98)
<i>lnRETI_EP</i> ²	−0.0086*** (−5.62)	−0.0010 (−1.04)	−0.0046*** (−6.05)	−0.0070*** (−7.92)
<i>lnRETI_EC</i>	0.0407*** (3.61)	0.0215*** (3.79)	0.0152*** (4.33)	0.0303*** (6.83)
<i>lnRETI_EC</i> ²	−0.0067*** (−5.67)	−0.0022*** (−2.78)	−0.0043*** (−7.07)	−0.0061*** (−8.12)
<i>lnRETI_EM</i>	0.0549*** (5.66)	0.0096** (2.07)	0.0299*** (7.07)	0.0380*** (8.39)
<i>lnRETI_EM</i> ²	−0.0081*** (−6.99)	−0.0006 (−0.82)	−0.0053*** (−8.27)	−0.0074*** (−10.54)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Obs	1034	1650	2684	2684

*, **, ***Significance at the 10%, 5%, and 1% level. *T* statistics in parentheses

indicate that the inverse U-shaped relationship between renewable energy technologies and carbon emissions exists locally, while the inverted U-shaped relationship with neighboring cities is uncertain. Conservation renewable energy technologies achieve carbon reduction faster than production and management renewable energy technologies. After a set of robustness tests and the elimination of endogenous issues, this empirical result is still valid. (2) Mechanism analysis shows that energy consumption structure and energy intensity are not the channels for renewable energy technologies to affect carbon emissions, but renewable energy technologies can affect carbon emissions through energy consumption scale. Furthermore, in terms of industrial factors, industrial agglomeration is the channel through which renewable energy technologies affect carbon emissions. The results show that the hidden carbon emissions generated by industrial agglomeration and the failure of energy consumption to achieve green upgrading are the main reasons for the inverted U-shaped relationship. (3) Heterogeneity analysis found that renewable energy technology can play a faster role in carbon emission reduction in non-resource-based cities and non-key cities for environmental protection. Production and management renewable energy technologies do not play a role in carbon reduction activities in non-eastern cities, suggesting that non-eastern cities are more likely to be affected by the pollution haven effect.

The policy implications related to the conclusion are as follows:

- (1) Improve a fiscal policy framework conducive to renewable energy technology innovation, to achieve accurate support for specific types of renewable energy technologies. This is not only beneficial to the coordinated development of different types of renewable energy technologies, avoiding redundant construction, but also effectively reduces the cost effect of renewable energy technologies and makes their carbon emission reduction effects more effective.
- (2) With the support of regional economic circles, deepen cooperation in renewable energy projects between different cities, eliminate the spatial spillover of carbon emissions, and improve the spatial diffusion of renewable energy technologies, especially renewable energy technology of energy production type.
- (3) Existing policies mainly focusses on renewable energy technologies such as solar energy, photovoltaic, or wind power, while other types of renewable energy technologies need further support. The establishment of an efficient and all-inclusive renewable energy technology policy support scheme is conducive to the rationalization and the transformation of the energy structure as soon as possible.
- (4) In China, most of non-eastern cities have superior renewable energy resources. We need actively to pro-

mote renewable energy technology of energy production type cooperation and project construction in the central and western cities, to improve the carbon emis-

sion reduction effect of renewable energy technologies in non-eastern cities, and prevent the harm caused by the transfer of polluting industries.

Appendix 1

Table 16 The international patent classification of renewable energy technology innovation¹

Classification	Patent type	IPC code
Energy production	Wind energy	F03D, H02K 7/18, B63B35/00, E04H12/00, B60K16/00, B63H13/00, B60L8/00
	Solar energy	F03G6, F24J2; F26B3/28; H01L27/142; H01L31/042-058, F24S, H02S, H01L27/142, H01L31/00-31/078, H01G9/20, H02S10/00, H01L25/00, H01L25/03, H01L25/16, H01L25/18, H01L31/042, C01B33/02, C23C14/14, C23C16/24, C30B29/06, G05F1/67, F21L4/00, F21S9/03, H02J7/35, H01G9/20, H01M14/00, H01L27/30, 51/42-51/48, F24D17/00, 18/00, F24D3/00, 5/00, 11/00, 19/00, F24S90/00, F03D1/04, 9/00, 13/20, F03G6/00, C02F1/14, F02C1/05, H01L31/0525, H02S40/44, F03G6/00-6/06, E04D13/00, 13/18, F22B1/00, F24V30/00, F25B27/00, F26B3/00, 3/28, F24S23/00, G02B7/183, F24S10/10
	Geothermal energy	F03G4, F24J3/08, F24T, F01K
	Marine (ocean) energy ²	E02B9/08, F03B13/10-26, F03G7/05
	Hydro energy	E02B9, F03B, F03C, F03B15/00-15/22, B63H19/02, B63H19/04, F03B13/12-13/26
Energy production	Biomass energy	C10L5/42-44, F02B43/08
	Waste-to-energy	F01K27/00, F01K23/06-23/10, F01N5/00, F02G5/00-5/04, F25B27/02, F01K17/00, 23/04, F02C6/18, F25B27/02, C02F1/16, D21F5/20, F22B1/02, F23G5/46, F24F12/00, F27D17/00, F28D17/00-20/00, C10J3/86
	Storage of electricity energy ³	B60K6/28, B60W10/26, H01M10/44-10/46, H01G11/00, H02J3/28, 7/00, 15/00
Energy conservation	Storage of thermal energy	C09K5/00, F24H7/00, F28D20/00, 20/02
	Measurement of electricity consumption	G01R, H02J, B60L3/00
Energy management	Treatment of energy waste	B09C, A61L11/00, A62D3/00, 101/00, G21F9/00, B03B9/06, D21B1/08, 1/32
	Reuse of energy waste materials	A43B1/12, 21/14, B22F8/00, C04B7/24-7/30, C04B18/04-18/10, C05F, C08J11/00-11/28, C09K11/01, C11B11/00, 13/00-13/04, C14C3/32, C21B3/04, C25C1/00, D01F13/00-13/04
	Pollution control	C02F, B01D53/14, 53/22, 53/62, B65G5/00, C01B32/50, E21B41/00, 43/16, E21F17/16, F25J3/02, B01D53/00-53/96, C10L10/02, 10/06, F23J7/00, B63J4/00

¹We have upgraded the IPC code of energy technologies (Wind, Solar, Geothermal, Marine, Hydro, and Biomass Energy) with reference to IPC GREEN INVENTORY from <https://www.wipo.int/classifications/ipc/green-inventory/home>. In addition, the IPC code of renewable energy technology is also used in related research (Johnstone et al. 2010; Qu et al. 2023; Noailly and Shestalova 2017; Noailly and Smeets 2021; Wang and Zhu 2020; Yang et al. 2019; Zhu et al. 2020). The classification of renewable energy technologies in this paper is only for research, and the conclusions are not concentrated here

²Some types of patents may have duplication of IPC codes (such as E02B9/08 in Marine energy and E02B9 in Hydro energy), and we will eliminate them to avoid recurring with patents

³Electric power is considered as a renewable energy, so accumulators technology should be regarded as a renewable energy technology, which is different from B60K 6/28, H01G 11/00, H02J 3/28 and other versatile battery, capacitor, power networking, and LED technologies

Table 17 Empirical results of the baseline model with control variable coefficients

Variables	<i>lnCO2</i>				
	(1)	(2)	(3)	(4)	(5)
<i>lnRETI</i>	0.0191*** (5.45)	0.0644*** (8.58)			
<i>lnRETI</i> ²		−0.0056*** (−7.32)			
<i>lnRETI_EP</i>			0.0460*** (7.28)		
<i>lnRETI_EP</i> ²			−0.0050*** (−5.95)		
<i>lnRETI_EC</i>				0.0264*** (5.88)	
<i>lnRETI_EC</i> ²				−0.0039*** (−5.98)	
<i>lnRETI_EM</i>					0.0406*** (7.96)
<i>lnRETI_EM</i> ²					−0.0052*** (−7.88)
<i>lnpGDP</i>	0.3264*** (5.16)	0.1602*** (2.97)	0.2291*** (4.14)	0.2284*** (4.06)	0.1565*** (2.95)
<i>lnpGDP</i> ²	−0.0131*** (−4.80)	−0.0060*** (−2.65)	−0.0090*** (−3.86)	−0.0088*** (−3.75)	−0.0059*** (−2.63)
<i>lnPOP</i>	0.0249*** (2.79)	0.0242*** (2.73)	0.0249*** (2.77)	0.0247*** (2.82)	0.0241*** (2.74)
<i>lnGS</i>	0.0013 (0.18)	0.0008 (0.11)	0.0011 (0.15)	0.0003 (0.04)	0.0002 (0.02)
<i>lnTI</i>	0.0153** (2.35)	0.0124** (2.03)	0.0139** (2.20)	0.0145** (2.26)	0.0143** (2.21)
<i>lnFDI</i>	−0.0023 (−1.39)	−0.0008 (−0.52)	−0.0014 (−0.83)	−0.0014 (−0.81)	−0.0009 (−0.54)
<i>lnGOV</i>	0.0243** (2.43)	0.0221** (2.24)	0.0232** (2.34)	0.0231** (2.31)	0.0218** (2.20)
<i>lnFD</i>	−0.0007 (−0.06)	−0.0207* (−1.74)	−0.0166 (−1.39)	−0.0183 (−1.51)	−0.0232* (−1.94)
<i>lnURB</i>	0.0335*** (8.51)	0.0330*** (8.64)	0.0336*** (8.77)	0.0352*** (9.19)	0.0366*** (9.39)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes
Constant	1.9127*** (5.21)	2.9797*** (9.17)	2.6387*** (7.76)	2.7041*** (7.77)	3.1090*** (9.65)
Adj <i>R</i> ²	0.9917	0.9920	0.9919	0.9918	0.9920
Obs	2684	2684	2684	2684	2684

*, **, ***Significance at the 10%, 5%, and 1% level. *T* statistics in parentheses. Clustering to the city level

Table 17 is a supplement to Table 2, where population density (*lnPOP*), transportation infrastructure (*lnTI*), government intervention (*lnGOV*), and urbanization (*lnURB*) have positive impacts on carbon emissions (Huang et al. 2021; Zhang and Cheng 2009). The main reason why government regulation increases carbon emissions is its one-size-fits-all intervention. The first term of economic development (*lnpGDP*) is positive, while the second term (*lnpGDP*²)

is negative, which is consistent with the assumption of the environmental Kuznets curve (EKC). This implies that there is an inverted U-shaped relationship between economic development and pollution emissions (Chen et al. 2022c), where initially pollution increases with economic development but eventually decreases. Finally, the impact of green space (*lnGS*), foreign direct investment (*lnFDI*), and financial development (*lnFD*) on carbon emissions is uncertain.

Appendix 2

Table 18 The Moran's *I* in 244 cities, 2007–2017

Year	Spatial weights matrix (W^1)		Spatial weights matrix (W^2)	
	Moran's <i>I</i> for $\ln CO_2$	Moran's <i>I</i> for $\ln RETI$	Moran's <i>I</i> for $\ln CO_2$	Moran's <i>I</i> for $\ln RETI$
2007	0.295*** (9.368)	0.212*** (6.772)	0.370*** (9.028)	0.388*** (9.491)
2008	0.299*** (9.475)	0.232*** (7.397)	0.374*** (9.126)	0.407*** (9.993)
2009	0.291*** (9.219)	0.253*** (8.031)	0.367*** (8.974)	0.457*** (11.147)
2010	0.290*** (9.209)	0.256*** (8.137)	0.370*** (9.041)	0.466*** (11.354)
2011	0.292*** (9.266)	0.278*** (8.818)	0.376*** (9.173)	0.461*** (11.234)
2012	0.292*** (9.251)	0.286*** (9.065)	0.375*** (9.150)	0.469*** (11.424)
2013	0.269*** (8.535)	0.258*** (8.212)	0.356*** (8.699)	0.445*** (10.843)
2014	0.267*** (8.464)	0.273*** (8.678)	0.352*** (8.611)	0.474*** (11.557)
2015	0.274*** (8.707)	0.285*** (9.041)	0.356*** (8.694)	0.476*** (11.603)
2016	0.273*** (8.657)	0.313*** (9.906)	0.351*** (8.587)	0.494*** (12.044)
2017	0.266*** (8.431)	0.341*** (10.798)	0.348*** (8.508)	0.510*** (12.412)

*, **, ***Significance at the 10%, 5%, and 1% level. Z statistics in parentheses

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References

- Acheampong AO, Amponsah M, Boateng E (2020) Does financial development mitigate carbon emissions? Evidence from heterogeneous financial economies. *Energy Econ* 88:104768. <https://doi.org/10.1016/j.eneco.2020.104768>
- Álvarez-herránz A, Balsalobre D, María J, Shahbaz M (2017) Energy innovations-GHG emissions nexus: fresh empirical evidence from OECD countries. *Energy Policy* 101:90–100. <https://doi.org/10.1016/j.enpol.2016.11.030>
- Balado-Naves R, Baños-Pino JF, Mayor M (2018) Do countries influence neighbouring pollution? A spatial analysis of the EKC for CO₂ emissions. *Energy Policy* 123:266–279. <https://doi.org/10.1016/j.enpol.2018.08.059>
- Berner A, Bruns S, Moneta A, Stern DI (2022) Do energy efficiency improvements reduce energy use? Empirical evidence on the economy-wide rebound effect in Europe and the United States. *Energy Econ*. 110:105939. <https://doi.org/10.1016/j.eneco.2022.105939>
- Chang JJ, Wang WN, Shieh JY (2018) Environmental rebounds/backfires: macroeconomic implications for the promotion of environmentally-friendly products. *J. Environ. Econ. Manage* 88:35–68. <https://doi.org/10.1016/j.jeem.2017.09.004>
- Chen J, Wang P, Cui L, Huang S, Song M (2018a) Decomposition and decoupling analysis of CO₂ emissions in OECD. *Appl. Energy* 231:937–950. <https://doi.org/10.1016/j.apenergy.2018.09.179>
- Chen Z, Kahn ME, Liu Y, Wang Z (2018b) The consequences of spatially differentiated water pollution regulation in China. *J Environ Econ Manage* 88:468–485. <https://doi.org/10.1016/j.jeem.2018.01.010>
- Chen X, Chen YE, Chang CP (2019) The effects of environmental regulation and industrial structure on carbon dioxide emission: a non-linear investigation. *Environ. Sci. Pollut. Res* 26:30252–30267. <https://doi.org/10.1007/s11356-019-06150-6>
- Chen J, Gao M, Cheng S, Liu X, Hou W, Song M, Li D, Fan W (2021) China's city-level carbon emissions during 1992–2017 based on the inter-calibration of nighttime light data. *Sci. Rep* 11:1–13. <https://doi.org/10.1038/s41598-021-81754-y>

- Chen X, Xu H, Zhang L, Cao H (2022a) Spatial functional division, infrastructure and carbon emissions: evidence from China. *Energy* 256:124551. <https://doi.org/10.1016/j.energy.2022.124551>
- Chen Y, Yao Z, Zhong K (2022b) Do environmental regulations of carbon emissions and air pollution foster green technology innovation: evidence from China's prefecture-level cities. *J Clean Prod* 350:131537. <https://doi.org/10.1016/j.jclepro.2022.131537>
- Chen Y, Zhu Z, Cheng S (2022c) Industrial agglomeration and haze pollution: evidence from China. *Sci Total Environ* 845:157392. <https://doi.org/10.1016/j.scitotenv.2022.157392>
- Dauda L, Long X, Mensah CN, Salman M, Boamah KB, Ampon-Wireko S, Kofi Dogbe CS (2021) Innovation, trade openness and CO2 emissions in selected countries in Africa. *J Clean Prod* 281:125143. <https://doi.org/10.1016/j.jclepro.2020.125143>
- Dilanchiev A, Nuta F, Khan I, Khan H (2023) Urbanization, renewable energy production, and carbon dioxide emission in BSEC member states: implications for climate change mitigation and energy markets. *Environ Sci Pollut Res* 30(25):67338–67350. <https://doi.org/10.1007/s11356-023-27221-9>
- Dong F, Zhu J, Li Y et al (2022) How green technology innovation affects carbon emission efficiency: evidence from developed countries proposing carbon neutrality targets. *Environ Sci Pollut Res* 29:35780–35799. <https://doi.org/10.1007/s11356-022-18581-9>
- Du Y, Li Z, Du J, Li N, Yan B (2019) Public environmental appeal and innovation of heavy-polluting enterprises. *J Clean Prod* 222:1009–1022. <https://doi.org/10.1016/j.jclepro.2019.03.035>
- Fernández AM, Ferrández E, Medina J (2022) The diffusion of energy technologies. Evidence from renewable, fossil, and nuclear energy patents. *Technol Forecast Soc Change* 178:121566. <https://doi.org/10.1016/j.techfore.2022.121566>
- Habiba U, Xinbang C, Anwar A (2022) Do green technology innovations, financial development, and renewable energy use help to curb carbon emissions? *Renew. Energy* 193:1082–1093. <https://doi.org/10.1016/j.renene.2022.05.084>
- Hu T, Wang T, Yan Q, Chen T, Jin S, Hu J (2022) Modeling the spatiotemporal dynamics of global electric power consumption (1992–2019) by utilizing consistent nighttime light data from DMS-OLS and NPP-VIIRS. *Appl Energy* 322:119473. <https://doi.org/10.1016/j.apenergy.2022.119473>
- Huang J, Li X, Wang Y, Lei H (2021) The effect of energy patents on China's carbon emissions: evidence from the STIRPAT model. *Technol Forecast Soc Change* 173:121110. <https://doi.org/10.1016/j.techfore.2021.121110>
- Jiang W, Cole M, Sun J, Wang S (2022) Innovation, carbon emissions and the pollution haven hypothesis: climate capitalism and global re-interpretations. *J Environ Manage* 307:114465. <https://doi.org/10.1016/j.jenvman.2022.114465>
- Jo HK (2002) Impacts of urban greenspace on offsetting carbon emissions for middle Korea. *J Environ Manage* 64:115–126. <https://doi.org/10.1006/jema.2001.0491>
- Johnstone N, Hascic I, Popp D (2010) Renewable energy policies and technological innovation: evidence based on patent counts. *Environ Resour Econ* 45:133–155. <https://doi.org/10.1007/s10640-009-9309-1>
- Kahn ME, Kotchen MJ (2011) Business cycle effects on concern about climate change: the chilling effect of recession. *Clim Chang Econ* 2:257–273. <https://doi.org/10.1142/S2010007811000292>
- Khan H, Weili L, Khan I, Zhang J (2023a) The nexus between natural resources, renewable energy consumption, economic growth, and carbon dioxide emission in BRI countries. *Environ Sci Pollut Res* 30:36692–36709. <https://doi.org/10.1007/s11356-022-24193-0>
- Khan H, Weili L, Khan I, Zhang J (2023b) Exploring the nexus between energy consumption, income inequality and poverty, economic growth, and carbon dioxide emission: evidence from two step system generalized method of moments. *Environ Sci Pollut Res* 30:35996–36011. <https://doi.org/10.1007/s11356-022-24695-x>
- Li W, Yang G, Li X (2021) Correlation between PM2.5 pollution and its public concern in China: evidence from Baidu Index. *J Clean Prod* 293:81–109. <https://doi.org/10.1016/j.jclepro.2021.126091>
- Lin B, Ma R (2022) Green technology innovations, urban innovation environment and CO2 emission reduction in China: fresh evidence from a partially linear functional-coefficient panel model. *Technol Forecast Soc Change* 176:121434. <https://doi.org/10.1016/j.techfore.2021.121434>
- Lin B, Zhu J (2019) The role of renewable energy technological innovation on climate change: empirical evidence from China. *Sci Total Environ* 659:1505–1512. <https://doi.org/10.1016/j.scitotenv.2018.12.449>
- Liu Z, He C, Zhang Q, Huang Q, Yang Y (2012) Extracting the dynamics of urban expansion in China using DMS-OLS nighttime light data from 1992 to 2008. *Landsc Urban Plan* 106:62–72. <https://doi.org/10.1016/j.landurbplan.2012.02.013>
- Liu X, Ji X, Zhang D, Yang J, Wang Y (2019) How public environmental concern affects the sustainable development of Chinese cities: an empirical study using extended DEA models. *J Environ Manage* 251:109619. <https://doi.org/10.1016/j.jenvman.2019.109619>
- Noailly J, Shestalova V (2017) Knowledge spillovers from renewable energy technologies: lessons from patent citations. *Environ Innov Soc Transitions* 22:1–14. <https://doi.org/10.1016/j.eist.2016.07.004>
- Noailly J, Smeets R (2015) Directing technical change from fossil-fuel to renewable energy innovation: an application using firm-level. *J Environ Econ Manage* 72:15–37. <https://doi.org/10.1016/j.jeem.2015.03.004>
- Noailly J, Smeets R (2021) Financing energy innovation: internal finance and the direction of technical change. *Environ Resour Econ* 83:145–169. <https://doi.org/10.1007/s10640-021-00602-9>
- O'Donoghue D, Gleave B (2004) A note on methods for measuring industrial agglomeration. *Reg Stud* 38:419–427. <https://doi.org/10.1080/03434002000213932>
- Obobisa ES, Chen H, Mensah IA (2022) The impact of green technological innovation and institutional quality on CO2 emissions in African countries. *Technol Forecast Soc Change* 180:121670. <https://doi.org/10.1016/j.techfore.2022.121670>
- Peng W, Yin Y, Kuang C, Wen Z, Kuang J (2021) Spatial spillover effect of green innovation on economic development quality in China: evidence from a panel data of 270 prefecture-level and above cities. *Sustain Cities Soc* 69:102863. <https://doi.org/10.1016/j.scs.2021.102863>
- Qu F, Xu L, Zheng B (2022) Directed technical change and pollution emission: evidence from fossil and renewable energy technologies in China. *Front Energy Res* 10:1–11. <https://doi.org/10.3389/fenrg.2022.794104>
- Qu F, Xu L, He C (2023) Leverage effect or crowding out effect? Evidence from low-carbon city pilot and energy technology innovation in China. *Sustain Cities Soc* 91:104423. <https://doi.org/10.1016/j.scs.2023.104423>
- Sadorsky P (2014) The effect of urbanization on CO2 emissions in emerging economies. *Energy Econ* 41:147–153. <https://doi.org/10.1016/j.eneco.2013.11.007>
- Shahbaz M, Destek MA, Dong K, Jiao Z (2021) Time-varying impact of financial development on carbon emissions in G-7 countries: evidence from the long history. *Technol Forecast Soc Change* 171:120966. <https://doi.org/10.1016/j.techfore.2021.120966>
- Shao S, Yang L, Yu M, Yu M (2011) Estimation, characteristics, and determinants of energy-related industrial CO2 emissions in Shanghai (China), 1994–2009. *Energy Policy* 39:6476–6494. <https://doi.org/10.1016/j.enpol.2011.07.049>
- Shao S, Hu Z, Cao J, Yang L, Guan D (2020) Environmental regulation and enterprise innovation: a review. *Bus Strateg Environ* 29:1465–1478. <https://doi.org/10.1002/bse.2446>

- Su Y, Fan Q m (2022) Renewable energy technology innovation, industrial structure upgrading and green development from the perspective of China's provinces. *Technol Forecast Soc Change* 180:121727. <https://doi.org/10.1016/j.techfore.2022.121727>
- Sufyanullah K, Ahmad KA, Sufyan Ali MA (2022) Does emission of carbon dioxide is impacted by urbanization? An empirical study of urbanization, energy consumption, economic growth and carbon emissions - using ARDL bound testing approach. *Energy Policy* 164:112908. <https://doi.org/10.1016/j.enpol.2022.112908>
- Sun H, Edziah BK, Sun C, Kporsu AK (2019) Institutional quality, green innovation and energy efficiency. *Energy Policy* 135:111002. <https://doi.org/10.1016/j.enpol.2019.111002>
- Wahab S (2021) Does technological innovation limit trade-adjusted carbon emissions? *Environ Sci Pollut Res* 28:38043–38053. <https://doi.org/10.1007/s11356-021-13345-3>
- Wang Z, Zhu Y (2020) Do energy technology innovations contribute to CO2 emissions abatement? A spatial perspective *Sci Total Environ* 726:138574. <https://doi.org/10.1016/j.scitotenv.2020.138574>
- Wang Z, Zhang B, Liu T (2016) Empirical analysis on the factors influencing national and regional carbon intensity in China. *Renew Sustain Energy Rev* 55:34–42. <https://doi.org/10.1016/j.rser.2015.10.077>
- Wang WZ, Liu LC, Liao H, Wei YM (2021a) Impacts of urbanization on carbon emissions: an empirical analysis from OECD countries. *Energy Policy* 151(7):112171. <https://doi.org/10.1016/j.enpol.2021.112171>
- Wang KL, Zhao B, Ding LL, Miao Z (2021b) Government intervention, market development, and pollution emission efficiency: evidence from China. *Sci Total Environ* 757:143738. <https://doi.org/10.1016/j.scitotenv.2020.143738>
- Wang X, Fan LW, Zhang H (2023) Policies for enhancing patent quality: evidence from renewable energy technology in China. *Energy Policy* 180:113660. <https://doi.org/10.1016/j.enpol.2023.113660>
- Xie R, Fang J, Liu C (2017) The effects of transportation infrastructure on urban carbon emissions. *Appl Energy* 196:199–207. <https://doi.org/10.1016/j.apenergy.2017.01.020>
- Xu B, Lin B (2015) How industrialization and urbanization process impacts on CO2 emissions in China: evidence from nonparametric additive regression models. *Energy Econ* 48:188–202. <https://doi.org/10.1016/j.eneco.2015.01.005>
- Xu L, Fan M, Yang L, Shao S (2021) Heterogeneous green innovations and carbon emission performance: evidence at China's city level. *Energy Econ* 99:105269. <https://doi.org/10.1016/j.eneco.2021.105269>
- Yang L, Li Z (2017) Technology advance and the carbon dioxide emission in China – empirical research based on the rebound effect. *Energy Policy* 101:150–161. <https://doi.org/10.1016/j.enpol.2016.11.020>
- Yang F, Cheng Y, Yao X (2019) Influencing factors of energy technical innovation in China: evidence from fossil energy and renewable energy. *J Clean Prod* 232:57–66. <https://doi.org/10.1016/j.jclepro.2019.05.270>
- Yang G, Zha D, Zhang C, Chen Q (2020) Does environment-biased technological progress reduce CO2 emissions in APEC economies? Evidence from fossil and clean energy consumption. *Environ Sci Pollut Res* 27:20984–20999. <https://doi.org/10.1007/s11356-020-08437-5>
- Zhang XP, Cheng XM (2009) Energy consumption, carbon emissions, and economic growth in China. *Ecol Econ* 68:2706–2712. <https://doi.org/10.1016/j.ecolecon.2009.05.011>
- Zhang C, Zhou X (2016) Does foreign direct investment lead to lower CO2 emissions? Evidence from a regional analysis in China. *Renew Sustain Energy Rev* 58:943–951. <https://doi.org/10.1016/j.rser.2015.12.226>
- Zhao M, Kong Z, Escobedo FJ, Gao J (2010) Impacts of urban forests on offsetting carbon emissions from industrial energy use in Hangzhou. *China J Environ Manage* 91:807–813. <https://doi.org/10.1016/j.jenvman.2009.10.010>
- Zheng S, Wu J, Kahn ME, Deng Y (2012) The nascent market for “green” real estate in Beijing. *Eur Econ Rev* 56:974–984. <https://doi.org/10.1016/j.euroecorev.2012.02.012>
- Zhu Y, Wang Z, Yang J, Zhu L (2020) Does renewable energy technological innovation control China's air pollution? A spatial analysis *J Clean Prod* 250:119515. <https://doi.org/10.1016/j.jclepro.2019.119515>

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