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Original Research

Spatial Effect Research on the Impact of Technological Innovation on Carbon Dioxide Emission Intensity

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Abstract

This article examines the impact of technological innovation on CO_2 emissions in China from 2003 to 2018 using 30 provincial panel data sets. Employing the Spatial Durbin Model (SDM), it examines the impact of technological innovation on CO_2 emissions intensity from a dual perspective of direct impact and spatial spillover. The findings indicate that regional spatial CO_2 emissions exhibit a positive spatial spillover effect; technological innovation can significantly reduce a region's CO_2 emission intensity and has a negative spillover effect on neighboring regions' CO_2 emission intensity, thereby dramatically reducing CO_2 emissions in neighboring provinces. Additionally, advanced industrial structure and foreign direct investment have the potential to significantly reduce total CO_2 emission intensity; environmental regulations have an inverted "U" effect on total CO_2 emission intensity; and the coal-based energy consumption structure increases total CO_2 emission intensity. On the basis of the aforementioned research, this article offers recommendations for policy changes aimed at reducing CO_2 emission intensity in order to achieve low-carbon growth.

Keywords: carbon emission intensity, technological innovation, Spatial Durbin Model

Introduction

Climate change has increasingly evolved into a global concern confronting all nations, garnering widespread attention from the international community as a result of continual industrialisation advancements. The question of how to establish a low-carbon economy and reduce CO_2 emissions has also become a prominent topic of discussion in academic study. Numerous studies have established that science and technology are key determinants of CO_2 emissions [1-3]. For starters, technical innovation may spur economic growth, boosting energy consumption and CO_2 emissions in the process. Additionally, technological innovation has the potential to dramatically increase labor productivity, reduce economic development's reliance on natural resources, increase the total energy usage rate, and alleviate the burden of mandatory emission reductions on businesses [4]. Simultaneously, the development of green technology, such as clean energy, renewable energy, and energy-efficient equipment, is critical for lowering CO_2 emissions [5].

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Since the late 1970s, China has been undergoing fast growth, resulting in an increase in energy consumption. However, owing to China's economic development limitations and technical constraints, inexpensive fossil fuels have become the most extensively used energy source, causing China's CO_2 emissions to expand fast. As part of its efforts to attain the low-carbon development goal, the Chinese government proposes to work toward reaching a peak in carbon emissions by 2030 and carbon neutrality by 2060 [6, 7]. It is vital to understand the direct influence and spatial spillover effect of technological innovation on carbon dioxide emissions in order to ease the burden on the ecological environment.

At present, academic research on technology innovation and carbon emission intensity mainly focuses on the impact effect. For example, Kang et al. constructed dynamic panel data to analyse the technological progress paths of low-carbon development in three major urban agglomerations in China, and the findings suggest that the main source of power for low-carbon development is independent innovation in science and technology [8]. Based on the perspective of carbon emission spillover effects, Zhang uses a three-region input-output model to analyze the carbon emission spillover feedback effect of China's economic regions [9]. Ding et al. further considered the spatial distribution characteristics of carbon emissions, studied the spillover effect of carbon emissions in the Yangtze River Economic Belt and the driving path of technological innovation and found that cross-regional technological innovation in energy conservation and emission reduction can reduce carbon dioxide emissions and promote regional green development transformation [10]. Zhang et al. used a linear regression model and mediating effects to verify the emission reduction effect of technological innovation and found that technological innovation effectively reduced carbon emissions in Chinese provinces, but energy consumption affected the emission reduction effect of technological innovation to some extent [11]. Cheng et al. further considered the heterogeneity between regions in China and used quantile regression to synthesize the potential heterogeneous effects between energy technology innovation and carbon emission intensity in different regions of China [12]. Cheng et al. analyzed the mediating effect of green technology innovation on the relationship between environmental regulatory policies and carbon emissions [13]. Lin and Ma studied the impact of different technological progress paths, such as domestic innovation, foreign technology introduction, and regional technology transfer, on CO_2 emissions [14]. Existing literature mainly examines the direct impact of technological innovation on carbon emission intensity or only considers the spatial spillover effect of technological innovation on carbon emission intensity. Few scholars incorporate both the direct impact effect and the spatial spillover effect into the research framework. Therefore, this article will use the Spatial Durbin Model (SDM) to examine the impact of technological innovation on carbon dioxide emission intensity from the dual perspectives of direct impact and spatial spillover.

Material and Methods

Measurement Model

According to prior study, control variables have included the advanced degree of industrial structure, the intensity of environmental regulation, and the energy structure [15, 16]. The impact of environmental regulation on carbon emissions is mainly divided into two viewpoints, one is the "Environmental Porter Hypothesis", that is, appropriate environmental regulation can reduce carbon emissions [17]. The other is the "green paradox", that is, the purpose of reducing emissions Environmental regulation may instead lead to an increase in carbon emissions [18]. In order to examine whether the intensity of environmental regulation has a nonlinear effect on the intensity of regional carbon emissions, this article proposes to add the quadratic term of environmental regulation into the measurement model, thereby fulfilling model (1):

$$\begin{aligned}\ln CEI_{it} &= \beta_1 Innq_t + \beta_2 IS_{it} + \beta_3 FDI_{it} + \beta_4 RE_{it} \\ &+ \beta_5 RE_{it}^2 + \beta_6 EC + C + \mu_t + \varepsilon_{it}\end{aligned} \tag{1}$$

In the formula, i and t denote the region and time, CEI indicates the intensity of CO_2 emissions, Inno symbolizes technological innovation, IS signifies the degree of advanced industrial structure, and FDI represents the level of foreign investment; ER and ER^2 denote the intensity of environmental regulations and their quadratic terms, respectively; μ represents the regional fixed effect; and ε represents the random error term.

Due to the fluidity of carbon dioxide emissions and the spread of technological innovations, a region's carbon emission intensity is influenced not only by its own economic activity but also by neighboring regions, showing a geographical spillover effect. Therefore, this study established a Spatial Durbin Model, as shown in (2), which has the advantage of incorporating spatial factors into the econometric analysis framework, while taking into account the spatial correlation between the explained variable and explanatory variable, and can significantly reduce the estimation error due to geographical interaction effects. In addition, a more significant advantage of the Spatial Durbin Model is that it can deal with spatial effects between variables, which include direct effects and spillover effects. Spatial effects are able to visualise the spatial interplay and spatial structure of observations in the Spatial Durbin Model. In this study, the direct effect can reflect the impact of changes in technological innovation on the region's carbon emission intensity, and the spillover effects can reflect the changes in carbon emission intensity in neighbouring geographic areas caused by changes in technological innovation in the region.

$$\ln CEI_{it} = \rho\sum_{j\neq 1}^{N} W_{ij}C_{jt} + \beta_1 Inno_{it} + \beta_2 IS_{it} + \beta_3 FDI_{it} + \beta_4 RE_{it} + \beta_5 RE_{it}^2 + \beta_6 EC_{it} + \beta_7\sum_{j\neq i}^{N} W_{ijt} Inno_{it} + \mu_i + \varepsilon_{it} \quad (2)$$

As shown in formula (2), W is the spatial weight matrix, which quantifies the degree of spatial individuals' mutual dependency and correlation. The remaining variables have the same meaning as those in the formula (1). This article makes use of the Rook adjacent space weighting matrix W, which means that if two regions share a border, $W_{ij} = 1$, otherwise $W_{ij} = 0$.

Variable Description

Table 1 summarizes the explained variables, explanatory variables, and control variables employed in the empirical model. Because China does not publicize its CO_2 emissions directly, and CO_2 emissions are mostly caused by the combustion of fossil fuels. As a result, this article employs the approach outlined in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories to determine the total CO_2 emissions in various areas. Formula (3) illustrates the calculation method:

$$CE = \sum_{i=1}^{8} CE_i = \sum_{i=1}^{8} E_i * NVC_i * CEF_i * COF_i * \frac{44}{12} \quad (3)$$

CE denotes a region's total CO_2 emissions, whereas i represents different forms of energy consumption, including coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas. E denotes the amount of energy expended. The abbreviations NVC, CEF, and COF represent the calorific value, carbon content, and oxidation factor of energy, respectively. The specific values are obtained from the 2006 IPCC Guidelines for National Greenhouse Gas Inventory and the China Greenhouse Gas Inventory Research.

Data Sources and Variable Processing

To assure the accuracy and availability of empirical data, this article conducts empirical analysis on panel data from 2003 to 2018 for 30 provinces in China (excluding Macau, Hong Kong, Taiwan, and Tibet). The sample data originates through the National Bureau of Statistics of China and the Wind database. Interpolation and average growth rate approaches are used to fill in certain missing variables. Simultaneously, using 2003 as the base year, each region's yearly nominal GDP will be deflated. To account for heteroscedasticity, the CO_2 emission intensity is processed in logarithm. Table 2 summarizes the descriptive statistics for the explanatory variables, explained variables, and control variables employed in the econometric model.

Results and Discussion

Spatial Correlation Test

Moran's I index was calculated to determine whether there is spatial autocorrelation in CO_2 emission strength. The following is the calculating formula:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}(X_i - \bar{X})(X_j - \bar{X})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}} \quad (4)$$

In the formula (4), $S^2 = \frac{1}{n}\sum_{j=1}^{n}(X_i - \bar{X})^2$, $\bar{X} = \frac{1}{n}\sum_{j=1}^{n} X_i$, Xi represents the observed value of the region, and w_{ij} represents the numeric elements in the space matrix.

Table 1. Variable and indicator description.

Index	Measure
CO_2 Emission Intensity(CEI)	$\frac{\text{Total carbon emission}}{\text{Actual GDP}}$
Technological Innovation (Inno)	Internal expenditure of R&D per capita
High-level Industrial structure (IS)	$\frac{\text{The tertiary industry output value}}{\text{GDP}}$
Environmental regulation (ER)	$\frac{\text{Industrial pollution control investment completed}}{\text{Industrial output value}}$
Foreign direct investment (FDI)	$\frac{\text{Actual utilization of foreign direct investment}}{\text{GDP}}$
Energy structure (ES)	$\frac{\text{Coal consumption}}{\text{Total energy consumption}}$

Table 2. Statistical description of variables.

Variable	Sample size	Min	Max	Average	Standard deviation
lnCEI	480	-0.926	2.847	1.173	0.664
Inno	480	14.961	8685.098	703.358	1094.835
IS	480	0.529	4.348	1.022	0.549
RE	480	0.036	2.855	0.411	0.340
FDI	480	0.0103	10.496	2.443	1.962
ES	480	0.029	0.903	0.587	0.174

Table 3. Moran's I test of CO_2 emission intensity.

Year	2003	2004	2005	2006	2007	2008	2009	2010
Moran I	0.181** (2.115)	0.250*** (2.727)	0.270** (2.882)	0.269*** (2.872)	0.308*** (3.236)	0.336*** (3.488)	0.306*** (3.210)	0.318*** (3.370)
Year	2011	2012	2013	2014	2015	2016	2017	2018
Moran I	0.305*** (3.397)	0.299*** (3.322)	0.281*** (3.158)	0.284*** (3.183)	0.266*** (3.023)	0.265*** (2.963)	0.234*** (2.773)	0.237*** (2.816)

Moran's I indexes from 2003 to 2018 are demonstrated in Table 3.

Table 3 demonstrates that the Moran index of carbon dioxide emission intensity is larger than zero 0 in each location. It is significant at the 5% level in 2003 and 2005, and at the 1% level in the subsequent years. This shows that the intensity of a region's CO_2 emissions will be positively impacted by the intensity of nearby regions' CO_2 emissions. Due to the natural flow of CO_2, frequent trade exchanges, similar resource reserves, and proximity of industrial transfer, places with similar geographical locations exhibit a positive spatial correlation [19]. As a result, spatial correlations between neighboring regions should be taken into account during the empirical analysis; otherwise, model estimates may be biased.

Regression Results

The estimation results for models (1) and (2) are shown in Table 4. The direct, indirect, and total impacts of each explanatory variable are listed in Table 5. According to Table 4, after accounting for geographical variables, the model's goodness of fit rose from 72% to 79%. The spatial regression coefficient ρ is statistically significant at the 1% level, demonstrating that CEI between provinces exhibits a strong spatial correlation, confirming the need of reintroducing the spatial model. The SDM regression findings indicate that Inno, HS, and FDI all have the ability to diminish CEI, whereas RE has an inverted "U"-shaped nonlinear influence on CEI.

The entire effect of Inno on CEI is then split into direct and indirect effects. The direct effect of Inno on CEI is -0.000125, and the significance test at the 5% level reveals that technological innovation has a strong direct promotion effect on reducing the region's CO2 emission intensity [20]. Technological innovation can reduce regional carbon dioxide emissions by

Table 4. Model estimation results.

	(1)	(2)
ρ		0.508*** (4.77)
Inno	-0.000151*** (-7.94)	-0.000117** (-2.19)
IS	-0.229*** (-5.60)	-0.114** (-2.08)
RE	0.430*** (7.43)	0.265*** (5.19)
RE^2	-0.125*** (-4.74)	-0.0806*** (-5.72)
FDI	-0.0174* (-2.40)	-0.0244** (-2.09)
ES	1.364*** (12.41)	0.630 (1.62)
Wx Inno		0.00000513 (0.11)
Cons	0.613*** (7.19)	
R^2	0.72	0.79
Log-pseudolikelihood		298.45
Sample size	480	480

Note: The Z value is in parentheses, *, **, *** indicate that it has passed the significance tests at the 10%, 5%, and 1% level respectively.

Table 5. The direct, indirect and total effects of SDM.

	Direct effect	Indirect effect	Total effect
Inno	-0.000125** (-2.32)	-0.000107** (-2.13)	-0.000232*** (-3.18)
IS	-0.128** (-2.50)	-0.112* (-1.82)	-0.240** (-2.36)
ER	0.290*** (5.05)	0.265** (2.15)	0.555*** (3.59)
ER^2	-0.0880*** (-5.34)	-0.0818** (-1.99)	-0.170*** (-3.28)
FDI	-0.0291** (-2.00)	-0.0284 (-1.32)	-0.0575* (-1.66)
ES	0.674 (1.64)	0.531 (1.57)	1.205* (1.73)

Note: The t value is in parentheses, *, **, *** indicate that it has passed the significance tests at the 10%, 5%, and 1% level respectively.

improving the utilization efficiency of traditional fossil energy, accelerating the production of renewable and clean energy, optimizing the industrial structure, and upgrading carbon capture and storage technologies. This is consistent with the research of Luo et al., endogenous innovation is of great significance for reducing China's carbon dioxide emissions [21]. Enhancing technological innovation capability may help accelerate the growth of industrial informatization, modernization, and intelligence, as well as significantly enhance the efficiency of energy resource consumption [22]. Simultaneously, increased innovation capacity encourages the flow of production factors to low- or even zero-carbon industries such as artificial intelligence, the Internet, and smart transportation, reduces economic development's reliance on natural resources, and thus lessens the intensity of CO_2 emissions [23]. Meanwhile, the indirect effect of innovation on CEI is -0.000107, and the significance test at the 5% level indicates that independent innovation in neighboring regions reduces the region's CO_2 emission intensity, whilst technological innovation has a significant negative spatial spillover effect on CO_2 emission intensity. This is in line with the views of Long et al., who believe that strengthening the technology innovation capability and expanding the knowledge spillover of innovation technology in various regions of China can effectively reduce carbon dioxide emissions [24]. According to Paul Romer's endogenous growth theory, knowledge, like labour and capital, is an important factor of production, and knowledge has spillover effects, and technological innovation driven by knowledge accumulation plays an important role in driving economic growth. With rapid socio-economic development, trade exchanges, labour flows, knowledge sharing and technology exchanges between regions have become more frequent, and contemporary industries and services are showing a trend of agglomeration. Consistent with Long et al.'s view that intra-regional industrial cooperation can enhance knowledge spillovers in different regions of China [25]. The region's scientific and technological achievements, such as the development of advanced manufacturing technology and clean energy, can overflow to neighboring regions via the industrial chain's upstream and downstream linkage and diffusion effects, increasing the CO_2 emission efficiency of adjacent areas while decreasing the CO_2 emission intensity of surrounding areas [26]. Specifically, when the region achieves the effect of energy conservation and emission reduction through technological innovation, the exchange and cooperation between the surrounding regions and the region in advanced technology, professional knowledge and management experience will continue to be strengthened, and the awareness of innovation and low-carbon awareness will also continue to increase. In order to achieve the organic unity of economic and environmental benefits, the surrounding areas will learn and introduce advanced low-carbon production technologies in the region, and make innovations on this basis, thereby reducing the intensity of carbon emissions. As pointed out by Chen et al., technological innovation promotes green and low-carbon development through knowledge spillovers such as R&D sharing, human capital training, and industrial chain collaboration [27]. Technological innovation has both direct and indirect negative impacts on the intensity of CO_2 emissions. Thus, the cumulative effect of technological innovation on CO_2 emissions is -0.000232, which exceeds the 1% significance threshold. Thus, technological innovation has the potential to significantly reduce the intensity of CO_2 emissions.

When control variables are taken into account, the overall effect of industrial structure upgrading on CO_2 emission intensity is negative, with both direct and indirect effects. On the one hand, an advanced industrial structure enables the development of high-tech industries and contemporary service industries, as well as the reduction of CO_2 emissions intensity through the elimination of high-emission businesses [28, 29]. On the other hand, through the impact of industrial linkage and agglomeration, an advanced industrial structure can help mitigate the CO_2 emission intensity of surrounding areas [30]. Environmental regulation has a cumulative influence on CO_2 emission intensity in the form of an inverted "U" shape that climbs and then drops [31-33]. The inflection point is preceded by a "green paradox" effect, in which fossil energy companies predict stricter environmental regulations in the future and increase their near-term energy production, leading to an increase in CO_2 emissions. After the inflection point, there is a " emission reduction" effect, which is consistent with the view of "Environmental Porter hypothesis" that appropriate environmental regulation can reduce carbon emission intensity. Environmental regulation to the enterprise signal potential green technology improved, if the enterprise existing green technology is not accord with the requirement of environmental regulation, enterprise through innovation to promote production technology progress and environmental emissions technology upgrading, improve the ability of pollution control, so as to offset the rising cost of environmental regulation brings to enterprises, at the same time of improve enterprise productivity and competitiveness, Reduce carbon dioxide emissions [17]. Foreign direct investment has a large negative influence on CO_2 emission intensity both directly and indirectly, while the indirect effects are insignificant. Foreign direct investment has increased the flow of regional capital, talent, technology, and other elements, hence increasing labor productivity and CO_2 emission efficiency [34]. As was pointed by Twum et al., FDI plays an important role in improving environmental efficiency [35]. All three effects of a coal-based energy consumption structure on CO_2 emission intensity are positive, but the direct and indirect effects were not significant. At the moment, coal consumption continues to account for a significant share of China's energy consumption structure, while clean, diverse, and efficient transformation of the energy consumption structure has not yet occurred. As pointed out by Dauda et al., renewable energy consumption has a positive effect on reducing CO_2 emissions [36]. It is vital to strengthen the function of energy structure optimization in boosting China's low-carbon economy's sustainable growth.Conclusions

The SDM is used to reach the following conclusions: regional spatial CO_2 emissions have a positive spatial spillover effect; technological innovation can not only significantly reduce regional carbon emissions, but also has a negative spillover effect on neighboring regions' carbon emission intensity, thereby dramatically reducing the CO_2 emissions of neighboring provinces. Additionally, advanced industrial structure and foreign direct investment can substantially decrease total CO_2 emission intensity; environmental regulations have an inverted "U" shape effect on total CO_2 emission intensity; and coal-based energy consumption structure has a positive effect on total CO_2 emission intensity.

This article makes five policy recommendations based on the empirical findings. To begin, emphasizing the role of technological innovation in the process of CO_2 emission reduction [37]. All regions should continue to invest in technological innovation in order to create a virtuous cycle of technological advancement and green growth. Meanwhile, it is essential to fully exploit the geographical spillover impact of technological innovation on carbon emissions and to widen the scope of multi-regional collaboration between governments and businesses [10]. In eligible cities, low-carbon pilot initiatives will be built, and the pilot cities' leadership and demonstration impacts on surrounding areas will be leveraged. The objective of lowering carbon emissions will be accomplished through a combination of direct and spatial spillover effects. Second, concentrating on industrial structure optimization. All regions should make reasonable progress toward industrial restructuring, expanding emerging strategic sectors and high-end service industries, and reducing economic and social development's reliance on fossil fuels [38]. Green technology transition should be facilitated for industries with high energy consumption and massive emissions, and tax and other measures should be implemented to compel firms to modify their production processes. Third, optimizing the foreign investment structure. To lower China's CO_2 emission intensity, various regions may need to depend on foreign capital. However, they cannot continue to rely on natural resources and inexpensive labor to do so. They should attract foreign capital to invest in new energy, new materials, productive services, and a series of high-tech and knowledge-intensive sectors that are pollution-free and emit minimal amounts of carbon dioxide [39]. Fourth, optimizing the structure of the energy. All regions should work to minimize their reliance on a single energy structure dominated by fossil fuels, accelerate energy pricing reform, and aggressively develop renewable energy [40]. Fifth, raising the rigor of environmental restrictions as necessary. All regions in China should appropriately strengthen environmental supervision and give enterprises certain compensation for pollution control, so as to reduce the innovation cost of enterprises and encourage enterprises to innovate and optimize production processes [41].

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Conflict of Interest

The authors declare no conflict of interest.

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