

## Article

# Impact of Green Innovation Efficiency on Carbon Emission Reduction in the Guangdong-Hong Kong-Macao GBA

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**Abstract:** Climate change has become a global issue of general concern to human society. It is not only an environmental issue, but also a development issue. As the second largest economy in the world, China has adhered to its commitments in the Paris Agreement and formulated a series of autonomous action targets. In this context, scholars have done a lot of research focusing on carbon emission reduction, but have neglected the spatial correlation of carbon emission, and lack of research on carbon emission reduction in urban agglomerations. The Guangdong-Hong Kong-Macao Greater Bay Area (GBA) has been at the forefront of China in terms of economy, politics, ecology, and civilization by taking advantage of the “one country, two systems” policy. This article innovatively proposes that there is a non-linear relationship between the efficiency of green innovation and the carbon emission intensity of the Guangdong-Hong Kong-Macao GBA, and has passed quantitative verification. Based on the panel data of the Guangdong-Hong Kong-Macao GBA from 2009 to 2019, we used the super-efficiency slacks-based measure (SBM) model to measure the efficiency of green innovation. We used the global Moran index and Theil index to discuss the spatial correlation of carbon emissions and regional differences in carbon emission intensity in the Guangdong-Hong Kong-Macao GBA, respectively. Then, we used the threshold model to verify the nonlinear relationship between the efficiency of green innovation and the intensity of carbon emissions in the Guangdong-Hong Kong-Macao GBA. The results of the study found that the green innovation efficiency of the Guangdong-Hong Kong-Macao GBA is increasing overall, carbon emissions have a certain spatial correlation, and the correlation is low overall. The impact of green innovation efficiency on carbon emission intensity has a non-linear relationship and there is an “inverted U” pattern between the two, and there is an inflection point in green innovation efficiency. Based on this, this article proposes carbon emission reduction measures within a reasonable range, and looks forward to future research directions and complement the research deficiencies.

**Keywords:** green innovation efficiency; carbon emission reduction; Moran index; SBM model; threshold model; Guangdong-Hong Kong-Macao GBA (GBA)



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## 1. Introduction

Environmental pollution and climate change have gained more and more attention as one of the most concerning issues in the world in the 21st century. There are still many uncertainties in the current forecast of climate change. However, a large amount of existing evidence shows that due to the influence of human activities, the concentration of carbon dioxide (CO<sub>2</sub>) in the atmosphere has increased from 280 mol/mol before the industrial revolution to 350 mol/mol in the early 1990s [1]. Corresponding to this, the annual average temperature of the earth's surface has also risen by 0.6 °C in more than a century [2]. Therefore, there is no doubt that the greenhouse effect caused by human activities is continuously strengthening, and carbon emission reduction has become a global consensus. In 2015, 197 parties reached the “Paris Agreement”. The “Paris Agreement” is

the world's first international convention to comprehensively control carbon dioxide and other greenhouse gas emissions, and to address the adverse effects of global warming on the human economy and society. In 2018, the parties conducted a new round of climate negotiations under the United Nations Framework Convention Climate Change (UNFCCC) framework in Bonn, Germany, and completed the details of the agreement. Environmental policies, green innovation, comprehensive risk index, and renewable energy research and development can help to control carbon emissions [3]. Based on this, governments have issued a series of laws and regulations to promote carbon emission reduction. Due to the "externality" or "publicity" of carbon emission reduction, every country hopes that it will be less restrictive and get more benefits when assuming responsibility. In this way, it will be difficult to reverse the deterioration of the climate (Ambec and Barla, 2002) [4]. The 2016 BP World Energy Statistical Yearbook [5] shows that China accounted for 23% and 34% of the world's total energy consumption and net energy consumption, respectively, and accounted for 27% of the world's total CO<sub>2</sub> emissions in 2015. As of 2015, China is still the country with the largest carbon emissions. According to BP data, China's CO<sub>2</sub> emissions in 2020 will be 9.894 billion tons. China's carbon emission intensity has been reduced by 18.8% compared with 2015, exceeding the 40–45% goal promised to the international community, and reversing the rapid growth of CO<sub>2</sub> emissions.

As the second largest economy in the world, China has consciously assumed its responsibilities. In September 2020, at the 75th session of the United Nations General Assembly, China stated that it would "take more powerful policies and measures, strive to reach the peak of CO<sub>2</sub> emissions by 2030, and strive to achieve carbon neutrality by 2060" [6]. That is to say, by 2030, the total amount of carbon emissions from regional economic activities will not increase with economic growth in China in 2030, and the total amount of carbon emissions from economic activities will not exceed the total amount that can be absorbed by the ecosystem by 2060. In March 2021, China issued the "14th Five-Year Plan and Outline of Long-Term Goals for 2035." It is stipulated that during the "14th Five-Year Plan" period, an action plan for peaking carbon emissions by 2030 will be formulated, anchoring efforts to achieve carbon neutrality by 2060, and adopting more powerful policies and measures [7].

China's economy is huge, and its regional development is extremely unbalanced, especially the economic, cultural, and ecological gaps between the eastern and western regions are huge. The current Chinese carbon trading market has not yet realized Porter's "weak" hypothesis [8]. There is a long way to go to achieve the global carbon emission reduction target and achieve the development of economic coordination. In the chessboard of regional economic development, carbon peaking and carbon neutrality are not isolated cases in one place. How to build a multi-dimensional coordinated development path of carbon peaking and carbon neutrality in the Guangdong–Hong Kong–Macao GBA to achieve environmental quality compliance and high-quality economic development has a greater feasibility [9,10]. Research on carbon emission reduction in some regions has a guiding role for other regions in China. The GBA has a reasonable industrial structure, a natural location advantage of the port area, a developed tertiary industry, and a sound ecological pattern. It is a pioneer in technological innovation in other regions of China. Therefore, it is extremely suitable for studying the characteristics of green transformation of Chinese urban agglomerations [11,12].

In order to achieve the goal of carbon emission reduction, the entire economy needs to give full play to the supporting role of scientific and technological innovation, to promote the continuous optimization of the energy structure, facilitate the reduction of carbon emission intensity, and promote the adjustment of the industrial structure [13]. Some cities in the Guangdong–Hong Kong–Macao GBA have entered the post-industrial era. The economic development level of the entire region has reached a relatively high level and the degree of urbanization has been high. Therefore, the achievement of carbon emission reduction targets cannot rely on cutting high-carbon emission industries and forcibly reducing the level of regional carbon emission, but need to start from a technical perspective

and give full play to the leading role of technological carbon emission reduction. The technological development of the entire economy can curb carbon emission intensity [14,15]; therefore, does the technological development of an individual region have an impact on the overall green innovation efficiency? Can increasing the level of regional green innovation curb the intensity of regional carbon emissions? What are the characteristics of the impact of green innovation efficiency on carbon emission reduction? It is only by clarifying these issues that we can sort out the current level of green innovation efficiency in the Guangdong-Hong Kong-Macao GBA, and accurately assess the impact of green innovation efficiency on carbon emissions reduction. Extending the experience of the Bay Area to the whole of China is extremely important for China to achieve the peak of carbon emissions in 2030 and achieve the goal of carbon neutrality by 2060.

In this context, this article creatively discusses the relationship between green innovation efficiency and carbon emission reduction in the Guangdong-Hong Kong-Macao GBA. Elaborating the non-linear relationship between them can study the influencing factors of carbon emission reduction of urban agglomeration from a new perspective. Based on the theoretical hypothesis, through empirical testing of this theory, we can provide carbon emission reduction experience for other urban agglomerations in China. The empirical evidence section of this article uses the relevant data of the “9 + 2” urban agglomeration in the Bay Area from 2009 to 2019. According to previous research methods, combined with the findings of Li and Du (2020) [16] based on DEA (Data Envelopment Analysis), the super-efficiency SBM model was used to measure the green innovation efficiency of 11 cities in the GBA. We discussed the spatial correlation of carbon emissions and differences in carbon emission reduction in the GBA, and empirically tested the factors influencing carbon emission reduction through a threshold model.

The other parts of this article are organized as follows: Section 2 is a literature review of related topics. In Section 3, we use the super-efficiency SBM model to measure the efficiency of green innovation in the Greater Guangdong-Hong Kong-Macao GBA, and analyze the characteristics of the status quo of green innovation in the Bay Area. In Section 4, we set the threshold model and analyze the empirical results. Section 5 provides conclusions, policy recommendations, and future research directions.

## 2. Literature Review and Mechanism of Action

### 2.1. Literature Review

The concept of green innovation was first proposed by Fussler and James in 1996 [17]. It refers to new products and new processes that can provide value to consumers and enterprises while greatly reducing their environmental impact. Faced with the greenhouse effect that needs to be dealt with urgently, some scholars gradually have begun to address environmental factors in the research of enterprise technological innovation [18,19]. This is how the efficiency of green innovation evolves from the efficiency of traditional technological innovation. Without green technological innovation and progress, there can be no real sustainable development, and the green growth of the economy cannot be achieved without technological innovation. Green innovation is the key to green development. The concept of ecological innovation was first introduced in the book *Driving Eco-innovation: A Breakthrough Discipline for Innovation and Sustainability*. Since then, “eco-innovation” has also been referred to as environmental innovation, green innovation, or sustainable innovation (Fussler and James, 1996) [17]. Specifically, green innovation refers to product innovation and technological innovation that aim to protect the environment and reduce the negative impact of economic activities on the environment (Blättel-Mink, 1998; Mirata and Emtairah, 2005) [20,21]. Studies have proved that stricter environmental regulations will promote high-quality economic development (Chen et al. 2020) [22]. This is because environmental regulations incentivize companies to carry out green innovations, and increased technological innovations allow companies to eliminate outdated production capacity and upgrade production efficiency while also reducing carbon emission intensity (Apergis et al. 2013) [23].

In terms of the measurement method of green innovation efficiency, the measurement of green innovation efficiency is usually based on two technical innovation measurement methods: parametric stochastic frontier production function and non-parametric data envelopment analysis. Among them, the DEA method can realize the measurement of innovation efficiency with multiple input and multiple output variables. Although the SFA method can avoid the random error problem that the DEA method cannot solve, it is necessary to set a suitable frontier production function form in advance when applying it [24–26]. The DEA method does not require setting a specific function form and is a non-parametric estimation method. Therefore, it can circumvent multiple limitations of parameter methods and has unique advantages in measuring the performance and relative efficiency of decision-making units (DMU) with multiple inputs and multiple outputs, such as the DEA-CCR (Data Envelopment Analysis-A. Charnes & W. W. Cooper & E. Rhodes) model proposed by Charnes et al. (1978) [27] and the DEA-BCC model proposed by Banker (1986) [28].

Compared with pollutants such as  $\text{SO}_2$  (sulfur dioxide) and  $\text{NO}_2$  (nitrogen dioxide), the impact of excessive  $\text{CO}_2$  (carbon dioxide) emissions is global and will cause a rise in global temperatures (Azomahou, Laisney, and Nguyen Van, 2006) [29]. Currently, scholars are doing more and more research on carbon emission reduction in urban agglomerations, focusing on the following aspects.

First, the decomposition of carbon emission drivers and the relationship between economic development and carbon emission reduction. Kaya (1990) [30] decomposes the driving factors by expressing carbon emissions as factor multiplication according to different weights. This method is also called the Kaya identity decomposition method. Many scholars have extended other methods for carbon emission decomposition based on Kaya's constant equation, such as the Laspeyres index method [31], simple average decomposition method (Boyd, Hanson, and Sterner, 1988) [32], adaptive weight decomposition method (Ang, Zhang, and Choi, 1998) [33], etc. Carbon emissions are closely related to economic activities. Some scholars have theoretically analyzed the impact of regional integration on the marginal cost of carbon reduction and found that China's increased regional integration would reduce the marginal cost of carbon emissions in China (He et al. 2018) [34].

Second, the impact of technological innovation on carbon emission intensity. Beinhocker's (Beinhocker et al. 2008) [35] research estimates that in the next 40 years, the global carbon productivity will increase by 10 times to meet the carbon emission reduction targets set by the IPCC. However, the only way to simultaneously achieve the goal of reducing the cost of carbon emissions reduction and maintaining economic growth is to increase carbon productivity. Carbon emission intensity is closely related to technological innovation. In the context of China, there is a spatial spillover effect of low-carbon technological innovation on carbon emission reduction, and the effect of emission reduction in different regions also shows regional heterogeneity (Lu Na et al. 2019) [36,37]. The impact of technology on carbon emissions varies depending on the subject of study. Tetsuya and Shunsuke [38] studied the effects of national technology in different income ranges on carbon emissions, and found that technological factors play a significant role in carbon emission reduction in high-income countries and a less significant role in low-income countries. Musolesi and Massimiliano [39] continue to study the relationship between long-term income and carbon emissions in developed countries. For developing countries such as China, as incomes increase, carbon emissions are gradually reduced (Alam et al. 2016) [40].

Carbon emissions have an obvious spatial correlation. China has a vast territory, and it may not be possible to obtain accurate research results using the whole country as a research object. Research on the carbon emissions of urban agglomerations can not only obtain more precise and detailed research, but also extend the experience of urban agglomerations to other regions of the country to promote the national carbon emission reduction reform. The Guangdong-Hong Kong-Macao GBA has efficient resource allocation, reasonable industrial structure, natural location advantages, and strong agglomeration spillover functions. Therefore, there are more studies on the process of economic integra-

tion in the Bay Area [41,42], and some scholars also discussed the possibility of using the Guangdong-Hong Kong-Macao GBA as a sample to build a green innovation system from the perspective of green innovation [43,44]. However, the research on the Bay Area still stays at the measurement and analysis of the current situation of economic, regional synergy, and green innovation level. There is a lack of research on carbon emission reduction from the perspective of green innovation.

The climate issue has received global attention, and the research on green technology innovation and carbon emission reduction has also achieved fruitful results, but there is still much room for expansion. First, most of the existing research has been conducted in terms of the current status of low-carbon development, current challenges faced, and the factors influencing carbon emissions. It rarely involves urban agglomerations, especially the impact of green innovative technologies on carbon emission intensity. In this part of the research, there is no unified conclusion about their relationship. Second, the research objects are limited to the national and provincial scopes, and there is little research on urban agglomerations, especially the carbon emission reduction in the Guangdong-Hong Kong-Macao GBA. This ignores the role of spatial spillover effects brought about by urban agglomerations in green innovation technologies on carbon emissions reduction. Today, with increasing emphasis on green innovative technologies, more and more research will inevitably emerge to discuss the balance between economic development and carbon emission reduction from the perspective of technological innovation.

This paper analyzes the non-linear relationship between green innovation efficiency and carbon emission intensity in the Guangdong-Hong Kong-Macao GBA from the perspective of green innovation. Based on the previous literature, the possible marginal contributions of the paper are: First, in terms of research content, the urban agglomerations in the Guangdong-Hong Kong-Macao GBA are the research objects. At the same time, the non-linear relationship between the efficiency of green innovation and carbon emission reduction in the Bay Area is also incorporated into the research framework, and the spatial correlation of carbon emissions and the regional differences in carbon emission intensity in the Bay Area are analyzed before studying the influencing factors of carbon emission reduction. Second, the super-efficiency SBM model is used to measure the green innovation efficiency of 11 cities in the Guangdong-Hong Kong-Macao GBA, and a threshold model is established to try to clarify the impact of green innovation on carbon emission reduction using green innovation efficiency as a threshold variable. This has enriched the research on carbon emission reduction of urban agglomerations to a certain extent, and proposed new ideas for the goal of carbon emission reduction and carbon neutrality in China.

## 2.2. Research Hypothesis

The mechanism of the green innovation efficiency of urban agglomerations on carbon emissions may have two aspects. First, green innovation technology can reduce the cost of carbon emission by improving the production technology of enterprises, thereby curbing the intensity of carbon emission. The government vigorously promotes the development of innovative technologies, grants certain subsidies and preferential policies to green industries, and also implements environmental regulations on high-carbon emission industries. Therefore, companies invest more in green technologies to reduce the cost of carbon emissions for long-term development. Second, green innovation inputs crowd out the resource inputs of other factors. Enterprises can only expand the scale of production to maintain profitability levels, leading to more carbon emissions and thus increasing carbon emission intensity. It will take a long time for new technologies and production systems before they are available on a large scale. Although the efficiency of green innovation has increased during this period, the intensity of carbon emissions will also increase. Previously, we needed to distinguish between high-polluting industries and low-tech industries. The heavy-polluting industries specified in the “List of Listed Companies’ Environmental Inspection Industry Classification Management Directory” published by the Chinese government in 2008 were merged into eight categories. These include the extractive industry,

textile clothing and fur industry, metal and non-metal industry, petrochemical and plastic industry, food and beverage industry, water, electricity, and gas industry, biomedicine industry, and paper printing industry. The Organization for Economic Cooperation and Development (OECD) classifies high-tech, medium-tech, and low-tech industries based on the R&D intensity of each industry. Combined with previous research, it is determined that low-tech industries are mainly identified here as new and traditional industries with relatively stable low-tech, low-knowledge content and low-technology content.

The impact of green innovation technologies on carbon emission intensity in the GBA is related to the level of urban green innovation efficiency. However, it is not clear what path the green innovation efficiency of the GBA will take to affect carbon emission reduction. Based on this, this article proposes the following hypotheses:

**Hypothesis 1 (H1).** *Green innovation efficiency is the determinant of the non-linear relationship between carbon emission intensity and the level of green innovation technology.*

Considering the high-carbonization characteristics of China's economy and energy system, the green innovation drive is one of the important ways to achieve the goal of carbon neutrality, and it is also one of China's main measures to actively adapt to climate change [45]. When the pollution intensity of a region in a given year is high and the investment in technological innovation is low, it will cause a "pollution effect". At this time, the efficiency of green innovation in the region is low, and the industrial structure is unreasonable. Resource-intensive industries represented by industry generate a large number of carbon emissions. In the meantime, the cost of carbon emissions is high. However, the Chinese government has stepped up its efforts to address climate issues in recent years, and industries with high carbon emissions are the first to bear the brunt. Environmental regulations are becoming more stringent, and local governments and companies can only invest a lot of money in carbon emission reduction technologies. The improvement of green innovation efficiency comes at the cost of compressing other inputs. At this time, the increase in green innovation efficiency may lead to an increase in carbon emission intensity. Only when green innovation technologies form spatial agglomeration, scaleup, and have a mature production system, technological reforms will reduce the cost of carbon emission reduction, and the intensity of regional carbon emissions will drop significantly. Green technological advancement is a fundamental measure to achieve carbon emission reduction. However, different levels of green innovation, independent technological innovation and technology introduction, and different levels of green technology in different countries and regions have different effects on carbon emission reduction [46–48]. Specifically, there may be a threshold effect between the efficiency of green innovation and carbon emissions in the Guangdong-Hong Kong-Macao GBA. As the efficiency of green innovation changes, there may be more than one threshold. In different threshold intervals, the impact of green innovation efficiency on carbon emissions is also different. In summary, this article proposes Hypothesis 2 and Hypothesis 3.

**Hypothesis 2 (H2).** *When the level of green innovation in cities is low, the government needs to invest a lot of money in carbon emission reduction technologies. This will instead squeeze the space for factors flow. Therefore, the increase in the efficiency of green innovation will increase the intensity of carbon emissions.*

**Hypothesis 3 (H3).** *When the level of green innovation in a city reaches a certain level, regional green innovation forms a spatial spillover to carbon emission reduction. At this time, an increase in the efficiency of green innovation will inhibit the growth of carbon emission intensity in cities.*

### 3. Measurement of Green Innovation Efficiency in the Guangdong-Hong Kong-Macao GBA

#### 3.1. Indicator System

There are three main definitions of green innovation: First, innovations that minimize environmental hazards; second, innovations that introduce environmental performance; and third, innovations that are equivalent to environmental innovations or environmental improvements. In this article, we chose the first definition to refer to innovations that minimize environmental hazards as green innovations, and the level of effect obtained by cities on green innovation input as green innovation efficiency. To clarify the impact of the green innovation efficiency on carbon emission reduction in the Guangdong-Hong Kong-Macao GBA, we had to first accurately measure the green innovation efficiency of the Guangdong-Hong Kong-Macao region. Starting from the status quo of economic development, referring to the current situation of resources and environment, and learning from the practices of Wang and Zhang [49,50], we constructed an evaluation system to measure the efficiency of green innovation from the two dimensions of input and output in the Guangdong-Hong Kong-Macao GBA. We selected seven indicators in total, as shown in Table 1. The input indicators were divided into three aspects, namely capital input, human capital, and energy input. These were the basic core resource elements of green innovation. The corresponding indicators selected in this article were R&D expenditure, the full-time equivalent of R&D employees, and total industrial energy consumption. Output indicators were divided into three aspects-economic output, technological output, economic growth and pollutant output-selected from the perspective of the economics of green innovation and environmental protection. The corresponding indicators selected in this article are new product sales revenue, patents authorization volume, GDP per capita, and pollution intensity. Among them, the pollution intensity was calculated by the three waste indicators through the entropy weight method. The “three wastes” refer to industrial wastewater, as the main component of the exhaust gas and industrial solid waste, which includes most of the pollution emissions in a region. Next, the “three wastes” indicators of the 11 regions were processed by the entropy method, to calculate the pollution intensity of 11 regions in the Guangdong-Hong Kong-Macao GBA from 2009 to 2019. The process of entropy method to calculate pollution intensity is as follows:

**Table 1.** Indicator system of green innovation efficiency.

| Indicator Categories | Index Composition  | Variable (Unit)                                     | Indicator Attributes |
|----------------------|--------------------|-----------------------------------------------------|----------------------|
| Input                | Capital investment | R&D expenditure (million yuan)                      | Negative indicator   |
|                      | Human capital      | The full-time equivalent of R&D employees (persons) | Negative indicator   |
|                      | Energy input       | Total industrial energy consumption (million tons)  | Negative indicator   |
| Output               | Economic output    | New product sales revenue (million yuan)            | Positive indicator   |
|                      | Technical output   | Number of patents granted (pieces)                  | Positive indicator   |
|                      | Economic growth    | GDP per capita (yuan)                               | Positive indicator   |
|                      | Pollutant output   | Pollution intensity                                 | Negative indicator   |

The first step is to calculate the proportion of the  $i$ -th indicator value in the  $j$ -th region [51,52]:

$$p_{ij} = r_{ij} / \sum_{i=1}^m su_{ij} \quad (1)$$

The second step is to calculate the entropy value  $e_j$  of the  $j$ -th indicator [53]:

$$e_j = -k / \sum_{i=1}^m p_{ij} \cdot \ln p_{ij}, \quad k = 1 / \ln m \quad (2)$$

The third step is to calculate the entropy weight  $w_j$  of the  $j$ -th indicator [54,55]:

$$w_j = (1 - e_j) / \sum_{j=1}^n (1 - e_j) \quad (3)$$

where  $w_j$  is the final weight coefficient for each indicator, and the weight coefficient obtained is substituted into:

$$y_i = \sum_{j=1}^m w_j x_{ij}^* \quad (4)$$

After calculation, we could attain the comprehensive evaluation value of 11 evaluated areas, that is, the pollution intensity of 11 areas.

The non-radial DEA model proposed by Tone (2002) [56] is a method for evaluating the efficiency of DMUs based on slack-based measure (SBM). Different from the traditional CCR or BBC model, the SBM model directly adds the slack variable to the objective function, so that the economic explanation of the SBM model is to maximize the actual profit, rather than just to maximize the benefit ratio. The traditional measurement method SBM model takes the slack variable into account in the objective function and solves the problem of the slackness of input and output variables. However, the efficiency values of effective decision-making units measured by the SBM model are all 1. It is difficult to distinguish the difference in efficiency among the effective decision-making units, which leads to bias in the final decision. The super-efficiency SBM model was also proposed by Tone (2002) [56], which can re-decompose the effective unit with an efficiency value of 1 to realize the comparison of effective decision-making units and improve the accuracy of the result comparison. Considering that the economic development level, economic development path, and factor endowments of different regions are greatly different in the Guangdong-Hong Kong-Macao GBA, this article adopted the super-efficiency SBM model of non-expected output to measure the green innovation efficiency of the Guangdong-Hong Kong-Macao GBA.

The super-efficiency SBM model with non-expected output is expressed as follows:

$$\min \phi = \frac{(1/m) \sum_{i=1}^m (\bar{x}/x_{ik})}{1/(r_1 + r_2) \left( \sum_{s=1}^{r_1} \bar{y}^d / y_{sk}^d + \sum_{q=1}^{r_2} \bar{y}^u / y_{qk}^u \right)} \quad (5)$$

Subject to:

$$\begin{aligned} x_{ik} &\geq \sum_{j=1, j \neq k}^n x_{ij} \lambda_j, i = 1, \dots, m \\ \bar{y}^d &\leq \sum_{j=1, j \neq k}^n y_{sj}^d \lambda_j, s = 1, \dots, r_1 \\ \bar{y}^u &\geq \sum_{j=1, j \neq k}^n y_{qj}^u \lambda_j, q = 1, \dots, r_2 \\ \lambda_j &> 0, j = 1, \dots, n; j \neq 0. \\ \bar{x} &\geq x_k, i = 1, \dots, m. \\ \bar{y}^d &\leq y_k^d, s = 1, \dots, r_1 \\ \bar{y}^u &\geq y_k^u, q = 1, \dots, r_2 \end{aligned} \quad (6)$$

Among them,  $\phi$  is the efficiency of urban green innovation, and  $n$  is the number of cities. In this model,  $n = 11$  and  $m$  is the number of inputs, and  $r_1, r_2$  represents the expected output and unexpected output of the model, respectively. In this model,  $r_1 = 3, r_2 = 4$ , and  $\bar{x}, \bar{y}^d, \bar{y}^u$  are the elements in the corresponding input matrix, expected input matrix and unexpected output matrix, respectively.

### 3.2. Measuring the Efficiency of Green Innovation

In the previous section, the super-efficient SBM model to measure the efficiency of green innovation was given in this article, and next, we measured the efficiency of green innovation in the Guangdong-Hong Kong-Macao GBA from 2009 to 2019. The data for measuring the efficiency of green innovation came from the following: China Statistical

Yearbook, China City Statistical Yearbook, China Environmental Statistical Yearbook, and China Patent Statistical Annual Report. Part of the data for prefecture-level cities came from local statistical yearbooks, and the data for Hong Kong and Macau were mainly from the Hong Kong Statistical Yearbook, Macao Statistical Yearbook, and Macao Environmental Reports. There were also missing data for individual years in individual regions. This article used interpolation to complete them. The green innovation efficiency of the Guangdong-Hong Kong-Macao GBA was calculated as shown in Table 2.

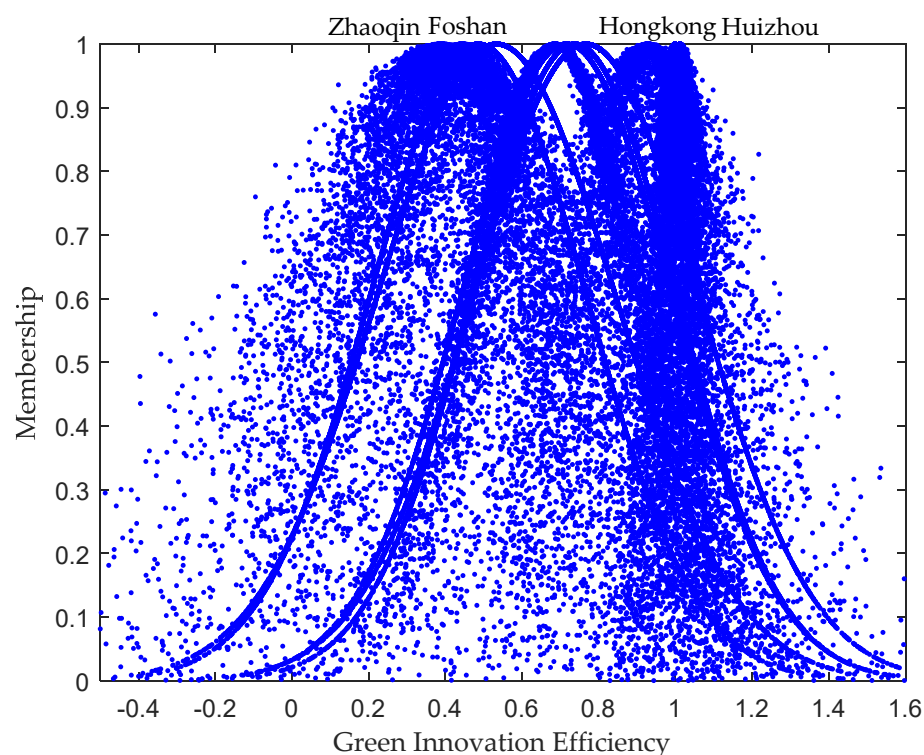
**Table 2.** Green innovation efficiency calculation results of the Guangdong-Hong Kong-Macao GBA.

| Region    | 2009  | 2010  | 2011  | 2012  | 2013  | 2014  | 2015  | 2016  | 2017  | 2018  | 2019  |
|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Guangzhou | 0.36  | 0.365 | 0.344 | 0.329 | 0.337 | 0.313 | 0.371 | 1.039 | 0.985 | 1.042 | 0.879 |
| Shenzhen  | 0.346 | 0.474 | 0.556 | 0.605 | 0.555 | 0.603 | 0.725 | 0.75  | 1.004 | 1.013 | 1.081 |
| Zhuhai    | 0.286 | 0.303 | 0.288 | 0.275 | 0.36  | 0.364 | 0.4   | 0.433 | 0.486 | 0.684 | 1.005 |
| Foshan    | 1.083 | 1.019 | 1.01  | 0.869 | 1.025 | 1.015 | 1.061 | 1.007 | 1.005 | 1.01  | 1.029 |
| Zhongshan | 0.544 | 0.502 | 0.706 | 0.639 | 0.572 | 0.461 | 0.437 | 0.498 | 1.005 | 1.03  | 1.038 |
| Dongguan  | 0.215 | 0.217 | 0.279 | 0.257 | 0.312 | 0.401 | 0.549 | 0.583 | 0.676 | 0.835 | 1.02  |
| Huizhou   | 0.447 | 0.462 | 0.494 | 0.544 | 0.578 | 0.609 | 0.676 | 1.008 | 1.005 | 1.013 | 1.04  |
| Jiangmen  | 0.557 | 0.646 | 0.784 | 0.653 | 0.529 | 0.423 | 0.442 | 0.579 | 0.632 | 0.607 | 0.791 |
| Zhaoqin   | 0.805 | 0.734 | 0.656 | 0.629 | 0.614 | 0.808 | 0.706 | 0.852 | 0.968 | 0.297 | 1.003 |
| Hongkong  | 1.017 | 1.022 | 1.004 | 1.016 | 0.899 | 1.002 | 0.933 | 1.016 | 1.004 | 1.011 | 1.062 |
| Macao     | 0.738 | 1.006 | 1.025 | 0.822 | 1.019 | 1.012 | 1.028 | 0.838 | 1.003 | 1.003 | 1.017 |
| Mean      | 0.627 | 0.614 | 0.650 | 0.603 | 0.618 | 0.637 | 0.666 | 0.782 | 0.888 | 0.868 | 0.942 |

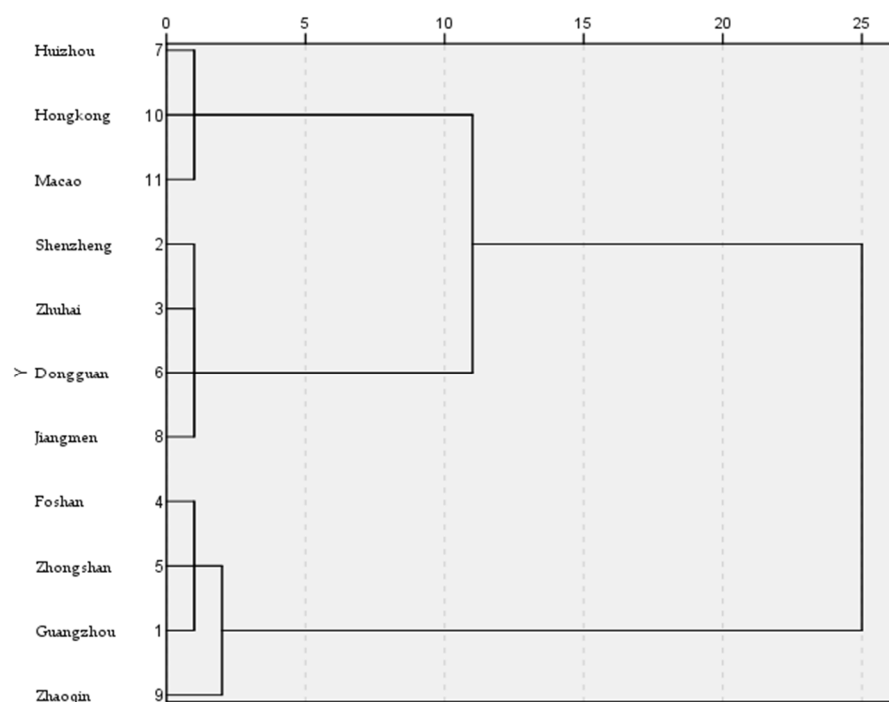
From Table 1, the green innovation efficiency of the Guangdong-Hong Kong-Macao GBA increased overall. The average value has increased from 0.627 in 2009 to 0.868 in 2019, with a slight decrease in 2013 and 2014. Guangzhou, Shenzhen, and other regions are located on the first gradient of China's economic development and were more severely affected by the 2008 financial crisis. The stagnant scientific research activities have also caused a decline in the efficiency of green innovation. The highest average green innovation efficiency in the Guangdong-Hong Kong-Macao GBA appeared in 2018. In these years, the economy of the GBA has been moderated and continues to increase steadily. On the whole, the green innovation efficiency of the GBA was relatively high, and the average growth rate was relatively small. This may be because the sample year was only ten years, and the economic development was relatively stable in the GBA during this period.

In terms of different cities, the green innovation efficiency of Guangzhou and Shenzhen increased significantly, with a certain increase every year. After the introduction of national policies to strongly encourage green innovation, local governments also simultaneously issued regulations to encourage innovation and invested in innovation funds to promote green innovation efficiency. The efficiency of green innovation has increased from about 0.3 in 2009 to about 1 in 2019. The green innovation efficiency of most cities in the GBA is slowly increasing, while the green innovation efficiency in Huizhou, Hong Kong, and Macau is relatively stable, especially in Huizhou and Hong Kong, where the efficiency of green innovation remains at about 1, and there is a high green innovation efficiency. However, the high efficiency of green innovation in Huizhou is due to the small size of the local industry, with two national development zones, Zhongkai High-Tech Industrial Development Zone and Daya Bay Economic and Technological Development Zone. Huizhou started early and developed fast, and its innovation efficiency has always been high. The Hong Kong and Macau regions, because of their early start in economic development, had already taken off by the time the People's Republic of China was founded. The policy of "one country, two systems" has enabled the economic, cultural, and social development of Hong Kong and Macau to reach maturity in the millennium, resulting in a stable and high level of green innovation efficiency since 2009. It is too crude to analyze the green innovation efficiency of different cities in the GBA from the value of green innovation efficiency. Next, the cloud model and system clustering are used to analyze the normal distribution and

optimal segmentation of green innovation efficiency in the GBA. The results are shown in Figures 1 and 2.



**Figure 1.** Distribution of normal cloud membership of green innovation efficiency in the Guangdong-Hong Kong-Macao GBA.



**Figure 2.** Cluster tree of green innovation efficiency in the Guangdong-Hong Kong-Macao GBA.

From Figure 1, the green innovation efficiency of the GBA has the characteristics of “urban gradient” development. The figure shows that the first gradient of green innovation

efficiency is Huizhou, Hong Kong, and Macau; the third gradient is Zhaoqing and Foshan cities, and the second gradient is the other 6 cities. The green innovation efficiency of Zhaoqing and Foshan is at a low level, and the development level of these cities is not as good as that of cities such as Guangzhou and Shenzhen. The flow of human resources and innovative elements to high-economic areas also requires the transfer of high-polluting industries in areas with high economic development to a certain extent, which has caused slow growth in green innovation efficiency in cities around Guangzhou. The green innovation efficiency of Huizhou, Hong Kong, and Macau is higher. In particular, Hong Kong and Macau have small-scale industries. After industrial upgrading, they now rely mainly on tertiary industries such as tourism, finance, and gaming.

Based on Figure 2, we found that the green innovation efficiency of cities in the GBA was quite different. The rankings of Hong Kong and Macau did not change much. Huizhou's ranking dropped, while Guangzhou, Shenzhen, and Dongguan's rankings increased. These cities, which rely on government policy dividends and economic scale advantages to attract a large number of high-quality talents, have successively introduced policies to enhance the positive guiding role of financial expenditures on green innovation, and at the same time enhance the motivation and sustainability of enterprises to carry out green innovation. The efficiency of green innovation in Zhuhai and Jiangmen regions continues to increase, but the economic scale is small, the number of employees is low, and the lack of regional capital and human input has seriously affected the scale of innovation output and hindered the improvement of regional green innovation efficiency.

#### 4. Empirical Test

##### 4.1. Model Setting and Variable Description

Due to the existence of the policy “one country, two systems”, there is significant heterogeneity in the carbon emission intensity of the Guangdong-Hong Kong-Macao GBA. The impact of green innovation efficiency on carbon emission intensity may be different in different cities at different times. Taking these conditions into account, this article uses the threshold panel model proposed by Hansen (1999) [57]. We use green innovation efficiency as a threshold variable and establish a threshold effect model to analyze the nonlinear relationship between carbon emission intensity and green innovation efficiency in the Guangdong-Hong Kong-Macao GBA. Since the number of thresholds cannot be determined, this article considers a threshold regression that includes “multiple thresholds”, and constructs a multi-threshold panel data model with green innovation efficiency as the threshold variable as follows:

$$\ln(\text{CR})_{it} = \eta_i + \lambda_1 \ln(\text{innov})_{it} \cdot I(\ln(\text{innov})_{it} < \gamma_1) + \lambda_2 \ln(\text{innov})_{it} \cdot I(\gamma_1 \leq \ln(\text{innov})_{it} < \gamma_2) + \dots + \lambda_n \ln(\text{innov})_{it} \cdot I(\ln(\text{innov})_{it} < \gamma_n) + \phi \ln(\text{con})_{it} + \varepsilon_{it} \quad (7)$$

Among them,  $i$  and  $t$  represent the region and time,  $\eta$  is the characteristic value of the observation value,  $\lambda$  is the coefficient of the core explanatory variable of different zones,  $\ln(\text{innov})_{it}$  is the threshold variable, and  $\gamma$  is the specific threshold value. Determined endogenously by the selected sample data,  $\phi$  represents the control variable coefficient,  $\text{concon}$  is a series of control variables, and  $\varepsilon$  is a random disturbance term. Next, this article lists the explanatory variables and the explained variables, as well as the selected control variables.

Independent variable: green innovation efficiency ( $\text{innov}$ ).

The efficiency of green innovation is mainly reflected in many aspects among the internal subjects within the region. In the previous section of this paper, the green innovation efficiency of the Guangdong-Hong Kong-Macao Bay Area was measured by selecting an appropriate evaluation system.

Dependent variable: carbon emission intensity ( $\text{CR}$ ).

This article selects carbon emission intensity to measure the effect of carbon emission reduction, so the research object is the carbon emission intensity of the Guangdong-Hong

Kong-Macao GBA. Here it is expressed by the ratio of regional CO<sub>2</sub> emissions to regional GDP. The formula for carbon emission intensity is as follows: carbon emission intensity:

$$CR_{it} = \frac{CO_{2it}}{GDP_{it}} \quad (8)$$

Among them, CO<sub>it</sub> is the carbon emissions of the *i* region in the *t* year, and GDP<sub>it</sub> is the GNP of the *i* region in the *t* year, thus calculating the carbon emissions intensity of the 11 cities in the GBA in 2009–2019.

Control variables: The advanced industrial structure (indind) reflects the process of transforming the regional industrial structure from low-level to high-level. It is expressed by the ratio of the tertiary industry and the secondary industry in this article. The intensity of environmental regulation (er) is closely related to the policies implemented by the local government every year. Therefore, the cost of corporate governance of the three wastes directly reflects the intensity of the environmental regulation to which the industry is experienced. This paper selected the operating costs of industrial wastewater and waste gas treatment facilities to represent the intensity of environmental regulations. The level of urbanization (urb) refers to the progress of civilization and the level of socialization of a city. This article used the ratio of urban permanent residents to the total permanent residents of the region to measure. Energy structure (ene) is an important content of energy system engineering research, as it directly affects the final energy use mode of various sectors of the national economy, and reflects the people's living standards. This article used the ratio of regional coal consumption to total energy consumption to measure. This article selected these 4 indicators as control variables.

The values of the green innovation indicators in this article have been calculated in the above section. Data on indicators such as carbon emissions, regional GDP, and control variables came from China Statistical Yearbook, China Environmental Statistical Yearbook, China Energy Statistical Yearbook, and China Urban Statistical Yearbook. Part of the data came from the local statistical yearbook, and the data for Hong Kong and Macau were mainly from the Hong Kong Statistical Yearbook and Macao Statistical Yearbook. A small number of missing values were processed by interpolation, which resulted in the data of 11 cities in the Guangdong-Hong Kong-Macao GBA from 2009 to 2019.

#### 4.2. Moran Index of Carbon Emissions

To further understand the overall trend and spatial correlation of carbon emissions in the Guangdong-Hong Kong-Macao GBA, we used the Moran index to analyze regional spatial autocorrelation. The global Moran index reflects the overall characteristics of the degree of spatial association of the research variables. Moran's *I* > 0 indicates a positive spatial correlation, and the larger the value, the more obvious the spatial correlation, Moran's *I* < 0 indicates a negative spatial correlation, and the smaller the value, the greater the spatial difference. Otherwise, Moran's *I* = 0 indicates that there is no spatial correlation effect. Table 3 shows the global spatial autocorrelation Moran's *I* index of the GBA from 2009 to 2019.

From Table 3, the spatial autocorrelation of carbon emissions from 2019 to 2017 is around 0.3, with individual years exceeding 0.33, and the Moran index is positive at a significant level of 5% in most years. This shows that there is obvious spatial autocorrelation of carbon emissions in the GBA, and the overall correlation is relatively high. The spatial aggregation effect of high-value areas and low-value areas is obvious. The trend of the global Moran index shows that the spatial autocorrelation of carbon emissions in the Bay Area is generally weakening from 2009 to 2019. The highest autocorrelation was in 2012, reaching 0.336; the lowest autocorrelation was in 2018 and 2019, which were 0.307 and 0.295, respectively. Different cities in the Bay Area have different economic development speeds and different civilization processes. Coupled with the influence of urban differences and policies, the degree of spatial correlation between regions has shown a gradual decrease.

**Table 3.** Global spatial autocorrelation Moran's I index of carbon emissions.

| Variable | Moran' I | Z(I)  | p-Value |
|----------|----------|-------|---------|
| 2009     | 0.323    | 1.751 | 0.04    |
| 2010     | 0.328    | 1.792 | 0.037   |
| 2011     | 0.333    | 1.819 | 0.034   |
| 2012     | 0.336    | 1.836 | 0.033   |
| 2013     | 0.333    | 1.817 | 0.035   |
| 2014     | 0.318    | 1.763 | 0.039   |
| 2015     | 0.315    | 1.759 | 0.039   |
| 2016     | 0.313    | 1.758 | 0.039   |
| 2017     | 0.311    | 1.744 | 0.041   |
| 2018     | 0.307    | 1.734 | 0.041   |
| 2019     | 0.295    | 1.685 | 0.046   |

Note: (1) Z(I) indicates that the new variable is a multiple of the standard deviation  $\sigma = 1$  under the standard normal distribution. The closer the Z-value is to 0, the closer the cumulative probability of the occurrence of that new variable is to 50%. (2) The p-value is obtained according to the significance test method  $p < 0.05$ . means a statistical difference  $p < 0.01$  means a significant statistical difference, and  $p < 0.001$  means an extremely significant statistical difference.

The global spatial autocorrelation Moran index cannot explain the heterogeneity between regions. Therefore, this article analyzes the spatial correlation of carbon emission levels in the Guangdong-Hong Kong-Macao GBA through Moran scatter plots for a total of four years, in 2009, 2011, 2015, and 2019. To further measure the localization of each region and surrounding areas. It is used to further measure the local spatial relationship between each area and the surrounding area, the degree of spatial difference and the spatial distribution pattern.

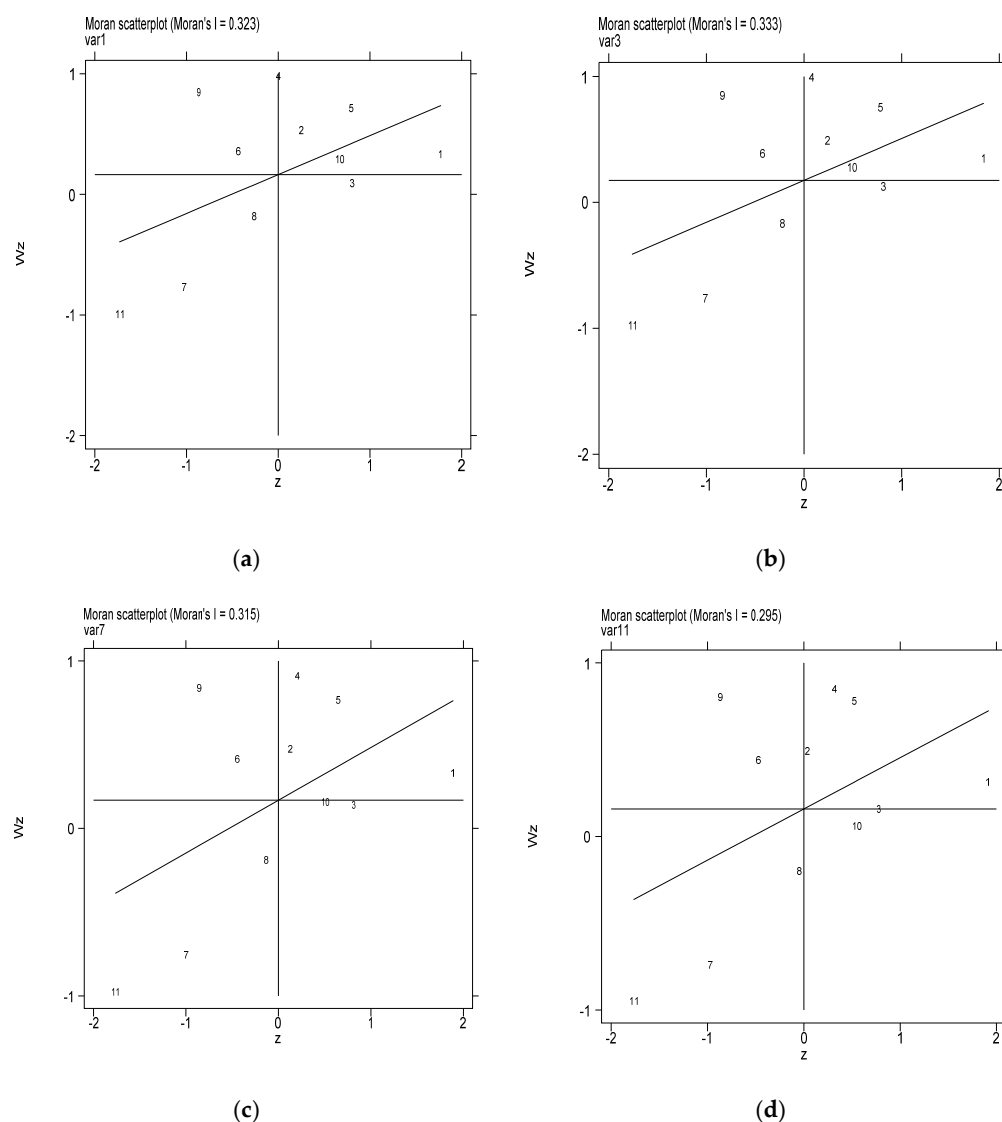
Figure 3 is a Moran scatter plot of carbon emissions in the Guangdong-Hong Kong-Macao GBA. Areas with high carbon emissions are concentrated in coastal port cities, such as Guangzhou and Hong Kong. Cities with lower carbon emissions have a faster-growing tertiary industry, dominated by tourism, such as Macau and Zhuhai. This is consistent with the previous conclusions, and it also reflects the current situation of two-level aggregation of carbon emissions in the Guangdong-Hong Kong-Macao GBA. To a certain extent, this also shows the "Matthew effect" of the carbon emissions in the Bay Area, which has caused the spatial correlation between regions to weaken. In general, there is spatial autocorrelation and spatial heterogeneity of carbon emissions in the Guangdong-Hong Kong-Macao GBA, and the spatial distribution is extremely unbalanced. A relatively stable spatial pattern has been formed in different regions, and the formation of this pattern is closely related to the geographical and historical characteristics of China.

#### 4.3. Carbon Emission Intensity Theil Index

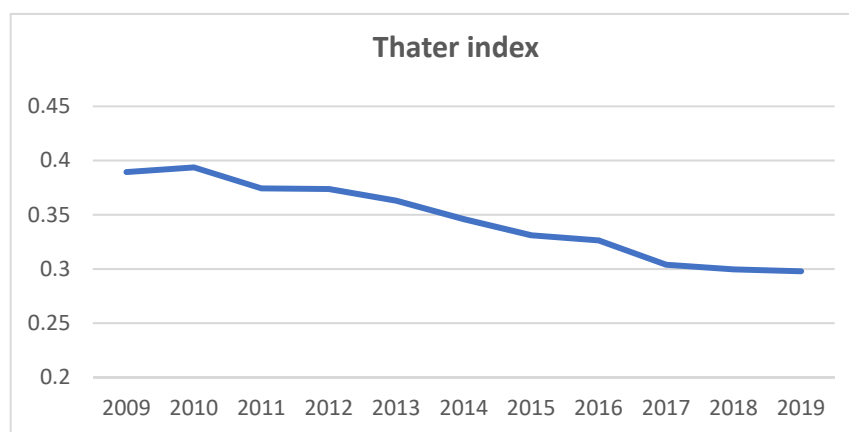
The Theil index is an index that measures inequality between individuals or regions. The greater the Theil index, the greater the difference. In order to measure the size of the difference in carbon emission intensity of the Guangdong-Hong Kong-Macao GBA, this paper used the Theil index to calculate the inequality of carbon emission intensity in the Bay Area from 2009 to 2019. As shown in Figure 4.

From Figure 4, the total Theil index of the Bay Area is hovering around 0.35, and there is a large difference in carbon emission intensity overall. In 2009, the Theil index was also lower than 0.4, and it has been decreasing year by year as time has progressed. By 2018 and 2019, it had dropped to 0.3. During the period from 2013 to 2016, the total Theil index had the greatest decline, with a gradual reduction in the difference in carbon emission intensity between cities in the Bay Area. Combining the previous part of the analysis of the current situation of the two-level accumulation of the spatial accumulation of carbon emissions, the economic development of the GBA also shows the phenomenon of aggregation, which a certain "Matthew effect". Regions with high carbon emissions also have faster economic development, so carbon emissions are clustered in two levels, while the gap in carbon emissions intensity keeps narrowing. This is also in line with reality.

The economic development of regions that mainly rely on the tertiary industry has not increased as much as the economic development of regions that rely on industry as the pillar industry. As a result, the spatial correlation of carbon emissions is getting lower and lower. The total difference in carbon emission intensity in the GBA shows a decreasing trend, with smaller values and lower inequality. The economic development level of the GBA is already at the forefront of China. The experience of the Bay Area in low-carbon development has an important guiding role for other regions in China. Next, this article used the threshold model to discuss the nonlinear relationship between the effect of green innovation efficiency on carbon emission intensity in the GBA.



**Figure 3.** Moran scatters plot of urban development in the Guangdong-Hong Kong-Macao GBA of China in 2009, 2011, 2015, and 2019. (a) Moran Index of Carbon Emissions in the Guangdong-Hong Kong-Macao GBA in 2009, (b) Moran Index of Carbon Emissions in the Guangdong-Hong Kong-Macao GBA in 2011, (c) Moran Index of Carbon Emissions in the Guangdong-Hong Kong-Macao GBA in 2015, (d) Moran Index of Carbon Emissions in the Guangdong-Hong Kong-Macao GBA in 2019.



**Figure 4.** The Carbon emission intensity Theil index of the Guangdong-Hong Kong-Macao GBA.

#### 4.4. Empirical Results

From the above research results, carbon emissions have obvious spatial aggregation characteristics. Only when the efficiency of green innovation between regions reaches a certain scale will the intensity of carbon emissions be reduced and the level of green development be increased in the Bay Area. Therefore, this paper took green innovation efficiency as a threshold variable to try to verify the non-linear relationship between green innovation efficiency and carbon emission intensity. According to the threshold model given above, this article needs to determine the number of thresholds first in order to determine the form of the model. Concerning the “self-sampling” approach of the threshold model of Lian and Cheng (2006) [58], the model is estimated with the setting of no threshold, one threshold, and two thresholds in turn. The  $p$ -values and critical values were obtained using the “self-sampling method”, and the regression results of the threshold effect test are shown in Table 4. It is clear that the single threshold and triple threshold model effects are not significant at the 1%, 5%, and 10% significance levels, with the corresponding  $p$ -values, are 0.2533 and 0.2233, respectively. In the double threshold test, it is significant at the 5% level, and the self-sampling  $p$ -value is 0.04. Therefore, this article chose the double threshold model to estimate the threshold. Table 5 is the estimated value of the double threshold and the 95% confidence interval. The 95% confidence interval of the estimated value of the two thresholds were [0.268, 0.3] and [0.401, 0.423]. Tables 5 and 6 clarify that the impact of green innovation efficiency on the carbon emission intensity of the Guangdong-Hong Kong-Macao GBA is non-linear.

**Table 4.** Regression results of the threshold effect test.

|                       | F-Value | $p$ -Value | Critical Value |        |        |
|-----------------------|---------|------------|----------------|--------|--------|
|                       |         |            | 1%             | 5%     | 10%    |
| Single threshold test | 11.25   | 0.2533     | 32.28          | 21.447 | 16.934 |
| Double threshold test | 15.28   | 0.04       | 22.457         | 14.907 | 10.824 |
| Triple threshold test | 8.05    | 0.2233     | 33.528         | 16.122 | 11.135 |

**Table 5.** Threshold estimation results.

|                            | Estimated Value | 95% Confidence Interval |
|----------------------------|-----------------|-------------------------|
| Threshold value $\gamma_1$ | 0.288           | [0.268, 0.3]            |
| Threshold value $\gamma_2$ | 0.405           | [0.401, 0.423]          |

**Table 6.** Regression results of the threshold model.

| Variable                    | Variable Interval                 | Coefficient | p-Value (t-Value) |
|-----------------------------|-----------------------------------|-------------|-------------------|
| Green innovation efficiency | $\text{innov} \leq 0.288$         | 1.83 ***    | 0.001<br>(3.42)   |
|                             | $0.288 < \text{innov} \leq 0.405$ | 0.426       | 0.241<br>(1.18)   |
|                             | $\text{innov} > 0.405$            | −0.4848 *** | 0.000<br>(−4.00)  |

\*\*\* indicates significance at the 1% level.

From Table 5, there is a significant threshold effect between green innovation efficiency and carbon emission intensity in the Guangdong-Hong Kong-Macao GBA. The estimated values of the threshold variables are 0.288 and 0.405, respectively. The estimated value of the double threshold can classify the degree of green innovation efficiency in the Guangdong-Hong Kong-Macao GBA into three intervals, which are low green innovation efficiency region ( $\text{innov} \leq 0.288$ ), medium green innovation efficiency region ( $0.288 < \text{innov} \leq 0.405$ ), and high green innovation efficiency region ( $\text{innov} > 0.405$ ).

Based on the above double threshold estimation results, the parameters of the double threshold model were estimated. The specific threshold regression results are shown in Table 6. The control variables are the same as above, and due to the limitations of space, the results of the estimation related to the control variables are no longer listed in the table.

In the double-threshold model, green innovation efficiency was used as the threshold. After distinguishing different degrees of green innovation efficiency, the measurement results of the threshold effect showed that the effect of green innovation efficiency on carbon emission intensity was positive when the regional green innovation efficiency was in the first and second intervals. When the green innovation efficiency of cities was in the first interval, the regression coefficient was 1.83, and it passed the 1% significance level test. When the green innovation efficiency of the city was in the second interval, the regression coefficient was 0.426, and the significance level test was not passed at this stage. In other words, the impact of green innovation efficiency on carbon emission intensity was unclear at this stage. When the green innovation efficiency of the city was in the third interval, the regression coefficient is −0.4848, and it passed the 1% significance level test. At this time, there was a suppressive effect of the green innovation efficiency on carbon emission intensity. Hong Kong and Macau were in the highest range, and they are pursuing the path of promoting economic development. They have relatively open and flexible economic policies and have a relatively high economic level. Hong Kong and Macau have already entered the post-industrial era, with lower demand for high-energy-consuming industrial products such as coal and steel. Although the nine cities in Guangdong Province are developed coastal cities, their economic development is still in the process of industrialization and urbanization. The continuous construction of houses and the investment in infrastructure, all have a high demand for high-energy-consuming industrial products such as coal and cement. Although the green innovation efficiency in some cities is relatively high and has reached the level of restraining carbon emission intensity, the industrial structure is unreasonable, and the secondary industry still occupies a dominant position. The restraining effect of green innovation efficiency was small, and the cost of carbon emission reduction was high. For example, Guangzhou's petrochemical industry and automobile manufacturing are its pillar industries. The petrochemical industry and automobile manufacturing are high-energy-consuming industries and generate large amounts of greenhouse gases. With high-tech, logistics, finance, and culture as its pillar industries, Shenzhen is undergoing a shift from extensive resource consumption to intensive high-efficiency.

It can be seen that the impact of green innovation efficiency on the carbon emission intensity of the Guangdong-Hong Kong-Macao GBA had a non-linear relationship. There was an “inverted U” pattern between them, and there was an inflection point in the

efficiency of green innovation. In the early days of green innovation, cities successively introduced carbon emission reduction policies one after another. Although many outdated production capacities have been eliminated, it has also increased the cost of carbon emission reduction, and a large number of small and medium-sized enterprises cannot afford to replace production equipment. Therefore, although the efficiency of green innovation in the initial stage has been continuously improved, enterprises have invested more funds in green technology innovation for green technology innovation. The increase in carbon emissions has been relatively large, the level of economic development has been lagging, and the intensity of carbon emissions has continued to increase. When the green innovation efficiency reaches a certain level and the green innovation industry becomes increasingly mature, the enterprise will have more funds to invest in technological innovation. The cost reduction of green innovation technology will further expand the scale of industrial agglomeration, and less investment can effectively curb the carbon emission intensity of the Guangdong-Hong Kong-Macao GBA. At the same time, the economy of the Bay Area has also emerged from the financial crisis, and the economy has developed rapidly. The tertiary industry in cities such as Hong Kong and Macau accounts for an increasing proportion of GDP. The industrial structure of the Bay Area has been continuously upgraded, and the efficiency of green innovation has brought about a reduction in the intensity of carbon emissions. This result is also in line with the real situation. Based on this, we can conclude that: First, the green innovation efficiency of the Guangdong-Hong Kong-Macao GBA has reached a relatively high level, but there is still room for development. Second, the efficiency of green innovation in the Bay Area has a suppressive effect on carbon emission intensity, and the impact may continue to strengthen.

## 5. Research Conclusions and Prospects

### 5.1. Research Conclusions

It is of great urgency and arduousness to improve the efficiency of green innovation and innovation of urban agglomerations, reduce the intensity of carbon emissions, and then achieve carbon peaks under the constraints of the “double control” goal of carbon emission reduction. Compared with previous studies, this article linked the efficiency of green innovation with urban carbon reduction, elaborating that there may be a non-linear relationship between them. This new theoretical framework complements the research on the direction of carbon emission reduction, and has reference significance for the future development trend of carbon emission reduction in urban agglomerations. In addition, this article also implements quantitative research on a theoretical basis. The steps of the empirical part are as follows. This article first measures the efficiency of green innovation of the Guangdong-Hong Kong-Macao GBA from 2009 to 2019 using the super-efficiency SBM. After analyzing the measurement results, the Moran index and Theil index were used to explore the spatial correlation of carbon emissions in the Bay Area and the regional differences in the intensity of carbon emissions in the Bay Area. Finally, a threshold model was established to verify that there is a non-linear relationship between green innovation efficiency and carbon emission intensity in the GBA. We summarized the following conclusions:

First, the evaluation system was constructed to measure the efficiency of green innovation in the Bay Area from the two dimensions of input and output. The super-efficiency SBM model was used to calculate the green innovation efficiency of the Guangdong-Hong Kong-Macao GBA. We found that there are certain differences in the efficiency of green innovation in the Bay Area, and there are characteristics of “urban gradient” development. The overall trend is increasing, and the efficiency of green innovation in the Bay Area will reach a relatively high level in 2019.

Second, the Moran index was used to analyze the regional spatial autocorrelation, and the results proved that there was a significant spatial autocorrelation of the carbon emissions in the Bay Area, and the overall correlation was relatively high. However, the spatial autocorrelation of carbon emissions in the Bay Area was generally weakening from

2009 to 2019. Then used the Theil index to estimate the degree of difference in the carbon emission intensity of the Bay Area from 2009 to 2019. Based on the results, we found that the carbon emission intensity of the Bay Area was generally quite different. The Theil index decreased year by year with the development of time, and the difference in carbon emission intensity between cities decreased.

Third, the impact of green innovation efficiency on the carbon emission intensity of the Guangdong-Hong Kong-Macao GBA had a non-linear relationship. There was an “inverted U” pattern of them, and the green innovation efficiency had an inflection point. The estimated value of the double threshold can classify the degree of green innovation efficiency in the Guangdong-Hong Kong-Macao GBA into three intervals, which are low green innovation efficiency region ( $\text{innov} \leq 0.288$ ), medium green innovation efficiency region ( $0.288 < \text{innov} \leq 0.405$ ), and high green innovation efficiency region ( $\text{innov} > 0.405$ ). When the regional green innovation efficiency was in the first and second intervals, the effect of green innovation efficiency on carbon emission intensity was positive. When the green innovation efficiency of the city was in the third interval, there was a suppressive effect of green innovation efficiency on the carbon emission intensity at this time.

## 5.2. Policy Recommendations

Under China’s basic national policy of “One Country, Two Systems”, there are certain differences in the carbon emission intensity of the Guangdong-Hong Kong-Macao GBA. The development path of green innovation is different, and the level is also uneven. According to the above conclusions, combining the economic development level and carbon emission intensity of different cities in the GBA, it is necessary to formulate appropriate policies based on local conditions. Based on this, this article puts forward the following recommendations:

First, cooperation between cities in the Bay Area should be strengthened. The carbon emission intensity of the Guangdong-Hong Kong-Macao GBA is quite different. At present, the Bay Area is limited by geographical reasons and historical legacy, and there is still the phenomenon of artificially fragmented economic ties and cooperation between regions. Therefore, local governments should try to break the old pattern and make full use of the spatial spillover effect of the Bay Area. We should make full use of the spatial spillover effects of green innovation in advanced regions to drive the level of green innovation in backward regions. At the national level, the government should promote the integration of resource elements in the GBA, narrow the regional differences, improve the spatial relevance of green innovation in the Bay Area, and promote the green development of the entire Bay Area.

Second, according to local conditions, appropriate policies to promote the development of green innovation should be formulated. Different cities have different levels of economic development and different green innovation efficiency in the Guangdong-Hong Kong-Macao GBA. Therefore, local policies should take full account of the local level of innovation, and different policies need to be formulated according to local conditions. For example, Guangzhou, Shenzhen, Hong Kong, and Macau have entered the post-industrial era and should vigorously develop low energy consumption and high output industries. Other cities in the Bay Area are still in the process of industrialization and urbanization. It is necessary to accelerate the modernization process, promote industrial upgrading and industrial rationalization, change the previous pattern of sacrificing the environment in exchange for economic development, and form an economic development pattern with innovation as the main driving force.

Third, the innovation transformation platform should be improved. Today, the efficiency of green innovation in most regions has reached a high level, which can curb carbon emission intensity to a certain extent, and maintaining the level of green innovation depends on the innovation transformation platform. Therefore, it is important to improve the green innovation platform and gradually form a good system of supply and transformation

effect of innovation elements. Establish a long-term mechanism for green innovation and development through the platform, gradually narrow the green innovation gap between regions, constantly transform energy use methods, seek renewable energy, and promote the low-carbon development of urban agglomerations in the Guangdong-Hong Kong-Macao GBA.

Fourth, the level of green innovation in urban agglomerations should be improved. Considering the threshold results given by the empirical results, the level of green innovation suppresses the carbon emission intensity only when the green innovation efficiency of the city is higher than 0.405. Below this value, an increase in the level of green innovation leads to an intensification of carbon emission intensity in the city. Therefore, cities with green innovation efficiency below 0.405 should speed up the process of green innovation, formulate policies to vigorously introduce innovative talents, increase investment in innovation funds, to raise the innovation efficiency to the level of restraining carbon emission intensity as soon as possible. Cities with green innovation efficiency higher than 0.405 should pay more attention to technological innovation related to carbon emission reduction, with the focus on strengthening the ability of technological innovation to suppress carbon emission intensity.

### 5.3. Prospects for Future Research

A comprehensive understanding and scientific assessment of the efficiency of green innovation in the Guangdong-Hong Kong-Macao GBA is a prerequisite for the development of a low-carbon economy. After a series of measurements and discussions on the non-linear relationship between green innovation efficiency and carbon emission intensity, the next research direction should be to find solutions to the influencing factors of low-carbon economic development. Based on the analysis of the current situation of carbon emission intensity in the GBA, we will continue to try to study the impact of different factors on the development of a low-carbon economy, and give appropriate suggestions and supplements to the green development policies that China is implementing.

Limited by the availability and applicability of the data, this article only used the data of the Guangdong-Hong Kong-Macao GBA from 2009 to 2019. The sample size was small and the time for the coordinated development of the GBA was short, so the research in this article has certain limitations in-depth and breadth. In future research, we will continue to focus on the development of a low-carbon economy in the GBA. We will try to find more suitable data and methods, further improve the research, and gradually expand the scope of research to other regions in China.

The spatial correlation of carbon emissions is very suitable for the research of urban agglomerations. Previous studies have often neglected the discussion of carbon emission reduction in urban agglomerations, which may be due to the limitations of the development of the times. Currently, the economy of urban agglomerations is getting more and more attention. We invite peer scholars to investigate and fill in the existing theories of carbon emission reduction in urban agglomerations in the future, so as to obtain better models and theories that keep pace with the times. At the same time, we can also conduct qualitative analysis with more appropriate data, and extend the experience of urban agglomerations to a wider range of economies, so as to provide a diversified path for the global carbon emission reduction target.

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