GREEN INNOVATION AND PROVINCIAL CARBON EMISSIONS IN CHINA FROM 2007 TO 2020: SPATIAL DURBIN EVIDENCE WITH CLIMATE-ECOLOGY AND POLICY IMPLICATIONS

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Abstract. Addressing the climate–ecology nexus requires evidence on how innovation translates into territorial decarbonization. Using a Spatial Durbin Model (SDM), this study examines the effects of green innovation on provincial carbon emissions in China from 2007 to 2020, distinguishing the roles of green R&D scale and innovation efficiency. Both indicators show upward trajectories with fluctuations and exert significant negative direct effects on local emissions. The spatial spillover of green R&D scale is statistically insignificant, whereas innovation efficiency exhibits a significant negative spillover, implying that efficiency-oriented innovation diffuses across borders to deliver broader mitigation benefits. Clustering provinces into three groups by the two innovation indicators uncovers regional heterogeneity: the spatial effect of R&D scale and the direct effect of innovation efficiency differ by cluster, while the efficiency spillover remains robustly negative. These results underscore that expanding R&D inputs and, critically, improving innovation efficiency can jointly accelerate low-carbon transitions. For applied ecology and environmental management, we recommend strengthening interregional collaboration and constructive competition to enhance technological diffusion; embedding place-based, adaptive innovation strategies in line with local ecological and economic contexts; and aligning green innovation policy with ecosystem services and ecological security goals to yield co-benefits under climate change.
Keywords: *spatial Durbin model, spatial econometrics, green innovation scale, innovation efficiency, carbon emissions, climate change mitigation, ecological economics, regional heterogeneity, technology diffusion, ecosystem services*

Introduction

In accordance with the IPCC report, recent increase in greenhouse gas emissions has significantly impacted the Earth's climate and economic systems, making climate change an urgent issue that should be addressed (IPCC, 2022). The GEO-6 (Global Environmental Outlook) asserts that there is substantial evidence indicating that climate change and intensifying climate variability have aggravating effects on existing poverty conditions, exacerbating societal inequality and causing new vulnerabilities. Furthermore, it elucidates that the swift progression of economic development and urbanization, coupled with the prevalent inadequacies in

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environmental governance in many regions, implies that, absent additional interventions, climate change and air pollution may potentially deteriorate further before experiencing amelioration (UN, 2019). As one of the most populous countries with rapid economic development, China bears a substantial responsibility and challenge in managing climate change and diminishing carbon footprints. In response to this issue, China has suggested the "Dual Carbon" goals, aiming to reach peak by 2030 and attain neutrality by 2060. Under the guidance of "Dual Carbon" targets, Chinese provincial-level administrative entities are actively promoting green innovation and playing a pivotal role in carbon emission diminution.

A substantial body of research indicates that the factors affecting regional carbon emissions are intricately complex. These factors primarily encompass energy consumption, green innovation, industrial structure, population growth and urbanization, technological levels, policies and regulations, as well as climate change, among other aspects (Wei et al., 2023; Qin and Gong, 2022; Xiao and Peng, 2023; Du et al., 2021). In addition to energy consumption, which has long been recognized as a primary factor influencing regional carbon emissions, there has been an increasing focus on studies pertaining to the nexus between carbon emissions and green innovation in recent years. Green innovation denotes the application of environmentally friendly technologies and products in order to reach sustainable advancement and ecological civilization (El-Kassar and Singh, 2019; Takalo and Tooranloo, 2021). These green innovative technologies and products contribute to the reduction of reliance on traditional energy sources, thus mitigating carbon emissions. The emergence of green innovation is rooted in the growing environmental awareness among individuals. Originating from Rachel Carson's profound reflections on environmental degradation caused by traditional industries in her 1962 work "Silent Spring," global attention to environmental conservation has steadily increased. The WCED emphasized the exploitation and efficient employment of new resources, as well as the lessening of pollution emissions in 1980s, as outlined in "Our Common Future." Currently, China is actively stimulating the steady progression of green innovation. In 2015, the CPC proposed "green development" firstly during the Fifth Plenary Session of the 18th Central Committee, incorporating it as a core tenet within the "Five Major Development Concepts". In 2017, the 19th National Congress of the Communist Party of China further stressed on the necessity to establish a green technology innovation system oriented by market, marking the first inclusion of the concept of green technology in official documents (Gao et al., 2022). In 2019, the "Guiding Opinions on Constructing a Market-oriented Innovation System for Green Technologies," is drafted, comprehensively unified the definition of green technology (Mansour, 2023). However, a series of challenges exist, such as considerations related to economic interests and technological feasibility (Desheng et al., 2021). These factors may impede the maximum potential of green innovation for economy, social and environment. Furthermore, the political, social, and economic backgrounds in different regions will also influence the adoption and implementation of green innovation (Söderholm, 2021).

Amounts of researches indicate that green innovation is an effective approach to mitigate carbon emissions and contribute to the low-carbon transition, which are through the following mechanisms. Firstly, it enhances productivity levels and ameliorate energy efficiency. From the perspective of production, utilizing advanced intelligent technology and automation systems to monitor and regulate energy use in

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real time can avoid unnecessary energy waste. By upgrading the energy efficiency of traditional industrial equipment and improving production processes, companies can also reduce energy consumption per unit of output and lower carbon emissions. From the perspective of consumption, as a representative type of green innovation, the application of new energy-saving appliances can significantly reduce energy consumption. This has also been discussed in the existing literature. For example, Habiba et al. (2022) identified that green innovation improves energy utilization efficiency throughout the development of advanced and energy conservation technologies and equipment.

Secondly, green innovation promotes the advancement and employment of clean energy, thereby getting less dependence on fossil fuels (Fang et al., 2023b))and improving the energy consumption structure. Meng et al. (2022) demonstrated that green innovation leads to increased consumption of renewable energy and a subsequent decrease in consumption-based carbon emissions. Similarly, Xie and Jamaani (2022). argued that green innovation facilitates the adoption of clean energy, consequently reducing carbon emissions. In fact, with advances in green energy technologies such as photovoltaics and wind power, the cost of producing clean energy is gradually decreasing, making it the mainstream energy choice. At the same time, with the development of energy storage technology, the storage and deployment capacity of intermittent energy sources such as wind and solar energy has been enhanced, enabling a stable supply of these energy sources independent of natural conditions. Currently, as one of the applications of clean energy, the development and popularization of clean transportation such as electric vehicles (EVs) in China not only reduces dependence on fossil fuels, but also lowers carbon emissions.

Thirdly, green innovation contributes to improving the structure of economy, boosting the boom of low-carbon industries, and advancing the principles of a circular economy (Aldieri et al., 2021). Xu et al. (2021) revealed that green innovation fairly cuts the performance of carbon emission through industrial reestablishing. By fostering the implementation of green innovation, it can be conducive to reach the objectives of reducing regional carbon emissions while simultaneously advancing sustainable development and ecological civilization progress (Li et al., 2023a; Shahzad et al.,2022; Fang, 2023). Green innovation emphasizes an economic development model centered on resource conservation, efficient energy use and low pollution emissions. By introducing green manufacturing technologies, companies can optimize production processes and reduce carbon emissions. The rise of green financial instruments, such as green bonds and green funds, can attract capital flows to clean energy, energy conservation and environmental protection, low-carbon technologies and other areas, contributing to the rise of low-carbon industries.

According to the dual carbon goals, China urgently needs to employ green innovation to cut down carbon emissions and sustain its path towards sustainable development. However, it is imperative to give primary consideration to the following critical questions: Can green innovation at the provincial degree in China be quantified, and does it exhibit multiple dimensions for quantification? Does green innovation have effect on carbon emissions, and if so, to what extent? Does this impact demonstrate spatial spillover effects among province, and if present, what are the specific characteristics of these effects?

To answer these questions, this study will employ data at the Chinese provincial scale, ranging the period between 2007 and 2020. A two-dimensional framework will

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be established to analyze green innovation, specifically decomposing it into two dimensions: green R&D scale and green innovation efficiency. The research process encompasses the following components. Firstly, the scale will be assessed using the entropy weight method, while the super-efficiency SBM-Malmquist index will be employed on quantifying the efficiency. Secondly, by utilizing data on energy consumption at the level of provinces in China, the study will calculate the carbon emissions of each province and analyze spatial correlation. Subsequently, the study will investigate the direct and spillover effects of green R&D scale and green innovation efficiency on Chinese provincial carbon emissions through the establishment of a spatial econometric model. Lastly, robustness checks and heterogeneity analysis will be conducted to guarantee the robustness of the findings.

There are still some limitations in the relevant researches. For instance, the spatial influence of green innovation on CO_2 exhibits disparities with respect to both scale and efficiency (Chen et al., 2025), and these impacts demonstrate significant variations among different regions (Li and Wang, 2023; Zhao et al., 2023). In light of these issues, the latent innovation points of this paper are shown below: (1) Quantitatively calculating the scale and efficiency of green innovation in Chinese provinces; (2) Evaluating the spatial effects of them on CO_2 among Chinese provinces, considering both the dimensions of scale and efficiency, encompassing direct effects as well as spillover effects; (3) Categorically explaining the heterogeneity in the spatial influences of them on CO_2 in Chinese provinces. The results may offer corresponding policy implications aiming to promote low-carbon transformation and sustainable development by achieving a balance between the scale and the efficiency of green innovation. Additionally, these findings are expected to serve as references and inspirations for developing countries seeking adaptive development through emission reduction via green innovation.

The remainder of this paper is organized as follows. “Literature review and research hypotheses” presents the theoretical and empirical foundations and develops the hypotheses. “Materials and methods” describes the model specifications, variables, and data sources. “Results and discussion” reports and interprets the empirical findings. Finally, “Conclusion, suggestion and limitation” summarizes the main conclusions and policy implications.

Literature review and research hypotheses

Spatial effects of green innovation on China’s regional carbon emissions

Due to the externalities of knowledge and technology (Ahmad et al., 2024; Yan et al., 2024), as economic and social connections between regions become increasingly extensive and close, knowledge and technologies related to green innovation are transferred among different regions, which can alter the production efficiency of spatially related regions (Aldieri et al., 2021). An increasing amount of researches have discussed the spatial spillover influences of green innovation on regional CO_2.

Most scholars support the negative spatial spillover effect, primarily because the diffusion of green knowledge and clean technologies enables firms to adopt environmentally friendly technologies at lower marginal costs. For examples, He et al. (2022) discovered that green innovation effectively foster carbon reduction within the Yangtze River Economic Belt, thus facilitating its stride toward a green and low-carbon development trajectory. Sun (2022) found a spillover impact of green

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innovation on reducing carbon intensity of neighboring cities. Shah et al. (2022) revealed a strong negative correlativity between carbon emissions and green innovation. However, some scholars argue that these spillover effects are positive and significant. Such effects typically arise when technology diffusion induces rebound effects, expands energy-intensive product demand or stimulates resource reallocation that increases emissions. For examples, Liang et al. (2022) found that green innovation promotes the growth of CO_2 related to logistics in neighboring regions through spatial spillover effect, resulting in a rebound effect. Xu et al. (2021) established a positive influence of green innovation on the carbon performance of China. There are also scholars who suggest that these spatial spillover effects are non-monotonic and even insignificant, reflecting the complex interactions between technology diffusion and regional absorptive capacity. For instance, Chen et al. (2023) identified the dual effect of green innovation on CO_2 and carbon performance of China, which is characterized by a U-shaped curve. Fang et al. (2022) found that the spatial spillover impact of green innovation measured by the quantity of green patents is not significant.

Moreover, these spatial spillover effects exhibit spatial heterogeneity. Such heterogeneity may stem from variations in regional technological foundations, industrial structures, and carbon emission baselines. For instance, some researches have indicated that the low-carbon effects of green innovation are not significant in low-carbon regions where the marginal emission-reduction potential is limited but remarkable in high-carbon regions with greater space for efficiency improvement (Sun et al., 2022), and in some cases, green innovation may even have a positive impact on CO_2 (Razzaq et al., 2021).

While existing studies confirm that heterogeneity exists, they rarely distinguish which dimension of green innovation drives such heterogeneity. As discussed below, green R&D scale reflects the quantity of innovation inputs and outputs, whereas green innovation efficiency reflects the quality and effectiveness of innovation activities; these two dimensions may diffuse across regions through substantially different mechanisms. These differences suggest that regional heterogeneity in spillover effects may arise not only from regional characteristics but also from the structural composition of green innovation itself.

Given the mixed empirical findings and the potentially distinct spatial mechanisms of green innovation scale and efficiency, the spatial spillover effects of green innovation and their heterogeneity remain empirical questions. Therefore, this study proposes the first hypothesis:

H1: Green innovation generates spatial spillover effects on China's regional carbon emissions and the magnitude and direction of these effects exhibit regional heterogeneity arising from differences in the dimensions of green innovation.

Key issues of the relevant research

To study green innovation's influence on regional carbon emissions, it is essential to think over how to quantify the research object, i.e. how to calculate green innovation. Currently, the measurement of green innovation mainly distinguishes between green R&D scale and green innovation efficiency. With respect to green R&D scale, most studies select output-based indicators (such as green patents) for quantification (Abbas et al., 2024). For lacking data support, the quantification of green R&D scale based on the input indicators are relatively limited, other

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indicators such as R&D expenditure (Ma et al., 2021) and R&D expenditure as GDP percentage (Afrifa et al., 2020) are adopted instead. In terms of the efficiency of green innovation, most researches concentrate on the measurement methods of green innovation indicators, including DEA model, DEA-Malmquist index model and super-efficiency SBM model (Shang et al., 2024), among others. Overall, due to significant differences in indicator selection and measurement methods, the current quantitative results for green innovation in China are not consistent. Comprehensive study and evaluation from multiple perspectives are needed to better quantify green innovation indicators.

When it comes to model the influence of green innovation, spatial econometric models have been widely used (Sun, 2022; Fang et al., 2022; Chang et al., 2023). They aim to tackle the challenges of heterogeneous carbon distribution, spatial dependence, and spatial heterogeneity, thereby showcasing significant merits (Corrado and Fingleton, 2012). By incorporating geospatial factors, spatial econometric models provide a precise and comprehensive analytical framework, including capturing spatial proximity relationships, spatial interactions, and spatial autocorrelation. They can reveal the spatial spillover effects and transmission mechanisms related to carbon emissions, show higher prediction capabilities and policy guidance potential, and provide scientific basis for decision-makers to assess the impact of various policy interventions. This burgeoning growth of such modeling endeavors has fostered extensive investigations into the connection between carbon emissions and green innovation among Chinese provinces.

Notwithstanding the substantial body of research investigating the spatial implications of green innovation on CO_2, most of these studies have primarily concentrated on a singular dimension of green innovation, such as the scale or the efficiency, as a foundation for analyzing its spatial effects, thus limiting the comparability of research findings. Notably, certain studies have revealed a negative spatial spillover impact of green R&D scale on CO_2 (Suki et al., 2022; Jiang et al., 2022; Razzaq et al., 2021), whereas others have identified a negative spatial spillover effect of green innovation efficiency. Additionally, there is evidence indicating that green innovation exhibits both positive and negative spatial spillover impacts (Sun et al., 2022). Overall, it can be determined that green innovation has a profound influence on CO_2 and manifests regional spatial spillover effects. However, due to the disparities in the dimensions of green innovation considered, the implications of spatial spillover for regional carbon emissions remain highly uncertain. Therefore, to comprehensively examine the differential influence of green R&D scale and green innovation efficiency on Chinese provincial CO_2, while accounting for regional heterogeneity, this study brings forward a second hypothesis:

H2: The spatial effects of green R&D scale or green innovation efficiency on regional carbon emissions are inconsistent.

Materials and methods

Green R&D scale measurement using entropy weight method for CO2 emission

Measuring the scale of green R&D involves a comprehensive evaluation of multiple indicators, and the key to the measurement lies in how to select indicators and set weights. In terms of indicator selection, to capture the factors influencing the scale of green R&D, the study adopts an approach that considers both input and

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output indicators. Specifically, it includes capital and human investment as input indicators, while green R&D outcome and market turnover are selected as output indicators. In terms of weight determination, the entropy weight method is a multi-criteria decision analysis approach, characterized by objectivity, accuracy, and effectiveness. It can objectively quantify the differences and importance of various indicators, thus avoiding subjective bias. In this case, the study uses the entropy weight method of non-subjective weighting to determine how heavy the indicators are, quantifying their importance on the basis of their discreteness degree. Specifically, the measurement of the scale of green R&D, with the foundation of the entropy method, is shown in *Equations 1–6*:

$$a_{ij}^{*} = \frac{a_{ij} - \max_i a_{ij}}{\max_i a_{ij} - \min_i a_{ij}} \quad \text{(Eq.1)}$$

$$p_{ij} = \frac{a_{ij}^{*}}{\sum_{i=1}^{m} a_{ij}^{*}} \quad \text{(Eq.2)}$$

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} \ln p_{ij} \quad \text{(Eq.3)}$$

$$g_j = 1 - e_j \quad \text{(Eq.4)}$$

$$Q_j = \frac{g_j}{\sum_{j=1}^{n} g_j} \quad \text{(Eq.5)}$$

Here, a represents the initial value of an indicator; a^* represents the normalized index of an indicator; subscripts i and j respectively represent the province and indicator number; m and n respectively represent the total quantity of provinces and indicators;p, e and g are parameters in the entropy weight approach, respectively representing the weight of an indicator, the entropy value of an indicator, and the coefficient of variation. Therefore, the scale of green R&D in province i (S_i) can be formulated as follows:

$$S_i = \sum_{j=1}^{n} Q_j \times a_{ij} \quad \text{(Eq.6)}$$

Green innovation efficiency quantification using super efficiency SBM-Malmquist for CO_2 emission

There are two normally used approaches to quantifying the efficiency of green innovation: Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). By contrast, DEA is more suitable for the quantification of this study because it will not be affected by the scale of data and is able to manage multiple output

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indicators simultaneously. In general, DEA model belongs to the radial and angular model, but because most actual situations do not conform to such model settings andthat it is impossible to measure slack variables and distinguish input-output directions, its application is subject to certain limitations. Comparatively, the super efficiency SBM model overcomes the single direction defect, not only can calculate efficiency values greater than 1 but also solves the problem of inability to compare and rank research objects. At the same time, this model places slack variables in the objective function to address measurement errors caused by radial and angular settings. In addition, the super efficiency SBM-Malmquist index can depict changes in total factor productivity at different time periods and decomposeit into efficiency and technical changes. Based on this, this study utilizes the super efficiency SBM-Malmquist index, with capital and labor as input indicators, and outcome and market turnover as output indicators, to measure green innovation efficiency.

Assuming there are m decision-making units, which represent China's provinces, refers to DMU, each DMU has l inputs denoted as I_d and q outputs denoted as O_r. The DMU that needs to be quantified currently is denoted as DMU_k. Under the constant returns scale (CRS) assumption, the expressions of super efficiency SBM model are provided there:

$$min\rho = \frac{1+\frac{1}{l}\sum_{d=1}^{l} s_i^- / I_{dk}}{1-\frac{1}{q}\sum_{r=1}^{q} s_r^+ / O_{rk}}$$
$$s.t.\begin{cases} \sum_{i=1,i\neq k}^{m} \lambda_i I_{di} - s^- \leq I_{dk} \\ \sum_{i=1,i\neq k}^{m} \lambda_i O_{ri} + s^+ \geq O_{rk} \\ \sum_{i=1,i\neq k}^{m} \lambda_i = 1 \\ \lambda, s^-, s^+ \geq 0 \end{cases} \tag{Eq.7}$$

Here λ represents the indicator weights, and s^- and s^+ represent the slack variables for inputs and outputs respectively.

Solving *Equation 7* yields DMU^t (x^t,y^t), which represents the distance between decision-making units and the production frontier in period t. At time t, the input vector is represented by x^t while the output vector is represented by y^t. Based on this, the following equation is the expression of global reference Malmquist index M between time t and t + 1 (*Eq. 8*):

$$M(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{DMU^g(x^{t+1}, y^{t+1})}{DMU^g(x^t, y^t)} \tag{Eq.8}$$

Here, g represents the global reference set based on the sum of the production frontier at all periods.

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Since the Malmquist index quantifies the change of total factor productivity between adjacent years, to conquer the problem of insignificant regression results caused by the negligible variation of the green innovation efficiency around 1, this study accumulates it by calculating the product of M as $E_t = M_1 \times M_2 \times \cdots \times M_{t-1}$. Here, E_t is defined as the green innovation efficiency at time t.

Calculation of carbon emissions with IPCC accounting method

Based on the methodology proposed by the IPCC for carbon emission calculation, the carbon emissions of each province are computed with the following equation (*Eq. 9*):

$$C = \sum_{i=1}^{n} Ec_i \times Ncv_i \times CC_i \times Cor_i \times \frac{44}{12} \quad \text{(Eq.9)}$$

Here, the subscript i represents the energy variety; n represents the total number of energy varieties; Ec represents energy consumption; Ncv represents net calorific value of energy variety; the carbon content per unit net calorific value is represented by CC and the rate of combustion carbon oxidation of energy is represented by Cor.

Autocorrelation test of variables by global Moran's I

Before conducting spatial econometric regression, analyzing the autocorrelation of key variables is indispensable. To achieve this, the global Moran's index is employed, and its formula is as shown in *Equation 10*:

$$Moran'sI = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(Z_i - \bar{Z})\left(Z_j - \bar{Z}\right)}{\sum_{i=1}^{n}\Sigma_{i=1}^{n} W_{ij} \sum_{i=1}^{n}(Z_i - \bar{Z})^2} \quad \text{(Eq.10)}$$

Here, the subscripts i,j represent the province numbers, n represents the sum of provinces. Z and $\bar{Z}$ denote the variable to be tested and its mean, respectively, W_{ij} is the matrix of spatial weight.

With the purpose of reflecting spatial influences comprehensively, our research establishes four spatial weight matrices, which includes spatial adjacency matrix ($W1$), geographic distance matrix ($W2$), economic distance matrix ($W3$), and economic-geographic embedding matrix ($W4$), with their corresponding generation methods given in *Table 1*.

Spatial econometric modeling of the effect on green innovation on carbon emissions

Considering the interdependent relationships among different provinces, analyzing the potential spatial autocorrelation is of necessity. This study introduces Spatial Durbin Model (SDM) that concurrently accounts for the influence of its own region and neighboring areas, enabling a more comprehensive examination of spatial interdependence on economic variables. The SDM is chosen for three reasons. First, regional CO_2 emissions and green innovation may exhibit significant spatial dependence due to interregional economic linkages and knowledge diffusion, OLS

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estimation would therefore be biased and inconsistent. Second, the SDM incorporates spatial lags of both the dependent and independent variables, allowing for simultaneous estimation of direct and indirect spillover effects; this is essential for capturing spatial effects across regions. Third, the SDM is the most general specification among common spatial econometric models, with the Spatial Autoregressive Model (SAR) and Spatial Error Model (SEM) being its restricted forms. Wald and LR tests further confirm that the SDM cannot be reduced to these simpler models in our setting. Thus, the SDM provides a robust and consistent framework for analyzing spatial spillover effects. The mathematical formulation of this model is as shown in *Equation 11*:

$$\begin{aligned} C_{it} &= \alpha + \rho\sum_{j=1}^{n}W_{ij}C_{it} + \beta_1 S_{it} + \beta_2 E_{it} + \beta_3 X_{it} + \varphi_1\sum_{j=1}^{n}W_{ij}S_{it} \\ &+\varphi_2\sum_{j=1}^{n}W_{ij}E_{it} + \varphi_3\sum_{j=1}^{n}W_{ij}X_{it} + \zeta_i + \eta_t + \varepsilon_{it} \end{aligned} \quad \text{(Eq.11)}$$

Here, the numbers of province and time are respectively represented by subscript i and t. C, S, and E denote carbon emissions, green R&D scale, and innovation efficiency, respectively. X represents control variables. The intercept is denoted by α and β_1, β_2, and β_3 denote the coefficients of the explanatory variables. The spatial impact coefficients of carbon emissions from other provinces are represented by ρ, φ_1, φ_2 and φ_3, respectively. ζ_i and η_t is the reference of the individual and time fixed impacts while ε_{it} refers to random error term.

Table 1. *Spatial weight matrixes*

Type	Generation method
$W1$	$W1_{i,j} = \begin{cases} 1, & Region\ i\ is\ adjacent\ to\ region\ j \\ 0, & Region\ i\ is\ not\ adjacent\ to\ region\ j \end{cases}$
$W2$	$W2_{i,j} = \begin{cases} \frac{1}{d_{ij}}, i \neq j \\ 0, i = j \end{cases}$, d_{ij} represents the distance from region I to region j
$W3$	$W3_{i,j} = \begin{cases} \frac{1}{\lvert \overline{pgdp_i} - \overline{pgdp_j} \rvert}, i \neq j \\ 0, i = j \end{cases}$, $\overline{pgdp}$ represents the mean per capita GDP
$W4$	$W4_{i,j} = \begin{cases} W2_{i,j} \times W3_{i,j}, i \neq j \\ 0, i = j \end{cases}$

i and j represent regions

In terms of variable selection, one of the theories used to analyze the factors influencing the environment is IPAT model proposed by Ehrlich and Holdren (1971). The IPAT equation can be written as:

$$I = P \times A \times T \quad \text{(Eq.12)}$$

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where I denotes environmental impact, P is population, A is affluence, and T is technology.

Based on IPAT model, Dieta and Roas (1994) propose a stochastic version called STIRPAT model. The STIRPAT equation can be written like:

$$I = \alpha P^{\beta} A^{\gamma} T^{\delta} e \tag{Eq.13}$$

where α, β, γ, δ are estimated terms and e is the error term. The STIRPAT model is widely used to study the influences on carbon emissions, where environmental impact (I) is often defined as the amounts of emission, population (P) is defined as the size of population, affluence (A) is defined as GDP per capita, and technology (T) is often defined as the environmental impact per unit of economic activity. For example, Li et al. (2015) and Xu et al. (2016) consider energy intensity and energy efficiency as independent variable in STIRPAT model respectively. In this paper, considering that both carbon emissions and energy intensity (or efficiency) are calculated by energy consumption, it is not suitable to use energy intensity (or efficiency) as explanatory variable. So as an alternative, this paper uses energy consumption structure.

Additionally, prior research has also provided evidence of the spatial impacts on amounts of population, economic development degree, structure of industry and openness on carbon emissions (Xiao et al., 2023; Lian et al., 2024). Hence, we draw on these findings in terms of variable selection, and choose environment policy, energy structure, population, economic development degree, structure of industry and globalization as control variables. The model's variables are specified in *Table 2*.

***Table 2.** Variables of the model*

Type	Name	Unit of measurement
Explained variables	Carbon Emissions (C)	Million tons
Key variables	Green R&D scale (S)	/
	Green Innovation Efficiency (E)	/
Control variables	Environment Policy (EP)	%
	Energy Consumption Structure (ES)	%
	Permanent Population at the End of the Year (POP)	10 thousand people
	GDP per Capita (PGDP)	Yuan/person
	Proportion of Tertiary Industry (PTI)	%
	Foreign Direct Investment (FDI)	100 million yuan

Data description and sources

According to the model design, this study uses 30 provinces, autonomous regions and municipalities of China between 2007 and 2020 to sample (Tibet, Hong Kong, Macao, and Taiwan were excluded owing to data absence).

The calculation of Carbon emissions (C) involves eight types of energy, including raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas. The

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consumption data for each energy source are from the National Bureau of Statistics, net calorific value data are from the “China Energy Statistical Yearbook,” and data on the carbon content per unit net calorific value and the combustion carbon oxidation rate of energy come from the “Provincial Greenhouse Gas Inventory Compilation Guide” (trial).

Existing studies generally measure innovation in terms of one of inputs or outputs. However, this study selects indicators to measure the green R&D scale and green innovation efficiency from the perspectives of both inputs and outputs, examining labor input and capital input in the input dimension and knowledge creation and knowledge transformation in the output dimension. Additionally, this study uses the number of green patents granted to reflect the greenness of innovation. Thus, the four indicators employed to quantify the green R&D scale (S) and green innovation efficiency (E) are listed: internal R&D expenditure (K), full-time equivalent R&D personnel (L), quantity of green patent grants (P), and technology market transaction amount (M). The sources for the four indicators used for quantifying the green R&D scale (S) and green innovation efficiency (E) are as follows: Data for P comes from China Research Data Services, while data for K, L, and M are from the “China Science and Technology Statistical Yearbook.”

Among the control variables, POP, PGDP, PTI, including the CPI and USD/CNY exchange rate, all come from the National Bureau of Statistics. FDI data are sourced from various provincial statistical yearbooks. Environmental Policy (EP) is measured as the share of investment completed in pollution treatment in the value added of the secondary sector. The data of investment completed in pollution treatment is from China Environmental Statistics Yearbook, and the data of value added of secondary industry is from National Bureau of Statistics. Energy Consumption Structure (ES) is measured as the share of coal, oil and natural gas consumption.

To ensure data stationarity through the unit root test, this study employs the following techniques to preprocess the relevant data: Firstly, to eradicate the impact of price factors, the CPI is employed to adjust the K, M, PGDP to a base year of 2006. Secondly, to eliminate the impact of fluctuations in the US dollar exchange rate, FDI is converted into Chinese yuan on the basis of annual average exchange rate. Finally, to mitigate such effects brought by differences in magnitudes, the absolute quantity data for C, POP, PGDP, and FDI is subjected to natural logarithmic transformation. The key point is that the research span of the study was set to 2007-2020 to be consistent with all indicators. This is because using the SBM-Malmquist index to quantify the efficiency will lead to missing data in the first year. From the matrix of correlation coefficients, although the correlation is statistically significant between some variables, the correlation coefficient is relatively small, suggesting a weak practical association between the variables (see *Appendix 1*).

Results and discussion

Green R&D scale, green innovation efficiency and carbon emissions

To be consistent with the research framework, the core variables that are considered in this study encompass green R&D scale, green innovation efficiency and carbon emissions. The subsequent analysis will be conducted on these variables.

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DOI: http://dx.doi.org/10.15666/aeer/2401_10651097

Green R&D scale of provincial level

The results show a steady growth trend in China's provincial green R&D scale from 2007 to 2020, as presented in *Figure 1* Specifically, the average green R&D scale across provinces ascended from 0.04 in 2007 to 0.19 in 2020, accompanied by the average growth rate of 12.17% a year. It is worth mentioning that a slight decrease in the green R&D scale was observed in 2019, which was attributed to a reduction in the number of green patent authorizations.

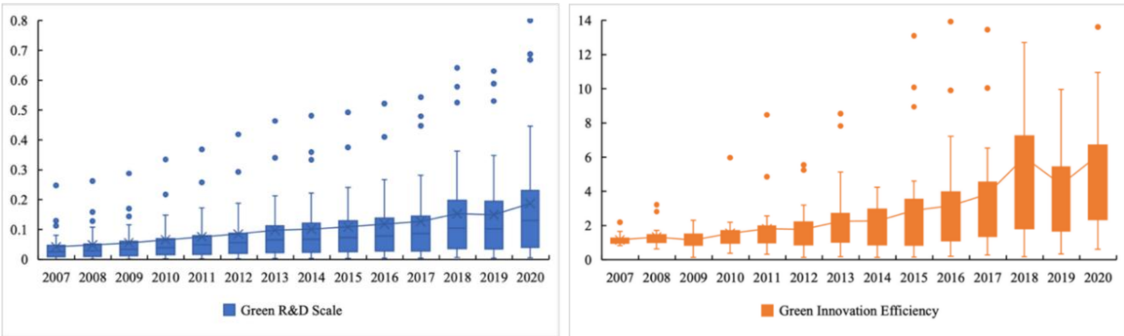

Figure 1. *Provincial green R&D scale and innovation efficiency from 2007 to 2020*

Table 3 and *Figure 2* present the provincial ranking of green R&D scale (S) and the spatial distribution of provincial green R&D scale in selected years, respectively. Although the dataset covers the full period from 2007 to 2020, this study reports tables and figures using four years: 2007, 2011, 2015, and 2020. These years are selected at regular intervals to illustrate the long-term evolution of green innovation and carbon emissions while avoiding redundant visualizations that may arise from presenting all annual data. The results reveal that Beijing, Shanghai, Jiangsu, Zhejiang, Shandong, and Guangdong have consistently ranked among those top six provinces with high green R&D scale, highlighting their abundant green R&D resources and leading green R&D input and output. In contrast, the green R&D scale of Hainan, Qinghai, Ningxia, and Xinjiang is relatively lower,suggesting that their green R&D input and output are not so robust. Moreover, the ranking changes over time suggest the possibility of enhancing green R&D scale in Liaoning and Heilongjiang provinces as they exhibit an upward trend. However, slow growth in green patent authorizations has resulted in a slight dwindles in the rankings of Anhui and Jiangxi provinces, implying that their potential for developing green R&D scale might be inadequate.

Green innovation efficiency of provincial level

Slightly different from green R&D scale, Chinese provincial-level entities have exhibited a fluctuating growth trend in green innovation efficiency between 2007 and 2020, as depicted in *Figure 1*. The average level of provinces rose from 1.16 in 2007 to 6.09 in 2020, accompanied with the growth rate of 13.63% a year. Notably, a marked decline in green innovation efficiency occurred in 2019 due to a considerable decrease in the number of green patents authorized nationwide, potentially attributable in part to the global COVID-19 pandemic. However, the significant

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DOI: http://dx.doi.org/10.15666/aeer/2401_10651097

fluctuations in green innovation efficiency contrasts with green R&D scale may also indicate the existence of bottlenecks in further improvement.

Table 3 and *Figure 3* present the ranking of provinces in terms of green innovation efficiency (E) and the spatial distribution in selected years, respectively. As the efficiency described above means the increment of total factor productivity, these rankings reflect the potential size of each province's development in green innovation efficiency. The data illustrates that Guangxi, Guizhou, Shaanxi, Gansu, and Qinghai are among the top-ranking provinces. This may be because these provinces have relatively small green innovation efficiency base, which means that their potential for improving green innovation efficiency is larger. In contrast, Chongqing, Xinjiang, and Yunnan rank relatively lower. This is partly since their early-stage innovation efficiency has already been greatly improved, and further breakthroughs may be relatively difficult, as in the case of Chongqing. Additionally, it is also because the newly added innovation resources are insufficient, resulting in limited development potential of green innovation efficiency, like Xinjiang and Yunnan.

Table 3. *Ranking of provincial green R&D scale and innovation efficiency in selected years*

	2007		2011		2015		2020	
	S	E	S	E	S	E	S	E
Beijing	1	14	1	3	1	5	3	15
Tianjin	10	4	9	13	8	10	14	9
Hebei	15	17	16	25	16	24	15	12
Shanxi	20	7	19	12	22	11	23	23
Inner Mongolia	24	8	23	22	25	29	24	7
Liaoning	7	18	7	17	15	16	16	21
Jilin	19	24	20	21	20	15	19	10
Heilongjiang	14	2	17	10	19	9	20	11
Shanghai	3	12	5	15	6	19	6	24
Jiangsu	4	20	3	9	2	17	2	16
Zhejiang	6	25	6	28	4	23	4	17
Anhui	17	3	14	8	11	13	10	14
Fujian	16	19	13	20	13	25	13	27
Jiangxi	21	23	21	7	18	12	17	19
Shandong	5	5	4	14	5	14	5	5
Henan	12	16	11	27	12	27	11	22
Hubei	9	15	8	18	7	7	7	13
Hunan	13	22	15	29	14	26	12	25
Guangdong	2	21	2	23	3	21	1	20
Guangxi	25	28	22	16	23	4	25	4
Hainan	30	27	30	26	30	28	29	26
Chongqing	18	26	18	19	17	22	18	30
Sichuan	8	11	12	11	9	8	8	8
Guizhou	26	9	26	1	26	3	22	1
Yunnan	23	13	25	24	21	18	21	28
Shaanxi	11	6	10	2	10	2	9	3
Gansu	22	10	24	4	24	6	26	6

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_10651097

Qinghai	29	1	28	5	29	1	30	2
Ningxia	28	30	29	6	28	20	28	18
Xinjiang	27	29	27	30	27	30	27	29

S represents green R&D scale and E represents green innovation efficiency

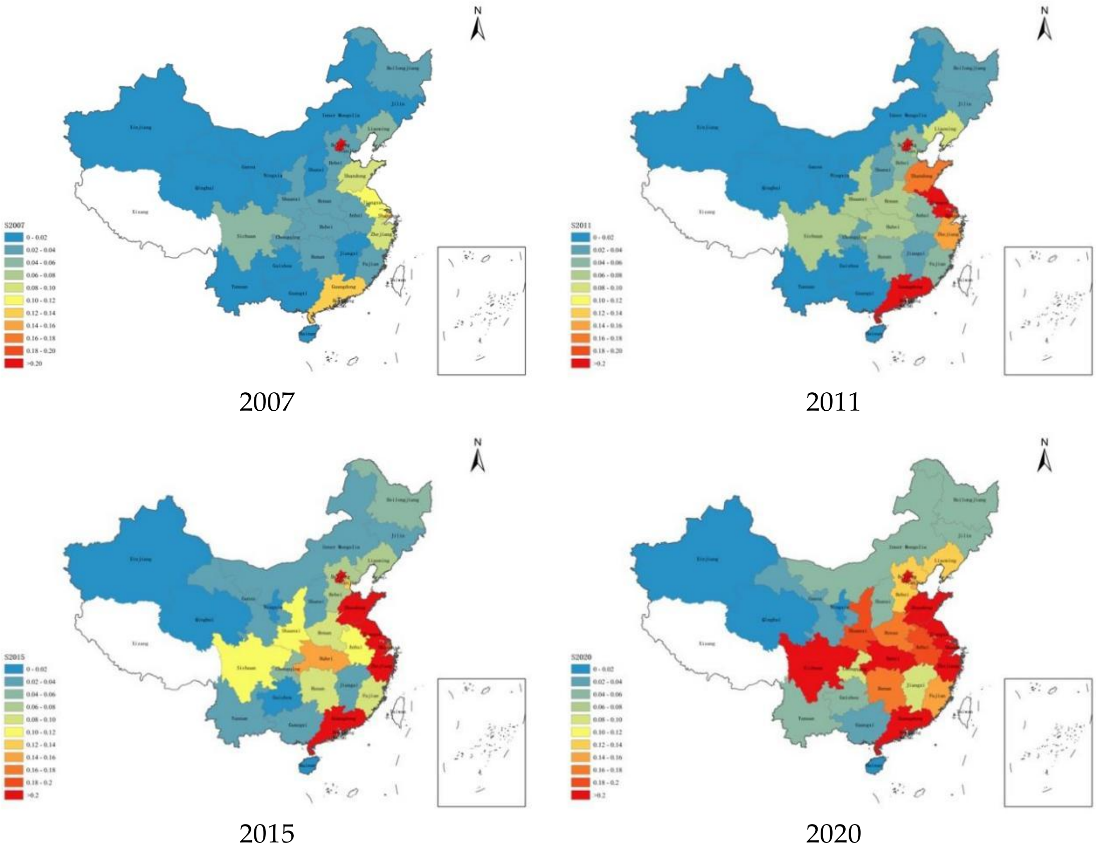

Figure 2. *Spatial distribution of provincial green R&D scale in selected years*

Carbon emissions at the level of provinces

Based on the findings in our study, the variation in carbon emissions across Chinese provinces can be distinguished into two stages from 2007 to 2020, as depicted in *Figure 4*.The first stage, spanning from 2007 to 2011, was characterized by a considerable upsurge in carbon emissions due to the augmented energy consumption that accompanied the rapid economic growth. Throughout this period, the nationwide growth rate of CO_2 across all provinces reached 7.76% a year in average. In contrast, the second phase, between 2012 and 2020, featured a lower growing percentage, attributed to the adjustment of energy structure and the improvement of energy utilization efficiency. Over this period, the nationwide average annual growing rate of CO_2 across all provinces decreased to 1.84%.

According to *Table 4*, Shandong, Shanxi, Inner Mongolia, and Hebei were provinces that exhibits the highest carbon emissions in China, retaining their positions among the top four throughout the entire study period. These provinces were identified as major energy-consuming regions, with coal constituting their primary energy source, leading to their high levels of carbon emissions. Conversely, Qinghai, Hainan, Beijing, and Chongqing were the four provinces with the lowest carbon emissions in

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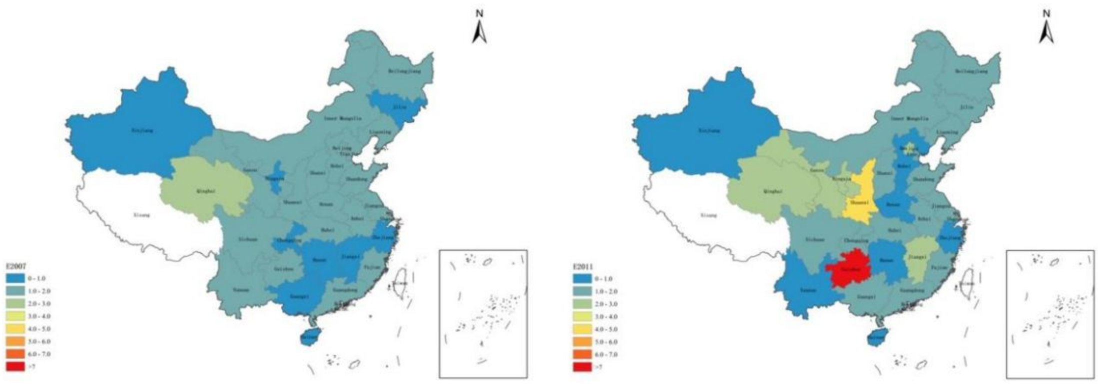
DOI: http://dx.doi.org/10.15666/aeer/2401_10651097

China, with their industrial structures not predominantly emphasizing heavy industry, resulting in their lower energy consumption levels. Notably, Beijing's low carbon emissions were mainly attributed to its reliance on natural gas as the primary energy source. *Figure 5* depicts the spatial distribution of provincial carbon footprints.

Table 4. *Ranking of provincial carbon emissions in selected years*

	2007	2011	2015	2020		2007	2011	2015	2020
Beijing	25	28	28	28	Henan	6	7	8	10
Tianjin	23	23	26	26	Hubei	10	10	14	13
Hebei	2	2	2	4	Hunan	13	15	16	18
Shanxi	3	5	5	2	Guangdong	7	8	7	7
Inner Mongolia	8	4	4	3	Guangxi	26	22	21	20
Liaoning	4	6	6	6	Hainan	29	29	29	29
Jilin	18	17	20	24	Chongqing	27	26	27	27
Heilongjiang	11	12	13	14	Sichuan	12	13	15	17
Shanghai	14	18	18	21	Guizhou	17	20	17	19
Jiangsu	5	3	3	5	Yunnan	19	21	24	22
Zhejiang	9	9	11	11	Shaanxi	16	11	10	9
Anhui	15	14	12	12	Gansu	22	24	25	25
Fujian	21	19	19	16	Qinghai	30	30	30	30
Jiangxi	24	25	22	23	Ningxia	28	27	23	15
Shandong	1	1	1	1	Xinjiang	20	16	9	8



2007 2011

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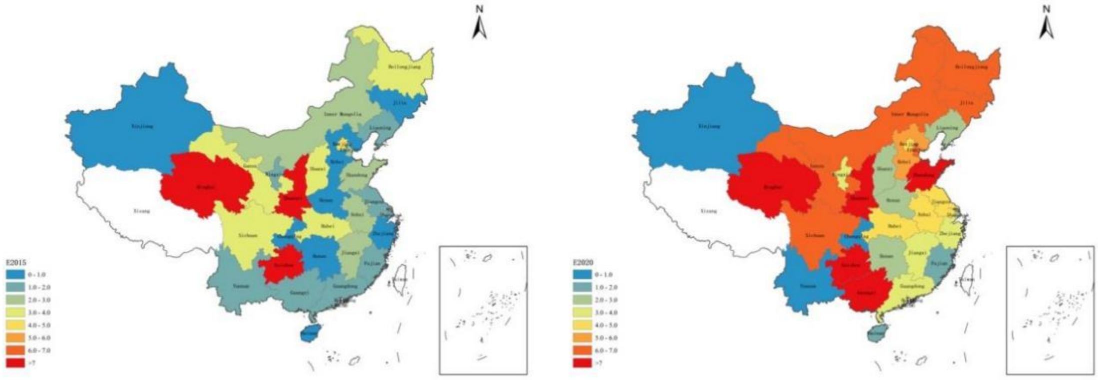


2015 2020

Figure 3. Spatial distribution of provincial green innovation efficiency in selected years

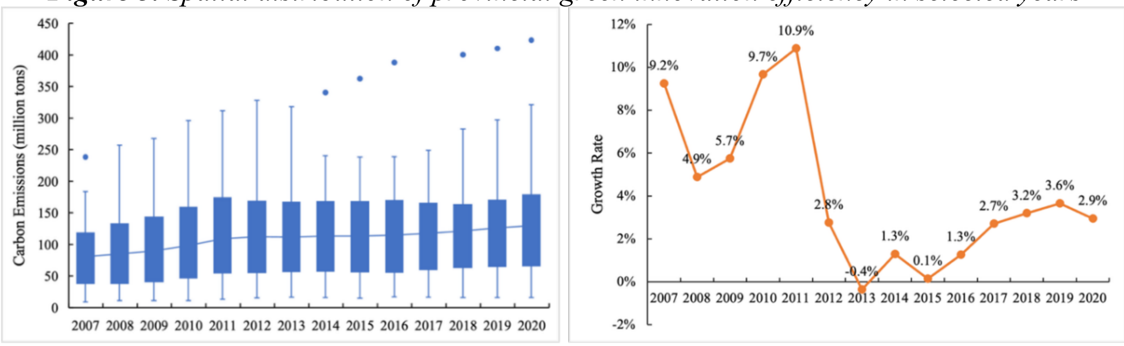
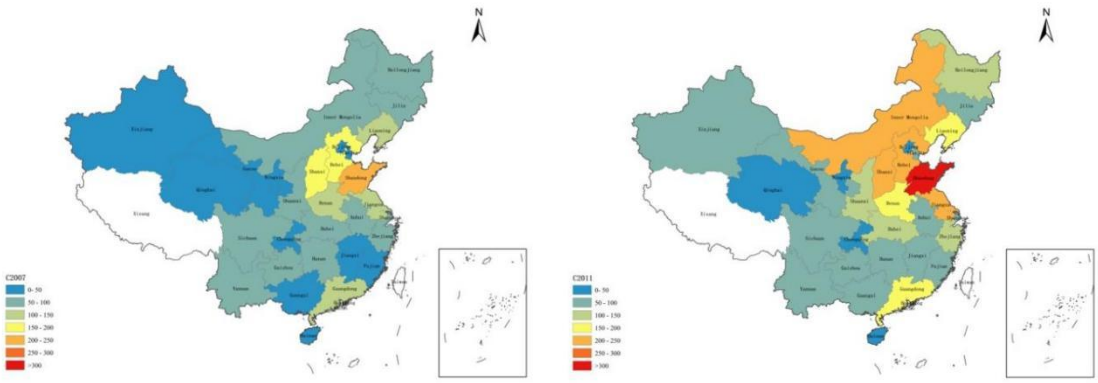
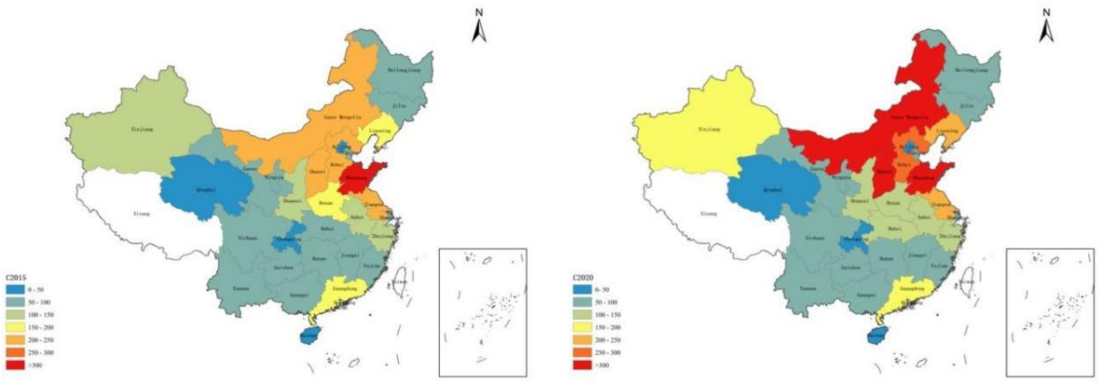


***Figure 4.** Provincial carbon emissions from 2007 to 2020*



2007 2011



http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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2015 2020

Figure 5. *Spatial distribution of provincial carbon emissions in selected years*

To establish a spatial econometric model, identifying the spatial autocorrelation of regional carbon emissions is imperative prior to parameter estimation. Global Moran's I index, as presented in *Table 5*, can indicate a significant spatial autocorrelation of carbon footprints at the level of provinces, and demonstrates it feasible in studying the influence that provincial green innovation has on carbon emissions. The spatial clustering is stable between 2007 and 2020, particularly under W1 and W4. Spatial clustering is shown in the tendency for provinces with high or low carbon emissions to be situated close to other provinces with similar values.

Table 5. *Global Moran's I of carbon emissions in 30 provinces*

	W1	**W2**	**W3**	**W4**		**W1**	**W2**	**W3**	**W4**
2020	0.186** (1.947)	0.046** (2.283)	0.147** (1.915)	0.258*** (2.846)	2013	0.229** (2.172)	0.051*** (2.398)	0.095* (1.350)	0.213*** (2.370)
2019	0.193** (1.907)	0.046** (2.298)	0.140** (1.942)	0.251*** (2.776)	2012	0.235** (2.231)	0.049*** (2.355)	0.097* (1.371)	0.208*** (2.331)
2018	0.205** (2.011)	0.049*** (2.390)	0.132** (1.965)	0.245*** (2.730)	2011	0.247*** (2.320)	0.053*** (2.443)	0.088 (1.274)	0.201** (2.258)
2017	0.196** (1.951)	0.042** (2.200)	0.099* (1.423)	0.201*** (2.313)	2010	0.245*** (2.320)	0.052*** (2.442)	0.071 (1.111)	0.182** (2.088)
2016	0.207** (2.066)	0.039** (2.149)	0.078 (1.209)	0.172** (2.046)	2009	0.244*** (2.310)	0.052*** (2.441)	0.067 (1.063)	0.182** (2.083)
2015	0.223** (2.172)	0.047*** (2.338)	0.092* (1.340)	0.197** (2.263)	2008	0.267*** (2.500)	0.057*** (2.583)	0.069 (1.079)	0.189** (2.156)
2014	0.220** (2.116)	0.048*** (2.340)	0.098* (1.394)	0.209*** (2.350)	2007	0.259*** (2.418)	0.0568*** (2.529)	0.069 (1.077)	0.193** (2.177)

***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively. Z-statistics are shown in parentheses

Decomposition effects of green innovation on carbon emissions

Model selection and parameter estimation

Regarding model selection, this study used the Hausman test to choose fixed effects or not. Although SDM is more general than the Spatial Autoregressive Model (SAR) and Spatial Error Model (SEM), it is still necessary to use LR and Wald tests to ascertain if SAR and SEM is as applicable as SDM or not. The parameter estimation results from the model selection process are represented in *Table 6*.

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DOI: http://dx.doi.org/10.15666/aeer/2401_10651097

Parameter estimation results in *Table 6* demonstrate that both the LR-lag and Wald-lag tests reject the null hypothesis that SDM can degenerate into SAR at the 1% significance degree, and both the LR-error and Wald-error tests reject the null postulate that SDM can degenerate into SEM at the 1% significance degree. These results imply that the specification of the SDM model is appropriate.

Because of the presence of spatial lag terms, the impact of independent variables and their spatial lags on the dependent variable cannot be accurately reflected by regression coefficients. This study employs direct and spillover Effects to characterize the influence of independent variables on the dependent variable as per the method of LeSage and Pace (2009). The direct effect measures the impact of a region's own innovation on its own carbon emissions, reflecting the localized influence of technological progress and innovation activities. In contrast, the indirect effect (also known as the spillover effect) captures the impact of the innovation in one region on neighboring region's carbon emissions, highlighting spatial interactions and interregional externalities. *Table 7* displays the spillover and direct effects for green R&D scale and green innovation efficiency on carbon emissions.

Table 6. *Model selection and parameter estimation*

	W1	W2	W3	W4
S	-0.6187*** (-5.02)	-0.8233*** (-6.64)	-0.6516*** (-5.98)	-0.6837*** (-4.73)
E	-0.0071*** (-3.02)	-0.0048** (-2.02)	-0.0017 (-0.70)	-0.0051** (-2.01)
EP	-0.2351 (-0.08)	-1.3132 (-0.42)	-1.1230 (-0.38)	-0.9155 (-0.31)
ES	0.5279*** (3.18)	0.2909 (1.63)	0.0540 (0.31)	0.1395 (0.79)
POP	1.0059*** (9.87)	0.7803*** (7.87)	0.7655*** (7.10)	0.8800*** (4.61)
PGDP	0.4476*** (4.77)	0.1087 (1.17)	0.0609 (0.73)	0.1232 (1.32)
PTI	0.4612* (1.78)	-0.2328 (-0.81)	-0.1518 (-0.56)	-0.5727* (-1.81)
FDI	-0.0301** (-3.4)	-0.0220* (-1.66)	-0.0244** (-1.96)	-0.0306** (-2.49)
wS	0.0297 (0.18)	-0.0780 (-0.15)	0.4435* (1.75)	-0.2665 (-0.93)
wE	-0.0122*** (-2.68)	-0.0085 (-0.78)	-0.0094* (-1.67)	-0.0124** (-2.05)
wEP	-5.3531 (-1.08)	-1.6944 (-0.22)	1.9030 (0.43)	19.4005*** (3.04)
wES	-1.1616*** (-3.26)	-0.7874 (-0.80)	-0.3824 (-0.83)	-1.1365** (-2.43)

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_10651097

wPOP	-0.5599*** (-3.13)	-1.1526** (-1.97)	-0.3607 (-1.28)	-0.7023 (-1.26)
wPGDP	0.1719 (1.26)	0.7890*** (2.98)	0.7116*** (5.11)	-0.0237 (-0.10)
wPTI	0.7910** (2.19)	1.5730** (2.20)	0.7500* (1.94)	-1.6659* (-1.86)
wFDI	-0.0719*** (-3.02)	0.0759 (1.01)	0.0696** (2.24)	0.0819** (2.30)
wC	0.4546*** (8.05)	0.3329** (2.51)	0.2597*** (3.37)	0.0937 (1.10)
Hausman	5.79	2.29	7.62	39.76***
Individual Fixed	/	/	/	YES
Time Fixed	/	/	/	YES
LR-lag	49.00***	32.57***	58.61***	38.85***
LR-error	63.58***	55.87***	84.80***	39.30***
Wald-lag	52.45***	31.52***	59.83***	40.55***
Wald-error	50.06***	25.84***	61.08***	41.04***

***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively. Z-statistics are shown in parentheses

Table 7. *The spillover and direct consequences for green innovation on carbon emissions*

		W1	W2	W3	W4
Direct effect	S	-0.6476*** (-4.90)	-0.8285*** (-6.60)	-0.6326*** (-4.74)	-0.6851*** (-4.54)
	E	-0.0093*** (-3.67)	-0.0052** (-2.20)	-0.0023 (-0.97)	-0.0054** (-2.23)
	EP	-0.6662 (-0.23)	-1.0452 (-0.35)	-0.7456 (-0.27)	-0.2501 (-0.09)
	ES	0.3975** (2.31)	0.2674 (1.46)	0.0343 (0.20)	0.1194 (0.70)
	POP	0.9914*** (9.97)	0.7571** (8.08)	0.7562*** (6.98)	0.8687*** (4.90)
	PGDP	0.5030*** (5.56)	0.1340*** (1.44)	0.1004 (1.24)	0.1296 (1.42)
	PTI	0.5990** (2.30)	-0.1940 (-0.65)	-0.1174 (-0.44)	-0.6063* (-1.83)
	FDI	-0.0422** (-3.23)	-0.0208 (-1.53)	-0.0218* (-1.76)	-0.0296** (-2.55)
Spillover effect	S	-0.4167 (-1.46)	-0.5325 (-0.63)	0.3781 (1.15)	-0.3531 (-1.12)
	E	-0.0266***	-0.0158	-0.0129*	-0.0139**

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		(-3.46)	(-0.93)	(-1.87)	(-2.15)
	EP	-8.9589	-2.5298	2.4910	21.0770***
		(-1.08)	(-0.21)	(0.42)	(3.00)
	ES	-1.6319***	-1.2479	-0.5420	-1.1997**
		(-2.62)	(-0.77)	(-0.92)	(-2.22)
	POP	-0.1848	-1.3906	-0.2347	-0.7165
		(-0.62)	(-1.45)	(-0.63)	(-1.20)
	PGDP	0.6217***	1.1950***	0.9339***	-0.0097
		(3.68)	(3.70)	(6.59)	(-0.04)
	PTI	1.6700***	2.1570**	0.8911**	-1.9309*
		(3.12)	(2.08)	(2.02)	(-1.91)
	FDI	-0.1432***	0.1124	0.0867**	0.0872**
		(-3.32)	(0.92)	(2.02)	(2.12)

***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively. Z-statistics are shown in parentheses

Direct impact of green R&D scale (S) and green innovation efficiency (E) on carbon emissions

The results in *Table 7* shows that the direct effect coefficient of green R&D scale (S) are significantly negative in all the matrices, indicating that green R&D scale (S) has a negative and direct effect on carbon emissions, i.e., the expansion of local green R&D scale will significantly reduce local carbon emissions. The directly reduction of carbon emissions dependent on both green inputs and outputs. At the input level, the increase in R&D personnel input directly enhances the knowledge stock, which in turn accelerates the research and application of cleaner production technologies and energy-efficiency enhancement technologies. Additionally, the increase in R&D expenditure squeezes out the R&D projects of high-carbon technologies and at the same time increases the research and development of renewable energy technologies and carbon capture technologies, directly promoting the low-carbon transformation of regional energy and industrial structure. At the output level, green technology innovation results in carbon emission reduction through technology substitution, whereby the industrialized application of patented technologies replaces some of the high-carbon production processes. Besides, the improvement of green processes reduces carbon emissions by lowering whole-life energy consumption. This synergy of inputs and outputs has led to a significant reduction in local carbon emissions as a result of the scaling up of local green R&D.

The direct effect of green innovation efficiency (E) on carbon emissions is significantly negative under the three matrices W1, W2 and W4, indicating that an increase in local green innovation efficiency (E) will reduce local carbon emissions. Green innovation efficiency is essentially a measure of the quality and transformation speed of the innovation output produced per unit of innovation input. On the one hand, the increase of green innovation efficiency means that the allocation structure of innovation resources to low-carbon technology has been more optimized. The iteration of green technologies has been increased by reducing ineffective and

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repeated R&D input, and the industrial application of these technologies replaces some of the high-carbon production methods, thus reducing local carbon emissions. On the other hand, improved efficiency means leaner green innovation processes, accelerating the formation of scale effects on low-carbon technologies, which in turn directly reduces carbon emissions through pathways such as improved production processes and increased energy use efficiency.

Spillover impact of green R&D scale (S) and green innovation efficiency (E) on carbon emissions

The results in *Table 7* show that green R&D scale (S) does not have significant spatial spillover effects on carbon emissions under any of the four matrices. On the one hand, the innovation resources and achievements may have technical locks and institutional barriers between regions, which makes it difficult for abundant innovation resources and technological achievements to break through regional boundaries, while the neighboring regions' industrial structure and institutional policies are difficult to effectively undertake the spillover of these resources and achievements. On the other hand, due to the existence of inter-regional competition, the expansion of local green R&D scale will crowd out a large number of innovation resources, leading to the reduction of resources in neighboring regions, which will hinder green R&D activities and make it difficult to effectively reduce carbon emissions. The combined effect of these two reasons may lead to the fact that the expansion of green R&D scale does not have a significant effect on carbon emissions in neighboring regions.

Differently, green innovation efficiency (E) exhibits negative spillover effects on carbon emissions, and is statistically verified under the W1, W3 and W4 matrices. The result shows that the improvement in a region's green innovation efficiency contributes to a reduction in carbon emissions among neighboring regions. The indicator green innovation efficiency (E) is a measure for relative ratio between output and input metrics differing from indicator green R&D scale (S). Therefore, an improvement in green innovation efficiency signifies the ability to produce greener outcomes with the same investment. These additional green outcomes, through spillover effects, contribute to raising green technology level in neighboring regions, consequently reducing CO_2 among those regions. In addition, this result is aligning with the previous literature which finds that innovation efficiency not only reduces regional carbon intensity, but also generates spatial spillovers that can reduce the carbon intensity of neighboring regions, and thereby realizing carbon reduction targets (Sun et al., 2021).

Robustness tests for direct and spillover effects

Regression results are shown in *Table 8* with lagged explanatory variables to reduce endogeneity issues including reverse causality, which are widely recognized in the literature (Wooldridge, 2001). The findings show that, for all spatial weight matrices (W1–W4), the direct effects of green R&D scale (S) are statistically significant but the spillover effects are not statistically significant. This suggests that these variables do not have a substantial direct impact on the estimation results when lag is used to account for potential endogeneity. Similarly, the direct effects of green innovation efficiency (E) are significantly negative under W1, W2 and W4, while the spillover effects are significantly

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negative under W1, W3 and W4. These findings generally match the baseline results, indicating that the model is quite robust.

Heterogeneity analysis

Through a comprehensive examination of the direct and spillover effects of indicator green R&D scale (S) and indicator green innovation efficiency (E) across 30 provinces in China, we have observed that, in terms of statistical outcomes, such as spillover effects, a certain level of insignificance is evident. This suggests that various types of provinces may exhibit inconsistent spatial impacts of green innovation on carbon emissions. Conducting heterogeneity tests will be instrumental in further analyzing provincial characteristics (Fang et al., 2023), thereby furnishing the government and relevant stakeholders with more reliable data and insights, thus aiding in the more effective operationalization of carbon reduction measures. For the purpose of conducting heterogeneity analysis, this study employed two metrics, namely green R&D scale and green innovation efficiency and utilized the K-means algorithm to cluster 30 provinces within China. The K-Means algorithm is unsupervised and iterative, which has advantages like easy implementation, good effect, strong interpretability, and wide application. Based on the clustering results, the 30 provinces were sorted into three categories: high-scale low-efficiency (HL), low-scale low-efficiency (LL), and low-scale high-efficiency (LH), which are presented in detail in *Table 9*.

It is important to highlight that the classification results do not encompass regions characterized by both high scale and high efficiency (HH). This absence is not coincidental, as China has not yet seen the emergence of regions that simultaneously possess high scale and high efficiency. In general, high-scale investments can, to some extent, enhance technological proficiency. However, in the case of regions characterized by a high green R&D scale and those already leading in technology, further progress in their technological capabilities requires overcoming specific technological bottlenecks. This often proves to be a challenging task accompanied by significant uncertainty. In other words, relying solely on high investments does not necessarily result in high output, or achieving high scale and high efficiency is a challenging combination to achieve.

Table 8. *The estimation results of explanatory variables lagged by one period*

		W1	W2	W3	W4
Direct effect	S	-0.7418***	-0.9541***	-0.7288***	-0.8733***
		(-4.71)	(-6.46)	(0.984)	(-1.190)
	E	-0.0092***	-0.0055**	-0.0022	-0.0060**
		(-3.47)	(-2.19)	(0.197)	(-0.021)
	EP	1.4013	1.5603	1.2970	2.4106
		(0.51)	(0.54)	(0.013)	(-1.144)
	ES	0.4546***	0.3607**	0.0827	0.1801
		(2.69)	(1.99)	(3.423)	(3.915)
	POP	0.9738***	0.7721***	0.7555***	0.9022***

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		(10.02)	(8.37)	(1.330)	(2.993)
	PGDP	0.5485*** (6.18)	0.2083** (2.24)	0.1436* (3.722)	0.1800** (3.341)
	PTI	0.6531** (2.51)	-0.0819 (-0.28)	-0.0545 (1.749)	-0.5463 (1.916)
	FDI	-0.0412*** (-3.19)	-0.0244* (-1.78)	-0.0194 (-0.170)	-0.0322*** (-0.471)
Spillover effect	S	-0.3807 (-1.07)	-0.3955 (-0.33)	0.4021 (2.720)	-0.6079 (1.833)
	E	-0.0288*** (-3.61)	-0.0201 (-1.10)	-0.0138* (-0.300)	-0.0177** (-1.258)
	EP	-1.7781 (-0.21)	0.4434 (0.04)	1.3764 (0.839)	21.1299*** (-1.832)
	ES	-1.2435** (-2.05)	-0.5160 (-0.32)	-0.6419 (2.288)	-1.1613** (2.596)
	POP	-0.1386 (-0.46)	-1.2147 (-1.23)	-0.2335 (-2.117)	-0.5935 (-0.172)
	PGDP	0.7546*** (4.55)	1.3401*** (3.97)	0.9071*** (-0.417)	-0.0632 (0.550)
	PTI	1.9990*** (3.59)	2.6294** (2.31)	0.9069** (-1.911)	-2.0092** (-3.298)
	FDI	-0.1828*** (-4.14)	0.0167 (0.13)	0.0825* (0.835)	0.0554 (0.166)

***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively. Z-statistics are shown in parentheses

Table 9. *Provincial classification based on indicator S and indicator E*

Categories	Regions
HL	Beijing, Shanghai, Jiangsu, Zhejiang, Shandong, Guangdong
LL	Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Anhui, Fujian, Jiangxi, Henan, Hubei, Hunan, Guangxi, Hainan, Chongqing, Sichuan, Yunnan, Gansu, Ningxia, Xinjiang
LH	Guizhou, Shanxi, Qinghai

HL/LL/LH respectively represent high-scale low-efficiency, low-scale low-efficiency, and low-scale high-efficiency regions

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According to the clustering consequences described above, our research employed the SDM developedto test the direct and spillover influences of green R&D scale (S) and green innovation efficiency (E) within each of the three identified categories. *Table 10* presents the significance of the SDM models for three categories mentioned above.

Table 10. *The direct and spillover influences of green R&D scale and green innovation efficiency on carbon emissions under the three categories*

Categories	Direct effect		Spillover effect	
	Scale	**Efficiency**	**Scale**	**Efficiency**
HL	Positive (W1/W2/W3/W4)	Positive W4	Negative (W2)	Negative (W3/W4)
LL	Negative (W1/W2/W3/W4)	/	Negative (W1/W2/W3/W4)	Negative (W2/W4)
LH	Positive (W4)	/	/	/

“HL/LL/LH” respectively represent high-scale low-efficiency, low-scale low-efficiency, and low-scale high-efficiency regions, “/” denotes insignificance, and “W1/W2/W3/W4” are spatial weightmatrices, “Positive/ Negative” represents the direction of significant spillover effects

Previous studies have found regional heterogeneity in the impact of green innovation on carbon emissions (Li et al., 2023). Although we categorize provinces differently than them in strict sense, our study provides a new perspective of regional heterogeneity at the level of provincial clustering. With regard to green R&D scale (S), based on consequences in *Table 10*, green R&D scale’s direct impacts exhibit provincial heterogeneity across the three identified categories. Specifically, in the HL regions, the direct effect is positive in all four matrices. This outcome can be attributed to two reasons. Firstly, the expansion of scale can trigger an increased requirement towards local resources as well as environment, which leads to a rise of CO_2. Secondly, due to the widespread efficiency bottleneck problems in regions such as Beijing and Shanghai, efficiency improvement effect brought by the scale expansion is not significant, and its carbon reduction effect is weak. As a result, the overall direct effect is positive. Conversely, in the LL regions, the direct effect is negative in all four matrices. Compared to HL regions, the expansion of scale in these regions can also promote local productivity and energy efficiency through other approaches, such as technology introduction. Due to the diversity of these approaches not being limited to R&D innovation alone, they can generate a wider and more practical carbon reduction effect in practical applications, thus making it easier to effectively reduce local CO_2. As for LH regions, the direct influence brought by scale expansion is positive in the W4 matrix, which is the consequence of a growth in local CO_2 owing to the increased demand for resources and the environment caused by scale expansion is larger than the cutting down in local CO_2 due to technological advances, as these regions already exhibit a high level of innovation efficiency, making further improvement difficult.

It is worth noting that the spillover effect of green R&D scale in HL and LL regions is significantly negative, which is different from the results before clustering. It may

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be because, compared with overall 30 provinces, the regions in the same category after clustering show higher similarity in industrial structure, weaker technology lock-in and institutional barriers, which promotes cooperation between regions. That is, the expansion of green R&D scale leads to more obvious negative spillover effects, while also reducing the competition for green innovation resources between regions and making resources more reasonably allocated. This incongruous research outcome suggests that, as the scale of green R&D expands, it may yield significant negative spillover impacts on carbon emissions in neighboring regions within same category. However, when examined at the national level, it does not significantly affect carbon emissions in surrounding areas.

With respect to the green innovation efficiency (E), on the basis of *Table 10*, in the HL region, the direct effect of green innovation efficiency on carbon emissions is significantly positive only under the W4 matrix, which is opposite to the original results and is not significant in the LL and LH regions. This result is mainly attributed to the dynamic change of the output index relative to the input index in green innovation efficiency. This change usually includes two paths. The first path is to stimulate local green innovation output by promoting local green innovation input. The second path is to increase local green output through the introduction of green technology driven by external market transactions. However, these two paths show differences in carbon reduction. The former requires a longer time to accumulate and has uncertainty, it may not reduce local carbon emissions in the process, and may even lead to an increase in carbon emissions. This makes the carbon emissions in the HL region increase with the improvement of green innovation efficiency. In contrast, the latter can usually be implemented quickly and produce carbon reduction effects in the short term. The combined effect of these two paths may result in the direct effect of green innovation efficiency on carbon emissions in LL and LH regions being insignificant. Besides, the spillover effect of green innovation efficiency is significantly negative in the first two regions, which is consistent with the results before clustering.

Discussion

This study provides new empirical evidence on the spatial spillover effects of green innovation on regional CO_2 emissions by employing the Spatial Durbin Model (SDM) and distinguishing green innovation into two dimensions: green R&D scale and green innovation efficiency. The results indicate that, both green R&D scale and green innovation efficiency exert significant negative direct impacts on local CO_2 emissions. This finding is consistent with a growing body of empirical studies demonstrating the emission-reduction benefits of green innovation (Meng et al., 2022; Xie and Jamaani, 2022; Li and Wang, 2023). For example, Sun (2022) confirms that green technology innovation contributes to low-carbon transitions within regions. This consistency reinforces the theoretical expectation that green innovation enhances local low carbon development. These consistent results collectively reinforce the theoretical expectation that green innovation facilitates local low-carbon development.

In contrast, prior research has produced mixed conclusions regarding the spatial spillover effects of green innovation (Sun., 2022; Chen et al., 2023; Fang et al., 2022). The study contributes to this debate by showing that the spillover effect of green

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R&D scale is statistically insignificant, while green innovation efficiency generates a significantly negative spillover effect on neighboring regions. This suggests that regions with higher innovation efficiency produce green technologies that are more transferrable and more easily adopted by surrounding regions, thereby enabling reductions in carbon emissions at lower marginal costs. These results provide an important refinement to the existing literature, which often implicitly assumes that different dimensions of green innovation produce similar environmental outcomes. Our empirical findings reveal that only efficiency—rather than scale—produces robust and consistent cross-regional mitigation effects. This distinction underscores that the quality and effectiveness of green innovation matter more than the sheer volume of innovation.

Moreover, the heterogeneity analysis conducted in this study further enriches the existing literature by revealing that the spatial impacts of green innovation differ substantially across regions. Although previous research recognizes the presence of regional heterogeneity (Sun et al., 2022; Razzaq et al., 2021), few studies have explicitly linked these differences to distinct dimensions of green innovation. By separately examining green R&D scale and green innovation efficiency across three regional clusters, this study reveals that heterogeneity does not originate from a single source but instead differs across innovation dimensions. These results offer a more nuanced and structured explanation for the region-specific mechanisms through which green innovation influences carbon emissions, providing more targeted implications for differentiated regional low-carbon development strategies.

Chen et al. (2023) provide one of the most comparable studies to ours, showing that green innovation—measured solely by green patent applications—exerts an inverted U-shaped effect on both direct and spillover impacts on regional carbon intensity. Their findings suggest that at early stages of innovation accumulation, technology upgrading may increase carbon intensity, and only after surpassing a technological threshold do emission reductions emerge. The differences in measurement partly explain the divergent conclusions. Patent counts primarily capture the output stage of innovation activities. By contrast, this study separately evaluates green R&D scale (representing both input and output dimensions) and green innovation efficiency (representing a performance dimension). This multidimensional framework better captures the substantive effectiveness of innovation activities and mitigates potential biases inherent in counting-based indicators. Consequently, our findings provide a more refined and representative characterization of how green innovation influences carbon emissions in contemporary China.

Conclusion, suggestion and limitation

According to the above results and discussion, this study reaches the conclusions that the green R&D scale (S) and green innovation efficiency (E) show steady increasing trends with some fluctuations. Beijing, Shanghai, Jiangsu, Zhejiang, Shandong, and Guangdong own high green R&D scale. However, Hainan, Qinghai, Ningxia, and Xinjiang, are found typical low green R&D scale. Further, Guangxi, Guizhou, Shaanxi, Gansu, and Qinghai have greater development potential in green innovation efficiency. However, Chongqing, Xinjiang, and Yunnan have smaller development potential in green innovation efficiency. Considering spatial effect

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decomposition, with direct impacts, both green R&D scale (S) and green innovation efficiency (E) cause significant negative impact on carbon emissions. However, concerning spillover effects, the impact of green R&D scale on carbon emissions is not significant, while the impact of green innovation efficiency on carbon emissions is significantly negative.

In terms of regional heterogeneity, the direct and spillover effects of green R&D scale on carbon emissions exhibit provincial heterogeneity among the three identified categories. The direct effect of green innovation efficiency on carbon emissions is different from the pre-clustering results and also has heterogeneity, while the spillover effect is consistent with the pre-clustering results.

Based on the findings, this study offers three policy suggestions. Firstly, provinces should focus more on both green innovation efficiency and green R&D scale to reduce carbon emissions through green innovation. Secondly, it is necessary to guide the cooperation and competition of R&D resources in a reasonable manner and strengthen the diffusion of green innovative technologies. Finally, it is important to coordinate provincial development and carbon emissions descending according to specific situations, considering the spatial impacts of provincial heterogeneity.

For the national level policies, in order to control pollution and protect the environment to higher standards, the government should create development rules, rewards, and punishments for green-developing enterprises that take into account resource input, energy consumption, output of achievements, and waste discharge. It should also offer tax incentives, green innovation subsidies, public praise, and other incentives for better green development, and penalize, correct, or even close down poor green development. It promotes sustainable development and provides a strong basis for the realization of high-quality, environmentally friendly development. To improve the rate at which green innovation achievements are converted, the government should optimize the portion of funds allocated to scientific research, allocate more funds and human resources to more innovative, low-emission, low-energy consumption, and high-output research, allocate more funds to basic application research, and reduce resource redundancy in other areas. In addition, it ought to boost the development of innovative talent and augment the allocation of educational funding towards innovation.

This study comprehensively evaluates green innovation degree on the Chinese provincial level by integrating the aspects of green innovation inputs and outputs. The advantage of this approach lies in its finer granularity, overcoming the limitations of existing studies that solely focus on green innovation outputs measured by indicators such as green patents or R&D expenditures, and even indirectly measure green innovation inputs through innovation inputs. In the research process, particular attention is paid to the nuances, for instance, the differential treatment of direct as well as indirect effects of R&D scale and innovation efficiency on regional carbon emissions in China. In an applied perspective, it is more targeted, for example, by categorizing the heterogeneity among provincial regions, it helps policymakers gain a more sophisticated insight on the diverse impacts of the scale and efficiency of green innovation on carbon emissions descending in specific provincial areas, and accordingly formulate corresponding policies.

However, noticing that this study still has certain limitations. Firstly, there are limitations regarding data selection and scope, indicator measurement, and model construction. Secondly, the analysis on the effects of the scale and efficiency of green

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DOI: http://dx.doi.org/10.15666/aeer/2401_10651097

innovation is restricted to provincial level. Besides further investigation and discussion are necessary regarding urban clusters and the enterprise level to grasp key factors for low-carbon emissions reduction. Thirdly, temporal heterogeneity needs to be considered, as some scholars argue that temporal variations exist in the spatial spillover effects.

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Data availability. Data can be obtained from the following given link: https://www.kaggle.com/datasets/zhuqianting/erc-paper-data.

REFERENCES

[1] Abbas, S., Saqib, N., Mohammed, K. S., Sahore, N., Shahzad, U. (2024): Pathways towards carbon neutrality in low carbon cities: the role of green patents, R&D and energy use for carbon emissions. – Technological Forecasting and Social Change 200: 123109. https://doi.org/10.1016/j.techfore.2023.123109.

[2] Afrifa, G. A., Tingbani, I., Yamoah, F., Appiah, G. (2020): Innovation input, governance and climate change: evidence from emerging countries. – Technological Forecasting and Social Change 161: 120256. https://doi.org/10.1016/j.techfore.2020.120256.

[3] Ahmad, M., Ahmed, Z., Alvarado, R., Hussain, N., Khan, S. A. (2024): Financial development, resource richness, eco-innovation, and sustainable development: Does geopolitical risk matter? – Journal of Environmental Management 351: 119824. https://doi.org/10.1016/j.jenvman.2023.119824.

[4] Aldieri, L., Brahmi, M., Bruno, B., Vinci, C. P. (2021): Circular economy business models: the complementarities with sharing economy and eco-innovations investments. – Sustainability 13(22): 12438. https://doi.org/10.3390/su132212438.

[5] Chang, K., Liu, L., Luo, D., Xing, K. (2023): The impact of green technology innovation on carbon dioxide emissions: the role of local environmental regulations. – Journal of Environmental Management 340: 117990. https://doi.org/10.1016/j.jenvman.2023.117990.

[6] Chen, H., Yi, J., Chen, A., Peng, D., Yang, J. (2023): Green technology innovation and CO_2 emission in China: evidence from a spatial-temporal analysis and a nonlinear spatial Durbin model. – Energy Policy 172: 113338. https://doi.org/10.1016/j.enpol.2022.113338.

[7] Chen, L., Lu, Y., Zhao, W. (2025): Research on the impacts of green technology innovation on carbon emissions: evidence from 282 Chinese cities. – Environment, Development and Sustainability 27: 16091-16112. https://doi.org/10.1007/s10668-024-04652-z.

[8] Corrado, L., Fingleton, B. (2012): Where is the economics in spatial econometrics? – Journal of Regional Science 52(2): 210-239. https://doi.org/10.1111/j.1467-9787.2011.00726.x.

[9] Desheng, L., Jiakui, C., Ning, Z. (2021): Political connections and green technology innovations under an environmental regulation. – Journal of Cleaner Production 298: 126778. https://doi.org/10.1016/j.jclepro.2021.126778.

[10] Dietz, T., Rosa, E. A. (1994): Rethinking the environmental impacts of population, affluence and technology. – Human Ecology Review 1(2): 277-300. https://www.jstor.org/stable/24706840.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_10651097

[11] Du, Q., Pang, Q., Bao, T., Guo, X., Deng, Y. (2021): Critical factors influencing carbon emissions of prefabricated building supply chains in China. – Journal of Cleaner Production 280: 124398. https://doi.org/10.1016/j.jclepro.2020.124398.
[12] Ehrlich, P. R., Holdren, J. P. (1971): Impact of population growth. – Science 171(3977): 1212-1217.https://www.jstor.org/stable/1731166.
[13] El-Kassar, A. N., Singh, S. K. (2019): Green innovation and organizational performance: the influence of big data and the moderating role of management commitment and HR practices. – Technological Forecasting and Social Change 144: 483-498. https://doi.org/10.1016/j.techfore.2017.12.016.
[14] Fan, J., Wang, J., Qiu, J., Li, N. (2023): Stage effects of energy consumption and carbon emissions in the process of urbanization: evidence from 30 provinces in China. – Energy 276: 127655. https://doi.org/10.1016/j.energy.2023.127655.
[15] Fang, G., Gao, Z., Wang, L., Tian, L. (2022): How does green innovation drive urban carbon emission efficiency?—Evidence from the Yangtze River Economic Belt. – Journal of Cleaner Production 375: 134196. https://doi.org/10.1016/j.jclepro.2022.134196.
[16] Fang, G., Yang, K., Chen, G., Tian, L. (2023a): Environmental protection tax superseded pollution fees, does China effectively abate ecological footprints? – Journal of Cleaner Production 388: 135846. https://doi.org/10.1016/j.jclepro.2023.135846.
[17] Fang, G., Chen, G., Yang, K., Yin, W., Tian, L. (2023b): Can green tax policy promote China's energy transformation?—A nonlinear analysis from production and consumption perspectives. – Energy 269: 126818. https://doi.org/10.1016/j.energy.2023.126818.
[18] Fang, Z. (2023): Assessing the impact of renewable energy investment, green technology innovation, and industrialization on sustainable development: a case study of China. – Renewable Energy 205: 772-782. https://doi.org/10.1016/j.renene.2023.01.014.
[19] Gao, P., Wang, Y., Zou, Y., Su, X., Che, X., Yang, X. (2022): Green technology innovation and carbon emissions nexus in China: Does industrial structure upgrading matter? – Frontiers in Psychology 13: 951172. https://doi.org/10.3389/fpsyg.2022.951172.
[20] Habiba, U., Xinbang, C., Anwar, A. (2022): Do green technology innovations, financial development, and renewable energy use help to curb carbon emissions? – Renewable energy 193: 1082-1093. https://doi.org/10.1016/j.renene.2022.05.084.
[21] IPCC (2022): Climate Change 2022: Mitigation of Climate Change. – Cambridge University Press, Cambridge.
[22] Jiang, Q., Rahman, Z. U., Zhang, X., Islam, M. S. (2022): An assessment of the effect of green innovation, income, and energy use on consumption-based CO_2 emissions: empirical evidence from emerging nations BRICS. – Journal of Cleaner Production 365: 132636. https://doi.org/10.1016/j.jclepro.2022.132636.
[23] Jiemin, H., Chen, W. (2022): The impact of private sector energy investment, innovation and energy consumption on China's carbon emissions. – Renewable Energy 195: 1291-1299. https://doi.org/10.1016/j.renene.2022.06.131.
[24] LeSage, J., Pace, R. K. (2009): Introduction to Spatial Econometrics. 1st Ed. – Chapman and Hall/CRC, New York. https://doi.org/10.1201/9781420064254.
[25] Li, B., Liu, X., Li, Z. (2015): Using the STIRPAT model to explore the factors driving regional CO_2 emissions: a case of Tianjin, China. – Natural Hazards 76(3): 1667-1685. https://doi.org/10.1007/s11069-014-1574-9.
[26] Li, C. J., Razzaq, A., Irfan, M., Luqman, A. (2023a): Green innovation, environmental governance and green investment in China: exploring the intrinsic mechanisms under the framework of COP26. – Technological Forecasting and Social Change 194: 122708. https://doi.org/10.1016/j.techfore.2023.122708.
[27] Li, X. H., Wang, J. W. (2023): The regional gap and its influencing factors of green development of urban and rural construction in China under the goal of common prosperity. – Journal of Natural Resources 38(2): 419-441. https://doi.org/10.31497/zrzyxb.20230210.
[28] Li, X., Qin, Q., Yang, Y. (2023b): The impact of green innovation on carbon emissions: evidence from the construction sector in China. – Energies 16(11): 4529.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_10651097

https://doi.org/10.3390/en16114529.
[29] Lian, Y., Lin, X., Luo, H., Zhang, J., Sun, X. (2024): Distribution characteristics and influencing factors of household consumption carbon emissions in China from a spatial perspective. – Journal of Environmental Management 351: 119564. https://doi.org/10.1016/j.jenvman.2023.119564.
[30] Liang, H., Lin, S., Wang, J. (2022): Impact of technological innovation on carbon emissions in China's logistics industry: based on the rebound effect. – Journal of Cleaner Production 377: 134371. https://doi.org/10.1016/j.jclepro.2022.134371.
[31] Liu, X., Jin, X., Luo, X., Zhou, Y. (2023): Quantifying the spatiotemporal dynamics and impact factors of China's county-level carbon emissions using ESTDA and spatial econometric models. – Journal of Cleaner Production 410: 137203. https://doi.org/10.1016/j.jclepro.2023.137203.
[32] Ma, Q., Murshed, M., Khan, Z. (2021): The nexuses between energy investments, technological innovations, emission taxes, and carbon emissions in China. – Energy Policy 155: 112345. https://doi.org/10.1016/j.enpol.2021.112345.
[33] Mansour, N. (2003): Green technology innovation and financial services system: evidence from China. – Businesses 3(1): 98-113. https://doi.org/10.3390/businesses3010008.
[34] Meng, Y., Wu, H., Wang, Y., Duan, Y. (2022): International trade diversification, green innovation, and consumption-based carbon emissions: the role of renewable energy for sustainable development in BRICST countries. – Renewable Energy 198: 1243-1253. https://doi.org/10.1016/j.renene.2022.08.045.
[35] Qin, J., Gong, N. (2022): The estimation of the carbon dioxide emission and driving factors in China based on machine learning methods. – Sustainable Production and Consumption 33: 218-229. https://doi.org/10.1016/j.spc.2022.06.027.
[36] Razzaq, A., Wang, Y., Chupradit, S., Suksatan, W., Shahzad, F. (2021): Asymmetric inter-linkages between green technology innovation and consumption-based carbon emissions in BRICS countries using quantile-on-quantile framework. – Technology in Society 66: 101656. https://doi.org/10.1016/j.techsoc.2021.101656.
[37] Shah, M. I., Foglia, M., Shahzad, U., Fareed, Z. (2022): Green innovation, resource price and carbon emissions during the COVID-19 times: new findings from wavelet local multiple correlation analysis. – Technological Forecasting and Social Change 184: 121957. https://doi.org/10.1016/j.techfore.2022.121957.
[38] Shahzad, M., Qu, Y., Rehman, S. U., Zafar, A. U. (2022): Adoption of green innovation technology to accelerate sustainable development among manufacturing industry. – Journal of Innovation & Knowledge 7(4): 100231. https://doi.org/10.1016/j.jik.2022.100231.
[39] Shang, Y., Niu, Y., Song, P. (2023): Regional differences and influencing factors of green innovation efficiency in China's 285 cities. – Sustainability 16(1): 334. https://doi.org/10.3390/su16010334.
[40] Söderholm, P. (2020): The green economy transition: the challenges of technological change for sustainability. – Sustainable Earth 3(1): 6. https://doi.org/10.1186/s42055-020-00029-y.
[41] Suki, N. M., Suki, N. M., Afshan, S., Sharif, A., Meo, M. S. (2022): The paradigms of technological innovation and renewables as a panacea for sustainable development: a pathway of going green. – Renewable Energy 181: 1431-1439. https://doi.org/10.1016/j.renene.2021.09.121.
[42] Sun, H. (2022): What are the roles of green technology innovation and ICT employment in lowering carbon intensity in China? A city-level analysis of the spatial effects. – Resources, Conservation and Recycling 186: 106550. https://doi.org/10.1016/j.resconrec.2022.106550.
[43] Sun, Y., Anwar, A., Razzaq, A., Liang, X., Siddique, M. (2022): Asymmetric role of renewable energy, green innovation, and globalization in deriving environmental

sustainability: evidence from top-10 polluted countries. – Renewable Energy 185: 280-290. https://doi.org/10.1016/j.renene.2021.12.038.
[44] Sun, Z., Li, H., Liu, B. (2021): Collaborative Innovation Efficiency and Regional Carbon Emission Reduction from the Perspective of Spatial Association. J. – Dalian University of Technology (Social Sciences), Dalian. https://link.cnki.net/doi/10.19525/j.issn1008-407x.2021.05.004.
[45] Takalo, S. K., Tooranloo, H. S. (2021): Green innovation: a systematic literature review. – Journal of Cleaner Production 279: 122474. https://doi.org/10.1016/j.jclepro.2020.122474.
[46] UN (2019): Outlooks in Geo-6 Global Environment Outlook. – Cambridge University Press, Cambridge.
[47] Wei, Z., Wei, K., Liu, J., Zhou, Y. (2023): The relationship between agricultural and animal husbandry economic development and carbon emissions in Henan Province, the analysis of factors affecting carbon emissions, and carbon emissions prediction. – Marine Pollution Bulletin 193: 115134. https://doi.org/10.1016/j.marpolbul.2023.115134.
[48] Weijun, H., Wenqin, L., Mingliang, D. (2022): Human capital, green technology innovation, and total factor carbon emission efficiency in the Yangtze River economic Belt. – Science & Technology Progress and Policy 39(9): 23-32. https://doi.org/10.6049/kjjbydc.C202108003.
[49] Wooldridge, J. M. (2010): Econometric Analysis of Cross Section and Panel Data. – MIT Press, Cambridge.
[50] Xiao, M., Peng, X. (2023): Decomposition of carbon emission influencing factors and research on emission reduction performance of energy consumption in China. – Frontiers in Environmental Science 10: 1096650. https://doi.org/10.3389/fenvs.2022.1096650.
[51] Xiao, Y., Yong, C., Hu, W., Wang, H. (2023): Factors influencing carbon emissions in high carbon industries in the Zhejiang Province and decoupling effect analysis. – Sustainability 15(22): 15975. https://doi.org/10.3390/su152215975.
[52] Xie, P., Jamaani, F. (2022): Does green innovation, energy productivity and environmental taxes limit carbon emissions in developed economies: implications for sustainable development. – Structural Change and Economic Dynamics 63: 66-78. https://doi.org/10.1016/j.strueco.2022.09.002.
[53] Xu, L., Fan, M., Yang, L., Shao, S. (2021): Heterogeneous green innovations and carbon emission performance: evidence at China's city level. – Energy Economics 99: 105269. https://doi.org/10.1016/j.eneco.2021.105269.
[54] Xu, S. C., He, Z. X., Long, R. Y., Shen, W. X., Ji, S. B., Chen, Q. B. (2016): Impacts of economic growth and urbanization on CO_2 emissions: regional differences in China based on panel estimation. – Regional Environmental Change 16(3): 777-787. https://doi.org/10.1007/s10113-015-0795-0.
[55] Yan, X., Han, Z., Zou, C., Cheng, C. (2024): Assessing the role of emerging green technology transfer in sustainable development and identification of key regions in Yangtze River Delta region. – Technological Forecasting and Social Change 200: 123099. https://doi.org/10.1016/j.techfore.2023.123099.
[56] Zhao, P., Lu, Z., Kou, J., Du, J. (2023): Regional differences and convergence of green innovation efficiency in China. – Journal of Environmental Management 325: 116618. https://doi.org/10.1016/j.jenvman.2022.116618.

APPENDIX

Appendix 1. *Correlation structure of variables*

Variables	1	2	3	4	5	6	7	8
S	1							

E	0.026	1						
ES	-0.182***	-0.338***	1					
POP	0.351***	-0.130**	0.013	1				
PGDP	0.690***	-0.095	-0.022	0.041	1			
PTI	0.543***	0.177***	-0.250***	-0.299***	0.562***	1		
FDI	0.577***	-0.276***	0.172***	0.613***	0.622***	0.120**	1	
EP	-0.324***	-0.101**	0.067	-0.371***	-0.256***	-0.190***	-0.423***	1

***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively

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