Low-carbon Innovation, Economic Growth and CO2 Emissions: Evidence from a Dynamic Spatial Panel Approach in China

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Low-carbon Innovation, Economic Growth and CO_2 Emissions: Evidence from a Dynamic Spatial Panel Approach in China

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Abstract

Low-carbon innovation plays an essential role in carbon reduction worldwide. This study investigates the nexus between low-carbon innovation, economic growth, and carbon emissions by the dynamic spatial Durbin model from 2007 to 2019, along with environmental policy, energy structure, industrial structure, foreign direct investment, energy intensity, and population density as the control variables. First, the results show that provincial agglomeration of carbon emissions exists. High emission provinces concentrate in major economic zones and energy extraction areas. Second, the effect decomposition results show that long-term and short-term effects are consistent. Low-carbon innovation has a significant mitigation effect on carbon emissions in local regions, which effect, however, is not significant in the adjacent areas. The environmental Kuznets curve hypothesis is validated locally, but all provinces and cities have not reached the inflection point of the environmental Kuznets curve, and the linkage effect in adjacent regions remains insignificant. There is both a direct local abatement effect and a demonstration effect in environmental policy. Third, the heterogeneity test results show that there are synergies between environmental policies and low carbon innovation, and for regulated pilot areas, there is a higher mitigation effect of low carbon innovation. Finally, robustness tests for replacing the spatial weight matrics confirmed the robustness of the previous results. Based on the above findings, policy recommendations include providing targeted financial support to stimulate green Research & Development input, building a regional green technology exchange system to enhance knowledge spillovers, promoting the application of carbon trading policies to more regions and industries, and setting comprehensive development goals for a green and high-quality economy.

Keywords: Carbon Emissions; Low-carbon Innovation; Economic Growth, EKC Hypothesis; Environmental Policy; Dynamic Spatial Durbin Model.

Classification codes: O360 R120 Q540 Q55

1 Introduction

Since the Industrial Revolution, the concentration of atmospheric greenhouse gas (GHG) produced by fossil fuels and biomass burning has caused global warming, leading to climate change (Atasoy, 2017). Climate change will impact the ecosystem and humanity of the earth and lead to increasing sea levels, extreme weather, and possible difficulties in food and water supply (Reuveny, 2007; Solomon et al., 2009). Therefore, it became a consensus to mitigate carbon emissions.

Carbon dioxide, when emitted, will spread rapidly around the globe and have a global greenhouse effect, not just where it is emitted, which means there are externalities to carbon emissions. Carbon emissions mitigation requires the concerted efforts of countries all over the world. Several agreements had been signed to slow down the process, such as the Kyoto Protocol and the Paris Climate Agreement[1], which Set a goal of limiting global temperature rise to 2°C (3.6°F) above pre-industrial levels and further limit to 1.5°C. Glasgow Climate Pact was adopted at COP26 in 2021, accelerating efforts toward the phase-down of unabated coal power and inefficient fossil fuel subsidies. Countries worldwide proposed carbon-neutral routes to reach the "2 °C" goal. As the developing country with the most carbon emissions, China proposed the *30-60 target* in 2020 to peak carbon emissions by 2030 and realize carbon neutrality by 2060. The Chinese government has advocated the circular economy and environmental regulations to achieve this milestone (Zhang et al., 2020).

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[1] the Kyoto Protocol: https://unfccc.int/process-and-meetings/the-kyoto-protocol/history-of-the-kyoto-protocol/text-of-the-kyoto-protocol;
the Paris Climate Agreement: https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement

Technological innovation is considered to play a crucial role in achieving CO2 neutrality and climate change mitigation goals. Low-carbon innovation is the technology innovations for renewable energy supply and efficient end-use energy consumption to reduce carbon emissions. The advantage of low-carbon innovation is that it can significantly reduce the cost of mitigating carbon emissions (Popp, 2012). Theoretically, low-carbon innovation increases energy efficiency and promotes the energy consumption structure turning into a cleaner one (Du and Li, 2019). Furthermore, some low-carbon technologies directly reduce the amount of carbon dioxide in the air, such as Carbon Capture, Utilization, and Storage (CCUS). However, the energy efficiency increased by low-carbon innovation may cause a higher level of energy consumption, called the rebound effect (Erdoğan et al., 2020), which often occurs in developing countries.

The study aims to investigate the relationship between low-carbon innovation and carbon emissions. Since China has the greatest contribution to global carbon dioxide emissions, it is essential to explore an emission reduction pathway for China, both for global carbon reduction and for developing countries with similar economic structures. Therefore, we selected thirty Chinese provinces for the analysis.

The contributions of this paper can be summarized in the following four main aspects. First, we extended the dynamic relationship between low-carbon innovation and carbon emissions in China. On the one hand, the dynamic model eliminates the time inertia of carbon emissions, solving the overestimating of low-carbon innovation in the static model; on the other hand, the dynamic characteristics include long-term and short-term nexus. Second, in accounting for the geography characteristics, we discussed spatial interaction. Geographic proximity plays an essential role in spatial spillover (Krugman, 1991), which due to the innovative corporation may cluster in specific regions, the knowledge may transfer to adjacent areas. Third, we examined the policy instrument for mitigating carbon emissions. The Porter hypothesis supposes that strict environmental policy promotes enterprises' innovation, which improves energy efficiency. Furthermore, existing research broadly points to improvements in energy efficiency resulting in a decline in total carbon emissions (Akram et al., 2020). Therefore, carbon emissions may be mitigated by environmental policy. Fourth, we investigated the EKC hypothesis under a dynamic framework. This paper constructs a new understanding of the relationship between low-carbon innovations, economic growth, and carbon emissions for policymakers, which has certain practical significance for policy formulation and policy orientation of carbon neutrality goals.

The rest of this paper is organized as follows. In the following section, we present the review of the literature. Moreover, in section 3, the theoretical framework and data are introduced in this paper. Section 4 illustrates the empirical results and discussions. Section 5 summarizes and discusses the empirical findings, then concludes with policy implications.

2 Literature review

2.1 Innovation and carbon emissions relationships

Innovation has been regarded as an essential channel to mitigate carbon emissions in countries (Ibrahim and Vo, 2021). For example, energy production innovations boost energy efficiency; through innovation, more energy-efficient production and living goods can be designed, such as new energy vehicles (NEVs) and energy-saving appliances, which reduce carbon emissions. Table 1 illustrates an overview of the research lineage on the innovation-carbon emission relationship.

The nexus between technological innovations and carbon emissions got widespread attention. Studies confirmed the carbon emission mitigating effect of technology innovation in 13 selected G-20 countries (Nguyen et al., 2020), Nordic countries (Irandoust, 2016), and Chinese industrial sectors and provinces (Liu and Liu, 2019; Zhang et al., 2016). However, the estimation results are conflicting due to the different samples, dataset periods, and estimation approaches. For instance, Ibrahim and Vo (2021) reported that technological innovation reduces carbon emissions at a low innovation level; however, technological innovation increases carbon emissions after it goes beyond a threshold level. Similarly, Li et al. (2021) observed the diminishing marginal effect of technological innovation on carbon emissions in 52 developed and developing countries. Zhao et al. (2021) argued that only the inhibitory effects exist in countries with technological innovations in

the top 10%, while the promoting effects are in the other countries. Furthermore, there is also a small amount of evidence that technological innovation has an insignificant impact on carbon emissions (Cheng et al., 2019; Cole et al., 2013).

To understand why there exist conflicting results, scholars thought maybe the measurement of innovation. For instance, Töbelmann and Wendler (2020) found evidence based on the 27 European Union (EU) countries that environmental innovation decreases carbon emissions while technological innovation insignificantly impacts carbon emissions. Evidence from 30 Chinese provinces proved that environmental innovation decreases carbon productivity more than technological innovation (Liu and Zhang, 2021). Studies focusing on the nexus between carbon emissions and environmental innovation found consistent results, such as in the current study based on the sample of G-7 countries, the U.S., and China, low-carbon innovation showed a significantly negative effect on carbon emissions (Ding et al., 2021; Khan et al., 2020; Lee and Min, 2015; Song et al., 2020; Wang et al., 2020; Xin et al., 2021; Zhang et al., 2017). In addition to the total carbon emissions perspective, similar results exist from the carbon emissions efficiency perspective. Evidence from 71 countries showed that environmental innovation increases carbon productivity in high-income countries (Du et al., 2019; Du and Li, 2019). Therefore, taking low-carbon innovation into empirical studies has gradually become mainstream.

Table 1 Selected literature on the innovation-carbon emission nexus.

Studies	Sample and time period	Methodology	Key findings
Technological innovation- Carbon emissions nexus			
(Irandoust, 2016)	4 Nordic countries, 1975-2012	Vector Autoregression (VAR)	technological innovation **reduces** carbon emissions.
(Zhang et al., 2016)	38 Chinese industrial sectors, 1990-2012	Malmquist index decomposition	Carbon emissions performance is driven by **technological change** from 2000 to 2012.
(Liu and Liu, 2019)	30 Chinese provinces, 2005-2016	Spatial Durbin Model (SDM)	Technological restriction is the main **driving force** of carbon emissions.
(Nguyen et al., 2020)	13 selected G20 countries, 2000-2014	Panel Quantile Regression (PQR)	technological innovation **reduces** carbon emissions.
(Zhao et al., 2021)	62 countries, 2003-2018	generalized method of moments (GMM), PQR	technological innovation **reduces** carbon emissions, but heterogeneity exists.
(Ibrahim and Vo, 2021)	27 industrialized countries, 1991-2014	System GMM	technological innovation **reduces** carbon emissions. Beyond a threshold, technological innovation **increases** carbon emissions.
(Li et al., 2021)	Firms in 52 countries, 2002-2015	GMM	technological innovation **reduces** carbon emissions, but the marginal effect **diminishes**.
(Cheng et al., 2019)	OECD countries, 1996-2015	PQR	The carbon emissions mitigating effect of technological innovation is **not significant**.
(Cole et al., 2013)	1961 Japanese firms, 2006	Spatial Error Model (SEM), SDM	The carbon emissions mitigating effect of technological innovation is **not significant**.
(Erdoğan et al., 2020)	14 G-20 countries, 1997-2017	Common Correlated Effect Mean Group (CCEMG); Augmented Mean Group (AMG)	Technological innovation **decreases** carbon emissions in the industrial sector.
Heterogeneity of technological innovation & Low-carbon innovation			
(Töbelmann and Wendler, 2020)	27 EU countries, 1992-2014	GMM	Environmental innovation **decreases** carbon emissions, while technological innovation **insignificantly** impacts carbon emissions.
(Liu and Zhang, 2021)	30 Chinese provinces, 1998-2017	Dynamic SDM	While technological innovation **decreases** carbon productivity, e**nvironmental innovation** decreases it more.
Low-carbon innovation- Carbon emissions nexus			
(Zhang et al., 2017)	30 Chinese provinces, 2000-2013	GMM	Environmental innovation **decreases** carbon emissions.
(Song et al., 2020)	30 Chinese provinces. 2009-2017	GMM	Information and communication technologies and innovation **reduce** CE; Green innovation reduces carbon emissions.
(Khan et al., 2020)	G-7 countries, 1990-2017	AMG; CCEMG	Environmental innovation **decreases** carbon emissions.

(Radmehr et al., 2021)	EU countries, 1995-2014	generalized spatial two-stage least squares (GS2SLS)	Environmental innovation and carbon emissions are **not relevant.**
(Wang et al., 2020)	G-7 countries, 1990-2017	Pooled Mean Group (PMG), AMG	Eco-innovation decreases carbon emissions.
(Ding et al., 2021)	G-7 countries, 1990-2018	AMG	Eco-innovation **decreases** carbon emissions.
(Xin et al., 2021)	US, 1990Q1-2016Q4	Regression Discontinuity Design (RDD)	Eco-innovation **decreases** carbon emissions during the expansion phase; **increases** carbon emissions during the contraction phase.
(Lee and Min, 2015)	Japanese manufacturing companies, 2001-2010	OLS	Green R&D **decreases** carbon emissions.
(Du and Li, 2019)	71 countries, 1992–2012	Panel threshold model	Green technology innovations **increase** carbon productivity in high income while showing no effect in low income.
(Du et al., 2019)	71 countries, 1996-2012	Panel threshold model	Green technology innovations **increase** carbon productivity in high income while showing no effect in low income.

2.2 Economic growth and carbon emissions relationships

EKC hypothesis was initially proposed by Grossman and Krueger (1995), which suggested an inverted U-shaped relationship between environmental pollution and economic growth (Bhattarai and Hammig, 2001; Stern, 2004). Economic growth exacerbates ecological degradation when the level of economic development is low, while a higher income lowers environmental pollution. The relationship between environmental pollution and economic growth in the existing research has not yet been clarified, and several empirical studies have attempted to validate this hypothesis and found positive results. For instance, Yao et al. (2019) and You and Lv (2018) confirm the EKC hypothesis in panel data of developing and developed countries, Atasoy (2017) confirms the EKC hypothesis in the U.S., whereas the findings of (Cheng et al., 2017; Shahbaz et al., 2020) reported the presence of EKC in China.

Although the major research finds an inverted U-shaped EKC relationship between carbon emissions and income, some suggest that the EKC hypothesis is invalid or appears to be a different type of curve rather than an inverted U-shape. For example, evidence from G-20 countries indicates that the EKC hypothesis is invalid through the Common Correlated Effect Mean Group (CCEMG) and Augmented Mean Group (AMG) model (Erdoğan et al., 2020). Balin and Akan (2015) found an N-shaped relationship between CO_2 per capita and GDP per capita in 20 countries, and Danesh Miah et al. (2010) argue that the curve of CO_2 and economic development showed a monotonous straight line in most cases in Bangladesh. In addition, a study for 120 countries from 1995 to 2015 noted that the EKC hypothesis exists only in high-income countries (Dong et al., 2020).

In summary, it is confusing whether the EKC hypothesis is correct. And it is difficult to find a simple answer about it in existing studies due to the heterogeneity in the samples of existing empirical studies. Therefore, this study verifies whether the EKC hypothesis is valid in thirty Chinese provinces from a spatial perspective.

2.3 Methods

The current studies use different estimation methods to study the relationship between carbon emissions and low-carbon innovations. GMM is a widely used mainstream empirical method due to its properties in eliminating endogeneity in short panels (Töbelmann and Wendler, 2020; Zhang et al., 2017), such as introducing a lag term of the dependent variable (Chen et al., 2017; Feng and Wang, 2020). When considering the heterogeneity of diverse countries and regions, a panel threshold model or panel quantile regression is often introduced to the investigations (Du et al., 2019; Du and Li, 2019; Nguyen et al., 2020; Zhao et al., 2021). Finally, if only to explore the two-way relationship between the two variables, some scholars have also used cointegration methods, such as VAR models in first-generation cointegration and Mean Group (MG) estimator in second-generation cointegration. For instance, Khan et al. (2020) explore the role of environmental innovation and renewable energy on carbon emissions based on Augmented MG.

However, the previous methods neglect the spatial connection between local and adjacent regions, which will cause important factors to be omitted. As a result, a spatial panel model is preferred in analysis when considering the spatial

correlations among regions (Jin, 2019; Radmehr et al., 2021; You and Lv, 2018). The spatial models are not the first to appear in Chinese empirical research on carbon emissions. For instance, Liu and Liu (2019) empirically examined the innovation limitation and carbon emissions in 30 Chinese provinces spanning 2005 to 2016. The results of the spatial Durbin model show that the innovation limitation positively impacts carbon emissions, and the results are robust in the east, middle, and west parts of China. However, the vast majority of existing empirical studies on spatial econometrics did not consider the dynamics nexus.

In summary, the spatial relationships between carbon emissions and low-carbon innovation should be considered. However, to our best knowledge, almost no studies have considered the dynamic spatial effects of low-carbon innovation on carbon emissions, especially in China. Therefore, the purpose of this paper is to fill the gaps by empirically examining the role of low-carbon innovation through the dynamic spatial Durbin model (DSDM).

3 Methodology and Data

3.1 STIRPAT model

IPAT model is a basic framework in environmental pollution research (Ehrlich and Holdren, 1971). The model indicates that environmental pressure is the product of population, affluence, and technology. To overcome the lacking of stochastic impacts in IPAT, Dietz and Rosa (1997) proposed the STIRPAT model based on the IPAT model. Subsequently, the STIRPAT model has been widely utilized in researching the driving forces of environmental pressure, such as haze pollution and carbon dioxide emissions. The model can be expressed as formula (1).

$$I_{it} = aP_{it}^{b}\, A_{it}^{c}\, T_{it}^{d}\, e \tag{1}$$

Where $I, P, A,$ and T represent the environmental pressure, population, affluence, and technology, respectively. After taking the logarithm to both sides of the equation, the model can express as follows:

$$ln\, I = ln\, a + b\, ln\, P + c\, ln\, A + d\, ln\, T + \varepsilon \tag{2}$$

Where a is a constant term, $b, c,$ and d are the parameters to be estimated. ε is the logarithm of e, the resid of the estimation.

3.2 Spatial panel model

3.2.1 Moran Index

It is necessary to verify the spatial dependence before using spatial econometrics in our analysis (Anselin, 2013). Moran Index (also called Moran's I) is widely used to measure global spatial autocorrelation (Anselin, 1995; Cliff and Ord, 1981; Ord and Getis, 1995). For variable x_i, the global Moran's I is presented as (Moran, 1948):

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x}\,)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i}^{n}(x_i - \bar{x}\,)^2} \tag{3}$$

where W_{ij} is the spatial weight matrix after row standardization. The value of the Moran Index is between -1 to 1; for $I > 0$, there is a positive spatial correlation, showing a "High-High" or "Low-Low" distribution state; the higher the Moran index, the stronger the positive autocorrelation. However, a negative value of I reflects a negative spatial correlation, showing a distribution of "High-Low" or "Low-High." When $I = 0$, it indicates that there is no spatial correlation. By decomposing the global Moran's I into the units of each province in China, the local spatial autocorrelation can be obtained, as shown in equation (4), for province i:

$$I_i = \frac{n(x_i - \overline{x})\sum_{j=1}^{n} W_{ij}(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{4}$$

3.2.2 Dynamic Spatial Durbin Model

In order to address the drawback of traditional panel models that cannot portray the spatial interactions between variables, spatial econometric models are proposed (Guo et al., 2019; Liu and Liu, 2019). As one of the spatial econometric models, the spatial Durbin model can portray the spatial relationship between explanatory variables and explained variables. Furthermore, the dynamic spatial Durbin model adds the dynamic relationship of the explanatory variables based on the SDM. This paper establishes the dynamic spatial Durbin model presented as follows:

$$\log CE_{i,t} = \tau \log CE_{i,t-1} + \rho \boldsymbol{W} \log CE_{i,t} + \eta \boldsymbol{W} \log CE_{i,t-1} + \boldsymbol{X}_{i,t}\boldsymbol{\beta_1} + \boldsymbol{W}\boldsymbol{X}_{i,t}\boldsymbol{\beta_2} + v_{i,t} \quad (5)$$

where $\log CE_{i,t}$ is the carbon emission of province i in period t, and $\boldsymbol{X}_{i,t}$ is the explanatory variable. The parameters $\tau, \rho,$ and η represent the corresponding parameters of the time lag effect, the spatial lag effect, and the time-spatial lag effect of the explained variable, respectively. W is the spatial weight matrix capturing the spillover effects (Lesage and Fischer, 2008). This paper uses the inverse squared distance matrix for the main model. The matrix is constructed as follows:

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}^2}, & i \neq j \\ 0, & i = j \end{cases} \quad (6)$$

where W_{ij} is the element of the inverse squared distance spatial weight matrix W, representing the spatial structure of connections among provinces of China. d_{ij} is the geographical distance between the province i and j. It is noteworthy that the estimated coefficients are biased in the spatial Durbin model; thus, the model should be decomposed into direct and indirect effects to separate the marginal effects of the explanatory variables (Lesage and Fischer, 2008; LeSage and Pace, 2010). The direct effect indicates the impact of explanatory variables on carbon emissions, while the indirect effect represents the impact of explanatory variables in neighbor on carbon emissions; the total effect is the summary of direct and indirect effects. While in the dynamic model, All the direct, indirect, and total effects can be divided into short-term and long-term effects. For the variable k in $\boldsymbol{X}$, short-term direct effects (SDE), short-term indirect effects (SIE); long-term direct effects (LDE), and long-term indirect effects (LIE) of DSDM can be expressed as:

$$SDE_k = [(I - \rho W)^{-1}(\beta_{1k} I + \beta_{2k} W)]^{\bar{d}} \quad (7)$$

$$SIE_k = [(I - \rho W)^{-1}(\beta_{1k} I + \beta_{2k} W)]^{\overline{rsum}} \quad (8)$$

$$LDE_k = \{[(1-\tau)I - \delta W]^{-1}(\beta_{1k} I + \beta_{2k} W)\}^{\bar{d}} \quad (9)$$

$$LIE_k = \{[(1-\tau)I - \delta W]^{-1}(\beta_{1k} I + \beta_{2k} W)\}^{\overline{rsum}} \quad (10)$$

where $\bar{d}$ denotes the mean diagonal element of the spatial weight matrix, I denotes an identify matrix, and $\overline{rsum}$ denotes the operator that calculates the mean row sum of the non-diagonal element. (In our scenario in analysis, $\eta = 0$.)

3.3 Variable selection and data source

A sample dataset utilized for analysis covers the thirty Chinese provinces from 2007 to 2019. Due to data unavailability and invalidity, Hongkong, Macao, Taiwan, and Tibet are not included in this study. The definition of variables is presented in Table 2. Notably, the purpose of this study is to address the concern about whether and how low-carbon innovation affects carbon emissions in China. Thus, the dependent variable in this paper is carbon emissions, which is estimated by the consumption of fossil fuels derived from China Energy Statistical Yearbook (2008-2020). The estimation method is proposed by the IPCC (Intergovernmental Panel on Climate Change):

$$CE = \sum_{j=1}^{17} EC_j \times NCV_j \times CC_j \times O_j \times \frac{44}{12} \quad (11)$$

where EC_j is the jth type of fossil fuel consumption, NCV_j is the net calorific value of the jth type of fossil fuel, and CC_j represents the carbon content of the unit heating value of the j types of energy. O_j is the carbon oxidation rate of the jth fossil fuel, and 44/12 is the ratio of the molecular weight of carbon dioxide to the carbon atom.

The other independent variables are illustrated as follows:

(1) Low-carbon innovation (LCI). Green innovation refers to a series of innovation outputs (i.e., improved products, processes, and technologies) for saving energy and reducing environmental pollution (Tariq et al., 2017). CPC (Cooperative Patent Classification) is one kind of patent classification proposed by EPO (European Patent Office) and USPTO (the United States Patent and Trademark Office), in which Y02 indicates patents against climate change. We introduce the count of patent applications under CPC-Y02 as the proxy variable of low-carbon innovation, sourced from the incoPat database[2].

(2) Economic development (GDP). Since Grossman and Krueger (1995) proposed the EKC hypothesis, many scholars

[2] IncoPat database contains more than 100 million pieces of patent information from 120 countries/organizations/regions worldwide. https://www.incopat.com/

have noticed that economic development nonlinear impacts carbon emissions (Atasoy, 2017; Yao et al., 2019; You and Lv, 2018). Hence, we introduce economic development and its square term, measured by real GDP in the base period of 2005, and the data are collected from China Statistical Yearbook (2008-2020).

(3) Energy structure (ES). Carbon dioxide is mainly generated by fossil energy, of which coal has a higher carbon emission factor than all other fossil energy sources. Constrained by resource endowment, coal accounts for the largest proportion of fossil energy consumption in China (Guan et al., 2022; Qiao et al., 2014; Zhang et al., 2018). Therefore, this research controls this factor in our model and proxy the ES by the share of coal consumption (converted into standard coal) in the total energy consumption of each province. The data are obtained from China Energy Statistical Yearbook (2008-2020).

(4) Industrial structure (IND). Generally speaking, the industrial sector is pollution-intensive with heavy energy consumption and carbon emission (Du and Li, 2019). The industrial structure is widely used in empirical environmental studies (Zhou and Li, 2020). Therefore, this paper employs the share of the industrial sector output to the whole economy as the proxy of industrial structure as a control variable, and the data are derived from China Statistical Yearbook (2008-2020).

(5) Foreign Direct Investment (FDI). The proposition of the pollution heaven and pollution halo hypothesis and empirical studies on verifying the above hypothesis implied the necessity of controlling FDI in our research. Therefore, we introduce FDI as a control variable, expressed by the share of the amount of foreign direct investment in real GDP. The data are derived from China Statistical Yearbook (2008-2020).

(6) Energy intensity (denoted as EI). Energy intensity reflects energy use efficiency and is tightly related to industrial production. Therefore, it is often considered one of the critical drivers of carbon emissions (Zhang and Da, 2015). We introduce energy intensity as another control variable, expressed by energy consumption per unit of real GDP, and the data are from China Energy Statistical Yearbook (2008-2020).

(7) Population density (PD). In general, population-dense regions are developed with low transport costs and convenient services, which reduces carbon emissions through intensive production and transportation (Jiang et al., 2020). We introduce population density expressed by the permanent residents per square kilometer, and the data are from China Statistical Yearbook (2008-2020).

(8) Environmental Policy (EP). The carbon emission trading (CET) policy, launched in 2011, is regarded as the most critical market-based environmental regulation in carbon emission mitigation in China (Du et al., 2021; Zhang et al., 2017). Therefore, this paper uses CET policy as a proxy to control policy effect. This study selects six provinces and cities (Beijing, Tianjin, Shanghai, Hubei, Guangdong, and Chongqing) that joined the pilot policy as pilot areas, and we set the beginning time as 2011.

Table 2 Variable definitions

Variables	Abbreviation	Unit	Definition
Carbon emissions	CE	Million ton	Calculated from fossil fuels consumption
Low-carbon innovation	LCI	Number	Low-carbon Patent counts
Economic growth	GDP	Yuan	Gross domestic product
Industrial structure	IND	Percent	The share of secondary industry in GDP
Energy intensity	EI	kg of standard coal/ Yuan	The ratio of energy consumption to GDP
Foreign direct investment	FDI	US dollar	Foreign direct investment (net inflow)
Energy structure	ES	Percent	The share of coal consumption in total energy consumption
Population density	PD	Number/km^2	The number of resident population per square kilometer
Environmental Policy	EP	Dummy variable	Carbon Emission Trading pilot. $EP = 1$ when the region is the pilot area and the year is after 2011

Table 3 summarizes the descriptive statistics of all the variables, including the specific descriptive statistics of all the selected variables. We winsorized all variables within region-year at the 99th percentile to eliminate outliers. Subsequently, we take logarithms for the variables based on the assumptions of the STIRPAT model.

Table 3 Descriptive analysis

Variables	Mean	Std. Dev.	Minimum	Median	Maximum

CE	467.957	392.001	30.942	330.454	2304.617
LCI	1987.641	2827.955	6.000	965.000	19241.000
GDP	15202.856	13546.710	630.930	11159.433	78346.039
IND	42.802	8.225	15.989	43.822	61.960
EI	18.574	16.030	2.749	13.691	88.260
FDI	7307.104	7509.792	4.769	4631.745	35759.559
ES	66.968	18.595	2.025	68.881	97.930
PD	455.338	673.892	7.637	282.310	3912.941
EP	0.138	0.346	0	0	1

4 Empirical analysis

The procedures of the estimations mainly consist of five steps in this paper. (1) Analyzing the spatial characteristics of carbon emissions across China; (2) Verifying the existence of spatial autocorrelation, including LM tests and LR tests; (3) Examing the impact of low-carbon innovation and economic growth on carbon emissions based on the DSDM, including the main results and effect decomposition results；(4) Heterogeneity test., (5) Robustness test.

4.1 Spatial characteristics of carbon emissions

The spatial differentiation characteristics of carbon emissions in 2007, 2011, 2015, and 2019 are shown in Fig. 1. The western, central, and eastern provinces are represented in Fig. 1. A slight polarization of carbon emissions has been detected, manifested by higher average carbon emissions in the eastern provinces than in the central and western provinces.

The high carbon emissions areas are concentrated in specific provinces all these years. The two highest carbon-emitting provinces in Central China are Shanxi and Inner Mongolia, two of the Chinese major coal mining producers. In the eastern province, high carbon emissions provinces are clustered in three major economic zones, which are relatively developed, including Circum-Bohai Sea Economic Zone (Shandong, Hebei, and Liaoning), Yangtze River Delta Economic Zone (Jiangsu), and Pearl River Delta Economic Zone (Guangdong).

In terms of the number of provinces, from 2007 to 2019, the percentage of provinces with consistently rising carbon emissions in the east, central and west are 44%, 37.5%, and 50%, respectively. However, in terms of volume, there is an upward trend in most provinces with larger emissions, although there is a decline in the growth rate, showing the time inertia of carbon emissions.

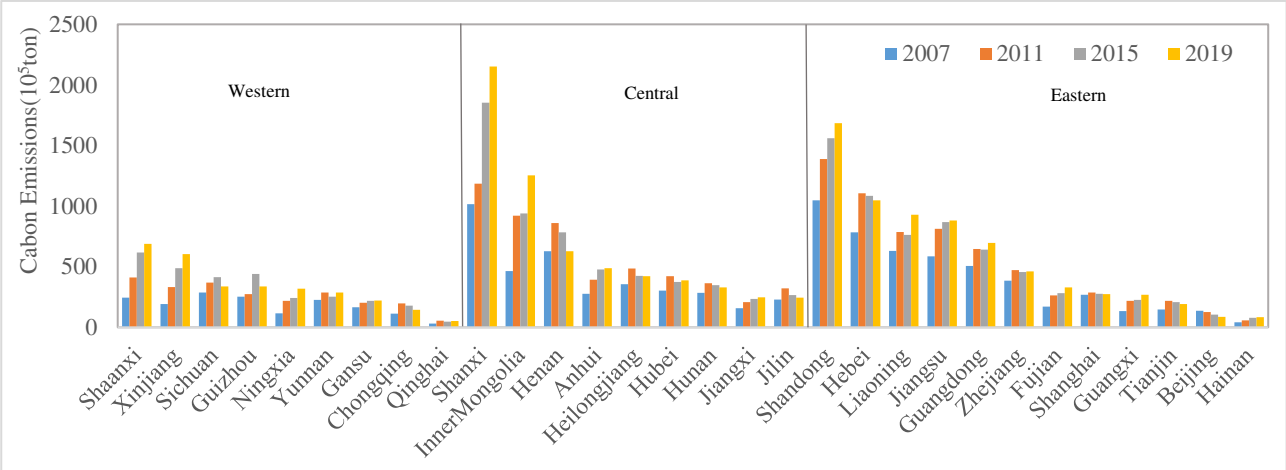

Fig. 1 The spatial differentiation of carbon emissions

4.2 Spatial autocorrelation test

The global spatial autocorrelation of carbon emissions in thirty selected Chinese provinces from 2007 to 2019 is shown in Table 4. The Moran index measures spatial autocorrelation in examining whether to introduce the spatial econometric model in empirical studies (Moran, 1948). Global Moran indexes are consistently positive and statistically significant at least the 5% level, which shows spatial agglomeration. In addition, the Moran index shows a downward trend from 2007 to 2019, indicating that the spatial effect gradually decreases. From 2007 to 2019, the Moran index of

carbon emissions shows a slight fluctuating downward trend within the level of ±0.015 from the mean, which implies a slight weakening of the spatial polarization effect of carbon emissions and a trend of convergence of provincial carbon emission levels.

Table 4 Global Moran index of carbon emissions.

Year	Global Moran Index	Prob.	Year	Global Moran Index	Prob.
2007	0.189***	0.009	2014	0.187***	0.010
2008	0.200***	0.006	2015	0.182**	0.011
2009	0.207***	0.005	2016	0.184**	0.011
2010	0.198***	0.007	2017	0.178**	0.012
2011	0.196***	0.007	2018	0.172**	0.015
2012	0.184***	0.010	2019	0.173**	0.014
2013	0.183**	0.011	Average	0.187	

Notes：*, **, *** imply the significance at the 10%, 5%, and 1% levels, respectively.

The Moran scatter plot is widely used to show the local Moran index in order to determine the spatial agglomeration characteristics of specific provinces. Fig.2 presents the results of Moran scatter plots. Similar to Fig.1, we report the results in 2007, 2011, 2015, and 2019, which correspond to a), b), c), and d), respectively. Moran scatter plots were divided into four quadrants, which are High-High (quadrants I), Low-High (quadrants II), Low-Low (quadrants III), and High-Low (quadrants IV). The majority of provinces were located in the first and third quadrants. There are 20 provinces (2007 and 2011, 66.7%) and 23 provinces (2015 and 2019, 76.7%) that were located in these two quadrants. Hebei, Henan, Shandong, Shanxi, and Inner Mongolia belonged to High-High clustering in all four selected periods, which are basically in Bohai Rim economic circle, and the major coal mining provinces, indicating a significant club convergence phenomenon. However, some provinces indicated negative spatial auto-correlation. As an illustration, Shanghai, Anhui, Jilin, and Ningxia are in quadrants II in 2019, indicating these provinces are low emitters and surrounded by high-emission

neighbors.

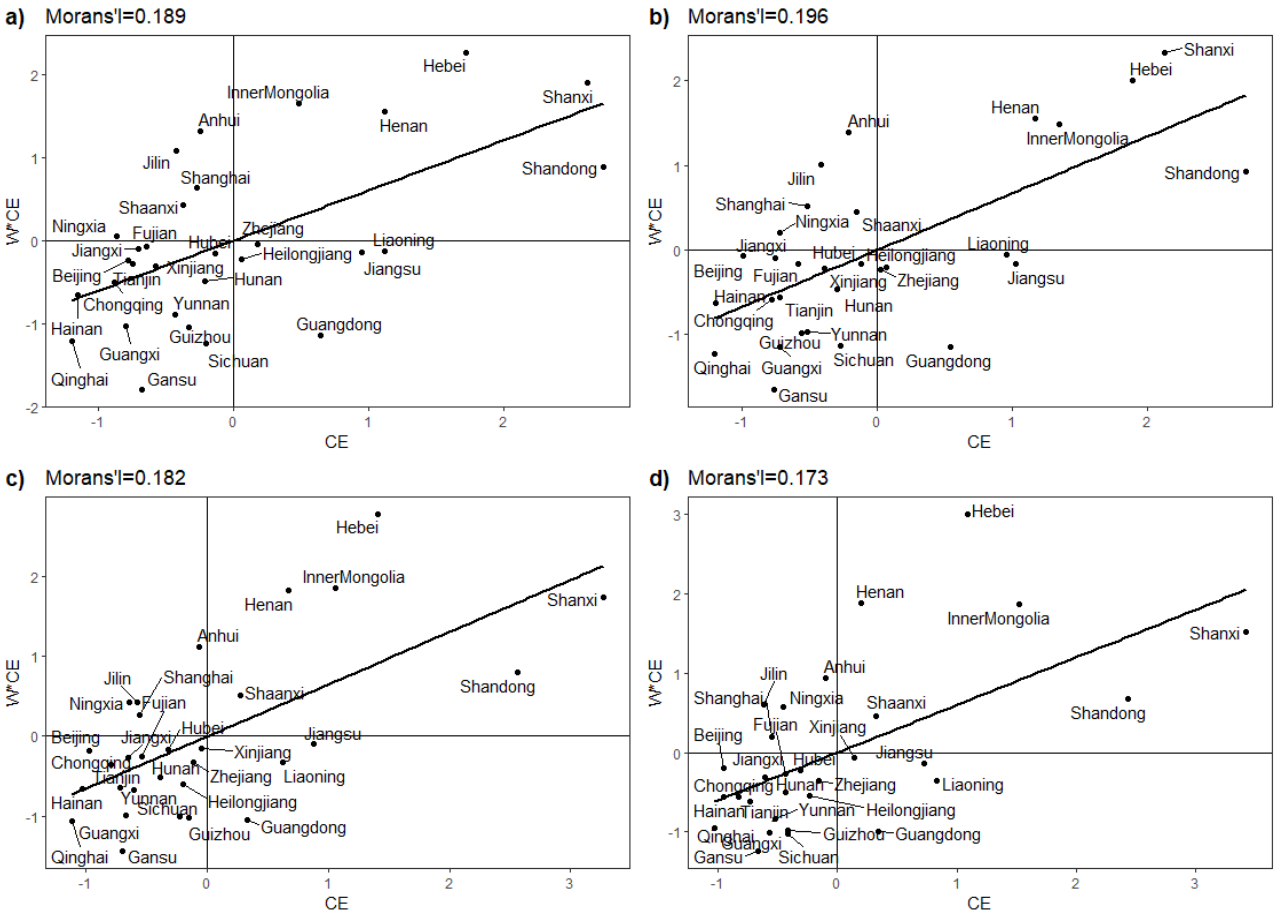

Fig. 2 Moran Scatter plot (a)2007, b)2011, c)2015, d)2019)

4.3 Panel unit root test and cointegration test

It is necessary to examine whether the variables are mean stationarity to avoid spurious long-term relationships in our analysis. Only when the error term of estimation follows a stationary process, which means all the variables are cointegrated (You and Lv, 2018), it is proper to carry out a spatial panel model. Therefore, first, we conduct the cross-sectional dependence (C-D) test (Pesaran, 2021), which is reported in Table 5. The null hypothesis of the C-D test is that the variable is weakly cross-sectional dependent. Table 5 shows that the cross-sectional dependence exists.

Table 5 Cross-section dependence tests

	$\log CE$	$\log LCI$	$\log GDP$	$\log IND$	$\log EI$	$\log ES$	$\log FDI$	$\log PD$
C-D test	75.133***	74.996***	75.196***	75.180***	74.893***	74.551***	74.783***	75.196***

Note: ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Next, we use panel unit root tests to analyze the existence of time stationarity in variables (Chica-Olmo et al., 2020), including LLC (Levin et al., 2002), IPS (Im et al., 2003), Fisher DF (Dickey and Fuller, 1979) and CIPS test (Pesaran, 2007). The first three approaches are the first-generation unit root tests, and the last one is the second-generation unit root test, which takes cross-section dependence into account. The null hypothesis of the unit root test is that there is a unit root in the panel. The unit root test results in Table 6 indicate that the variables are stationary after first differencing. Therefore, the panel cointegration test is necessary.

Table 6 Panel unit root tests

Variables		LLC	IPS	Fisher DF	CIPS
$\log CE$	Level	-10.441***	-2.978***	10.819***	-2.01
	First difference	-9.004***	-4.126***	11.028***	-3.17***
$\log LCI$	Level	-7.519***	-1.653***	18.196***	-1.92
	First difference	9.655***	-6.932***	7.732***	-3.29***
$\log GDP$	Level	-16.581***	-9.254***	5.810***	-1.38

	First difference	-14.289***	-0.017	15.164***	-2.72***
$\log IND$	Level	0.070	3.049	6.090***	-1.86
	First difference	-6.511***	-3.757***	-1.698	-2.91***
$\log EI$	Level	0.070	2.199	6.116***	-2.05
	First difference	-2.034**	-4.905***	4.369**	-3.11***
$\log ES$	Level	-2.085**	-7.949***	3.302***	-2.12
	First difference	9.819	-11.980***	-2.732	-4.55***
$\log FDI$	Level	-11.959***	-4.608	4.229***	-1.83
	First difference	-6.564***	-1.315*	4.953***	-2.93***
$\log PD$	Level	3.541	2.658	1.674**	-1.61
	First difference	-5.667***	-3.267***	1.385*	-2.97***

Note: ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively. The critical values of CIPS are -2.14, -2.25, and -2.45, respectively.

This study introduces the Pedroni cointegration test, shown in Table 7 (Pedroni, 2004). The panel cointegration test assesses the existence of a long-term relationship. The within-dimensional cointegration test statistics (ν, ρ, PP, ADF statistic) and between-dimensional cointegration test statistics (ρ, PP, ADF statistic) indicate that all variables are cointegrated. Therefore, a long-term relationship between the variables exists.

Table 7 Pedroni cointegration test

	χ^2	Prob.
Within-dimension cointegration test		
Panel $\nu-$ statistic	-3.927***	0.000
Panel $\rho-$ statistic	8.467***	0.000
Panel $PP-$ statistic	-9.215***	0.000
Panel $ADF-$ statistic	-9.210***	0.000
Between-dimension cointegration test		
Group $\rho-$ statistic	10.460***	0.000
Group $PP-$ statistic	-12.831***	0.000
Group $ADF-$ statistic	-11.386***	0.000

Note: ***, **, and * represent statistical significance at 1%, 5%, and 10% levels. H_0: no cointegration relationship between the variables

4.4 Specification of the spatial panel model

To examine the existence of spatial dependence and decide which spatial model is more appropriate, we employ Lagrange Multiplier (LM) tests, the robust LM tests, and Likelihood Ratio (LR) tests. The null hypothesis of the LM tests is that there is no spatial lagged term (LM-lag and robust-LM-lag) or spatial error term (LM-error and robust-LM-error). The null hypothesis of the LR test is that there is no spatial error term (LR-SDM-SAR) or spatial lagged term (LR-SDM-SEM) in the model. The results of the specification test are presented in Table 8. LM-Lag, LM-Error, robust-LM-Lag, and robust-LM-Error statistics are 357.325, 198.600, 2610.778, and 2253.652. The results reject the null hypothesis at the 1% significance level. The LR-SDM-SAR and LR-SDM-SEM statistics are 49.91 and 49.92, respectively, rejecting the null hypothesis. Therefore, it is reasonable to introduce the spatial Durbin model into the empirical study. The result of the Hausman test justifies the fixed effects model.

Table 8 Specifications of the spatial panel model

	Statistics	Prob.
LM lag (Anselin)	357.325***	0.000
LM Error (Burridge)	198.600***	0.000
LM lag (Robust)	2610.778***	0.000
LM Error (Robust)	2253.652***	0.000
LR-SDM-SAR	49.91***	0.000
LR-SDM-SEM	49.92***	0.000
Hausman test	172.36***	0.000

Note: ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively

4.5 Spatial panel model estimation results

Table 9 reports the spatial panel results estimated by bias-corrected Quasi-Maximum Likelihood estimation (Lee and Yu, 2010; Yu et al., 2008). Model II is the static SDM; Models III is the Dynamic SDM with the time-lagged dependent variables; Model IV is the DSDM with time-lagged dependent variables and square term of $\log GDP$. And Model V is with time-lagged and spatial-time-lagged dependent variables. The Wald and LR test confirm the validity of the Spatial Durbin Model in our analysis, and the DSDM is better than the SDM from the more significant coefficients in DSDM.

However, the insignificance of the spatial-time-lagged coefficient (η) allows us to exclude model V. It is reasonable to use model IV in our analysis.

The time-lagged coefficient (τ) is positive and significant, which shows inertia characteristics of carbon emissions, meaning that carbon emissions in the previous period positively affect the current period. The result of Model IV indicates that the CE in the next period will increase by 0.153% on average if CE increases by 1% in the current year, which indicates that if carbon emissions are not mitigated promptly, they will become more challenging to control the emission process as the base of carbon emissions grows larger.

The spatial-lagged coefficient (ρ) is significantly positive, indicating the contagion effect of synchronous change, meaning that carbon emissions in adjacent regions positively impact carbon emissions in the local region. For every 1% increase of CE in adjacent provinces, the CE in the local province will increase by 0.19% on average. The result reveals that the control on a single region is ineffective, as high-emission enterprises will transfer to adjacent regions, increasing the emission level in the local province. Therefore, the control policy conducive to carbon emissions mitigation should take joint precautions in neighboring regions. Furthermore, the spatial-lagged effect of carbon emissions is greater than the time-lagged effect, confirming that CE is influenced more by CE from adjacent provinces, which indicates that more attention should be paid to inter-regional joint prevention and control when implementing policies.

The estimated coefficients before the effect decomposition are biased. However, observing the sign of the estimated coefficients helps construct a basic understanding of our model. Concerning the effect of low-carbon innovation on carbon emissions, the coefficient of $\log LCI$ shows a significantly negative impact on CO2 emissions, while the coefficient of $W \times \log LCI$ is negative but not significant. It can be concluded that the mitigating effect of low-carbon innovations exists only in local regions.

Environmental policy is an essential part of business decisions, such as energy consumption and innovation input decisions, and is, therefore, one of the drivers of carbon emissions. The coefficient of EP shows a significant negative effect on carbon emissions, confirming the validity of the mitigating effect of environmental policy, which is consistent with the results of (H. Sun et al., 2021). Furthermore, the coefficient of $W \times EP$ showed similar result, indicating that the mitigating effect includes both a regulatory effect on the local area and a demonstration effect on adjacent areas.

Regarding the nexus between economic developments and carbon emissions, the sign of $\log GDP$ is positive, during the sign of $(\log GDP)^2$ is negative, which indicates the presence of the EKC hypothesis in local regions. However, there are no similar results from adjacent regions.

In the regression results of the control variables, the coefficient of industrial structure (IND), energy intensity (EI), and energy structure (ES) indicate the positive interaction of these control variables on carbon emissions, which implies that for a region with higher industrialization, less efficient energy use, and a relatively high share of high carbon emission energy use leads to higher carbon emissions. Carbon emissions are relatively higher for a region with a developed secondary sector that consumes mostly coal and relies on energy consumption to drive its economy. These impact factors from adjacent regions are insignificant.

Furthermore, foreign direct investment (FDI) shows negative but insignificant effects on carbon emissions, which is consistent with (Cheng et al., 2017). On the one hand, FDI in China concentrates on labor-intensive and resource-intensive industries, driving the rise of carbon emissions. On the other hand, the pollution halo hypothesis also states that FDI brings new technologies that will help host countries reduce pollution. Considering the spillover effect, however, the effect of FDI from adjacent regions is significantly positive, indicating that more FDI in the adjacent regions leads to greater local carbon emissions. Regions with a concentration of foreign investment have developed energy-intensive industries with high carbon emissions, which will cause the agglomeration of similar industries locally, leading to an increase in carbon emissions.

Finally, population density (PD) shows insignificant impacts on carbon emissions from local and adjacent regions. The above results suggest that at this stage, resource intensification due to rising population density is not significantly reflected at the provincial level, probably due to inconsistent urban development within Chinese provinces. In developed

cities, resource intensification leads to more efficient energy consumption, but in less developed cities, this effect is largely absent, leading to the inability to observe significant results at the provincial level in the current context.

Table 9 Estimation results of OLS model, SDM, and DSDM.

	Model I OLS-FE	Model II SDM	Model III DSDM	Model IV DSDM	Model V DSDM
ρ		0.273***	0.190**	0.190**	0.187*
		(2.878)	(2.035)	(1.983)	(1.892)
τ			0.158***	0.153***	0.151***
			(10.308)	(9.759)	(9.675)
η					-0.040
					(-0.732)
$\log LCI$	-0.007	-0.028***	-0.026***	-0.022***	-0.022***
	(-0.816)	(-3.454)	(-3.463)	(-2.884)	(-2.915)
$\log GDP$	0.988***	1.058***	0.892***	1.034***	1.036***
	(43.588)	(96.359)	(47.145)	(24.500)	(24.749)
$(\log GDP)^2$				-0.008***	-0.008***
				(-3.788)	(-3.824)
EP	-0.016*	-0.058***	-0.046***	-0.045***	-0.045***
	(-1.734)	(-6.067)	(-5.363)	(-5.114)	(-5.224)
$\log IND$	0.023	0.660***	0.592***	0.630***	0.631***
	(0.307)	(8.940)	(8.724)	(8.934)	(9.046)
$\log EI$	1.067***	1.041***	0.892***	0.898***	0.900***
	(96.893)	(142.639)	(56.541)	(55.949)	(56.049)
$\log ES$	0.020***	0.033***	0.024***	0.024***	0.024***
	(5.087)	(4.763)	(3.953)	(3.868)	(3.965)
$\log FDI$	0.003	-0.013***	-0.008**	-0.005	-0.005
	(0.992)	(-3.186)	(-2.032)	(-1.415)	(-1.381)
$\log PD$	-0.195***	0.007	0.005	0.006	0.006
	(-3.916)	(1.337)	(1.266)	(1.485)	(1.445)
$W \times \log LCI$		-0.010	-0.005	-0.014	-0.014
		(-0.538)	(-0.280)	(-0.737)	(-0.762)
$W \times \log GDP$		0.253**	0.138	0.142	0.198
		(2.318)	(1.289)	(0.902)	(1.216)
$W \times (\log GDP)^2$				-0.000	-0.001
				(-0.017)	(-0.204)
$W \times EP$		-0.142***	-0.126***	-0.139***	-0.141***
		(-4.577)	(-4.461)	(-4.819)	(-4.953)
$W \times \log IND$		-0.022	0.094	0.192	0.222
		(-0.128)	(0.587)	(1.120)	(1.294)
$W \times \log EI$		0.251**	0.132	0.128	0.164
		(2.512)	(1.351)	(1.288)	(1.606)
$W \times \log ES$		0.022	0.008	0.006	0.009
		(1.369)	(0.573)	(0.457)	(0.633)
$W \times \log FDI$		0.047***	0.044***	0.037***	0.037***
		(5.107)	(5.265)	(4.073)	(4.151)
$W \times \log PD$		-0.023	-0.018	-0.007	-0.007
		(-1.522)	(-1.282)	(-0.443)	(-0.458)
N	390	390	360	360	360
R^2	0.981	0.971	0.972	0.966	0.965
Wald	-	47.71***	46.91***	32.17***	33.99***
LR	-	40.05***	349.07***	343.43***	73.06***

Note: ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively; the parentheses' values represent the t-statistics.

To get the accurate marginal effects, we estimated the direct, indirect, and total effects in the short-term and long-term of model IV according to the equation (7) to (10). The results are reported in Table 10. Regarding our core explanatory variable, the Short-term direct effect (SDE) and Short-term indirect effect (SIE) of low-carbon innovation are -0.021 and -0.008, respectively. Similar results also appeared in the long term. However, only the direct effects are significant at the 5% level. It can be concluded that low-carbon innovations reduced carbon emissions only locally, while the spillover effect of LCI can not be observed. Improving the regional low-carbon innovation can significantly inhibit local CE. However, it does not affect adjacent regions significantly, which may result in that low-carbon innovation resources are mainly applied to local development currently, lacking the linkage effect with the adjacent regions. Therefore, the progress of low-carbon technologies can only reduce local carbon emission levels, making it difficult to obtain a more efficient mitigating mode overall. In addition, the regions with higher levels of low-carbon innovation are developed regions, while the number of developing regions is much larger among all regions, which is not conducive to the overall reduction of carbon emissions if the spillover effect continues to remain at a low level.

After the effect decomposition, the relationship between economic development and carbon emissions becomes clearer. The direct effects in both the long term and short term show that the inverted U-shaped relationship between GDP and CE exists, supporting the validity of the EKC hypothesis, in line with the results of the other studies (Apergis, 2016; Grossman and Krueger, 1995; Jiang et al., 2021; Y. Sun et al., 2021). However, after obtaining the inflection points for SDE and LDE (64.375 and 61.51, respectively) and comparing the inflection points with provincial real GDP, we find that none of the provinces is close to the inflection point yet. Therefore, if the current economic development structure keeps unchanged, improving economic development in China still promotes local carbon emissions in the short and long term, which possibly results from that economic growth increasing energy consumption and thus contributes to the carbon emissions (Mikayilov et al., 2018), the effect of low-carbon development has not yet been fully demonstrated. The indirect effects of GDP and its square term are not significant, which indicates that improving GDP from adjacent regions can not affects local carbon emissions statistically significantly in the short term or the long term.

Regarding our other critical explanatory variable, EP, the direct and indirect effects are all negative at a 1% significant level in the long and short run, proving that environmental policy contributes to carbon emissions mitigation in pilot regions and their adjacent regions. The direct effects of the carbon emission trading policy have been widely observed in previous studies (Gao et al., 2020). However, the spillover effects of the carbon emission trading policy have not been proposed. The existence of spillover effects indicates that the launching of the policy also leads to the mitigation of carbon emissions in adjacent regions. Furthermore, the indirect effects are higher than the direct effects in both the short and long term, which indicates that the adjacent regions may react more intensely to the possible further regulation when the environmental policy is rolled out.

Table 10 Direct, indirect and total effect in short-term and long-term.

Variables	Short-term			Long-term		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
$\log LCI$	-0.021***	-0.008	-0.030**	-0.025***	-0.009	-0.034**
	(-2.761)	(-0.479)	(-1.980)	(-2.735)	(-0.439)	(-1.977)
$\log GDP$	1.034***	-0.055	0.979***	1.223***	-0.099	1.124***
	(24.069)	(-0.611)	(10.418)	(24.002)	(-0.956)	(10.547)
$(\log GDP)^2$	-0.008***	0.002	-0.006	-0.010***	0.002	-0.007
	(-3.790)	(0.322)	(-1.260)	(-3.777)	(0.366)	(-1.259)
EP	-0.041***	-0.114***	-0.155***	-0.047***	-0.131***	-0.178***
	(-4.889)	(-4.658)	(-5.889)	(-4.779)	(-4.551)	(-5.787)
$\log IND$	0.625***	0.056	0.681***	0.739***	0.043	0.782***
	(9.121)	(0.446)	(4.267)	(9.137)	(0.302)	(4.281)
$\log EI$	0.899***	-0.036*	0.863***	1.062***	-0.072***	0.990***
	(54.326)	(-1.785)	(37.808)	(53.938)	(-3.711)	(44.258)
$\log ES$	0.024***	0.001	0.025**	0.028***	0.001	0.029**
	(3.790)	(0.110)	(1.967)	(3.782)	(0.051)	(1.968)
$\log FDI$	-0.007*	0.033***	0.027***	-0.008*	0.038***	0.031***
	(-1.709)	(4.058)	(3.175)	(-1.754)	(4.056)	(3.152)
$\log PD$	0.006	-0.007	-0.001	0.007	-0.009	-0.002
	(1.621)	(-0.586)	(-0.097)	(1.634)	(-0.600)	(-0.097)
ρ						0.190**
						(1.983)
τ						0.153***
						(9.759)
N						360

Note: ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively; the parentheses' values represent the t-statistics.

4.6 Heterogeneity test

The inducement hypothesis suggests that environmental regulations will force firms to undertake innovative activities and improve R&D performance, which leads to improved energy efficiency (Noailly, 2012). Therefore, the abatement effects of low-carbon innovations may vary depending on whether regions are subject to policy intervention. Based on the above analysis, we conduct the heterogeneity test of low-carbon innovation to in-depth explore the interaction between environmental policy and low-carbon innovation. Specifically, we introduce the interaction terms of logLCI and EP into the main model (model IV), and the results of the heterogeneity test are shown in Table 11.

As shown in model IV, both environmental policy and low-carbon innovation have a mitigating effect on carbon emissions. However, the coefficient of the interaction term is significantly smaller than zero after the introduction of the

interaction term, and the coefficient of environmental policy is not significant at this point, which implies that there is a synergy between the mitigation effect of environmental policy and low-carbon innovation. Each 1% increase in the counts of low-carbon patents will reduce carbon emissions by 0.024% on average in areas without pilot policies, while this mitigation effect will reach 0.042 in pilot areas. The results show a synergistic mitigation effect of policy and low-carbon innovation on local carbon emissions. The mitigation effect of environmental policy is mainly on increasing low carbon innovation, then mitigating carbon emissions. The possible reason may be that policy intervented regions are incentivized to applicate innovations that benefit by increasing energy efficiency and mitigating carbon emissions, which is consistent with the study of Lv and Bai (2021) and Zhu et al. (2019).

As for the spillover effect, the spatial spillover effect of low-carbon innovation is not significant in model IV, the main model. Therefore, in the heterogeneity test, it is reasonable that the spatial interaction of $W \times EP \times \log LCI$ on carbon emissions is insignificant in model VI. This insignificant coefficient implies that local carbon emissions are largely unaffected by low-carbon innovations in adjacent areas regulated by CET policy, suggesting that inter-provincial spillovers from low-carbon innovations are currently negligible.

Table 11 Heterogeneity test of low carbon emissions under the environmental policy.

	Model IV	Model VI
$\log LCI$	-0.022***	-0.024***
	(-2.884)	(-2.963)
EP	-0.045***	0.100
	(-5.114)	(1.268)
$EP \times \log LCI$		-0.018*
		(-1.844)
$W \times \log LCI$	-0.014	-0.018
	(-0.737)	(-0.942)
$W \times EP$	-0.139***	0.231
	(-4.819)	(0.971)
$W \times EP \times \log LCI$		-0.047
		(-1.561)
ρ	0.190**	0.229**
	(1.983)	(2.284)
τ	0.153***	0.150***
	(9.759)	(9.634)
control	Y	Y
N	360	360

Note: ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively; the parentheses' values represent the t-statistics.

4.7 Robustness test

In order to verify the robustness of the spatial Durbin model, two different spatial weight matrices are adopted to replace the previous inverse squared distance weight matrix, which is the binary spatial weight matrix (W_2) and inverse economic-distance matrix (W_3). The estimation results showed in Table 12. The results estimated from different spatial weight matrices remain consistent, especially in that the effects of low-carbon innovation and economic development on carbon emissions remain consistent in Model IV, model VII, and Model VIII. Therefore, the robustness of the model has been verified.

Table 12 the results of the robustness check

	Model IV W	Model VII W_2	Model VIII W_3
$\log LCI$	-0.022***	-0.042***	-0.024***
	(-2.884)	(-5.460)	(-3.734)
$\log GDP$	1.034***	1.113***	0.490***
	(24.500)	(26.188)	(2.914)
$(\log GDP)^2$	-0.008***	-0.011***	0.020**
	(-3.788)	(-5.057)	(2.299)
EP	-0.045***	-0.048***	-0.034***
	(-5.114)	(-5.282)	(-3.819)
$W \times \log LCI$	-0.014	0.005	-0.038**
	(-0.737)	(0.296)	(-2.242)
$W \times \log GDP$	0.142	0.222*	0.985***
	(0.902)	(1.808)	(3.273)
$W \times (\log GDP)^2$	-0.000	-0.016***	-0.035**
	(-0.017)	(-3.396)	(-2.350)
$W \times EP$	-0.139***	-0.092***	-0.073***
	(-4.819)	(-4.947)	(-2.776)

ρ	0.190**	0.020	0.144*
	(1.983)	(0.266)	(1.824)
τ	0.153***	0.142***	0.142***
	(9.759)	(9.499)	(9.911)
Control	Y	Y	Y
N	360	360	360

Note: ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively; the t-statistics are given in parentheses.

5 Conclusion and policy implications

In this study, focusing on China, we address low carbon innovation, economic growth, and carbon emissions nexus to help the economy develop green and high-quality. Therefore, we study the period from 2007 to 2019, considering environmental policy, energy structure, industrial structure, foreign direct investment, energy intensity, and population density in the Chinese economy. We applied the LLC, IPS, Fisher DF, and CIPS unit root tests to verify the integration order of the variables and carried out cointegration tests to determine the existence of a cointegration relationship between carbon emissions on its determinants. Spatial analysis was then carried out to determine the situation. Subsequently, we applied the dynamic spatial Durbin model and estimated the long-run and short-run effects. In addition, we estimated the heterogeneity analysis of green innovation before and after being subjected to environmental policies. Finally, this paper tests the robustness of the above estimation results.

Our evidence-based study provides significant results for the role of low-carbon innovation in reducing carbon emissions in developing countries. The provincial agglomeration of carbon emissions exists through the results of the Moran index; the high-emission provinces mainly concentrate in major economic zones and energy extraction areas.

First, we verify the inertia characteristics from the time perspective and contagion effect from the spatial perspective of carbon emissions through the dynamic spatial Durbin model. The carbon emissions in current periods are positively influenced by the previous periods' carbon emissions and in the adjacent regions.

Second, we find that low-carbon innovation can mitigate carbon emissions by DSDM. After the effect decomposition, however, the mitigation effect of low-carbon innovation exists only locally; the spillover effect can not be observed.

Third, regarding the relationship between GDP and carbon emissions. Our results validate the EKC hypothesis locally in a dynamic framework, which holds in the long and short term, although none of the provinces reach the inflection point of the inverted U-shaped curve.

Fourth, we use the CET scheme as a proxy variable for the environmental policy in our analysis. We find a significant negative effect of policy shocks on carbon emissions, and this negative effect includes both direct and spillover effects, which holds in both the long and short term.

Several policy implications are made in response to the previous findings. First, low-carbon innovation is the key to achieving carbon emission reduction, which requires the local governments to mobilize the market enthusiasm to incentivize companies to increase their R&D investments in low-carbon technologies when voluntary participation is insufficient. Local governments can consider introducing and improving targeted market-based incentive mechanisms (Qin et al., 2021; Sun et al., 2019), such as green government subsidies and green credit policies, which are able to increase the green R&D investment of high R&D-input enterprises by targeting them to alleviate their financing constraints and moderately restricting the financing channels of high-pollution, high-energy-consumption, and high-water-consumption enterprises to prevent these enterprises from over-expanding.

Second, the spatial spillover effect of low-carbon innovation should be considered. Previous studies have suggested that knowledge spillover effects exist between regions, but in this study, it is found that the spillover effects of low-carbon innovation are not significant at the provincial level in China. Therefore, the government needs to construct an inter-regional technology exchange system to enhance the spillover effect of provincial knowledge, which is conducive to both the emergence of new knowledge and the achievement of carbon emission mitigation.

Third, promote the landing and implementation of environmental policies related to carbon emissions, such as the carbon emissions trading policy. This study confirms the synergistic effect of the enviromental policy and low-carbon

innovation on carbon emissions. Therefore, policymakers should extend the experience of the pilot regions to the national carbon emissions trading market to form a synergy between regions and jointly promote the development of a low-carbon economy. In addition, policymakers need to explore the inclusion of industries other than electricity under the carbon market regulation in the pilot regions to make the carbon market system more comprehensive.

Last, the government should make integrated growth performance a development goal and develop a green economy based on controlling carbon emissions. According to the empirical results, Chinese provinces have not yet reached the inflection point of the inverted U-shaped environmental Kuznets curve, but carbon emission reduction pressure is imminent. Specific paths concentrating on low-carbon development may include. (1) adjusting the industrial structure and guiding industrial upgrading, which requires, on the one hand, reducing the share of the secondary industry in output, especially the high-energy-consuming industries, and on the other hand, developing more high-end manufacturing industries with low energy consumption and high added value. (2) guiding domestic and foreign capital to invest in the aforementioned industries, especially the latter. this paper finds a negative externality of FDI on carbon emissions, which stems from massive FDI in energy-intensive industries (Bakhsh et al., 2021). (3) improving energy efficiency and encouraging comprehensive conservation of energy on the production, transportation, and consumption sides to reduce per capita energy consumption. (4) encouraging the use of renewable energy, such as solar and wind energy, and gradually reducing the proportion of coal in energy consumption until gradually withdrawing from coal consumption.

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