

Regional Convergence of Carbon Emissions in China

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Abstract: To explore efficient ways to reduce emissions, the analysis draws on provincial-level data from 30 regions in China spanning 2002 – 2018 and adopts β Convergence to reveal the current situation of China's carbon emissions. The findings show that: (1) Although the total carbon emissions have been growing, the growth rate has slowed down since 2011. (2) Carbon emission intensity displays a persistent downward pattern. (3) The total amount and intensity of carbon emissions show exhibit spatial positive correlation. Total carbon emissions do not exist β convergence, but carbon emission intensity not only exists in traditional β Convergence but there is still space β Convergence also has a spatial spillover effect.

Keywords: Carbon Emission; Convergence; β Convergence; Space β Convergence.

1. Introduction

The climate crisis is an important topic on the international governance agenda at present. With the rise of global temperature, various extreme climate impacts are superimposed on each other, which seriously threatens human, property security, economic development, food security, biodiversity, and the ecosystem [1-4]. Controlling carbon emissions and tackling the climate crisis have gradually become an international consensus. China's 12th Five-Year Plan proposes to build a resource-saving and environment-friendly society. Since 2013, China carried out trial work related to carbon trading in eight provincial-level regions. China gives high priority to advancing ecological civilization. At its fifth plenary session from October 26 to 29, 2015, the 18th CPC Central Committee took green development as one of the Five Concepts for Development. From a series of policies and measures, we can see China's determination and courage in reducing carbon emissions, preserving the natural environment while advancing green economic progress.

The spatial pattern of carbon emissions in China exhibits significant disparities, largely driven by variations in regional economic development, industrial composition, energy utilization, and the degree of openness [5, 6]. As a result, China's carbon emission pattern, measures, and results show spatial heterogeneity, which hinders the realization of China's carbon peak and neutrality goals. Accurately measuring the temporal and spatial characteristics and convergence of China's carbon emissions will help to clarify the existing state of China's carbon emissions. Meanwhile, clarifying the current situation of China's carbon emissions is helpful to understand the achievements of the Chinese government in reducing emissions in recent years, and can provide new ideas and inspiration for the next work of reducing emissions.

Domestic and foreign scholars generally take the total carbon emissions as the research object. For example, Wang et al. (2016) discussed the Spatio-temporal pattern of total carbon emissions and quantified its dynamic coupling relationship with economic growth and energy consumption [7]. Wang et al. (2022) and Wu et al. (2022) studied the temporal and spatial differences, regional characteristics, and driving factors of total carbon emissions [8, 9]. Nejat et al. (2015) and Sun et al. have respectively studied the current situation, trend, and Spatio-temporal evolution characteristics

of total CO₂ emissions from global and Chinese housing [10, 11]. Worrell et al. (2001) and Su et al. (2017) respectively focused on the carbon dioxide emissions of the cement industry and the electricity sector. [12, 13]. Some domestic and foreign scholars also use carbon emission intensity as the research object. For example, Wang et al. (2022) studied the change in carbon dioxide intensity in urban agglomerations in China and its causes [14]. Canadell et al. (2022) analyzed the contribution of global economic activities, carbon intensity, and natural sink efficiency to accelerating the growth of atmospheric carbon dioxide [15]. Raupach et al. (2007) provided suggestions for the division of global carbon emission responsibilities [16]. Some scholars use CO₂ emissions efficiency as the research object. For example, Zhou et al. (2010) explored both the changes and the driving forces behind carbon emission performance in the world's 18 leading carbon-emitting countries [17]. Zhang et al. (2020) analyzed the effects of urbanization on carbon emission efficiency [18]. Yang et al. (2021) and Cui et al. (2021) measured the convergence, influencing factors, and Spatio-temporal evolution characteristics of China's industrial and agricultural carbon emission efficiency respectively [19, 20].

There are a number of well-established literatures about carbon emissions, however, some shortcomings of them still exists. First, the existing research only measures the regional carbon emission level from the total amount or intensity or efficiency. If the paper only focuses on the total carbon emissions, it may lead to the blind pursuit of reducing the total carbon emissions in the economic society, which will affect economic development. Analyzing carbon emission intensity alone cannot indicate whether the increase in carbon emission intensity is due to economic growth or total carbon emissions. To sum up, only when the total carbon emissions and intensity indicators are used at the same time, can the paper comprehensively reveal the current situation, the effectiveness and progress of emission reduction. Secondly, the existing literature research on the current situation of China's carbon emissions mostly uses descriptive statistical analysis, ESDA, the Dagum's Gini coefficient, and other methods to explore the regional differences and dynamic evolution of China's carbon emissions. Few works of literature use the β convergence, club convergence, and other methods are used to analyze carbon emissions. However, the convergence characteristics are of great significance for a comprehensive analysis of the current situation.

To explore the above issues, we use the relevant data from 30 provinces in China from 2002 to 2018. The contributions are as follows: (1) This paper describes the current situation of China's carbon emissions in terms of total carbon emissions and intensity. This paper overcomes the limitations of existing literature that only considers the total amount or intensity or efficiency of carbon emissions, and can comprehensively study the current situation of carbon emissions in China. (2) The existing literature mostly adopts descriptive statistical analysis, ESDA, and the Dagum's Gini coefficient to explore carbon emissions. The quantitative analysis of convergence of China's carbon emissions is relatively lacking. This study adds the β convergence to complement related research. (3) Compared with the existing literature, this paper can provide quantitative support for the smooth promotion of the "Double carbon" goal, and provide supplement and expansion for similar research.

2. Data and Methods

2.1. Data Description

2.1.1. Description of Carbon Emission Data

This paper calculates the total carbon emissions for each province in China using the following formula.

$$totalco2emission = \sum_{i=1}^n M_i \times p_i \times q_i \times o_i \times \frac{44}{12} \quad (1)$$

Where, $totalco2emission$ denotes the total carbon emissions of each province; M_i , P_i , q_i , and O_i represent, respectively, the consumption of the i th type of energy in each province, the average low calorific value of the i th energy, the

carbon content per unit of calorific value, and the carbon oxidation rate.

The carbon emission intensity ($co2intensity$) is measured by dividing the total carbon dioxide emission calculated above by the local GDP.

2.1.2. Influencing Factors of Carbon Emissions

In the convergence study, this paper selects the industrial structure (is), government intervention (gov), innovation (rd), an education level ($jiaoyu$), openness ($lnrow$), and population ($lnperson$) of each province as the control variables. This paper uses the sum of the output value of the secondary industry and the tertiary industry divided by the gross product of the region to measure the upgrading of the industrial structure (is) of each province. We measure government intervention by dividing government expenditure by GDP. This paper uses the total number of the number of invention patents, utility model patents, and design applications to represent the regional innovation level (rd). We calculate average length of education ($jiaoyu$) according to the number of primary school students, junior high school students, senior high school students, technical secondary school students, college students and above who have been educated for 6, 9, 12 and 16 years respectively. In this paper, the total value of imports and exports is divided by the gross local product, and logarithms are taken to measure the degree of opening up of the region ($lnrow$). We use the number of permanent residents and logarithm to measure the population size of the region ($lnperson$). The descriptive analysis of the variables is as follows:

Table 1. Descriptive statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|------------------|-----|----------|-----------|----------|----------|
| totalco2emission | 510 | 33.85777 | 25.94563 | 0.60601 | 149.307 |
| co2intensity | 510 | 3.298288 | 2.447096 | 0.382 | 18.5 |
| is | 510 | 1.000673 | 0.527239 | 0.499599 | 4.34758 |
| gov | 510 | 0.209652 | 0.094062 | 0.079152 | 0.626863 |
| lnrd | 510 | 9.631001 | 1.685639 | 4.820282 | 13.58461 |
| jiaoyu | 510 | 8.642276 | 1.03212 | 6.0405 | 12.555 |
| lnrow | 510 | 5.551818 | 0.994013 | 3.210703 | 7.842188 |
| lnperson | 510 | 8.166482 | 0.751927 | 6.270232 | 9.336621 |

2.1.3. Data Sources

The data are from Guotai'an Database, China Statistical Yearbook, and provincial statistical yearbooks. Data period: 2002–2018.

2.2. Statistical Model

The convergence hypothesis is one of the core contents of economic growth research. The convergence hypothesis is concerned with whether there are a "steady state" and "conditional convergence" in the economy. The convergence can be used to analyze the long-term change characteristics of research objects and has been widely used in the economic field [21]. Therefore, this paper mainly adopts β Convergence

and club convergence study of the long-term change characteristics of total carbon emissions and intensity. the β Convergence can be separated into absolute β Convergence and conditions β Convergence. Absolutely β Convergence stands for the state that the total carbon emissions (intensity) of different provinces will eventually converge to the same stable level over time without considering other influencing factors. Formulas (2) and (3) show absolute β Convergent general panel regression model and spatial Dubin model.

$$\ln\left(\frac{X_{i,t+1}}{X_{i,t}}\right) = \alpha + \beta \ln X_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \quad (2)$$

$$\ln\left(\frac{X_{i,t+1}}{X_{i,t}}\right) = \alpha + \rho w_j \ln\left(\frac{X_{i,t+1}}{X_{i,t}}\right) + \beta \ln X_{i,t} + \theta w_j \ln X_{j,t} + \mu_i + \eta_t + \varepsilon_{i,t} \quad (3)$$

The condition β Convergence means that after controlling

other influencing factors, the total amount (intensity) of

carbon emissions finally converges to its steady state level. This study selects the industrial structure (is), government intervention (gov), innovation (lnrd), an education level (jiaoyu), openness (lndow), and population (lnperson) of each province as the control variables. Formula (4) and Formula (5)

respectively show the conditions β Convergent general panel regression model and spatial Dubin model.

$$\ln\left(\frac{X_{i,t+1}}{X_{i,t}}\right) = \alpha + \beta \ln X_{i,t} + \gamma Z_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \quad (4)$$

$$\ln\left(\frac{X_{i,t+1}}{X_{i,t}}\right) = \alpha + \rho w_{ij} \ln\left(\frac{X_{j,t+1}}{X_{j,t}}\right) + \beta \ln X_{i,t} + \theta w_{ij} \ln X_{j,t} + \gamma Z_{i,t} + \delta w_{ij} Z_{j,t} + \mu_i + \eta_t + \varepsilon_{i,t} \quad (5)$$

In the above formula, $X_{i,t}$ and $X_{i,t+1}$ respectively represents the total carbon emissions (intensity) of the i th province in t and $t+1$ periods. $Z_{i,t}$ indicates the control variable. β is the convergence coefficient, if $\beta < 0$ and significant, indicating absolute β Convergence, otherwise divergence. ρ and W_{ij} are the spatial autoregression coefficient and weight matrix. In this paper, the spatial weight matrix adopts adjacency matrix. μ_i , η_t and $\varepsilon_{i,t}$ denote, respectively, the regional fixed effects, the time fixed effects, and the random error term.

during 2002-2018, and the growth rate slowed down after 2011 (see Figure 1). The carbon emission intensity has been declining since 2003. The growth rate of total carbon emissions and intensity decreased significantly before 2008 and stabilized after 2011 in Figure 2. It is evident from the growing trend of total carbon emissions that China is still a long way from reducing carbon emissions. From the downward trend of carbon dioxide emissions per unit of GDP, we can see that China's low-carbon transformation of economic structure has achieved some results, and the decoupling of economic development from carbon emissions has made some progress.

3. Empirical Results

3.1. Trend of Change

China's total carbon emissions showed a growing trend

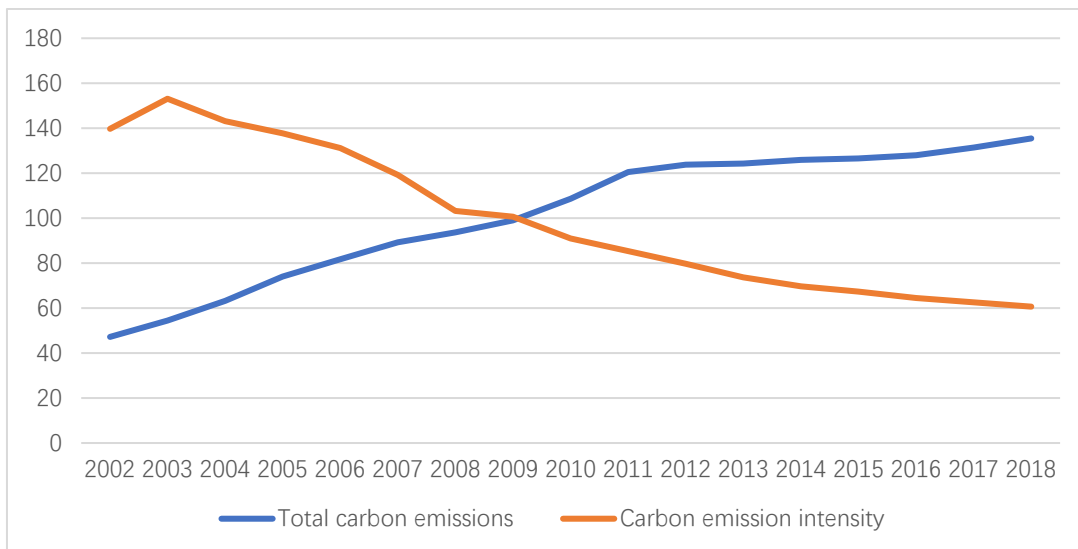


Figure 1. Broken line chart of total carbon emissions and intensity

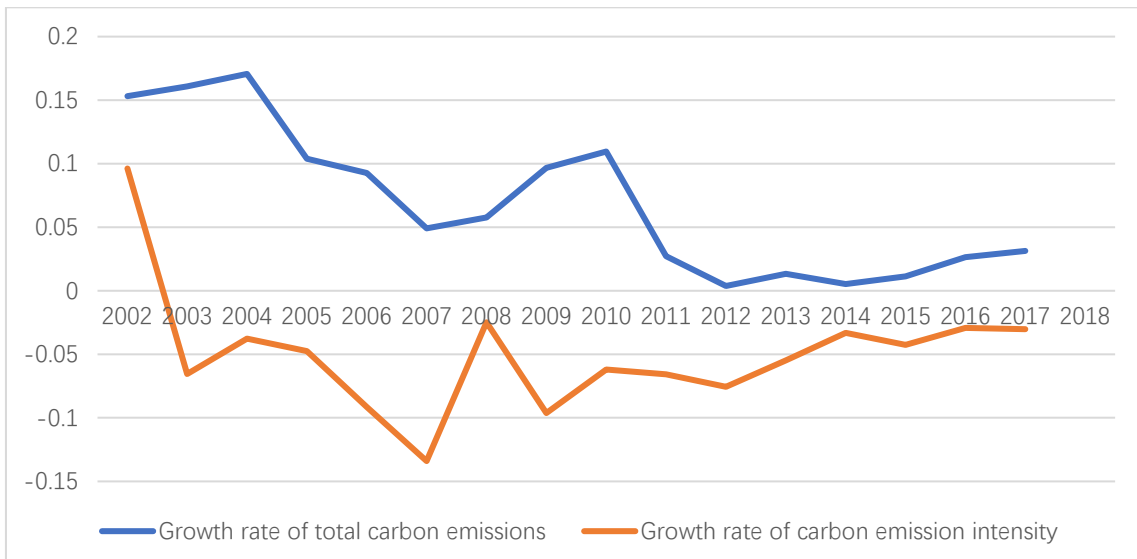


Figure 2. Growth rate trend of total carbon emissions and intensity

3.2. Spatial Characteristics

This paper uses exploratory spatial data analysis methods to study the spatial correlation between total carbon emissions and intensity. In this paper, we used the adjacency matrix. The

global Moran's I indices of total carbon emissions and carbon emission intensity during 2002–2018 are all positive and statistically significant, suggesting a notable positive spatial correlation in China's total emissions and intensity (see Tables 2 and 3).

Table 2. Moran'I Index of Total Carbon Emissions

| year | I | E(I) | Sd(I) | Z | P-value |
|------|--------|---------|--------|--------|---------|
| 2002 | 0.2028 | -0.0345 | 0.122 | 1.9453 | 0.0517 |
| 2003 | 0.187 | -0.0345 | 0.1218 | 1.8193 | 0.0689 |
| 2004 | 0.2254 | -0.0345 | 0.1226 | 2.1188 | 0.0341 |
| 2005 | 0.2633 | -0.0345 | 0.1217 | 2.4474 | 0.0144 |
| 2006 | 0.2551 | -0.0345 | 0.1215 | 2.3833 | 0.0172 |
| 2007 | 0.2578 | -0.0345 | 0.1212 | 2.4112 | 0.0159 |
| 2008 | 0.2662 | -0.0345 | 0.1206 | 2.4937 | 0.0126 |
| 2009 | 0.2427 | -0.0345 | 0.1206 | 2.299 | 0.0215 |
| 2010 | 0.2437 | -0.0345 | 0.1203 | 2.3129 | 0.0207 |
| 2011 | 0.2428 | -0.0345 | 0.122 | 2.273 | 0.023 |
| 2012 | 0.234 | -0.0345 | 0.1207 | 2.2241 | 0.0261 |
| 2013 | 0.223 | -0.0345 | 0.1213 | 2.1229 | 0.0338 |
| 2014 | 0.2137 | -0.0345 | 0.1202 | 2.0642 | 0.039 |
| 2015 | 0.2237 | -0.0345 | 0.1186 | 2.1771 | 0.0295 |
| 2016 | 0.2098 | -0.0345 | 0.1177 | 2.0756 | 0.0379 |
| 2017 | 0.1955 | -0.0345 | 0.1176 | 1.955 | 0.0506 |
| 2018 | 0.1982 | -0.0345 | 0.1191 | 1.9541 | 0.0507 |

Table 3. Moran'I Index of Carbon Emission Intensity

| year | I | E(I) | Sd(I) | Z | P-value |
|------|--------|---------|--------|--------|---------|
| 2002 | 0.1658 | -0.0345 | 0.098 | 2.0436 | 0.041 |
| 2003 | 0.2207 | -0.0345 | 0.1123 | 2.2723 | 0.0231 |
| 2004 | 0.2852 | -0.0345 | 0.116 | 2.7557 | 0.0059 |
| 2005 | 0.3036 | -0.0345 | 0.117 | 2.8909 | 0.0038 |
| 2006 | 0.2898 | -0.0345 | 0.1168 | 2.7762 | 0.0055 |
| 2007 | 0.2957 | -0.0345 | 0.1181 | 2.7961 | 0.0052 |
| 2008 | 0.3624 | -0.0345 | 0.1192 | 3.3287 | 0.0009 |
| 2009 | 0.3366 | -0.0345 | 0.1195 | 3.1052 | 0.0019 |
| 2010 | 0.3547 | -0.0345 | 0.1191 | 3.2688 | 0.0011 |
| 2011 | 0.3429 | -0.0345 | 0.1165 | 3.2396 | 0.0012 |
| 2012 | 0.3541 | -0.0345 | 0.1166 | 3.3317 | 0.0009 |
| 2013 | 0.342 | -0.0345 | 0.1162 | 3.2408 | 0.0012 |
| 2014 | 0.3397 | -0.0345 | 0.1162 | 3.2216 | 0.0013 |
| 2015 | 0.303 | -0.0345 | 0.1156 | 2.9191 | 0.0035 |
| 2016 | 0.3235 | -0.0345 | 0.1171 | 3.057 | 0.0022 |
| 2017 | 0.3535 | -0.0345 | 0.1166 | 3.328 | 0.0009 |
| 2018 | 0.3537 | -0.0345 | 0.1154 | 3.3646 | 0.0008 |

3.3. Convergence Analysis

The results show that the absolute β convergence coefficient of total carbon emissions is negative but not significant. After considering the industrial structure (is), innovation (lnrd), education level (jiaoyu), openness (ln Dow), and population (ln person) of each province, the condition β

convergence coefficient of the total carbon emissions is significant (Table 4). It indicates that absolute and condition β Convergence of total carbon emission does not exist. When this paper verifies whether spatial convergence exists, the model fails to pass the LM test. It indicates that there is no spatial convergence for total carbon emissions.

Table 4. Tradition β Convergence results of total carbon emissions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|--------------------------------|----------|------------|---------|---------|---------|---------|
| | y | y | y | y | y | y |
| ln _{totalco2emission} | 0.0044 | 0.1402*** | -0.0654 | -0.0382 | 0.0191 | -0.0799 |
| | (0.47) | (3.78) | (-1.50) | (-1.82) | (0.28) | (-1.58) |
| is | | | | -0.0099 | 0.0004 | -0.0270 |
| | | | | (-0.71) | (0.02) | (-0.81) |
| gov | | | | 0.1885 | -0.0150 | -0.0790 |
| | | | | (1.35) | (-0.07) | (-0.48) |
| lnrd | | | | 0.0064 | 0.0234 | -0.0031 |
| | | | | (0.66) | (1.21) | (-0.19) |
| jiaoyu | | | | 0.0354 | 0.0450 | 0.0317 |
| | | | | (1.60) | (1.83) | (0.73) |
| ln _{dow} | | | | -0.0061 | 0.0101 | -0.0193 |
| | | | | (-0.91) | (0.46) | (-0.61) |
| ln _{person} | | | | 0.0581 | 0.0351 | -0.0979 |
| | | | | (1.27) | (0.39) | (-1.00) |
| _cons | -0.0835* | -0.5285*** | 0.1453 | -0.7850 | -1.0898 | 0.8985 |
| | (-2.36) | (-4.18) | (1.00) | (-1.71) | (-1.39) | (0.96) |
| R^2 | 0.197 | 0.183 | 0.284 | 0.240 | 0.222 | 0.288 |
| N | 480 | 480 | 480 | 480 | 480 | 480 |

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The annotations are identical to those in the table below.

Results show that the absolute β convergence coefficient of carbon emission intensity is significantly negative. Considering the differences caused by the industrial structure, innovation, education level, openness, population, and other factors of each province, the conditions β convergence

coefficient of carbon emission intensity is negative and significant (Table 5). It indicates that absolute and condition β Convergence of carbon emission intensity does exist. The condition β convergence speed is faster than the absolute convergence speed.

Table 5. Tradition β Convergence results of carbon emissions intensity

| | (1) | (2) | (3) | (4) | (5) | (6) |
|----------------------------|-----------|-----------|------------|-----------|------------|------------|
| | y | y | y | y | y | y |
| ln _{co2intensity} | -0.0433* | -0.0582** | -0.1470*** | -0.0579 | -0.1448*** | -0.1582*** |
| | (-2.28) | (-2.71) | (-3.86) | (-1.93) | (-4.56) | (-4.15) |
| is | | | | -0.0137 | -0.0742* | -0.0246 |
| | | | | (-0.90) | (-2.33) | (-0.75) |
| gov | | | | 0.2693 | 0.1232 | 0.1820 |
| | | | | (1.64) | (0.77) | (1.03) |
| lnrd | | | | 0.0046 | -0.0274* | -0.0055 |
| | | | | (0.33) | (-2.11) | (-0.33) |
| jiaoyu | | | | 0.0259 | -0.0076 | 0.0275 |
| | | | | (1.25) | (-0.30) | (0.65) |
| ln _{dow} | | | | -0.0196** | 0.0345 | -0.0105 |
| | | | | (-2.63) | (1.56) | (-0.33) |
| ln _{person} | | | | 0.0229 | 0.0566 | -0.0956 |
| | | | | (0.66) | (0.43) | (-0.85) |
| _cons | 0.1000*** | 0.1140*** | 0.1980*** | -0.2777 | -0.0777 | 0.8494 |
| | (7.11) | (7.00) | (5.63) | (-0.82) | (-0.07) | (0.86) |
| R^2 | 0.145 | 0.106 | 0.214 | 0.167 | 0.136 | 0.218 |
| N | 480 | 480 | 480 | 480 | 480 | 480 |

Secondly, we use the LM test to select the spatial error model (SEM) and spatial autoregression model (SAM). Table

6 shows that LM error and Robust LM error pass the 1% significance test respectively. Elhorst (2010) pointed out that

if the results of the LM test support the establishment of either or both the SEM and SAM, we apply the spatial Dubin model (SDM) to estimate. The LR test shows that we should use the

SDM to estimate the spatial convergence analysis of carbon emission intensity. The Haus-man test shows that we should select the fixed effect spatial Dubin model.

Table 6. LM and LR results of Space Panel Model

| Test | absolutely β convergence | | condition β convergence | |
|----------------------------|--------------------------------|---------|-------------------------------|---------|
| | Statistic | p-value | Statistic | p-value |
| Spatial error: | | | | |
| Lagrange multiplier | 3.561 | 0.059 | 5.286 | 0.022 |
| Robust Lagrange multiplier | 3.761 | 0.052 | 8.179 | 0.004 |
| Spatial lag: | | | | |
| Lagrange multiplier | 1.764 | 0.184 | 2.078 | 0.149 |
| Robust Lagrange multiplier | 1.964 | 0.161 | 4.972 | 0.026 |
| LR spatial lag | 6.37 | 0.0415 | 11.06 | 0.004 |
| LR spatial error | 4.75 | 0.0931 | 10.24 | 0.006 |

Table 7. Space β Convergence result of carbon emission intensity

| | (1) | (2) |
|----------------|------------|------------|
| | y | y |
| y | | |
| lnco2intensity | -0.1202*** | -0.1961*** |
| | (-3.80) | (-4.62) |
| is | | -0.0854** |
| | | (-2.75) |
| gov | | -0.0039 |
| | | (-0.02) |
| lnrd | | 0.0038 |
| | | (0.18) |
| jiaoyu | | -0.0011 |
| | | (-0.04) |
| ln dow | | 0.0372 |
| | | (1.58) |
| ln person | | -0.0608 |
| | | (-0.40) |
| W | | |
| lnco2intensity | 0.0870* | 0.1491** |
| | (2.22) | (2.95) |
| y | 0.0918 | 0.1282 |
| | (0.46) | (0.80) |
| e.y | 0.1567 | 0.0667 |
| | (0.80) | (0.39) |
| sigma_e | | |
| _cons | 0.1268*** | 0.1247*** |
| | (29.90) | (29.95) |
| R^2 | | |
| N | 480 | 480 |

Then, we use the fixed effect spatial Dubin model to carry out absolute and conditions β Convergence test for carbon emission intensity and regression results are shown in the first column of Table 7. The absolute β convergence coefficient is

less than 0 and passes the significance test of 1%. It indicates that the carbon emission intensity is an absolute β Convergence trend. The coefficient of Wlnco2intensity is positive and significant. It shows that the carbon emission

intensity of surrounding provinces has a positive impact on the growth rate of local carbon emission intensity.

Finally, after introducing the industrial structure, innovation, education level, openness, and population of each province into the spatial Dubin model, the results show that the convergence coefficient of carbon emission intensity is significantly negative. It indicates that there are significant spatial conditions β Convergence for carbon emission intensity. The coefficient of $W\ln CO_2$ intensity is positive and significant at the 5% significance level. Again, it shows that the carbon emission intensity of surrounding provinces has a positive impact on the growth rate of local carbon emission intensity. In other words, the higher the carbon emission intensity in the adjacent areas, the faster the growth rate of local carbon emission intensity, thus promoting the spatial convergence of carbon emission intensity.

4. Conclusion and Suggestions

4.1. Conclusion

Reducing carbon emissions and coping with the climate crisis has become the world consensus. The effective implementation of China's emission reduction methods can provide a reference for the world to reduce emissions. The premise of exploring effective ways to reduce emissions in China is to comprehensively and accurately measure the current situation. Therefore, we use the relevant data from 30 provinces in China from 2002 to 2018, using β Convergence to reveal the current situation of China's carbon emissions. Research findings: (1) Although the total carbon emissions have been growing, the growth rate has slowed down since 2011. Total carbon emissions exist positive spatial correlation and do not exist β convergence. (2) The carbon emission intensity shows a downward trend, exists positive spatial correlation and not only exists in traditional β Convergence but there is still space β Convergence also has a spatial spillover effect.

The difference from previous literature is that we use two indicators to measure the convergence characteristics of carbon emissions. This study overcomes the limitation of existing literature that only considers a single indicator of carbon emissions. We add β Convergence supplements relevant research to explore the current situation of China's carbon emissions. The conclusions of this paper are helpful to understand the emissions reduction policies in recent years and provide new ideas and inspiration for carbon peaking and carbon neutrality.

4.2. Suggestions

First, China can control carbon emissions according to the specific conditions of each province. For regions with high total carbon emissions but low intensity, carbon emissions should be strictly controlled from the total amount while maintaining high-quality economic development. For regions with high total carbon emissions and high intensity, we should focus on two aspects: one is to improve the economic development of the region and to control the total carbon emissions of the region. The second is to promote economic growth, low-carbon transformation, and upgrading of the economic structure, and strive to get rid of the status quo that economic growth is linked to carbon emission growth, to achieve green and coordinated development in the region. For regions with low total carbon emissions but high intensity, it indicates that the economic growth of the region is poor. At

present, the region should focus on promoting high-quality economic development while maintaining low total carbon emissions. For the dual low regions with low carbon emissions and low intensity, we should further improve the adjustment of the green industrial structure, improve the level of high-quality economic development and promote the green development of the region while maintaining the dual low advantages.

Second, the total carbon emission has no spatial convergence. However, there is a spatial spillover effect on carbon emission intensity, which is traditional and spatial β Convergence. Therefore, the spatial spillover effect of regions with low carbon emission intensity should be actively exerted to reduce the total amount and intensity.

In the future, the data from Chinese cities can be used for further detailed analysis. We can explore the effect of global COVID-19 on total carbon emissions and intensity.

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