



Low-carbon innovation, economic growth, and CO₂ 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 2020. First, the Moran index results verify the provincial spatial agglomeration of carbon emissions. 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. The above results have been tested to be robust. Third, the results of the mechanism analysis show that environmental policies, absorptive capacity, and financial development play a moderating role in the relationship between low-carbon innovation and carbon emissions. Finally, the heterogeneity test showed significant differences between Eastern, Central, and Western. The direct effect of low-carbon innovation exists in Eastern and central regions; the spillover effect of low-carbon innovation is only in the eastern region. In addition, corresponding measures are proposed based on the conclusions.

Keywords Carbon emissions · Low-carbon innovation · Economic growth · EKC hypothesis · Environmental policy · Dynamic spatial Durbin model

JEL Classification O36 · R12 · Q54 · Q55

Introduction

Since the Industrial Revolution, the concentration of atmospheric greenhouse gas 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 emission 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.

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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>

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).

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. 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.

China is currently transitioning from high economic growth to high-quality development. To promote green economic development, the Chinese government regards innovation as an essential part of its national strategy. However, after years of green development, there are still questions that have not yet been answered. First, whether the carbon mitigation effect of low-carbon innovation exists? Second, what is the interaction effect of low-carbon innovation between provincial levels in China, and are there any spillover effects? Third, what low-carbon innovative carbon emission mitigation mechanisms currently exist in China? A systematic review of the mitigation effects of low-carbon innovations will facilitate the development of targeted policies to achieve China's carbon neutrality goals efficiently. Furthermore, 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, this study investigates the spatial relationship between low-carbon innovation and carbon emissions.

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; 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 a review of the literature. In "Research hypothesis," the theoretical framework is introduced in this paper. "Methodology and data" illustrates the methodology and data. The empirical results and discussion are presented in "Empirical analysis" and "Discussion," respectively. Moreover, "Conclusion and policy implications" summarizes and discusses the empirical findings, then concludes with policy implications.

Literature review

Innovation and carbon emission 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 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 Group-20 countries (Nguyen et al. 2020), Nordic countries (Irandoost 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

Table 1 Selected literature on the innovation-carbon emission nexus

Studies	Sample and time period	Methodology	Key findings
Technological innovation-carbon emission 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 Group-20 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)	Organisation for Economic Co-operation and Development 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 Group-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 and low-carbon innovation			
Töbelmann and Wendler (2020)	27 European Union 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, environmental 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)	Group-7 countries, 1990–2017	AMG; CCEMG	Environmental innovation decreases carbon emissions
Radmehr et al. (2021)	21 European Union countries, 1995–2014	Generalized spatial two-stage least squares (GS2SLS)	Environmental innovation and carbon emissions are not relevant
Wang et al. (2020)	Group-7 countries, 1990–2017	Pooled mean group (PMG), AMG	Eco-innovation decreases carbon emissions
Ding et al. (2021)	Group-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

Table 1 (continued)

Studies	Sample and time period	Methodology	Key findings
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

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 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 Group-7 countries, the USA, 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.

Economic growth and carbon emission 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 USA, whereas the findings of Cheng et al. (2017) and 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 Group-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 CO₂ per capita and GDP per capita in 20 countries, and Danesh Miah et al. (2010) argue that the curve of CO₂ 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.

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).

Research hypothesis

Existing macroeconomic theories emphasize that technology is the main driver of economic growth. Despite the inconsistent results obtained in empirical observations, it is indisputable that from a theoretical perspective, there is a negative effect of innovation on carbon emissions. Environmentally relevant low-carbon innovations focused on reducing carbon emissions are more beneficial than ordinary technological innovations (Dong et al. 2022). For example, Shao et al. (2021) found that green innovations significantly reduced carbon emissions. The emission reduction of low carbon innovation may act on two points: first, low-carbon innovations that directly reduce carbon emissions, such as carbon capture and new energy innovations, which are low-carbon innovations that will either directly reduce carbon dioxide levels in the atmosphere or introduce new energy sources into the market to replace the use of traditional fossil energy sources, thereby directly reducing carbon emissions, and second, indirectly reducing carbon emissions, such as innovations that improve energy efficiency. These

innovations may be achieved by improving energy efficiency. Therefore, this study proposes hypothesis 1.

Hypothesis 1: Low-carbon innovation negatively impacts carbon emissions.

In general, carbon emissions are influenced by technological innovation along with the state of economic development. Although, as mentioned in the previous section, the relationship between carbon emissions and economic growth has not been unified in empirical studies, affected by the heterogeneity of the samples under study. From a theoretical perspective, Grossman and Krueger (1995) have proposed a relationship between environmental stress and economic development. In the early stages of development, an increase in output at lower levels of economic development will lead to an increase in carbon emissions, while in the middle and late stages of development, higher levels of development will give regions more incentive to invest in emission reductions, leading to a decrease in carbon emissions. In conclusion, it can be inferred that there is a positive and then negative effect of economic growth on carbon emissions over time; i.e., there is an inverted U-shaped relationship between economic growth and carbon emissions. Accordingly, hypothesis 2 is proposed as follows:

Hypothesis 2: Economic growth has an inverted U-shaped impact on carbon emissions.

The impact of environmental policies on regional carbon emissions has been confirmed by empirical studies (Abbas et al. 2022). In regions where environmental policies are implemented, the cost of carbon emissions for firms rises due to external government regulation. Firms will be pushed to control their emission levels. At the macro-level, it can be observed that environmental policies lead to a decrease in carbon emissions. On the other hand, based on hypothesis 1, low-carbon innovation helps to reduce carbon emissions. Furthermore, in addition to the direct effect, environmental policy may play a moderating role on the relationship between low-carbon innovation and carbon emissions. Specifically, low-carbon innovations in regions regulated by environmental policies have better emission reduction effects. Droste et al. (2016) argue that innovation is more likely to achieve sustainable development goals under government intervention. As environmental policies persistently put cost pressure on firms in regulated regions, firms are more likely to target their research and development to develop low-carbon innovations with more emission reduction potential to reduce their own carbon emissions effectively. Therefore, we argue that environmental policy formulation can help enhance the mitigation effect of green innovation on

carbon emissions. The above arguments lead to the following hypothesis:

Hypothesis 3: Environmental policy plays a moderating role between low-carbon innovation and carbon emissions.

According to the absorptive capacity theory of firms proposed by Cohen and Levinthal (1990), absorptive capacity is the ability to recognize the value of external knowledge, assimilate it, and apply it to commercial ends, which determines the capacity and efficiency of technological transformation. Regions with high absorptive capacity are able to identify precisely and efficiently how innovations should be applied, and are therefore able to reap greater benefits from the emission reduction effects of low-carbon innovations. In this regard, this study proposes hypothesis 4:

Hypothesis 4: Absorptive capacity plays a moderating role between low-carbon innovation and carbon emissions.

Financial frictions permeate every corner of economic activity, including the innovation process. Moreover, financial development can reduce the level of financial friction. Although the impact of financial development on carbon emissions is not consistent in empirical studies, as noted in Acheampong et al. (2020), financial development presents heterogeneous results on carbon emissions in different economies. In reality, the type of impact presented often depends on the relationship between the strength of the innovation and the rebound effect (Dasgupta et al. 2001; Zagorchev et al. 2011). According to the three-stage innovation theory, innovation is divided into innovation input, patent output, and new product output stages. The output of low-carbon innovation patents may reduce carbon emissions by both producing new products and improving production processes. In the process of low-carbon patent transformation, both existing innovation patent results and significant capital investment are required. Regions with higher levels of financial development have more comprehensive and complete financial infrastructures, which can better meet the capital needs of the local low-carbon innovation transformation process. Therefore, we believe that the higher the degree of financial development, the higher the intensity of the mitigation effect of low-carbon innovation on carbon emissions.

Hypothesis 5: Financial development plays a moderating role between low-carbon innovation and carbon emissions.

Methodology and data

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).

$$I_{it} = aP_{it}^b A_{it}^c T_{it}^d e \quad (1)$$

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:

$$\log I_{it} = \log a + b \log P_{it} + c \log A_{it} + d \log T_{it} + \varepsilon \quad (2)$$

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

Spatial panel model

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):

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

where W_{ij} is the spatial weight matrix after row standardization. The value of the Moran index is between -1 and 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 Eq. (4), for province i :

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

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:

$$\log CE_{i,t} = \tau \log CE_{i,t-1} + \rho W \log CE_{i,t} + \eta W \log CE_{i,t-1} + X_{i,t} \beta_1 + W X_{i,t} \beta_2 + v_{i,t} \tag{5}$$

where $\log CE_{i,t}$ is the carbon emission of province i in period t , and $X_{i,t}$ is the explanatory variable. The parameters τ , ρ , 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:

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

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 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:

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

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

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

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

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

Spatial moderating effect model

The moderating effects model focuses on the role of moderating variables in the relationship between the core explanatory variables and the explanatory variables. We construct a moderating effects model followed by Brambor et al. (2006) to examine the role of environmental policy, absorptive capacity, and financial development in the abatement effects of low-carbon innovation. The model is shown in Eq. (11).

$$\log CE_{i,t} = \tau \log CE_{i,t-1} + \rho W \log CE_{i,t} + \eta W \log CE_{i,t-1} + \alpha_1 \log LCI_{i,t} + \alpha_2 D_{it} + \alpha_3 W \log LCI_{i,t} + \alpha_4 W D_{it} + \alpha_5 D_{it} \log LCI_{i,t} + \alpha_6 W D_{it} \log LCI_{i,t} + X_{i,t} \beta_1 + W X_{i,t} \beta_2 + \mu_i + v_{i,t} \tag{11}$$

where D_{it} are the moderating variables, including environmental policy (EP), absorbing capacity ($\log AC$), and financial development ($\log FD$).

Variable selection and data source

A sample dataset utilized for analysis covers the thirty Chinese provinces from 2007 to 2020. 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 are estimated by the consumption of fossil fuels derived from China Energy Statistical Yearbook (2008–2021). Equation (11) is based on the method recommended by the IPCC (Intergovernmental Panel on Climate Change).

$$CE = \sum_{j=1}^{17} EC_j \times NCV_j \times CC_j \times O_j \times \frac{44}{12} \tag{12}$$

where EC_j is the j th type of fossil fuel consumption, NCV_j is the net calorific value of the j th type of fossil fuel, and CC_j represents the carbon content of the unit heating value

Table 2 Variable definitions

Variables	Abbreviation	Unit	Definition
Carbon emissions	<i>CE</i>	Million ton	Calculated from fossil fuels consumption
Low-carbon innovation	<i>LCI</i>	Number	Low-carbon Patent counts
Economic growth	<i>GDP</i>	Yuan	Gross domestic product
Industrial structure	<i>IND</i>	Percent	The share of secondary industry in GDP
Energy intensity	<i>EI</i>	kg of standard coal/Yuan	The ratio of energy consumption to GDP
Foreign direct investment	<i>FDI</i>	US dollar	Foreign direct investment (net inflow)
Energy structure	<i>ES</i>	Percent	The share of coal consumption in total energy consumption
Population density	<i>PD</i>	Number/km ²	The number of resident population per square kilometer
Environmental Policy	<i>EP</i>	Dummy variable	Carbon emission trading pilot. <i>EP</i> = 1 when (1) the region is the pilot area and (2) the year is after 2011
Absorptive capacity	<i>AC</i>	Man-year	The full-time equivalent of R&D personnel by region
Financial development	<i>FD</i>	%	The share of the year-end loan balance of financial institutions to GDP

of the j types of energy. O_j is the carbon oxidation rate of the j th 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 have noticed that economic development nonlinearly 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 (2008–2021).
- (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 (2008–2021).
- (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 (2008–2021).
- (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 (2008–2021).
- (6) Energy intensity (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 (2008–2021).
- (7) Population density (PD). In general, population-dense regions are developed with low transport costs and convenient services, which reduces carbon emissions

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

Table 3 Descriptive analysis

Variables	Mean	Std. Dev	Minimum	Median	Maximum
<i>CE</i>	467.957	392.001	30.942	330.454	2304.617
<i>LCI</i>	1987.641	2827.955	6.000	965.000	19,241.000
<i>GDP</i>	15,202.856	13,546.710	630.930	11,159.433	78,346.039
<i>IND</i>	42.802	8.225	15.989	43.822	61.960
<i>EI</i>	18.574	16.030	2.749	13.691	88.260
<i>FDI</i>	7307.104	7509.792	4.769	4631.745	35,759.559
<i>ES</i>	66.968	18.595	2.025	68.881	97.930
<i>PD</i>	455.338	673.892	7.637	282.310	3912.941
<i>EP</i>	0.138	0.346	0	0	1
<i>AC</i>	114,258.6	134,542.5	1,262	67,721.5	872,238
<i>FD</i>	2.818	2.500	1.368	2.097	16.809

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 (2008–2021).

The moderating variables are illustrated as follows:

- (1) 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.
- (2) Absorptive capacity (AC). Absorptive capacity is mainly influenced by human input and material investment, where human input determines the extent to which new technologies and methods are understood and digested (Zhao et al. 2019). Therefore, this paper uses the full-time regional equivalent of R&D personnel to measure absorptive capacity. Data were collected from the China Science and Technology Statistical Yearbook (2008–2021).
- (3) Financial development (FD). Referring to the study by Khan and Ozturk (2021), financial development is measured by the share of the year-end loan balance of financial institutions to GDP. Data are obtained from the statistical yearbooks of each Chinese province.

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.

Empirical analysis

The procedures of the estimations mainly consist of six 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) examining 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) mechanism analysis; (5) heterogeneity test; (6) robustness test.

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 have 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

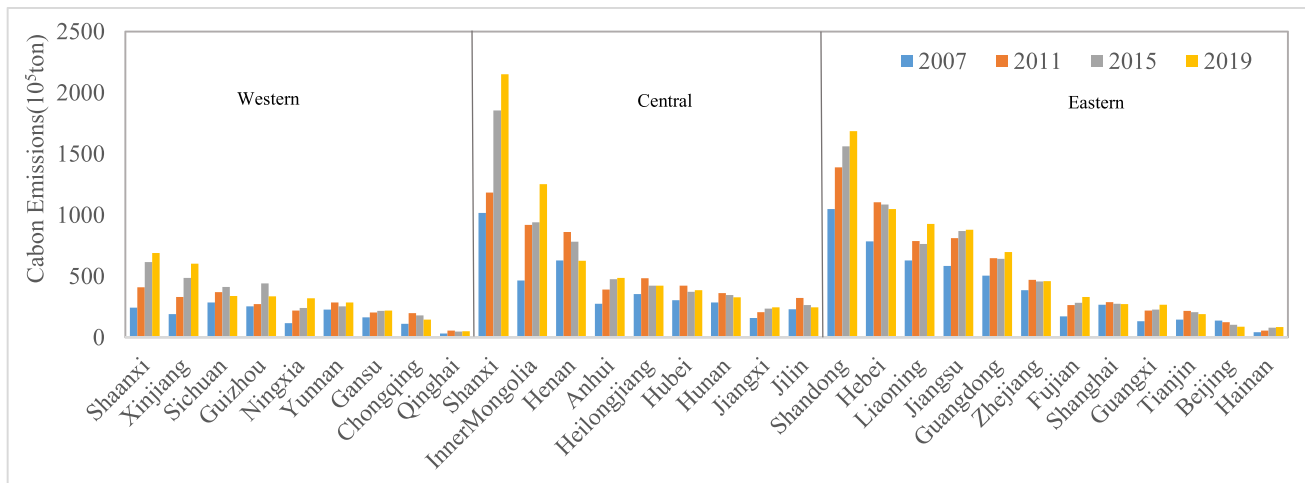


Fig. 1 The spatial differentiation of carbon emissions

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.

Spatial autocorrelation test

The global spatial autocorrelation of carbon emissions in thirty selected Chinese provinces from 2007 to 2020 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 2020, indicating that the spatial effect gradually decreases. From 2007 to 2020, 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.

The Moran scatter plot is widely used to show the local Moran index in order to determine the spatial agglomeration characteristics of specific provinces. Figure 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.

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

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	2020	0.172***	0.009

** and *** imply the significance at the 5% and 1% levels, respectively

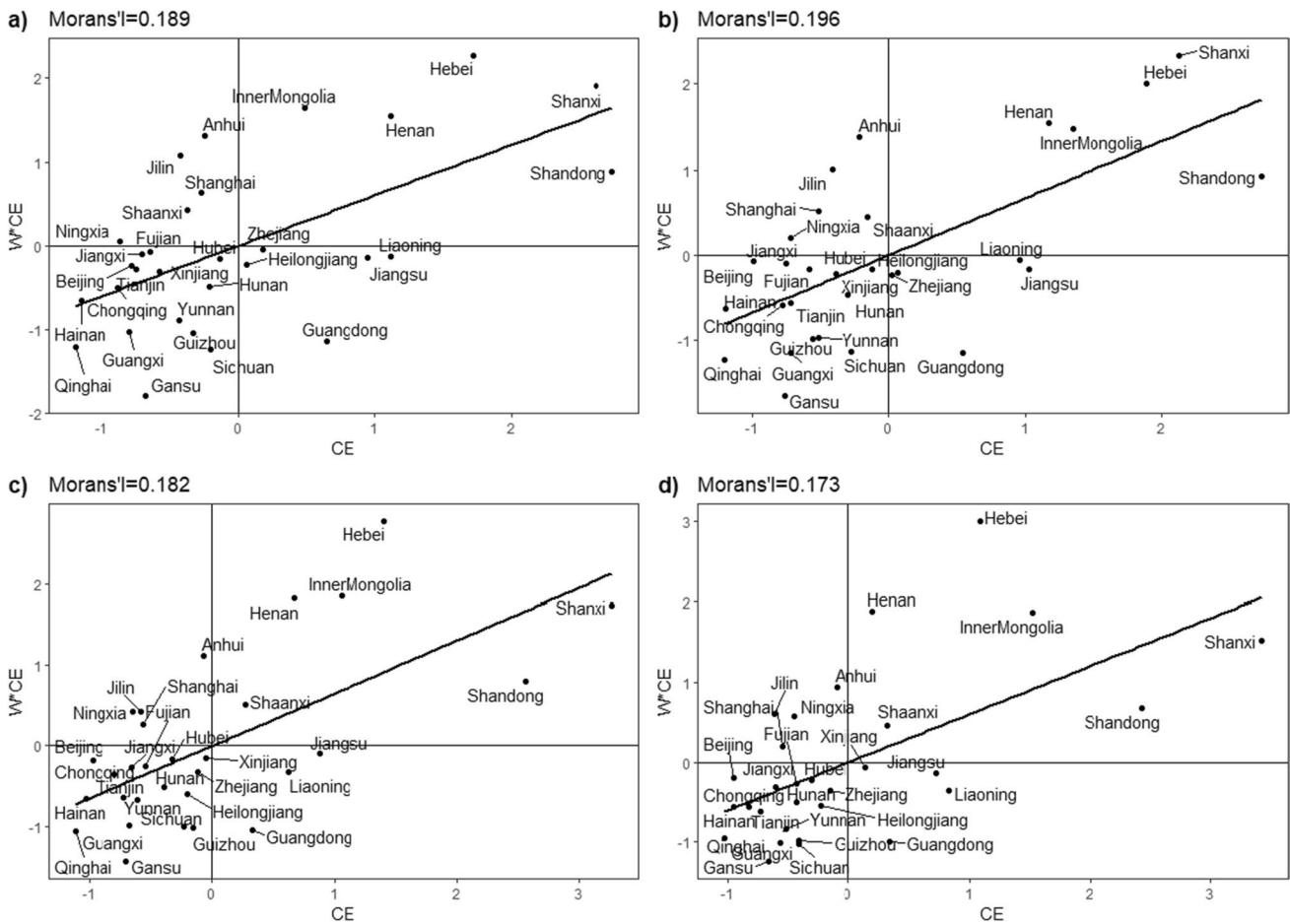


Fig. 2 Moran scatter plot: **a** 2007, **b** 2011, **c** 2015, and **d** 2019

Table 5 Cross-sectional dependence tests

	logCE	logLCI	logGDP	logIND	logEI	logES	logFDI	logPD
C-D test	77.966***	77.790***	78.034***	77.836***	77.678***	77.235***	77.897***	78.035***

***represents statistical significance at 1% level

is weakly cross-sectional dependent. Table 5 shows that the cross-sectional dependence exists.

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.

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.

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

Table 6 Panel unit root tests

Variables		LLC	IPS	Fisher DF	CIPS
log <i>CE</i>	Level	−10.441***	−2.978***	10.819***	−2.01
	First difference	−9.004***	−4.126***	11.028***	−3.17***
log <i>LCI</i>	Level	−7.519***	−1.653***	18.196***	−1.92
	First difference	9.655***	−6.932***	7.732***	−3.29***
log <i>GDP</i>	Level	−16.581***	−9.254***	5.810***	−1.38
	First difference	−14.289***	−0.017	15.164***	−2.72***
log <i>IND</i>	Level	0.070	3.049	6.090***	−1.86
	First difference	−6.511***	−3.757***	−1.698	−2.91***
log <i>EI</i>	Level	0.070	2.199	6.116***	−2.05
	First difference	−2.034**	−4.905***	4.369**	−3.11***
log <i>ES</i>	Level	−2.085**	−7.949***	3.302***	−2.12
	First difference	9.819	−11.980***	−2.732	−4.55***
log <i>FDI</i>	Level	−11.959***	−4.608	4.229***	−1.83
	First difference	−6.564***	−1.315*	4.953***	−2.93***
log <i>PD</i>	Level	3.541	2.658	1.674**	−1.61
	First difference	−5.667***	−3.267***	1.385*	−2.97***

***, **, 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

Table 7 Pedroni cointegration test

	χ^2	Prob
Within-dimension cointegration test		
Panel ν – statistic	−3.927***	0.000
Panel ρ – statistic	8.467***	0.000
Panel <i>PP</i> – statistic	−9.215***	0.000
Panel <i>ADF</i> – statistic	−9.210***	0.000
Between-dimension cointegration test		
Group ρ – statistic	10.460***	0.000
Group <i>PP</i> – statistic	−12.831***	0.000
Group <i>ADF</i> – statistic	−11.386***	0.000

*** represents statistical significance at 1% level. H_0 : no cointegration relationship between the variables

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 (Burrige)	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

*** represents statistical significance at 1% level

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

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

	Model I	Model II	Model III	Model IV	Model V
	OLS-FE	SDM	DSDM	DSDM	DSDM
ρ		0.263*** (2.946)	0.234*** (2.736)	0.158* (1.767)	0.127 (1.365)
τ			0.177*** (10.821)	0.171*** (10.524)	0.171*** (10.470)
η					0.007 (0.124)
$\log LCI$	0.004 (0.546)	-0.018*** (-2.600)	-0.015** (-2.400)	-0.015** (-2.513)	-0.015** (-2.516)
$\log GDP$	1.104*** (28.014)	1.064*** (100.286)	0.877*** (44.910)	1.020*** (23.408)	1.020*** (23.371)
$(\log GDP)^2$				-0.008*** (-3.662)	-0.008*** (-3.661)
$\log IND$	-0.307*** (-2.992)	0.569*** (7.709)	0.488*** (7.215)	0.517*** (7.557)	0.517*** (7.555)
$\log EI$	1.076*** (101.145)	1.053*** (146.484)	0.883*** (52.123)	0.889*** (52.975)	0.889*** (52.404)
$\log ES$	0.029*** (7.409)	0.049*** (7.340)	0.037*** (6.218)	0.038*** (6.367)	0.038*** (6.328)
$\log FDI$	-0.002 (-0.597)	-0.016*** (-3.748)	-0.010*** (-2.597)	-0.008** (-2.112)	-0.008** (-2.115)
$\log PD$	-0.237*** (-5.316)	-0.001 (-0.161)	-0.003 (-0.740)	-0.001 (-0.291)	-0.001 (-0.278)
$W \times \log LCI$		-0.009 (-0.513)	-0.015 (-0.912)	-0.010 (-0.586)	-0.010 (-0.592)
$W \times \log GDP$		0.109 (1.063)	0.082 (0.826)	-0.142 (-0.937)	-0.148 (-0.927)
$W \times (\log GDP)^2$				0.008 (1.450)	0.008 (1.443)
$W \times \log IND$		-0.241 (-1.364)	-0.122 (-0.741)	-0.105 (-0.615)	-0.108 (-0.626)
$W \times \log EI$		0.051 (0.541)	0.011 (0.120)	-0.056 (-0.612)	-0.060 (-0.620)
$W \times \log ES$		0.023 (1.528)	0.012 (0.909)	0.009 (0.645)	0.008 (0.621)
$W \times \log FDI$		0.044*** (4.644)	0.040*** (4.652)	0.031*** (3.538)	0.031*** (3.529)
$W \times \log PD$		-0.070*** (-5.495)	-0.061*** (-5.245)	-0.051*** (-4.325)	-0.051*** (-4.292)
N	420	420	390	390	390
Wald	-	47.71***	46.91***	32.17***	33.99***
LR	-	40.05***	349.07***	343.43***	73.06***

***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively; the values in parentheses represent the t -statistics

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 0.171% 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.

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 <i>LCI</i>	-0.016*** (-2.643)	-0.009 (-0.525)	-0.024** (-2.032)	-0.019*** (-2.642)	-0.010 (-0.527)	-0.029** (-2.029)
log <i>GDP</i>	1.023*** (23.980)	-0.144 (-1.319)	0.879*** (7.491)	1.234*** (23.969)	-0.171 (-1.310)	1.064*** (7.577)
(log <i>GDP</i>) ²	-0.008*** (-3.990)	0.008 (1.470)	0.001 (0.086)	-0.010*** (-3.987)	0.010 (1.460)	0.001 (0.086)
log <i>IND</i>	0.520*** (7.709)	-0.092 (-0.557)	0.428** (2.128)	0.627*** (7.700)	-0.110 (-0.550)	0.517** (2.128)
log <i>EI</i>	0.888*** (52.239)	-0.051** (-2.021)	0.837*** (27.062)	1.072*** (52.212)	-0.058** (-2.541)	1.013*** (32.215)
log <i>ES</i>	0.038*** (6.566)	0.010 (0.787)	0.048*** (3.449)	0.046*** (6.559)	0.012 (0.798)	0.058*** (3.451)
log <i>FDI</i>	-0.008** (-2.016)	0.032*** (3.568)	0.024** (2.476)	-0.010** (-2.012)	0.038*** (3.525)	0.029** (2.447)
log <i>PD</i>	-0.052*** (-4.133)	-0.001 (-0.305)	-0.053*** (-3.814)	-0.063*** (-4.042)	-0.001 (-0.312)	-0.064*** (-3.733)
ρ						0.158* (1.767)
τ						0.159*** (10.092)
<i>N</i>						390

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

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 0.158% on average. The result reveals that the control on a single region is ineffective, which may result from high-emission enterprises would 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.

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 Eq. (7) to (10). The results are reported in Table 10. It can be concluded from Table 10 that the long-term and short-term effects are in the same direction, and the long-term effect is higher than the short-term effect, which is consistent with the reality and the theory of the dynamic spatial model.

Regarding the core explanatory variable, the Short-term direct effect (SDE) and Short-term indirect effect (SIE) of low-carbon innovation are -0.016 and -0.009, respectively. Similar results also appeared in the long term. However, only the direct effects are significant at the 1% level. It can be concluded that low-carbon innovations reduced carbon emissions only locally, while the spillover effect of LCI cannot be observed, which is consistent with Liang et al. (2019). Improving the regional low-carbon innovation can significantly inhibit local carbon emissions. 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. Based on the effect decomposition results, Hypothesis 1 is verified. Carbon emissions can be reduced by an increase in low-carbon innovation.

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 carbon emissions 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; Sun et al. 2021). However, after obtaining the inflection points for SDE and LDE (63.94 and 61.7, 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 cannot affect local carbon emissions statistically significantly in the short term or the long term. Therefore, hypothesis 2 is verified.

For the control variables in the effect decomposition results, the total effect results show that industrial structure optimization, energy intensity reduction, and energy structure optimization help to mitigate carbon emissions, while the rise in population density will reduce carbon emissions. Overall, the total carbon emissions will be relatively high for an economy with a high industrial share, high energy consumption per unit of output, and a high dependence on coal as the main energy source, which is in line with previous studies (Ma et al. 2019; Zhang et al. 2014; Zhu 2022). For more densely populated areas, which are generally relatively more developed, resource intensification in developed areas can lead to more efficient energy consumption. The results for the direct effects were generally consistent with the results for the total effects, which implies that 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. In contrast, the industrial structure, energy intensity, and energy structure do not affect carbon emissions in the adjacent regions. The spillover effect is not significant.

It should be noted that the decomposition of the effect of foreign direct investment (FDI) shows opposite results for the direct effect (negative) and the indirect effect (positive). On the one hand, FDI in China is concentrated in labor-intensive and resource-intensive industries, which drive up carbon emissions. On the other hand, the pollution halo hypothesis also points out that the new technology brought by FDI will help the host country reduce pollution. In addition, FDI also squeezes out the market share of local firms to some extent. FDI in China can reduce local carbon emissions, suggesting that the pollution halo effect and crowding out effect are higher than the effect of FDI directly contributing to carbon emissions. New technologies brought by FDI will help host countries to reduce pollution. However, there is a significant negative effect of FDI on

carbon emissions in the surrounding area. There may be two possible reasons for this (Cheng et al. 2017): first, projects crowded out by FDI are transferred to nearby areas, leading to an increase in carbon emissions in nearby areas; second, for local governments, the promotion tournament system for officials incentivizes local governments to increase local investment attraction when they find that neighboring areas receive more foreign investment. However, in the process of attracting investment, both foreign and domestic enterprises are attracted. On the one hand, domestic firms may be less energy efficient and correspond to higher carbon emissions. On the other hand, areas with foreign investment concentrated develop energy-intensive industries with high carbon emissions, which will cause a local agglomeration of similar industries, leading to an increase in carbon emissions.

Mechanism analysis: moderating effect model

Based on the preceding theoretical study, we now examine hypotheses 3 through 5, which relate to the moderating effects of environmental policy, absorptive capacity, and level of financial development between low carbon innovation and carbon emissions. The results of the effect decomposition of the DSDM model are shown in Table 11. Among them, Models VI, VII, and VIII represent the results of model estimation of the moderating effects of introducing the interaction terms of low carbon innovation with environmental policy, absorptive capacity, and financial development, respectively. Since the indirect effects of the baseline model (model IV) are not statistically significant, we focus on the direct and total effects in the mechanism analysis.

First, this study analyzes the moderating effect of environmental policy. In terms of direct effects, the coefficient of low-carbon innovation is negative and significant both in the short-term and long-term. In addition, we find that the short-term and long-term direct effects of environmental policy on carbon emissions are -0.095 and -0.109 , respectively, indicating the negative effect of environmental policy on carbon emissions when the level of carbon emissions is fixed. The interaction term ($\log LCI \times EP$) enters with negative coefficients, which suggests that implementing environmental policies will further enhance the ability of low-carbon innovations to reduce emissions locally. The results of total effects show identical results with direct effects, indicating that a significant moderating effect of environmental policy is still presented even when non-significant spillover effects are taken into account. Overall, environmental policy has a moderating effect on the mitigation effect of low-carbon innovation on carbon emissions, i.e., environmental policy can enhance the mitigation level of low-carbon innovation on carbon emissions (Lv and Bai 2021). Market-based emissions trading policies enhance the low-carbon

Table 11 The effect decomposition results of moderating effect model

	Model IV: Baseline model			Model VI: Environmental policy			Model VII: Absorptive capacity			Model VIII: Financial development		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Short-term												
$\log LCI$	-0.016*** (-2.643)	-0.009 (-0.525)	-0.024** (-2.032)	-0.019*** (-3.128)	-0.010 (-0.682)	-0.028** (-2.303)	-0.058*** (-2.477)	-0.002 (-0.338)	-0.060** (-2.461)	-0.004** (-2.306)	-0.024 (-1.404)	-0.028 (-1.231)
D				-0.016 (-1.242)	-0.079** (-2.324)	-0.095** (-2.525)	-0.029** (-2.534)	-0.110*** (-4.215)	-0.139*** (-4.717)	-0.045*** (-2.868)	-0.137*** (-3.198)	-0.182*** (-4.037)
$\log LCI \times D$				-0.021*** (-2.680)	-0.042** (-2.036)	-0.063*** (-2.800)	-0.025*** (-7.886)	0.026 (0.431)	0.001 (0.065)	-0.014*** (-4.281)	-0.008 (-0.932)	-0.022** (-2.527)
$\log GDP$	1.023*** (23.980)	-0.144 (-1.319)	0.879*** (7.491)	0.997*** (23.034)	-0.151 (-1.583)	0.846*** (8.920)	0.318*** (3.157)	0.412 (1.131)	0.730* (1.831)	0.741*** (8.577)	-0.501* (-1.835)	0.240 (0.824)
$(\log GDP)^2$	-0.008*** (-3.990)	0.008 (1.470)	0.001 (0.086)	-0.006*** (-2.934)	0.007 (1.431)	0.001 (0.205)	0.032*** (5.793)	-0.020 (-1.018)	0.012 (0.536)	0.010** (2.075)	0.032** (2.090)	0.042** (2.572)
$\log IND$	0.520*** (7.709)	-0.092 (-0.557)	0.428** (2.128)	0.521*** (7.935)	-0.163 (-1.091)	0.358** (2.001)	0.407*** (5.022)	0.273 (1.363)	0.679*** (2.729)	0.391*** (5.845)	-0.246 (-1.308)	0.145 (0.652)
$\log EI$	0.888*** (52.239)	-0.051** (-2.021)	0.837*** (27.062)	0.898*** (54.875)	-0.030 (-1.458)	0.868*** (37.601)	0.919*** (58.843)	-0.033 (-1.470)	0.887*** (33.534)	0.905*** (54.738)	-0.027 (-1.195)	0.879*** (33.859)
$\log ES$	0.038*** (6.566)	0.010 (0.787)	0.048*** (3.449)	0.029*** (5.168)	-0.008 (-0.687)	0.022* (1.802)	0.032*** (6.048)	0.009 (0.814)	0.041*** (3.175)	0.037*** (6.583)	0.011 (0.956)	0.048*** (3.725)
$\log FDI$	-0.008** (-2.016)	0.032*** (3.568)	0.024** (2.476)	-0.005 (-1.308)	0.037*** (4.844)	0.032*** (3.990)	0.000 (0.034)	0.047*** (4.921)	0.047*** (4.504)	-0.011*** (-2.759)	0.023** (2.370)	0.012 (1.109)
$\log PD$	-0.052*** (-4.133)	-0.001 (-0.305)	-0.053*** (-3.814)	0.006* (1.662)	-0.009 (-0.758)	-0.003 (-0.216)	-0.009** (-2.418)	-0.034*** (-3.162)	-0.044*** (-3.591)	0.002 (0.562)	-0.020* (-1.673)	-0.018 (-1.290)
Long-term												
$\log LCI$	-0.019*** (-2.642)	-0.010 (-0.527)	-0.029** (-2.029)	-0.022*** (-3.088)	-0.010 (-0.636)	-0.033** (-2.301)	-0.067** (-2.449)	-0.003 (-0.341)	-0.070** (-2.433)	-0.005** (-2.613)	0.033 (1.400)	0.029 (1.225)
D				-0.019 (-1.201)	-0.090** (-2.296)	-0.109** (-2.504)	-0.034** (-2.533)	-0.129*** (-4.120)	-0.162*** (-4.614)	-0.054*** (-2.837)	-0.160*** (-3.142)	-0.214*** (-3.965)
$\log LCI \times D$				-0.025*** (-2.641)	-0.047** (-2.004)	-0.072*** (-2.796)	-0.029*** (-7.867)	0.030** (2.426)	0.001 (0.067)	-0.016*** (-4.266)	-0.010 (-0.910)	-0.026** (-2.506)
$\log GDP$	1.234*** (23.969)	-0.171 (-1.310)	1.064*** (7.577)	1.183*** (23.033)	-0.211** (-1.978)	0.972*** (9.145)	0.370*** (3.151)	0.481 (1.130)	0.851* (1.824)	0.881*** (8.582)	-0.600* (-1.871)	0.281 (0.820)
$(\log GDP)^2$	-0.010*** (-3.987)	0.010 (1.460)	0.001 (0.086)	-0.007*** (-2.947)	0.009 (1.466)	0.001 (0.207)	0.037*** (5.782)	-0.024 (-1.014)	0.014 (0.533)	0.011** (2.057)	0.038** (2.065)	0.049** (2.546)
$\log IND$	0.627*** (7.700)	-0.110 (-0.550)	0.517** (2.128)	0.619*** (7.966)	-0.208 (-1.209)	0.411** (2.001)	0.473*** (5.020)	0.318 (1.357)	0.791*** (2.715)	0.465*** (5.860)	-0.295 (-1.335)	0.169 (0.648)
$\log EI$	1.072*** (52.212)	-0.058** (-2.541)	1.013*** (32.215)	1.065*** (54.298)	-0.068*** (-3.556)	0.997*** (45.788)	1.069*** (58.729)	-0.036* (-1.865)	1.033*** (39.796)	1.075*** (54.577)	-0.043** (-2.164)	1.031*** (40.500)

Table 11 (continued)

	Model IV: Baseline model			Model VI: Environmental policy			Model VII: Absorptive capacity			Model VIII: Financial development		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
log <i>ES</i>	0.046*** (6.559)	0.012 (0.798)	0.058*** (3.451)	0.035*** (5.172)	-0.010 (-0.775)	0.025* (1.803)	0.037*** (6.042)	0.011 (0.821)	0.048*** (3.178)	0.044*** (6.572)	0.012 (0.925)	0.056*** (3.733)
log <i>FDI</i>	-0.010** (-2.012)	0.038*** (3.525)	0.029** (2.447)	-0.006 (-1.368)	0.043*** (4.822)	0.037*** (3.950)	0.000 (0.036)	0.055*** (4.826)	0.055*** (4.414)	-0.013*** (-2.774)	0.028** (2.375)	0.015 (1.105)
log <i>PD</i>	-0.063*** (-4.042)	-0.001 (-0.312)	-0.064*** (-3.733)	0.007* (1.682)	-0.010 (-0.774)	-0.003 (-0.216)	-0.011** (-2.419)	-0.040*** (-3.107)	-0.051*** (-3.533)	0.003 (0.574)	-0.024* (-1.670)	-0.021 (-1.285)
ρ	0.158*			0.196**			0.191***			0.161*		
τ	0.159***			0.155***			0.140***			0.157***		
<i>N</i>	390			390			390			390		

***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively; the values in parentheses represent the *t*-statistics

innovation performance of enterprises, optimize the allocation of innovation resources, and improve innovation effectiveness. The mitigation effect of low carbon innovation on carbon emissions is stronger in regions where environmental policies are implemented. Therefore, hypothesis 3 is verified.

Second, for analyzing the moderating effect of absorptive capacity on the relationship between low-carbon innovation and carbon emissions, the interaction term of log*LCI* and log*AC* was generated. Model VII in the table is a spatial moderation effect model used to verify hypothesis 4 to portray how absorptive capacity moderates the relationship between low carbon innovation and carbon emissions. Considering the direct effects, the short-term and long-term effects of log*LCI*, log*AC*, and log*LCI* × log*AC* are negative at the 1% significance level. In conclusion, the above results suggest that absorptive capacity has a significantly enhanced moderating effect on the carbon mitigation effect of low-carbon innovations in the short and long term, which verifies hypothesis 4. In other words, regions with greater absorptive capacity benefit more from the emission reduction effect of low-carbon innovation because they are able to use the low-carbon innovation patents more effectively. The mitigation effect of low carbon innovation on carbon emissions will continue to increase as regional absorptive capacity grows (Zhao et al. 2019).

Third, Model VIII is the moderating effect model to verify hypothesis 5. The coefficients of the moderating variable log*FD* show a mitigating effect of financial development on carbon emissions, which can also spillover to adjacent regions. The results are consistent in the long and short term. In terms of direct effects, the short-term and long-term effects of log*LCI* and the interaction term (log*LCI* × log*FD*) are negative and statistically significant. Furthermore, the total effects of the interaction terms are consistent with the direct effect results. It can be concluded that low-carbon innovation has a significant mitigation effect on carbon emissions, and the magnitude of this effect depends heavily on financial development locally. This result verifies hypothesis 5 and emphasizes the critical moderating role of financial development on the carbon mitigation effect of low carbon innovation. A well-functioning financial system can provide substantial investment for innovative enterprises (Hsu et al. 2021; Lv et al. 2021), help build fail-safe mechanisms, and increase the proportion of low-carbon innovation patents applied to production and consumption.

Heterogeneity analysis

China is a vast country with uneven development and obvious heterogeneity between regions. Generally speaking, the eastern coastal regions of China with more developed

Table 12 Heterogeneity test results

	Eastern: Model IX			Central: Model X			Western: Model XI		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Short-term									
log <i>LCI</i>	-0.021** (-2.439)	-0.084*** (-3.715)	-0.105*** (-3.847)	-0.005** (-2.395)	0.001 (0.209)	-0.004** (-2.056)	0.010 (0.886)	0.074 (0.508)	0.085 (-0.445)
log <i>GDP</i>	1.113*** (10.787)	-1.111*** (-4.981)	0.002 (0.006)	1.484*** (9.512)	0.157 (0.486)	1.641*** (4.191)	1.094*** (15.702)	-0.986*** (-5.309)	0.108 (0.548)
(log <i>GDP</i>) ²	-0.004 (-0.973)	0.064*** (6.069)	0.059** (4.505)	-0.033*** (-4.086)	-0.010 (-0.555)	-0.043** (-1.986)	-0.011*** (-2.812)	0.044*** (4.790)	0.033*** (3.154)
log <i>IND</i>	-0.071 (-0.280)	-1.279*** (-3.070)	-1.351** (-2.079)	0.293*** (2.804)	0.583*** (3.334)	0.875*** (3.368)	-1.002*** (-7.923)	0.242 (0.643)	-0.760* (-1.693)
log <i>EI</i>	0.992*** (49.450)	0.037 (0.840)	1.029** (19.640)	0.951*** (89.551)	0.060*** (4.218)	1.011*** (62.480)	0.977*** (48.566)	0.122*** (4.339)	1.100*** (28.375)
log <i>ES</i>	0.039*** (6.403)	0.014 (1.276)	0.053*** (3.886)	0.006 (0.939)	-0.014 (-1.004)	-0.008 (-0.454)	0.013* (1.870)	0.015 (0.913)	0.028 (1.340)
log <i>FDI</i>	-0.041*** (-5.740)	0.027 (1.581)	-0.013 (-0.637)	0.009 (1.599)	0.023*** (2.812)	0.032*** (2.795)	0.003 (0.805)	0.002 (0.212)	0.005 (0.462)
log <i>PD</i>	-0.043*** (-2.800)	-0.103*** (-3.856)	-0.145*** (-3.688)	0.029*** (4.159)	0.026 (1.637)	0.055** (2.535)	0.069*** (13.955)	0.186*** (9.108)	0.255*** (10.684)
Long-term									
log <i>LCI</i>	-0.023** (-2.434)	-0.091*** (-3.695)	-0.114*** (-3.826)	-0.007** (-2.393)	0.001 (0.214)	-0.053** (-2.052)	0.011 (0.883)	0.074 (0.504)	0.085 (0.445)
log <i>GDP</i>	1.213*** (10.728)	-1.212*** (-4.981)	0.002 (0.005)	1.543*** (9.513)	0.161 (0.478)	1.704*** (4.186)	1.219*** (15.595)	-1.098*** (-5.288)	0.120 (0.548)
(log <i>GDP</i>) ²	-0.005 (-0.964)	0.069*** (6.030)	0.065*** (4.467)	-0.034*** (-4.087)	-0.010 (-0.552)	-0.044** (-1.984)	-0.013*** (-2.789)	0.049*** (4.786)	0.037*** (3.147)
log <i>IND</i>	-0.078 (-0.281)	-1.397*** (-3.042)	-1.476** (-2.067)	0.304*** (2.794)	0.605*** (3.299)	0.909*** (3.341)	-1.117*** (-7.917)	0.266 (0.634)	-0.851* (-1.692)
log <i>EI</i>	1.082*** (49.418)	0.041 (0.892)	1.123*** (20.413)	0.988*** (89.543)	0.061*** (4.059)	1.050*** (60.253)	1.090*** (48.473)	0.140*** (3.980)	1.230*** (26.338)
log <i>ES</i>	0.043*** (6.404)	0.015 (1.274)	0.058*** (3.885)	0.006 (0.940)	-0.015 (-1.004)	-0.009 (-0.454)	0.015* (1.870)	0.017 (0.915)	0.031 (1.340)
log <i>FDI</i>	-0.044*** (-5.727)	0.030 (1.586)	-0.014 (-0.634)	0.010 (1.595)	0.024*** (2.793)	0.034*** (2.779)	0.003 (0.806)	0.002 (0.213)	0.005 (0.462)
log <i>PD</i>	-0.047*** (-2.796)	-0.112*** (-3.785)	-0.159*** (-3.644)	0.030*** (4.152)	0.027 (1.627)	0.057** (2.524)	0.078*** (13.842)	0.208*** (9.081)	0.286*** (10.628)
ρ	0.049***			0.046***			0.041*		
τ	0.083***			0.038***			0.103***		
<i>N</i>	156			117			117		

***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively; the values in parentheses represent the *t*-statistics

economies and more intensive innovation activities. Therefore, it is necessary to conduct heterogeneity analysis and study the internal relationship between different regions. This study divides China's 30 provinces into three regions, namely, eastern, central, and western, and carries out estimation using DSDM separately. The results of the effect decomposition are shown in Table 12, where models IX, X, and XI denote the estimation results for the eastern, central, and western regions, respectively.

As can be seen in Table 12, low-carbon innovation in the eastern region has a significant negative effect on carbon emissions. The negative effects include both direct and indirect effects. That is, low carbon innovation is able to spillover between eastern provinces while reducing local carbon emissions. Moreover, the above effects hold in both the long and short term. The reason may be that the eastern region has an overall more developed economy and better innovation infrastructure. And the strong R&D capability

and absorptive capacity of eastern regions make the innovation output higher and able to absorb the innovation output in the eastern regions. Thus, the transformation of low-carbon innovation into economic activities reduces carbon emissions.

For the central region, there is a direct effect of low carbon innovation on carbon emissions, but the coefficient of the direct effect is significantly lower than that of the eastern region. In addition, the indirect effect is not significant. The possible reason is that the independent R&D capability of the central region is weaker than that of the eastern region, and the quality of low-carbon innovation output is insufficient, so the emission reduction effect of low-carbon innovation is weaker compared to the eastern region. However, the current situation of insufficient low-carbon innovation output in the central region makes the spatial spillover effect of low-carbon innovation not strong enough to observe a statistically significant spillover effect.

For the western region, no significant impact of low-carbon innovation on carbon emissions could be observed. One possible reason is that the overall economic strength of the western region is weak, and local governments focus their main efforts on economic development, with insufficient incentives for low-carbon innovation in enterprises. In addition, the west may have taken over some of the high energy consumption and low energy efficiency enterprises from the eastern and central regions, resulting in a less significant mitigation effect of low carbon innovation on carbon emissions in these regions. On the other hand, the topography of the western region is mostly mountainous, and the exchange between provinces is not frequent enough, so the spillover effect is not significant.

Robustness test

In order to verify the validity of the dynamic spatial Durbin model, this paper tests the robustness from two aspects. First, the spatial weight matrix is replaced with an adjacency spatial weight matrix. Second, the core explained variable low-carbon innovation is replaced by the count of the low-carbon patents granted, denoted by *LCI2*. The effect decomposition results of the robustness test are presented in Table 13. Comparing the results of models XII and XIII with those of model IV, it can be observed that the sign and significance of the estimated coefficients remain broadly consistent. Therefore, the robustness of the model has been verified.

Discussion

Based on the dynamic spatial Durbin model, this study investigates the spatial effects of low-carbon innovation and economic development on carbon emissions.

Consistent with the general findings, low-carbon innovation is effective in reducing local carbon emissions. However, the indirect effects are statistically insignificant in both the short and long term. In other words, the carbon emissions mitigating effects of low-carbon innovation do not spillover to the adjacent areas, which is in line with the results of Liang et al. (2019). Generally, innovation not only helps to relieve local environmental pressure but also relieves pressure in surrounding areas through spillover effects. However, This finding of this study is inconsistent with our expected results. Why does the result appear? We try to explain this phenomenon from the perspective of regional heterogeneity.

In the heterogeneity analysis, it can be found that the within-group spillover effect of low-carbon innovation on carbon emissions is significant only in the eastern region but not in the central and western areas. The indirect effect of the spatial Durbin model measures the spillover effect within the group, and there is a spillover effect between each other in the eastern region, while the spillover effect is insignificant in the western region. Innovation externalities make knowledge spillovers possible, and there may be a threshold for this spillover effect, i.e., the ability to receive and learn from advanced technologies from other regions only when the local level of innovation reaches a certain threshold, leading to a macro-level spillover effect.

In fact, the differences between regions in China are very large. In particular, the eastern region has a well-developed innovation infrastructure, abundant human capital, and a large amount of low-carbon innovation output. In contrast, the western region has insufficient research and development inputs, a shortage of high-quality talents, and relatively low innovation output in China. To support the point, we plot a bar chart of the amount of low-carbon innovation within the three regions (the eastern, the center, and the western) from 2007 to 2020, as shown in Fig. 3. According to Fig. 3, we can find that the innovation level in the central and western regions is much lower than that in the eastern region. Moreover, the current level of economic development in the western region is still relatively low. The lower level of economic development and innovation could result in insufficient intra-regional communication in innovation (Dauda et al. 2021). Currently, the level of low-carbon innovation in the central and western regions may not reaches the threshold of knowledge spillovers. Therefore, the indirect effects are statistically insignificant in both the short and long term when all subsamples are combined. However, it should be noted that the results of the sub-sample estimation in the heterogeneity analysis also have some limitations. In our model, it is impossible to examine the between-group spillover effects of low-carbon innovation, i.e., between the eastern, the center, and the western.

Table 13 The results of the robustness test

	Replace weight matrix: model XII			Replace explanatory variable: model XIII		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Short-term						
log <i>LCI</i>	−0.013*** (−2.588)	0.014 (0.953)	0.002 (0.109)			
log <i>LCI</i> ²				−0.022*** (−3.816)	0.020 (1.181)	−0.002 (−0.099)
log <i>GDP</i>	1.016*** (24.092)	−0.150 (−1.369)	0.866*** (7.250)	1.035*** (24.518)	−0.156 (−1.358)	0.878*** (7.050)
(log <i>GDP</i>) ²	−0.008*** (−3.919)	0.007 (1.114)	−0.001 (−0.188)	−0.008*** (−4.140)	0.006 (0.981)	−0.002 (−0.351)
log <i>IND</i>	0.548*** (8.062)	0.074 (0.421)	0.622*** (2.948)	0.533*** (7.892)	0.088 (0.478)	0.621*** (2.809)
log <i>EI</i>	0.890*** (52.144)	−0.060** (−2.315)	0.830*** (25.943)	0.890*** (52.659)	−0.068** (−2.442)	0.822*** (24.499)
log <i>ES</i>	0.037*** (6.445)	0.013 (0.968)	0.050*** (3.474)	0.038*** (6.521)	0.012 (0.928)	0.050*** (3.412)
log <i>FDI</i>	−0.007* (−1.723)	0.034*** (3.625)	0.027*** (2.642)	−0.008** (−2.013)	0.035*** (3.778)	0.027*** (2.700)
log <i>PD</i>	−0.003 (−0.803)	−0.054*** (−4.311)	−0.056*** (−4.063)	0.001 (0.190)	−0.055*** (−4.351)	−0.054*** (−3.844)
Long-term						
log <i>LCI</i>	−0.015*** (−2.582)	0.017 (0.947)	0.002 (0.113)			
log <i>LCI</i> ²				−0.026*** (−3.813)	0.024 (1.166)	−0.002 (−0.092)
log <i>GDP</i>	1.225*** (24.071)	−0.171 (−1.300)	1.054*** (7.320)	1.245*** (24.489)	−0.173 (−1.261)	1.072*** (7.152)
(log <i>GDP</i>) ²	−0.009*** (−3.913)	0.008 (1.096)	−0.001 (−0.187)	−0.010*** (−4.131)	0.007 (0.957)	−0.003 (−0.349)
log <i>IND</i>	0.661*** (8.046)	0.096 (0.449)	0.757*** (2.938)	0.642*** (7.870)	0.117 (0.514)	0.759*** (2.790)
log <i>EI</i>	1.073*** (52.108)	−0.063*** (−2.677)	1.010*** (31.044)	1.071*** (52.619)	−0.068*** (−2.783)	1.004*** (30.113)
log <i>ES</i>	0.045*** (6.441)	0.016 (0.994)	0.061*** (3.470)	0.045*** (6.517)	0.016 (0.965)	0.061*** (3.405)
log <i>FDI</i>	−0.008* (−1.712)	0.041*** (3.567)	0.033*** (2.606)	−0.009** (−1.995)	0.043*** (3.704)	0.033*** (2.657)
log <i>PD</i>	−0.003 (−0.824)	−0.065*** (−4.209)	−0.069*** (−3.975)	0.001 (0.159)	−0.067*** (−4.237)	−0.066*** (−3.757)
ρ	0.138**			0.155***		
τ	0.170***			0.169***		
<i>N</i>	390			390		

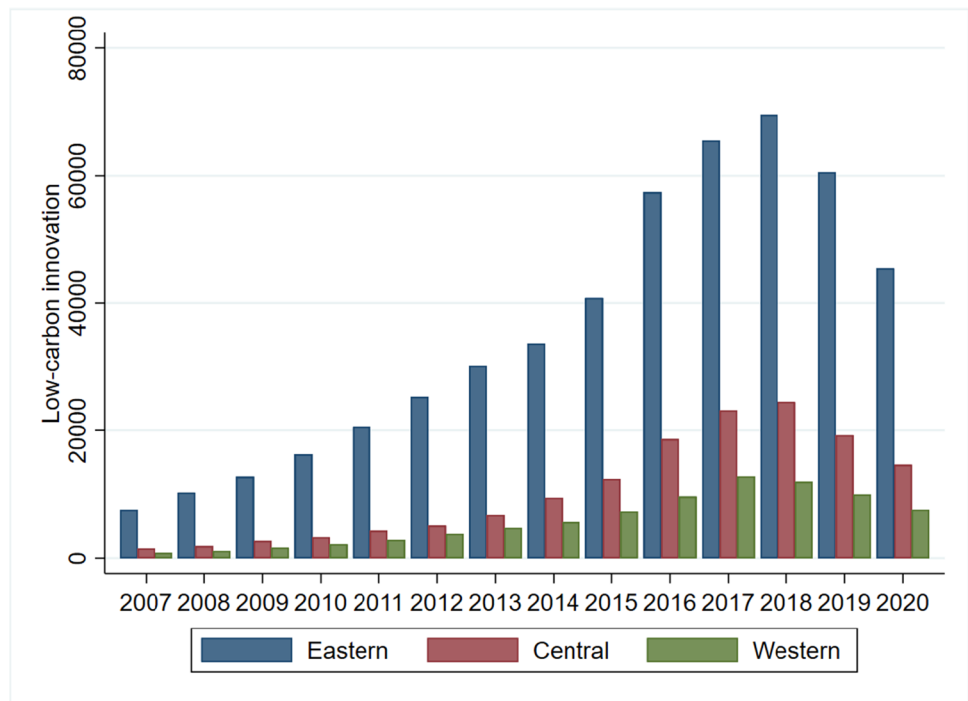
***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively; the *t*-statistics are given in parentheses

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 2020, considering energy structure, industrial structure, foreign direct investment, energy intensity, and population density in the Chinese

Fig. 3 Low-carbon innovation in eastern, central, and western China



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. A spatial analysis was then performed to select an appropriate spatial econometric model. Subsequently, we applied the dynamic spatial Durbin model and estimated the long-term and short-term effects. In addition, we analyzed the moderating effects of environmental policy, absorptive capacity, and financial development in the role of low-carbon innovation on carbon emission mitigation. Furthermore, we divided the sample into eastern, central, and western to conduct heterogeneity analysis. 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 Moran index results verify the provincial agglomeration of carbon emissions. The high-emitting 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 employing DSDM. After the effect decomposition, however, the mitigation effect of low-carbon innovation exists only locally; the spillover effect cannot 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 find that there are moderating effects of environmental policy, absorptive capacity, and financial development, which indicates that they can enhance the emission reduction effect of low-carbon innovations. Finally, The results of heterogeneity analysis show that the direct effect of low carbon innovation on carbon emissions exists in the eastern and central regions; the indirect effect exists only in the eastern region.

Several policy implications are made in response to the previous findings. First, encourage low-carbon innovation inputs. Low-carbon innovation is the key to achieving carbon emission reduction. Low-carbon innovation has already achieved direct emission reduction effects in the central and eastern regions, and the output and transformation of innovation results need to be further encouraged. This requires local governments to mobilize market incentives to motivate enterprises to increase R&D investment 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, to increase high R&D investment enterprises by targeting to alleviate the financing constraints of high R&D investment enterprises and moderately restricting the financing channels of high pollution, high energy consumption, and high water

consumption enterprises to prevent these enterprises from over-expansion of green R&D investment.

Second, enhance the spatial spillover effect of low-carbon innovation. Previous studies have shown 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. Further research found the weak spillover effect of innovation in central and western China. Therefore, local governments need to work together and strengthen cooperation among themselves to build an interregional technology exchange system, especially for east-central and east–west technology exchange systems. Sharing low-carbon technologies through platforms can help enhance the spillover effect of provincial knowledge. It is conducive to the emergence of new knowledge, improving long-term environmental efficiency, and promoting carbon emission reduction.

Third, promote the implementation and enforcement of environmental policies related to carbon emissions, such as carbon emissions trading policies. This study confirms the moderating role of environmental policies between low-carbon innovation and carbon emissions. Therefore, policymakers should further extend the experience of pilot regions to the national carbon emissions trading market to form a synergy between regions to promote the development of a low-carbon economy jointly. Currently, the Chinese government has launched a national carbon emissions trading market, but only the power sector is included in the trading scope. Policymakers need to explore the inclusion of sectors other than electricity in the carbon market regulation in the pilot regions to make the carbon market system more comprehensive.

Fourth, focus on developing absorptive capacity in the central and western regions. Repeatedly building innovation infrastructure and repeatedly investing too much capital may be inefficient from an overall perspective. Especially for the central and western regions, which currently have low average incomes and limited resources for local governments, it is effective and helpful to divert some resources to develop local innovation absorptive capacity while vigorously developing the economy. Absorptive capacity contributes to the absorption and transformation of innovations, and increased absorptive capacity in central and western regions can help these regions absorb innovations from regions with high levels of innovation in the eastern regions (Hao et al. 2021), thus efficiently achieving carbon reduction targets.

Fifth, promote financial development, especially for green credit. This study confirms the moderating role of financial development in the carbon emission reduction path of low-carbon innovation. China's current financial market is still dominated by the credit market, and to enhance the emission reduction effect of low-carbon innovation, we can consider

vigorously promoting green credit, increasing the amount of green credit to the total loans in the banking sector, and encouraging enterprises to carry out low-carbon innovation.

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.

Abbreviations *EKC hypothesis*: Environmental Kuznets curve hypothesis; *STIRPAT*: Stochastic Impacts by Regression on Population, Affluence, and Technology; *SDM*: Spatial Durbin model; *DSDM*: Dynamic spatial Durbin model; *SDE*: Short-term direct effects; *SIE*: Short-term indirect effects; *LDE*: Long-term direct effects; *LIE*: Long-term indirect effects; *VAR*: Vector autoregression; *GMM*: Generalized moment method; *PQR*: Panel quantile regression; *CCEMG*: Common Correlated Effect Mean Group; *SEM*: Spatial error model; *AMG*: Augmented Mean Group; *PMG*: Pooled Mean Group; *GS2SLS*: Generalized spatial two-stage least squares; *RDD*: Regression discontinuity design; *IPCC*: Intergovernmental Panel on Climate Change; *R&D*: Research and development

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Declarations

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