How does renewable energy technology innovation affect manufacturing carbon intensity in China?

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Abstract
Renewable energy technology innovation (RETI) is a crucial driver for promoting the manufacturing green transformation. However, few studies have explored the impact of RETI on manufacturing carbon intensity (MCI) from the perspective of spatial spillover and regional boundary. Based on the manufacturing panel data of 30 provinces in China from 2006 to 2020, this study examines the mechanism, spatial spillover effects, regional boundaries, and industry heterogeneity of RETI on MCI using the spatial Durbin model. The results show that (1) RETI significantly inhibits local and neighboring MCI. (2) The spatial spillover effect of RETI on MCI has a significant regional boundary, which is inhibitory in the range of 800 km and shows a significant “half-decay” characteristic at 400 km. However, in the range of 800 to 1400 km, RETI significantly promotes neighboring MCI. (3) The inhibitory effect of RETI on MCI has temporal and regional heterogeneity, which gradually increases over time, and the effect from high to low is central, west, and east. (4) RETI has a significant inhibitory effect on MCI of pollution-intensive, high-income, capital-intensive, and labor-intensive manufacturing in local and neighboring areas, but it has a more negligible effect on non-pollution-intensive, low-income, and technology-intensive MCI. The findings provide empirical evidence for formulating targeted and differentiated policy in manufacturing low-carbon development.

Keywords Renewable energy technology innovation · Manufacturing carbon intensity · Spatial spillover effect · Regional boundary

Introduction
Controlling greenhouse gas emissions is a crucial way to deal with climate change. Nowadays, the current situation of international carbon emission reduction remains grim (Bekun et al. 2019). In 2020, global carbon emissions reached 32.28 billion tons, China’s carbon emissions reached 9.90 billion tons, accounting for 30.7% of the worldwide total, and China became a major carbon emitter in the whole world (British Petroleum, 2021; Ma et al. 2019). As the world’s largest developing country, China proactively takes responsibility for carbon emission reduction. President Xi Jinping has clearly stated that strive to reach the carbon peak by 2030 and achieve carbon neutrality by 2060. By 2030, carbon dioxide emissions per unit of GDP will be 65% lower than that in 2005, and non-fossil energy will account for about 25% of primary energy consumption, demonstrating China’s determination to combat climate changes. More importantly, a series of important meetings, such as the Fifth Plenary session of the 19th CPC Central Committee, the 2020 Central Economic work Conference, and the National two sessions in 2021, have made essential arrangements for promoting carbon peak and carbon neutrality. Undeniably, the strengthening of carbon emission reduction has gradually risen to the national strategic level in China.

As the pillar industry of China’s economy, the manufacturing industry has developed rapidly since the reform and opening up (Hang et al. 2019). In 2020, the manufacturing added value in China reached 26.6 trillion yuan, accounting for about 30% of the world. China has maintained its position as the world’s largest manufacturing country for 11 consecutive years. However, China’s manufacturing industry has made remarkable achievements, but it also brought
a series of problems such as resource depletion, environmental pollution, and greenhouse effect (Hang et al. 2019; Wang et al. 2018a; Wang et al. 2018b; Li et al. 2019a; Li et al. 2019b). According to statistics, from 2006 to 2020, manufacturing energy consumption increased by 7.28% from 2.84 million tons to 5.74 million tons, and manufacturing carbon emissions increased by 3.09% from 2.51 million tons to 3.59 million tons. In 2020, manufacturing sector accounts for 39.46% of the total energy consumption and 36.29% of the total carbon emissions in China. The rapid growth of energy consumption has brought significant challenges to carbon emissions governance, so it is urgent for manufacturing to reduce carbon emissions. To alleviate the tremendous pressure on China’s energy conservation and emission reduction in manufacturing sectors (Lin and Chen, 2015), the strategic plan of “Made in China 2025” promulgated by the State Council has proposed to promote the transformation and upgrading of the traditional manufacturing industry to green, intelligent, and high-end, and set the goal of reducing energy consumption in the manufacturing industry by 18% and carbon intensity by 40% by 2025 compared to 2015. The National Energy Administration has proposed that renewable energy becomes the primary source of incremental energy consumption during “the 14th five-year plan” period, achieving the strategic goal of 20% of non-fossil energy consumption by 2030. Also, it stressed the need to vigorously promote the nearby utilization of distributed renewable electricity, heat, and gas, combined with new technologies such as energy storage and hydrogen energy to increase the proportion of renewable energy in the energy supply. These measures to develop renewable energy provide possible pathways for manufacturing low-carbon development and global climate governance.

Energy technology innovation, as a critical driver of renewable energy development, is a vital way to accelerate the energy transition and low-carbon development (Lin and Zhu, 2019). On the one hand, fossil energy technology innovation helps improve energy efficiency and then restrain the overall growth of energy consumption (Wang and Zhu, 2020). On the other hand, renewable energy technology innovation (RETI) can significantly reduce the cost of energy production and consumption, which is conducive to the large-scale development of renewable energy, further improving the energy structure and mitigating climate change (Irandoust, 2016). With the emergence of a new round of energy technology revolution, renewable energy scientific and technological achievements are constantly emerging. All countries worldwide regard energy technology as a breakthrough in green industrial transformation under the scientific and technical revolution and continuously strengthen technological innovation in renewable energy. Without exception, China is also increasing the importance of renewable energy technological innovation. China has actively supported energy technological innovation and promoted wind power and photovoltaic construction. In 2020, wind and solar capacity installed in China was 450 million kW, accounting for about 26% of the total, more than one-third of the global total. Wind power grid-connected capacity has increased fifteen times in 10 years, and photovoltaic grid-connected capacity has increased more than a thousand times in 10 years. As a result, the rapid development of wind power and photovoltaic power generation has led China to become the world’s largest and fastest-growing country in terms of new energy generation. Specifically, China’s renewable energy consumption has increased by 15%, accounting for 25% of global renewable energy demand and 36% of global growth, respectively (British Petroleum, 2021). Energy technology innovation is conducive to promoting renewable energy consumption, advancing energy transformation, and providing technical support for manufacturing green transformation and carbon emission reduction, which is of significance and theoretical and practical implications for China to achieve the goal of carbon peak and carbon neutrality.

With the increasing problems such as the global energy crisis and climate warming, the topic of relying on renewable energy technology innovation to reduce carbon emissions has attracted wide attention in academic areas (Khan et al. 2021; Wang et al. 2018a, b). The existing studies on the relationship between RETI and carbon emissions are mainly divided into three types:

1. Emission reduction effect—Wang and Zhu (2020) verified that RETI has a significant carbon emission reduction effect based on the spatial perspective, while nonrenewable energy technology innovation has no significant impact on carbon emissions. Ulucak (2021) took the data of the USA and China as the sample and empirically found that RETI significantly reduces the carbon emissions of the USA but not in China. Lin and Zhu (2019) found that RETI significantly lowers carbon emission agglomeration and contributes to global climate governance. Wahab et al. (2020) used the G-7 countries dataset to confirm that RETI and export commodities effectively reduce carbon emissions from international trade, while imported commodities increase carbon emissions. Guo et al. (2011) found that energy technology innovation and consumption structure adjustment effectively reduce regional carbon emissions.

2. Non-linear effect—Lin and Zhu (2019) found that the carbon reduction effect of RETI is significantly different among energy consumption structures. When the energy consumption is centered on coal, the carbon reduction effect of RETI is gradually weakened. Still, when the proportion of renewable energy increases, the
carbon reduction effect of RETI is gradually enhanced. Bai et al. (2020a) found that with rising income inequality, the effect of RETI on reducing carbon emissions is steadily weakening. When a certain threshold is exceeded, RETI promotes carbon emissions. He et al. (2021) found that the carbon reduction effect of RETI was affected by market factors, and the decrease of the market segmentation level and the increase of market potential contributed to improving the carbon reduction effect of RETI.

(3) No effect—Chen and Lei (2018) used the global dataset of 30 countries and found that there is no significant correlation between RETI and carbon emission reduction, which is because the proportion of renewable energy is low caused by global energy consumption which is still dominated by fossil energy. However, some scholars have argued that although energy technology innovation can improve energy efficiency and reduce carbon emissions, the improvement of energy efficiency may bring a “rebound effect” and lower the implicit price of energy, which leads to more energy consumption demand, thus offsetting the expected effect of technology emission reduction (Herring and Roy, 2007; Gillingham et al., 2016; Liu et al., 2018, 2019; Gu et al. 2019).

In summary, although existing studies have extensively explored the relationship between RETI and carbon emissions, the following insufficiencies remain: first, from the point of the research object, the existing studies are mainly conducted on the macro-level such as national or inter-provincial level, and lack the exploration of meso-scale industries, especially the manufacturing sector. In fact, the manufacturing sector is the main consumer of fossil energy and produces nearly half of China’s carbon emissions (Lin and Chen, 2020). Therefore, it is essential to actively develop renewable energy and explore the effect between RETI and manufacturing carbon emissions for climate governance and energy poverty eradication in China and globally. Second, in terms of the research perspective, some studies have analyzed the spatial spillover effect of RETI on carbon emissions in consideration of the spatial diffusion characteristics of carbon emissions (Wang and Zhu, 2020). However, they ignore the effects of spatial distance and regional administrative boundaries, especially the impact that technological innovation can be hindered by geographic distance and geopolitical boundaries, reducing its knowledge spillover (Jang et al. 2017; Carlino and Kerr, 2015). In other words, existing studies have not explored the impact of RETI on carbon emissions based on spatial distance attenuation and regional boundary perspectives. Finally, previous studies have mostly adopted the number of renewable energy technology patents to characterize RETI (Grafström, 2018; Wang and Zhu, 2020; Ren et al. 2021), ignoring the diffusion effect and time lag in the process of patenting from R&D to application, and the depreciation issues of obsolete technologies in the context of the continuous development of emerging technologies, which may lead to estimation deviation of the results (Popp, 2002; Lin and Zhu, 2019; Bai et al. 2020a; He et al. 2021).

Therefore, using manufacturing data of 30 provinces in China from 2006 to 2020, this paper examines the impact mechanisms, spillover effects, attenuation boundaries, and industry heterogeneity of RETI on manufacturing carbon intensity (MCI). Compared with previous studies, the possible marginal contributions are as follows: (1) based on the meso-scale level, the study is sunk to the manufacturing industry to explore the relationship between the RETI and MCI. This paper attempts to provide empirical references for developing targeted, differentiated policies in manufacturing carbon emission reduction and low-carbon development. (2) From the perspective of spatial spillover and regional boundary, the spatial impact effect of RETI on MCI is examined, which contributes to filling the gap of related studies and promoting cross-regional cooperation of RETI in manufacturing carbon emission reduction. (3) Taking technology diffusion and depreciation effects into full consideration, a more scientific and reasonable RETI index is constructed by adopting the method of Popp (2002), minimizing estimation bias, and striving for objectivity and robustness of research results. (4) Based on the perspective of industry heterogeneity, this paper further investigates the spatial heterogeneity of RETI on MCI of manufacturing seven types and provides new ideas for carbon emission reduction in manufacturing subsectors.

The rest of the paper is as follows: the “Methodology and data” section describes methodology and data; the “Empirical results” section analyzes empirical results; the “Conclusions and discussions” section presents conclusions and recommendations.

Methodology and data

Model selection

Spatial correlation

Global Moran’s I Moran’s I test is used to identify the spatial correlation of MCI and RETI in this paper. Referring to Geniaux and Martinetti (2018), the calculation formula is as follows:
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\[ I_t = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (x_i - \bar{x}) (x_j - \bar{x}) / \sum_{i=1}^{n} (x_i - \bar{x})^2 \]  

(1)

where \( x_i \) and \( x_j \) are the observed values, \( n \) is the sample number, \( \bar{x} \) is the sample mean, and \( W_{ij} \) is the spatial weight matrix.

**Spatial weighting matrix (W)** Since the selection of the spatial weight matrix may cause estimation bias (Xu et al., 2019), this paper uses the adjacency matrix, geographic distance matrix, and economic distance matrix to test the spatial correlation. The adjacency matrix reflects the spatial connection between two adjacent units (Morton et al., 2018). It can be defined as follows:

\[ W_1 = \begin{cases} 1 & \text{if provinces } i \text{ and } j \text{ are adjacent} \\ 0 & \text{if provinces } i \text{ and } j \text{ are not adjacent} \end{cases} \]  

(2)

The geographical distance weight matrix is constructed using the reciprocal distance between provinces in this paper (Wang and Zhu, 2020). It can be defined as follows:

\[ W_2 = \begin{cases} 1/d_{ij} & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases} \]  

(3)

where \( d_{ij} \) is the geospatial distance between provinces \( i \) and \( j \), which is calculated from the latitude and longitude of the capital city.

The economic distance matrix is constructed using the inter-provincial economic distance (Han et al. 2018) and is defined as follows:

\[ W_3 = \begin{cases} 1/(\bar{Y}_i - \bar{Y}_j) & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases} \]  

(4)

where \( \bar{Y}_i - \bar{Y}_j \) is the average value of per capita GDP in the province \( i \) and \( j \) from 2006 to 2020.

**Spatial econometric model**

The IPAT model of Ehrlich and Holdren (1971) is concerned with the relationship between human activities and the ecological environment, which is often used to discuss the effect of the population \((P)\), affluence \((A)\), and technology \((T)\) on the environment \((I)\), as shown in Formula (5). Since the regression results caused by spatial correlation are biased, the revised STIRPAT model (Anselin, 1989) is used to determine the impact of RETI on MCI, as shown in Formula (6):

\[ I = PAT \]  

(5)

\[ I_{it} = a_i P_{it}^b A_{it}^c T_{it}^d e_{it} \]  

(6)

where \( I_{it} \), \( P_{it} \), \( A_{it} \), and \( T_{it} \) represent the environment \((I)\), population size \((P)\), affluence \((A)\), and technology \((T)\) of the \( i \) province in \( t \) year, respectively; \( a_i \) is the model coefficient; \( b, c, \) and \( d \) are the parameters to be estimated; and \( e_{it} \) stands for the random disturbance. In order to test the effect of RETI on MCI, referring to the previous studies, important factors affecting the environment such as the population size \((POP)\), industrial structure \((IS)\), energy consumption structure \((ES)\), and human capital \((HC)\) are incorporated into the model based on previous research results (Hao et al. 2016; Dong et al., 2019; Li and Mao, 2020; Yuan et al. 2020) and logarithmic processing is carried out to obtain model (7):

\[ \ln MCI = \lambda_0 + \lambda_1 \ln RETI_{it} + \lambda_2 \ln POP_{it} + \lambda_3 \ln IS_{it} + \lambda_4 \ln HC_{it} + e_{it} \]  

(7)

where MCI represents the manufacturing carbon emissions intensity; \( \lambda_0 \) is the constant; \( \lambda_1, \lambda_2, \lambda_3, \lambda_4 \), and \( \lambda_5 \) represent the coefficients to be estimated; and \( e_{it} \) stands for the random error.

In order to empirically examine the spatial spillover effect and attenuation boundary of RETI on MCI, the spatial Durbin model (SPDM) is constructed as follows:

\[ \ln MCI_i = \rho \sum_{j=1}^{n} W_{ij} \ln MCI_j + \delta_1 \sum_{j=1}^{n} W_{ij} \ln RETI_{ij} + \delta_2 \sum_{j=1}^{n} W_{ij} \ln POP_{ij} + \delta_3 \sum_{j=1}^{n} W_{ij} \ln IS_{ij} + \delta_4 \sum_{j=1}^{n} W_{ij} \ln ESP_{ij} + \delta_5 \sum_{j=1}^{n} W_{ij} \ln HC_{ij} + u_i + e_{it} \]  

(8)

where \( u_i \) is the individual fixed effect; and \( e_{it} \) stands for the random error.

**Decomposition of direct and indirect effects**

This paper uses partial differentiation to decompose the direct and indirect effects and further explore the spatial spillover effects of RETI on MCI. Based on Le Sage and Pace (2009), the SPDM model is converted as follows:

\[ Y_{it} = (I_{NT} - \rho W_{ij})^{-1} X_{it} (I_{NT} \beta + W_{ij} \delta) + [I_{NT} - \rho W_{ij}]^{-1} e_{it} \]  

(9)

where \( Y \) is the vector of \( N \times 1 \) dimensional dependent variable and \( I_{NT} \) represents \( N \times T \) dimensional matrix. The partial derivative of \( X \) is as follows:
\[ MEM = \frac{\partial Y_{it}}{\partial X_{it}} = (I_{NT} - \rho W_{ij})^{-1}(I_{NT} \beta + W_{ij} \delta) \]  

(10)

\[ ME_{\text{Total}} = \frac{1}{NT} \text{Trace}(MEM) \]

\[ ME_{\text{Direct}} = \frac{1}{NT} \text{Trace}(MEM) \]  

\[ ME_{\text{Indirect}} = ME_{\text{Total}} - ME_{\text{Direct}} \]  

(11)

Data

Explained variable: manufacturing carbon intensity (MCI)

Based on data availability and authenticity, this paper adopts the carbon emission coefficient method to calculate manufacturing carbon emissions. According to the methodology of IPCC (2007), manufacturing carbon emissions is measured as follows:

\[ MCE_{ij} = \sum_{i}^{30} \sum_{j}^{17} MCE_{ij} = \sum_{i}^{30} \sum_{j}^{17} F_{ij} \times CV_{j} \times CEF_{i} \times COF_{j} \times \frac{44}{12} \]  

(12)

\[ MCI_{ij} = \frac{MCE_{ij}}{GDP_{ij}} \]  

(13)

among them, \( i = 1, 2, ..., 30 \) represents the manufacturing sector; \( j = 1, 2, ..., 17 \) denotes the type of energy; \( MCE \) is the total manufacturing carbon emission; \( F \) is the terminal fossil energy consumption; and \( CV \) represents the average low calorific value of different fossil fuels, \( CEF \) is the carbon content of the fuel, \( COF \) is the oxidation efficiency of energy, and \( 44/12 \) is the ratio of \( CO_{2} \) to carbon molecular weight. MCI represents manufacturing carbon emissions as a share of GDP.

Explanatory variable: renewable energy technology innovation (RETI)

R&D investments and the number of patents in renewable energy technology are often used to analyze RETI (Nesta et al. 2014; Irandoust, 2016; Pitelis et al. 2020; Hille and Lambernd, 2020). However, the direct adoption of the indicators may cause estimation bias as the two indicators do not consider technological depreciation and diffusion. To eliminate estimation bias, the RETI index is constructed by the knowledge stock method. According to the study of Popp (2002) and Lin and Zhu (2019), the RETI calculation formula is as follows:

\[ RETI_{it} = \sum_{s=0}^{t} RPAT_{it} \exp \left\{ -\beta_{1}(t-s) \right\} \left\{ 1 - \exp \left\{ -\beta_{2}(t-s) \right\} \right\} \]  

(14)

where \( RPAT_{it} \) represents the total number of authorized renewable energy patents in province \( i \) in period \( t \); \( \beta_{1} \) represents the depreciation rate, reflecting the decay of obsolete technologies; and \( \beta_{2} \) represents the diffusion rate of new authorized patents, reflecting the diffusion speed of innovation technologies. Referring to the study of Popp (2002), \( \beta_{1} \) and \( \beta_{2} \) are set to be 0.36 and 0.3, respectively.

This paper collects the number of renewable energy patents granted in 30 Chinese provinces (excluding Tibet), which the data originated from 2006 to 2020, and finally calculates the \( RETI_{it} \) of each province.

Control variables

(1) Population (POP). Population expansion is an important cause of increased energy consumption and air pollution, especially in developing countries (Hao et al. 2016). Therefore, the population size is incorporated into the model, the total population at the end of the year represents the population size in this paper, and its impact is expected to be positive.

(2) Industrial structure (IS). The increasing industrialization is accompanied by strong energy consumption, which increases pollutant emissions (Wen and Lee, 2020). This study measures the industrial structure in terms of the proportion of the added value of the tertiary sector to that of the secondary sector, and the coefficient sign for IS is expected to be negative.

(3) Energy consumption structure (ES). Energy consumption structure plays an essential role in strengthening environmental governance and promoting green economic transformation in China, with coal consumption contributing one-third of China’s carbon emissions (Li and Mao, 2020). Therefore, the proportion of coal consumption in total energy consumption is the proxy variable of the energy consumption structure in this paper, and its impact is expected to be positive. The coefficient sign for ES is expected to be positive.

(4) Human capital (HC). The accumulation of human capital is a crucial factor that affects economic development and environmental quality (Yuan et al. 2020). Therefore, the proportion of college students in the total population is used to express human capital in this paper, and the coefficient sign for HC is expected to be negative.
Data source

This paper selects the manufacturing panel data of 30 provinces in China (except Tibet, Hong Kong, Macao, and Taiwan) from 2006 to 2020. Data on renewable energy patents of provinces come from the Patent Search and Analysis System (PSAS) of the China National Intellectual Property Administration (CNIPA). Other data comes from China Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, and China Industrial Statistical Yearbook. The data of geographic information comes from the National Geographic Information Center. The specific variable definitions and descriptive statistics are shown in Tables 1 and 2.

Empirical results

Temporal and spatial evolution analysis

Temporal characteristics analysis

To clarify the temporal characteristics of MCI and RETI, this study plots the trend of MCI and RETI using the average values of 30 provinces in China from 2006 to 2020 (Fig. 1). MCI and RETI showed a trend of steady decline and fluctuating growth, respectively, which preliminarily confirmed the inhibitory effect of RETI on MCI. The Chinese government formulates new economic development policies and strategies every 5 years; the MCI and RETI have undergone periodic changes. During the “11th five-year plan” period (2006–2010), MCI dropped from 0.96 to 0.72, a decrease of 25%; RETI increased from 0.53 to 4.67, an increase of more than seven times. It may be closely related to the Chinese government’s proposal to speed up the revitalization of the equipment manufacturing industry and improve the capacity for independent innovation. During the “12th five-year plan” period (2011–2015), MCI decreased from 0.64 to 0.52, a drop of 18.75%. RETI increased from 7.89 to 31.49, an increase of nearly three times. It may be because the Chinese government requires the manufacturing industry to optimize its industrial structure, speed up transformation and upgrading, and change from extensive development to intensive development (Liu et al. 2017). During the “13th five-year plan” period (2016–2020), MCI dropped from 0.48 to 0.41, down 14.58%, and RETI increased from 43.95 to 60.67, an increase of 38.04%. It shows that, with the rapid development of global information technology, intelligent manufacturing has become an important development trend of manufacturing transformation, which will promote digital transformation and green and low-carbon development in the manufacturing industry.

Spatial characteristics analysis

The results show that MCI decreased obviously, showing a spatial differentiation pattern of “high in the north and low in the south” (Fig. 2). Specifically, the high MCI areas are mainly concentrated in Hebei, Shanxi, and Ningxia. The spatial range of the area with higher carbon emission intensity is significantly reduced, the proportion decreased from 30 to 16.67%, and the spatial distribution evolved from aggregated distribution to sporadic distribution. The spatial range of lower and low MCI areas gradually expanded, with the proportion increasing from 60 to 73.33%, and the spatial distribution formed a trend of extending from the eastern coastal areas to the central and western regions. It may be that the Chinese government promotes the transfer of industries to the west and central, including both high-tech industries and traditional manufacturing industries such as building materials and chemicals. The transfer of industries is accompanied to optimize its industrial structure, speed up transformation and upgrading, and change from extensive development to intensive development (Liu et al. 2017). During the “13th five-year plan” period (2016–2020), MCI dropped from 0.48 to 0.41, down 14.58%, and RETI increased from 43.95 to 60.67, an increase of 38.04%. It shows that, with the rapid development of global information technology, intelligent manufacturing has become an important development trend of manufacturing transformation, which will promote digital transformation and green and low-carbon development in the manufacturing industry.

Table 1 Variable definitions

| Symbol | Variable                        | Definition                                                                 | Unit       |
|--------|---------------------------------|---------------------------------------------------------------------------|------------|
| MCI    | Manufacturing carbon intensity  | Manufacturing carbon emissions as a share of GDP                           | t/10000 yuan|
| RETI   | Renewable energy technology innovation | Renewable energy technology innovation knowledge stock level | /          |
| POP    | Population                      | Total population at the end of the year                                   | Ten thousand |
| IS     | Industrial structure            | The proportion of the added value of the tertiary industry to the added value of the secondary industry | %          |
| ES     | Energy consumption structure    | Proportion of coal consumption in total energy consumption                | %          |
| HC     | Human capital                   | Proportion of college students in the total population                    | %          |

Table 2 Descriptive statistics

| Variables | Obs | Mean | Max | Min | S.D |
|-----------|-----|------|-----|-----|-----|
| MCI       | 450 | 0.619| 2.706| 0.008| 0.373|
| RETI      | 450 | 25.73| 291.7| 0.013| 43.87|
| POP       | 450 | 4524 | 12,624| 547.7| 2772|
| IS        | 450 | 0.122| 0.530| 0.053| 0.68|
| ES        | 450 | 0.416| 0.748| 0.008| 0.156|
| HC        | 450 | 82.02| 249.2| 3.6 | 50.34|
by the transfer of pollution, which leads to a gradual increase in MCI from east to west (Zhao et al. 2021).

The level of RETI has increased rapidly from 2006 to 2020. RETI in 2020 is more than one hundred times higher than that in 2006, showing a spatial differentiation pattern of “high in the southeast and low in the northwest,” which is consistent with the study of Bai et al. (2020a, b). Specifically, the areas with high RETI are mainly concentrated in Beijing, Shandong, Jiangsu, Shanghai, Zhejiang, and Guangdong. The areas with higher RETI are eastern coastal and surrounding areas, and the areas with lower RETI are the northwest and southwest regions. It is because the southeast coastal areas are rich in hydropower and tidal energy resources. The high level of economic development provides financial support for renewable energy and technological innovation. However, although the northwest region is rich in solar and wind energy resources, the infrastructure construction is relatively backward, hindering the development of renewable energy technology innovation in western provinces (Apergis and Payne, 2010; Wang et al. 2011). The above results indicate that both RETI and MCI have a significant and positive spatial correlation. That is, the regions with higher and lower RETI and MCI tend to be clustered, and the spatial autocorrelation gradually increases, so this paper takes into account the spatial effect to explore its influencing mechanism. Since the spatial autocorrelation results under $W_1$ are better, $W_1$ is used for empirical analysis, and $W_2$ and $W_3$ are used for the robustness tests.

**Spatial correlation analysis**

![Temporal evolution characteristics of MCI and RETI from 2006 to 2020 in China](image)

The global Moran’s index is used to test the spatial autocorrelation of MCI and RETI. To avoid the deviation caused by the selection of spatial weight matrix, adjacency matrix ($W_1$), geographical distance matrix ($W_2$), and economic distance matrix ($W_3$) are used to test the spatial autocorrelation (Table 3). The results indicate that the Moran’s $I$ of RETI in China from 2006 to 2020 is positive under the three spatial weight matrices, increasing from 0.176 to 0.326 and passing the 1% significance test. The Moran’s $I$ of MCI is positive and rising from 0.147 to 0.267, which is passing the 1% significance test under $W_1$ and $W_2$ and passing the 5% significance test under $W_3$. The above results indicate that both RETI and MCI have a significant and positive spatial correlation. That is, the regions with higher and lower RETI and MCI tend to be clustered, and the spatial autocorrelation gradually increases, so this paper takes into account the spatial effect to explore its influencing mechanism. Since the spatial autocorrelation results under $W_1$ are better, $W_1$ is used for empirical analysis, and $W_2$ and $W_3$ are used for the robustness tests.

**Estimation result analysis**

**Results of model selection**

The results of the spatial econometric model are shown in Table 4. LM test results demonstrate that SPLM and SPEM are applicable to examine the relationship between RETI and MCI. Wald and LR test prove SPDM is most suitable for exploring the influence of RETI on MCI. In addition, the Hausman test demonstrates that the fixed-effect model is better. Therefore, this study adopts the fixed-effect model of SPDM to examine the effect of RETI on MCI.

**Results of the spatial Durbin model**

The results in Table 5 demonstrate that the spatial rho of spatial fixed, time fixed, and spatial-time fixed have passed the significance test. Considering $R^2$ and Variance sigma2_e, this study selects SPDM of time fixed effect as the optimal fitting mode.

The coefficient of RETI is $-0.094$ at the significance level of 1%, indicating that RETI has a significant inhibitory effect on MCI, which is similar to the conclusion of Lin and Zhu (2019) and believes that RETI effectively reduces per capita carbon emissions in China. It may be that the improvement of RETI prompts the manufacturing industry to reduce fossil energy consumption, improve energy efficiency, and reduce MCI (Cai et al. 2020). On the other hand, the improvement of RETI may help to accelerate the large-scale development for emerging industries, reduce the dependence on the traditional high-carbon growth model, promote the green and low-carbon transformation in the manufacturing industry, and reduce greenhouse gas emissions. The coefficient of POP is $0.372$ at the significance level of 1%, indicating that POP has a significant promoting effect on MCI, which supports the conclusion of Wang and Zhu (2020). It may be because demand for energy consumption increases with the growth of population size, which brings tremendous pressure...
on manufacturing to reduce carbon emissions. The coefficient of IS is $-0.130$, which is significant at the 1% level, demonstrating that IS significantly and negatively impacts MCI. The result is consistent with the study of Zheng et al. (2018), indicating that the optimization and upgrading of the industrial structure contribute to promoting the development of emerging industries with low energy consumption and high added value and advancing energy-saving and emission reduction in manufacturing. The coefficient of ES $0.431$ at a significance level of 1%, indicating that ES has a significant positive impact on MCI, which demonstrates that the coal-based energy consumption structure is the main cause of a large number of greenhouse gas emissions (Ma et al. 2019). The coefficient of HC is $-0.352$, which is significant at the 1% level, indicating that HC has a significant inhibitory effect on MCI. This finding is similar to the conclusion of Yuan et al. (2020), which believes that HC contributes to promoting economic development and production efficiency. The improvement of human capital helps to improve the overall quality of employees, stimulate the vitality of research and innovation, and improve the efficiency of manufacturing resource allocation through technological progress, thus effectively reducing MCI.

### Table 3 Spatial autocorrelation test

| Year | Moran’s $I$ | RETI $W_1$ | RETI $W_2$ | RETI $W_3$ | MCI $W_1$ | MCI $W_2$ | MCI $W_3$ |
|------|-------------|------------|------------|------------|------------|------------|------------|
| 2006 | 0.176**     | 0.039**    | 0.370***   | 0.147**    | 0.035**    | 0.091*     |
|      | Z value     | (1.776)    | (2.130)    | (4.482)    | (1.631)    | (2.146)    | (1.362)    |
| 2007 | 0.285***    | 0.030**    | 0.479***   | 0.179**    | 0.045***   | 0.109*     |
|      | Z value     | (2.889)    | (1.974)    | (6.087)    | (1.894)    | (2.392)    | (1.532)    |
| 2008 | 0.282***    | 0.035**    | 0.450***   | 0.172**    | 0.052***   | 0.144**    |
|      | Z value     | (2.750)    | (2.053)    | (5.526)    | (1.742)    | (2.490)    | (1.811)    |
| 2009 | 0.262***    | 0.042**    | 0.383***   | 0.220**    | 0.056***   | 0.119*     |
|      | Z value     | (2.495)    | (2.196)    | (6.060)    | (2.093)    | (2.539)    | (1.514)    |
| 2010 | 0.261***    | 0.040**    | 0.366***   | 0.228**    | 0.056***   | 0.085*     |
|      | Z value     | (2.487)    | (2.134)    | (4.425)    | (2.173)    | (2.577)    | (1.595)    |
| 2011 | 0.281***    | 0.049***   | 0.361***   | 0.213**    | 0.053***   | 0.148**    |
|      | Z value     | (2.683)    | (2.437)    | (4.410)    | (2.062)    | (2.482)    | (1.825)    |
| 2012 | 0.231**     | 0.030**    | 0.311***   | 0.272**    | 0.077***   | 0.186*     |
|      | Z value     | (2.306)    | (1.926)    | (3.938)    | (2.524)    | (3.135)    | (2.183)    |
| 2013 | 0.258***    | 0.046**    | 0.316***   | 0.214**    | 0.063***   | 0.188**    |
|      | Z value     | (2.493)    | (2.337)    | (3.920)    | (2.066)    | (2.785)    | (2.224)    |
| 2014 | 0.266***    | 0.040**    | 0.344***   | 0.203**    | 0.061***   | 0.204***   |
|      | Z value     | (2.594)    | (2.210)    | (4.297)    | (1.990)    | (2.728)    | (2.404)    |
| 2015 | 0.257***    | 0.053***   | 0.343***   | 0.206**    | 0.063***   | 0.192**    |
|      | Z value     | (2.475)    | (2.538)    | (4.205)    | (2.019)    | (2.811)    | (2.283)    |
| 2016 | 0.296***    | 0.068***   | 0.286***   | 0.222**    | 0.050***   | 0.135**    |
|      | Z value     | (2.826)    | (3.008)    | (3.606)    | (2.136)    | (2.405)    | (1.699)    |
| 2017 | 0.227**     | 0.047***   | 0.351***   | 0.246**    | 0.059***   | 0.100*     |
|      | Z value     | (2.237)    | (2.378)    | (4.325)    | (2.293)    | (2.616)    | (1.319)    |
| 2018 | 0.210**     | 0.061***   | 0.278***   | 0.198**    | 0.054***   | 0.041*     |
|      | Z value     | (2.093)    | (2.801)    | (3.510)    | (1.960)    | (2.549)    | (1.320)    |
| 2019 | 0.263***    | 0.087***   | 0.288***   | 0.269**    | 0.080***   | 0.034*     |
|      | Z value     | (2.506)    | (3.489)    | (3.564)    | (2.558)    | (3.284)    | (1.543)    |
| 2020 | 0.326***    | 0.100***   | 0.297***   | 0.267***   | 0.078***   | 0.003*     |
|      | Z value     | (3.081)    | (3.947)    | (3.719)    | (2.534)    | (3.234)    | (1.353)    |

### Table 4 Identification test of spatial panel econometrics model

| Tests                  | Statistics | Tests                  | Statistics |
|------------------------|------------|------------------------|------------|
| LM (lag) test          | 30.120***  | Wald.spatial_lag       | 37.950***  |
| Robust LM (lag) test   | 3.187**    | LR.spatial_lag         | 37.580***  |
| LM (error) test        | 46.348***  | Wald.spatial_error     | 39.140***  |
| Robust LM (error) test | 19.415***  | LR.spatial_error       | 38.560***  |
| Hausman test           | 21.230***  |                        |            |
spatial interaction coefficients of IS, ES, and HC are 0.092, 0.534, and 0.221 at the 5% significance level, respectively, indicating that these variables have significant positive spatial effects on MCI. However, there may be some bias in the regression results of point estimation, so this study uses the method of Lesage and Pace (2009) to decompose

Fig. 2  Spatial characteristics of MCI and RETI from 2006 to 2020 in China
low-carbon transformation. The indirect effect coefficient of industry on fossil energy and promoting the manufacturing adjustment, reducing the dependence of the manufacturing technology is conducive to the manufacturing energy structure MCI. It may be because the development of local clean tech-

coeeficient of RETI is 1% level, indicating that RETI significantly suppresses local RETI and its further decomposition, shown in Table 6. The direct effect coefficient of ES are 0.493 and 0.960, respectively, which is significant at the 1% level, indicating that ES has a promoting significant impact on local and neighboring MCI. Although the manufacturing industry strives to promote clean energy substitution, low-cost coal is still the dominant fuel for manufacturing energy consumption. The dependence of local and neighboring manufacturing industries on coal remains high, which puts enormous pressure on manufacturing to reduce carbon emissions (Li and Mao, 2020). The direct effect coefficient of HC is −0.341 at a significance level of 1%, and the indirect effect

### Table 5 Estimation results of the spatial Dublin model

| Variables | Spatial fixed | Time fixed | Spatial-time fixed |
|-----------|--------------|------------|--------------------|
| lnRET1    | −0.001       | −0.094***  | −0.012             |
|           | (−0.07)      | (−4.80)    | (−0.75)            |
| lnPOP     | 0.442**      | 0.372***   | 0.348***           |
|           | (2.50)       | (5.72)     | (1.95)             |
| lnIS      | −0.024       | −0.130***  | −0.011             |
|           | (−0.74)      | (−5.84)    | (−0.29)            |
| lnES      | 0.073        | 0.431***   | 0.075              |
|           | (1.56)       | (5.27)     | (1.61)             |
| lnHC      | −0.245***    | −0.352***  | −0.232***          |
|           | (−3.12)      | (−6.17)    | (−2.97)            |
| W×lnRET1  | −0.049***    | −0.084***  | 0.017              |
|           | (−2.85)      | (−2.59)    | (0.49)             |
| W×lnPOP   | −0.050       | −0.406***  | −0.111             |
|           | (−0.18)      | (−3.51)    | (−0.39)            |
| W×lnIS    | 0.054        | 0.092***   | 0.157***           |
|           | (1.16)       | (2.13)     | (1.85)             |
| W×lnES    | 0.146        | 0.534***   | 0.094              |
|           | (1.57)       | (3.02)     | (0.98)             |
| W×lnHC    | −0.115       | 0.221***   | −0.111             |
|           | (−1.01)      | (2.02)     | (−0.81)            |
| Spatial rho | 0.202***   | 0.325***   | 0.128*             |
|           | (3.14)       | (5.33)     | (1.87)             |
| Variance sigma2_e | 0.011*** | 0.058***   | 0.011***           |
|           | (14.93)      | (14.81)    | (14.96)            |
| R²        | 0.245        | 0.491      | 0.025              |
| N         | 450          |            |                    |

* *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The *t* values are in parentheses.

### Table 6 Result of effect decomposition

| Variable | Direct effect | Indirect effect | Total effect |
|----------|---------------|-----------------|--------------|
| lnRET1   | −0.089***     | −0.075*         | −0.164*      |
|          | (−4.49)       | (−1.87)         | (−1.71)      |
| lnPOP    | 0.345***      | −0.389**        | −0.044**     |
|          | (5.69)        | (−2.53)         | (−2.29)      |
| lnIS     | −0.125***     | 0.067           | 0.057        |
|          | (−5.39)       | (1.06)          | (−0.75)      |
| lnES     | 0.493***      | 0.960***        | 1.453***     |
|          | (6.03)        | (4.06)          | (5.44)       |
| lnHC     | −0.341***     | 0.140           | −0.200       |
|          | (−6.56)       | (0.95)          | (−1.35)      |

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The *t* values are in parentheses.

the spatial effect and further investigate the spatial spillover effect by using the partial differential method.

### Result of direct and indirect effects

The above research found that the spatial coefficients of all variables passed the significance test, and the total effect is further decomposed, shown in Table 6. The direct effect coefficient of RETI is −0.089, which is significant at the 1% level, indicating that RETI significantly suppresses local MCI. It may be because the development of local clean technology is conducive to the manufacturing energy structure adjustment, reducing the dependence of the manufacturing industry on fossil energy and promoting the manufacturing low-carbon transformation. The indirect effect coefficient of RETI is −0.075 at a significance level of 10% level, indicating that RETI inhibits the neighboring MCI, which is similar to the conclusion of Wang and Zhu (2020). On the one hand, the improvement of local RETI generates knowledge and technology spillover effects, driving the manufacturing industry in the surrounding areas to transform to cleaner production. On the other hand, local governments gradually shift from competing for economic growth to competing for environmental protection; the low-carbon development in local manufacturing forms a “benchmarking effect,” which is conducive to prompting surrounding areas to imitate one after another and reducing MCI. The direct effect coefficient of POP is 0.345 at a significance level of 1%, and the indirect effect coefficient is −0.389 at a significance level of 5%, indicating that every 1% increase in population size significantly increases local MCI by 0.345% and reduces neighboring MCI by 0.389%, which may be caused by rapid growth of local infrastructure construction and energy consumption driven by the expansion of population size. At the same time, with the increasing urban centrality, resource elements from the surrounding areas are concentrated in the central city, leading to an increase in local MCI and a decrease in neighboring MCI (Liu et al. 2021). The direct effect coefficient of IS is −0.125 at a significance level of 1%, and the indirect effect coefficient is 0.067 and is not significant, indicating that the optimization and upgrading of the industrial structure are conducive to reducing local MCI, but it does not produce significant industrial cluster effect to drive carbon emission reduction in surrounding areas. The coefficients of direct effect and indirect effect of ES are 0.493 and 0.960, respectively, which is significant at the 1% level, indicating that ES has a promoting significant impact on local and neighboring MCI. Although the manufacturing industry strives to promote clean energy substitution, low-cost coal is still the dominant fuel for manufacturing energy consumption. The dependence of local and neighboring manufacturing industries on coal remains high, which puts enormous pressure on manufacturing to reduce carbon emissions (Li and Mao, 2020).
coefficient is 0.140 and is not significant, indicating that HC effectively reduces local MCI, but the carbon emission reduction effect on neighboring manufacturing industries is not apparent. It may be because the accumulation of human capital helps to improve the efficiency and productivity of local manufacturing resource allocation. However, due to the differences in regional development levels, there are barriers in inter-regional human capital markets and mechanisms, making it difficult for the carbon emission reduction effect in cross-regional talent mobility to be effective.

**Result of the regional boundary of RETI on MCI**

According to the attenuation law of geographical distance, a spatial distance attenuation weight matrix is constructed to test the attenuation boundary of the spillover effect of RETI on MCI. In general, the spatial correlation gradually decreases with distance increase. To further explore the attenuation boundary of the spatial spillover of RETI on MCI, this study refers to Hao et al. (2020) and sets different distance thresholds, assuming that the province \( j \) of distance province \( i \) is outside the distance threshold, it is \( 1/d_{ij} \); otherwise, it is 0. The calculation method is as follows:

\[
Deca_{ij} = \begin{cases} 
\frac{1}{d_{ij}} & \text{when } d_{ij} \text{ is outside the distance threshold} \\
0 & \text{otherwise} 
\end{cases}
\]

\( Deca_{ij} \) reflects whether the spatial correlation coefficient decreases with increasing distance between spatial units. Firstly, the initial distance threshold of \( d_{ij} \) is set as 200 km and increased by 200 km. Secondly, SPDM is employed to examine and record the spatial spillover coefficient of RETI.

The results of the spatial spillover effect show that the coefficient of RETI passes the significance test of 1% within the range of 200 to 1400 km and is not significant after 1400 km, which demonstrates that there is an attenuation boundary of the spatial spillover of RETI on MCI. Overall, it can be roughly divided into three areas in Fig. 3: (1) within 800 km, RETI significantly inhibits neighboring MCI, the spatial spillover coefficient changes from \(-0.411\) to \(-0.102\), and the closer the distance, the stronger the effect. The “half-decay” spatial spillover effect appeared at 400 km when the spatial spillover coefficient changed from \(-0.411\) to \(-0.215\). Generally, 400 km is the provincial boundary range, which indicates that RETI has a strong inhibitory effect on MCI in the local region and restricted range. In contrast, the spatial spillover effect significantly decreases when it exceeds the provincial boundary. It may be because although the level of marketization in China has improved, the phenomenon of market segmentation is still prominent. Local protectionism in various provinces prompts advanced RETI to prioritize the low-carbon development of the local manufacturing industry, but it has certain administrative obstacles to the technology spillovers in other regions. (2) Within 800–1400 km, RETI significantly promotes MCI in neighboring areas and reaches a peak of 0.152 at 1000 km. It may be because the distance between provinces in China’s eight major economic regions is about 1000 km. The farther the distance is, the higher the cost of regional collaborative development is, resulting in relatively poor radiation effect of information technology and talent elements and the higher the dependency on fossil energy in neighboring manufacturing industries, which is not conducive to the manufacturing low-carbon transformation. (3) After 1400 km, with the sharp reduction of spatial units in the weight matrix, the spatial spillover coefficient fluctuates randomly and is not significant, indicating that the spatial
spillover effect of RETI on MCI is limited by regional boundaries. Overall, the effect of RETI on neighboring MCI shows a first negative and then positive attenuation process, which verifies the spatial attenuation boundary hypothesis.

Heterogeneity analysis

Temporal heterogeneity analysis

It is considering that China’s economic development changes every 5 years; this study further examines the impact of RETI on MCI in different periods by dividing samples according to “11th five-year plan” (2006–2010), “12th five-year plan” (2011–2015), and “13th five-year plan” (2016–2020). From model (1) to model (3) in Table 7, the results show that during the “12th five-year plan” and “13th five-year plan,” RETI has a significant inhibitory effect on MCI, which is more effective in “13th five-year plan.” It is because the “12th five-year plan” proposes to accelerate the structural adjustment in manufacturing and promote the transformation and upgrading from low-end to high-end, but not directly and effectively promote industrial technology progress. In contrast, the “13th five-year plan” clearly proposes to vigorously develop new energy technologies and realize green energy transformation, which helps RETI to promote manufacturing low-carbon transformation. It is worth noting that the spatial spillover effect of RETI on MCI is significant in the “13th five-year plan,” indicating that as China’s economy enters the stage of high-quality development, regional integration continues to advance and promote production factors such as capital, talent, and technology to break through administrative barriers and have a radiation-driven effect on neighboring areas, which is conducive to realizing the collaborative governance of manufacturing carbon emission reduction.

In terms of the control variables, POP has a significant promoting effect on MCI and IS and HC have a significant inhibitory effect on MCI, which proves the robustness of the empirical results. Among them, the impact of Table 7 Temporal and regional heterogeneity results

| Variable | (1) 11th five-year plan | (2) 12th five-year plan | (3) 13th five-year plan | (4) Eastern | (5) Central | (6) Western |
|----------|-------------------------|-------------------------|-------------------------|------------|------------|------------|
| lnRETI   | −0.049                  | −0.128***               | −0.139***               | −0.013*    | −0.148***  | −0.039***  |
|          | (−1.24)                 | (−4.31)                 | (−4.38)                 | (−1.69)    | (−5.92)    | (−2.61)    |
| lnPOP    | 0.282**                 | 0.403***                | 0.480***                | 0.323***   | 0.090      | 0.140***   |
|          | (2.10)                  | (3.86)                  | (4.62)                  | (4.75)     | (1.08)     | (2.80)     |
| lnIS     | −0.224***               | −0.116***               | −0.113***               | −0.054***  | −0.031     | −0.035**   |
|          | (−3.65)                 | (−3.06)                 | (−4.51)                 | (−2.18)    | (−1.09)    | (−2.06)    |
| lnES     | 0.488***                | 0.209                   | 0.494***                | 0.420***   | 0.085      | 0.068      |
|          | (2.58)                  | (1.53)                  | (4.60)                  | (4.96)     | (0.82)     | (1.09)     |
| lnHC     | −0.336***               | −0.317***               | −0.425***               | −0.251***  | −0.263***  | −0.322***  |
|          | (−2.90)                 | (−3.54)                 | (−4.65)                 | (−4.22)    | (−3.64)    | (−7.25)    |
| W×lnRETI | −0.008                  | −0.083                  | −0.231***               | −0.223***  | −0.036     | −0.076***  |
|          | (−0.12)                 | (−1.63)                 | (−4.24)                 | (−6.64)    | (−0.88)    | (−2.96)    |
| W×lnPOP  | −0.266                  | −0.504***               | −0.776***               | −0.526***  | −0.445***  | −0.320***  |
|          | (−1.15)                 | (−2.77)                 | (−3.84)                 | (−4.33)    | (−2.98)    | (−3.48)    |
| W×lnIS   | 0.060                   | 0.121                   | 0.047                   | 0.288***   | −0.187***  | 0.003      |
|          | (0.52)                  | (1.55)                  | (0.91)                  | (6.26)     | (−3.40)    | (0.09)     |
| W×lnES   | 0.960**                 | 0.795†                  | 0.466†                  | 0.120      | 0.436**    | 0.023      |
|          | (2.33)                  | (1.87)                  | (1.90)                  | (0.67)     | (2.02)     | (0.17)     |
| W×lnHC   | 0.220                   | 0.259                   | 0.410*                  | 0.306***   | 0.532***   | 0.330***   |
|          | (1.00)                  | (1.51)                  | (2.20)                  | (2.66)     | (3.70)     | (3.63)     |
| Spatial rho | 0.238**               | 0.320***               | 0.353***               | 0.189***   | 0.057*    | 0.513***   |
|          | (1.96)                  | (3.19)                  | (3.53)                  | (2.84)     | (1.69)     | (9.51)     |
| Variance | 0.089***                | 0.043***                | 0.035***                | 0.063***   | 0.094***   | 0.034***   |
|          | (8.59)                  | (8.57)                  | (8.55)                  | (14.93)    | (14.99)    | (14.50)    |
| $R^2$    | 0.426                   | 0.492                   | 0.529                   | 0.107      | 0.179      | 0.438      |
| $N$      | 150                     | 150                     | 150                     | 165        | 120        | 165        |

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The $t$ values are in parentheses.
POP, ES, and HC on MCI increases over time, while that of IS on MCI decreases, which shows that the structural transformation and upgrading in China’s manufacturing industry has achieved preliminary results. However, efforts are still needed in the adjustment of energy consumption structure and the cultivation of talents to control MCI effectively. In terms of spatial spillover effect at different periods, POP has a significant inhibitory effect on neighboring MCI. The effect is enhanced in the “13th five-year plan” period compared with the “12th five-year plan” period, which indicates that with the accelerating urbanization process, the population continues to move to the central cities, and the agglomeration effect is further strengthened, causing pressure on manufacturing carbon emission reduction.

ES has a significant promoting effect on neighboring MCI in different periods, but the effect gradually decreases, indicating that a series of measures implemented in China, such as coal-to-gas and coal-to-electricity conversions, are helping to promote the adjustment and optimization of energy consumption structure, improve energy efficiency, and thus reduce MCI. HC has significantly advanced MCI in neighboring areas during the “13th five-year plan” period. It may be due to the “siphon effect” caused by the active RETI in the central city, which attracts scientific and technological talents from the surrounding areas to accelerate the outflow and hinders the low-carbon and green development in neighboring manufacturing.

Regional heterogeneity analysis

The samples are divided into eastern, central, and western groups to test further the regional heterogeneity of the impact of RETI on MCI in the study. From model (4) to model (6) in Table 7, it can be seen that the inhibitory effect of RETI on MCI in the central region is more vital than that in the eastern and western areas. It may be that with the industrial transfer from the east to the west and central, the manufacturing industry gradually forms an industrial agglomeration pattern in the central area, which aggravates air pollution (Dong et al., 2020) and enhances the inhibitory effect of RETI on air pollution in the central area (Zhu et al., 2019). At the same time, RETI has the strongest spatial spillover effect on MCI in the east, showing that the east with a developed economy is an essential support for technological innovation, which also proves the east plays a leading and exemplary role in promoting low-carbon and green development in surrounding manufacturing.

In terms of control variables, POP has a significant promoting effect on MCI in the eastern and western regions and has a negative spatial spillover effect on the surrounding areas. The population distribution presents a polarization pattern of “more in the east and less in the west,” leading to the gradual increasing difference in inter-regional industrial scale, which is not conducive to the manufacturing carbon emission reduction. However, IS has a significant inhibitory effect on MCI in the eastern and western regions. Light and tertiary industries in the east of China are more developed and technology-intensive industries are more distributed, which promotes the development of RETI and helps reduce MCI. In contrast, western economic growth has a strong dependence on heavy industry; the development of the tertiary sector is relatively backward, so it is a crucial way for the west to optimize and upgrade the industrial structure to promote the manufacturing green development. ES has a significant promoting effect on MCI in the eastern region and a significant positive spatial spillover effect on MCI in the central area. Although the rapid economic development and large energy demand in the east cause severe environmental pollution, restricted by strict environmental protection policies, the high energy-consuming industries in the east have gradually transferred to the central and western areas, which results in an increase in energy consumption in the central region and tremendous pressure on the manufacturing carbon emission reduction in the surrounding areas. HC has a significant inhibitory effect and a negative spatial spillover effect on MCI in the eastern, central, and western regions. The effect is the strongest in the western region, indicating that the western region promotes the transformation of economic development pattern, strengthens the soft environment, and attaches importance to human capital accumulation and technological innovation, which contributes to realizing energy-saving and carbon reduction in the manufacturing industry.

Industry heterogeneity analysis

Due to the differences in income, development scale, energy consumption, and factor input of segmented industries, the carbon emissions of segmented industries are heterogeneous (Wang and Jiang, 2019; Aslan et al., 2018). This paper is based on three classification criteria: pollution emission intensity, core operating income, and factor density (Li and Cheng, 2020; Huang and Du, 2020); the manufacturing industry is subdivided into three groups and seven types: pollution-intensive manufacturing (PIM) and non-pollution-intensive manufacturing (NPIM) in group A, high-income manufacturing (HCM) and low-income manufacturing (LCM) in group B, capital-intensive manufacturing (CIM), technology-intensive manufacturing (TIM), and labor-intensive manufacturing (LIM) in group C.
This paper further examined the spatial heterogeneity of RETI for different types of MCI, and the results in Table 8 show that the impact of RETI on MCI has both inter-group and intra-group differences. The results of group A show that RETI has a significant inhibitory effect on PIM and NPIM carbon intensity in both local and neighboring areas and has a more substantial impact on PIM carbon reduction. It may be because that PIM is more vulnerable to environmental regulation, and the cost of environmental governance is relatively high, which promotes PIM to develop RETI to improve energy efficiency actively and effectively alleviate MCI in surrounding areas through technology spillover. The result verifies the industry heterogeneity of the impact of RETI on MCI and confirms the validity of the Porter hypothesis in the manufacturing industry.

The results of group B show that RETI has a significant inhibitory effect on the carbon intensity of local HCM and LCM and has a stronger impact on HCM carbon emission reduction. HCM has more sufficient capital than LCM for technology R&D and innovation in RETI and the introduction of green technology, which can effectively improve industrial green total factor productivity and promote the manufacturing green transformation and upgrading. However, taking into account the high cost of RETI, long payback period, and high uncertainty, LCM is difficult to obtain economic benefits in the short term, which weakens the inhibition effect of RETI on LCM carbon intensity.

The results of group C show that RETI significantly inhibits the carbon intensity of local CIM and LIM and has a significant negative spatial spillover effect on the carbon intensity of CIM, TIM, and LIM. It is because China’s industrialization development is in the transitional stage from the middle to the later stage (Li et al., 2019a, b), and TIM increases R&D funding and vigorously strengthens RETI in transformation and upgrading, which is conducive to reducing MCI by improving resource allocation efficiency and energy utilization efficiency. On the other hand, TIM has stronger technological innovation and more advanced green process equipment, with good primary conditions for low-carbon development, and strengthening RETI is not significantly playing the carbon emission reduction effect in the technology-intensive manufacturing industry.

**Robustness test**

**Endogenous test**

To deal with the potential endogenous problems, this paper adopts the explained variable lag one period as an instrumental variable and systematic generalized moment estimation (SYS-GMM) to deal with the possible endogeneity between RETI and MCI (Yuan et al., 2020). From the results of model (1) in Table 9, we can see that the time-lag term of MCI is 0.904, which is significant at the 1% level, indicating that the development of MCI is time-dependent. The estimated results of other variables are consistent with the previous ones, which proves the robustness of the main findings.

**Changing the space weight matrix**

In order to avoid the estimation bias caused by the selection of spatial weight matrix (Xu et al., 2019), this study replaces adjacent weight matrix ($W_1$) with geographic distance matrix.

| Variables | Group A | Group B | Group C |
|-----------|---------|---------|---------|
| $\ln{RETI}$ | $-0.088^{***}$ | $-0.006^{**}$ | $-0.086^{***}$ |
|           | ($-4.46$) | ($-2.01$) | ($-4.45$) |
| $W \times \ln{RETI}$ | $-0.072^{**}$ | $-0.009^{*}$ | $-0.076^{**}$ |
|           | ($-2.20$) | ($-1.90$) | ($-2.38$) |
| Control variables | YES | YES | YES |
| Spatial rho | $0.313^{***}$ | $-0.096$ | $0.282^{***}$ |
|           | ($5.09$) | ($1.29$) | ($4.56$) |
| Variance $\sigma^2_e$ | $0.059^{**}$ | $0.001^{***}$ | $0.057^{**}$ |
|           | ($14.83$) | ($14.98$) | ($14.86$) |
| $R^2$ | 0.496 | 0.053 | 0.465 |
| N | 450 | 59797 | 59797 |

* *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The $t$ values are in parentheses.
(W₂) and economic distance matrix (W₃) to estimate the model again. From model (2) and model (3) in Table 9, it can be seen that RETI has a significant inhibitory effect on local and neighboring MCI in different spatial weight matrices, which proves the robustness of the research results.

Replace the explained variable

Manufacturing carbon emissions (MCE) are re-estimated as explained variables. From model (4) in Table 9, we can see that RETI has a significant inhibitory effect on local and neighboring MCE, which proves the robustness of the main research results.

Adding control variables

The above control variables are selected from social and economic factors, but climatic conditions also affect carbon emissions. Thus, the meteorological factors such as average annual temperature, average annual precipitation, and average annual sunshine duration are included in the model again as control variables (Table 9). The results of model (5) demonstrate that the increase of control variables does not change the relationship between RETI and MCI, which again verifies the robustness of the research findings.

Table 9 Robustness test

| Variables          | (1) SYS-GMM | (2) W₂   | (3) W₃   | (4) MCE | (5) Adding control variables |
|--------------------|-------------|---------|---------|--------|-----------------------------|
| L.MCI              | 0.904***    | −0.003*| −0.107***| −0.028*| −0.088***                   |
|                   | (21.37)     | (−1.69)| (−5.75) | (−1.80)| (−2.96)                     |
| lnRETI             | −0.003*     | −0.107***| −0.028*| −0.088***| −0.086***                   |
|                   | (−1.69)     | (−1.80)| (−2.96)| (−4.61)|                             |
| W × lnRETI         | −0.372***   | −0.032*| −0.162***| −0.320*| −0.032*                     |
|                   | (−3.03)     | (−1.78)| (−3.31)| (−1.88)|                             |
| Control variables  | YES         |         |         |        |                             |
| Spatial rho        |             | 0.562***| 0.363***| 0.244***| 0.002*                      |
|                   |             | (2.61) | (3.60) | (3.76) | (1.70)                      |
| Variance sigma²ₑₑ |             | 0.056***| 0.067***| 0.135***| 0.046***                    |
|                   |             | (14.99)| (14.76)| (14.27)| (15.00)                     |
| AR(1)             | −3.010      |         |         |        |                             |
|                   | (0.003)     |         |         |        |                             |
| AR(2)             | 0.170       |         |         |        |                             |
|                   | (0.865)     |         |         |        |                             |
| Sargan             | 195.690     |         |         |        |                             |
|                   | (1.00)      |         |         |        |                             |
| N                 | 420        | 450     | 450     | 450    | 450                         |

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The t values are in parentheses.

Conclusions and discussions

Based on the manufacturing panel data of 30 provinces in China from 2006 to 2020, this paper first measures MCI and RETI and adopts spatial autocorrelation analysis to clarify the spatiotemporal differentiation characteristics of RETI and MCI. Second, under three different spatial weight matrices, this paper uses the spatial Durbin model to explore the influence mechanism, spatial spillover effect, and regional boundary of RETI on MCI and further examines the spatial heterogeneity of seven-type manufacturing industry segments. The main conclusions are as follows:

1. MCI decreases steadily, forming a ladder decreasing pattern from north to south. RETI fluctuates and increases as a whole, showing a spatial differentiation pattern of “high in the southeast and low in the northwest.” The spatial correlation between MCI and RETI is gradually enhanced, and the spatial clustering trend gradually emerges.

2. RETI significantly suppresses local and neighboring MCI, and the local effect of carbon reduction is greater than that of the adjacent effect.

3. There is a significant attenuation boundary of the spatial spillover effect of RETI on MCI. Within the range of 800 km, RETI has a significant inhibitory effect on
neighboring MCI. And the closer the distance is, the stronger the effect is, and the “half-decay” distance of spatial spillover effect appears at 400 km. RETI has a significant promoting effect on neighboring MCI in the range of 800 to 1400 km. The spillover effect first increases and then decreases, while the spatial spillover effect is not significant beyond 1400 km.

(4) The inhibitory effect of RETI on MCI gradually increases over time, and the effect from high to low is central, west, and east.

(5) RETI has a significant inhibitory effect on MCI of pollution-intensive, high-income, capital-intensive, and labor-intensive manufacturing in local and neighboring areas, but its effect is more negligible on non-pollution-intensive, low-income, and technology-intensive MCI.

Based on the above findings, the following policy implications for manufacturing energy conservation and emission reduction in China and other developing countries are as follows: firstly, the research results show that RETI significantly suppresses local and neighboring MCI, indicating that the focus of manufacturing carbon emission reduction is energy substitution and transformation. We should optimize the energy consumption structure and actively promote the deployment of clean energy, especially to accelerate the innovation and application of renewable energy technology, which is conducive to building a low-carbon production chain and creating a green manufacturing production system for manufacturing carbon emissions.

Secondly, the results show that RETI has a significant spatial spillover effect and attenuation boundary on MCI. Therefore, we should improve regional integration and weaken the barriers that restrict the flow of production factors such as local protection and market segmentation. The regions should strengthen the sharing of innovative achievements and the flow of talent information to expand the regional boundary of RETI spatial spillover. In addition, we should actively build a regional innovation cooperation platform; promote the deep integration of industry, academia, and research; accelerate the application of scientific and technological achievements; and promote the manufacturing green and low-carbon transformation.

Thirdly, the results show that the effect of RETI on MCI has significant regional heterogeneity. Therefore, the government should formulate differential carbon emission reduction policies according to the regional characteristics. For example, the eastern region with relatively scarce energy resources has a relatively high level of economic development, should actively promote clean energy use, increase investment in renewable energy technology research and development, and strive to become the vanguard in technology emission reduction and low-carbon development. While the central and western regions are the leading suppliers of energy resources, they should make full use of advantageous local resources and encourage the use of clean energy such as natural gas, wind power, and photovoltaic power generation to promote the low-carbon transformation of energy consumption structure and boost the manufacturing green development.

Fourthly, the results demonstrate significant industry heterogeneity in the impact of RETI on MCI. The government should implement targeted and differentiated measures to promote the low-carbon transformation in manufacturing. For example, for pollution-intensive manufacturing industries, the government should strengthen environmental regulatory standards, strict environmental governance requirements, and restrain industry emissions behavior by adjusting environmental functions layout and improving comprehensive evaluation mechanisms to accelerate the manufacturing green transformation and upgrading. For the high-income manufacturing industry, it should continuously increase investment in energy technology research and development, introduce advanced green technology, and improve supporting facilities in environmental pollution control to promote intelligent and green production in manufacturing. For capital-intensive and labor-intensive manufacturing industries, the government should increase preferential policies for environmental protection and green technology innovation, and take tax breaks and other diversified incentives to stimulate the innovation vitality of enterprises, which can help promote manufacturing transformation from labor-intensive and low value-added to technology-intensive and high value-added, and improve the quality of manufacturing development. This study provides new evidence for RETI to promote manufacturing carbon emission reduction from the perspective of spatial spillover and regional boundary. Although this study takes China as an example, how to achieve low-carbon development in manufacturing is not only a concern for China but also the focus of the world. Especially in the post-COVID-19 era, more and more countries have begun to pay attention to the environmental problems in economic development. The findings can provide empirical support for manufacturing carbon emission reduction in other developing countries, especially those with energy-dependent and rapidly growing manufacturing sectors. However, there are still some limitations. First of all, due to data availability, this paper only discusses at the industry level; subsequent studies can be conducted at the prefectural or enterprise level. Secondly, there are only three criteria for manufacturing subdivided, and future research could explore industry heterogeneity in more dimensions. Finally, most of the existing studies are based on Chinese data, and future studies could try to compare the impact of RETI on MCI among different countries, which contributes to formulating targeted policies for manufacturing energy
transformation and carbon emission reduction in various national conditions.

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