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Study on the Impact of GGDP on Carbon Peak Pathways in Beijing-Tianjin-Hebei Region

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Abstract: GGDP accounting, as a new green economy measurement system, can more accurately assess carbon emissions and change trends, and provide important support for the Beijing-Tianjin-Hebei region to achieve carbon peak and carbon neutrality. In this paper, the improved GGDP accounting system based on EAMFP was firstly selected according to the economic development characteristics of the Beijing-Tianjin-Hebei region, and the scale of carbon emissions and the GGDP of the Beijing-Tianjin-Hebei region from 2007 to 2021 were accounted for. The LMDI method was used to decompose the energy carbon emissions in the Beijing-Tianjin-Hebei region, and combined with the STIRPAT model to dynamically analyze the emission trend in 2022-2050, and the imbalance was found by the Mann-Kendall test. The results point out that enhanced emission reduction can enable Beijing and Tianjin to achieve carbon peak by 2030, while Hebei reaches the peak around 2040, but does not show a significant decline five years after the peak. The SVAR model confirms the correlation between GGDP and carbon emissions in the Beijing-Tianjin-Hebei region and the trend of the future impact. This paper suggests that the Beijing-Tianjin-Hebei region should learn from domestic and international experiences in carbon emission reduction and strengthen the communication and interoperability among the three regions. The Beijing-Tianjin-Hebei region has different status quo in terms of energy consumption and carbon emissions, and the policies implemented should be different.

Keywords: Carbon-darling; log-averaged Diels-Alder index method; Mann-Kendall test; vector autoregression; Beijing-Tianjin-Hebei region.

1. Introduction

Climate change is a significant challenge globally, threatening humanity's survival and development. Nations worldwide have committed to emission reduction goals, actively promoting carbon emission reduction and peaking.[1] As one of the largest carbon emitters, China, particularly the Beijing-Tianjin-Hebei region, plays a crucial role in achieving these targets. Effective measures are needed in this region to reach carbon peaking and neutrality goals, promoting sustainable economic development. The emergence of carbon markets and trading has underscored the importance of carbon peaking and neutrality in the region's economic and environmental agendas.[2] The GGDP accounting system, a novel carbon emission assessment method, offers precise insights into emission trends, aiding the region's efforts towards carbon goals. This study focuses on utilizing the GGDP framework to explore pathways to carbon peaking in the Beijing-Tianjin-Hebei region, aiming to offer theoretical and practical guidance for its realization.[3-4]

Previous research on GGDP suggests ongoing refinement, particularly in deducing environmental costs, yet lacks international precedents or comprehensive government-backed green GDP data. Various nations employ differing methods, some considering specific resource depletion or pollution types, while others focus on physical or value stocks and flows. Carbon emission prediction studies, employing models like STIRPAT, highlight the complex relationship between urbanization and CO2 emissions, suggesting varied impacts across regions. Analyzing factors influencing CO2 emissions in different countries and regions, scholars employ diverse methodologies such as IDA, IO models, and STIRPAT. These studies underscore the multifaceted nature of the urbanization-CO2 emissions relationship, emphasizing the need for nuanced, region-specific policies to align urbanization with emission reduction goals, crucial for sustainable urban development amidst global climate change.[5-7]

The team advocates for an inclusive approach to GGDP improvement, considering developing countries' short-term adaptability and acknowledging the economic benefits of environmental resource consumption. This paper aims to fill gaps in previous GGDP research by providing targeted improvement measures for diverse country types. By applying the GGDP system, the study analyzes carbon emission trends in the Beijing-Tianjin-Hebei region, predicts future trends, compares them with peak carbon targets, and assesses the feasibility and timeline for achieving peak carbon. Additionally, it explores pathways and measures for carbon peaking, evaluates policy impacts, and offers recommendations for achieving carbon peak in the region, facilitating informed decision-making.[8]

2. Theoretical Analysis and Research Hypotheses

2.1. Effects of GGDP accounting system adoption on peak carbon pathways

The Beijing-Tianjin-Hebei region, located in the north of China and comprising the cities of Beijing, Tianjin and Hebei Province, is one of the core economic regions of China. This region has played an important role in industrialization and urbanization, but also faces environmental problems, including air pollution and carbon emissions. The GGDP accounting system is a method of measuring the economic activity of a region or country, usually including the value of production in different industrial sectors. In research, GGDP can be used to analyze the trend and structure of economic growth in different regions or countries. Peak Carbon is when a region or country reaches a peak in carbon emissions, after which it begins to reduce its carbon emissions. A peak carbon pathway is a policy or strategy that aims to achieve reductions in carbon emissions and to reach peak carbon emissions at a certain point in time.[9-10] The effect of GGDP accounting system adoption on the peak carbon pathway involves several factors. First, the accounting method of GGDP may reflect the contribution of different industrial sectors to carbon emissions, thus affecting the path to peak carbon. Second, government policies, technological innovation and investment may also affect the realization of the peak carbon path. The government may adopt a series of policy measures in the Beijing-Tianjin-Hebei region to encourage carbon peaking and carbon emission reduction. These policies may include carbon markets, energy efficiency improvements, clean energy promotion, and industrial restructuring. The choice of GGDP accounting system can interact with these policies and influence the implementation and effectiveness of the policies. Studying the impact of GGDP accounting system adoption on carbon peak pathways usually requires research based on actual data. Researchers can analyze the impacts of different methods of GGDP accounting systems on the measurement and forecasting of carbon emissions to assess their effects on the peak carbon pathway. The results of the study can provide recommendations to governments and policy makers on how to adjust the GGDP accounting system to better support the peak carbon target. This could contribute to the achievement of environmental protection and sustainable development goals.[11]

Studying the effect of GGDP accounting system adoption on the carbon peaking pathway in the Beijing-Tianjin-Hebei region can help to better understand the relationship between economic growth and carbon emissions, and how policies can affect these relationships. This is an important topic in order to develop more effective policies in reducing carbon emissions and combating climate change.[12] We propose the following hypothesis:

H1: Under the GGDP accounting system, the peak carbon pathway in the Beijing-Tianjin-Hebei region will be easier to realize.

3. Data Sources and Model Construction

3.1. Data sources

In this study of industrial energy consumption in the Beijing-Tianjin-Hebei region of China, we employ the index decomposition analysis method to analyze the factors impacting carbon emission reduction. Two categories of exponential analysis methods, Diels' index and Rasch index, are utilized. Diels' index offers a simple calculation process but yields relatively large residuals. Conversely, Rasch's index, employing logarithmic mean decomposition, eliminates the residual term and proves more adaptable.

To ensure continuity and comparability in industry classification before and after the study period, traditional industry classifications are organized and merged. This results in 36 final industrial sectors, including manufacturing, transportation, and product industries. Additionally, 18 types of energy are identified to calculate energy consumption and carbon emissions in economic enterprises' sub-industries.

Empirical analysis spans 15 years from 2007 to 2021, utilizing data from various statistical yearbooks. Green GDP (GGDP) reflects GDP after deducting resource consumption and environmental degradation costs, while also considering green inputs and outputs. The growth rate of carbon dioxide (CO2) emissions is examined to understand resource conservation effects in the region and explore the linkage between GGDP and CO2 emissions.

Data sources include China Statistical Yearbook, Beijing Statistical Yearbook, Tianjin Statistical Yearbook, and Hebei Statistical Yearbook. Three composite indicators are employed to analyze economic development, environmental governance, and natural resource utilization. Economic development factors such as GDP, investment, and labor force directly impact GGDP. Environmental governance indicators like carbon dioxide emissions and pollutant emissions affect GGDP calculations. Natural resource utilization factors including water resources utilization and energy consumption are critical for the region's future development and influence GGDP.

Throughout the research process, "GGDP" represents green GDP, "t" denotes the year, and "Ṫ" denotes the growth rate of CO2 emissions. The base period for the study is 2007, denoted as "t=0," ensuring comparability across variables.

3.2. Construction of the factor decomposition model

The carbon emissions are decomposed into the following model with the following expression:

$$\mathrm{C}=\sum_{i=1}^{36}\sum_{i=1}^{18}P\times\frac{G}{P}\times\frac{G_i}{G}\times\frac{E_i}{G_i}\times\frac{E_{ij}}{E_i}\times\frac{C_{ij}}{E_{ij}}=\sum_{i=1}^{36}\sum_{i=1}^{18}P\times ED\times IS_i\times EI_i\times ES_{ij}\times R$$

C is the carbon emissions due to energy consumption, P is the total population of the region, G is the gross regional product GDP, C_{ij} is the i th industry to which the industry belongs, where the carbon emissions from the j th energy source, i is the number of industry sectors, j is the amount of energy consumption, G_i is the economic output of the i th industry, E_i is the energy consumption of the i th industry, and C_{ij} is the carbon emissions of the i th industry through the consumption of the j th energy source. carbon emissions generated. In this paper, the added value of each industry is used to represent the economic benefits generated by the industry, i.e., IS_i is the proportion of the economic output value of the i th industry in the sub-industry sector of the Beijing-Tianjin-Hebei enterprises in the city's output value, which represents the factor of industrial structure effect in the decomposition of the factor. EI_i is the energy consumption per unit of economic output value per unit of total energy consumption in the i th industry in the sub-industry sector compared to the value-added value of the industry, which represents the factor of energy consumption intensity effect in the decomposition of the factor. ES_{ij} represents the value of GGDP in the factor decomposition. R is the carbon emission generated by resource consumption, and then the formula is deformed as follows.[13-15]

$$\Delta C = C^t - C^0 = \sum_{i=1}^{36}\sum_{j=1}^{18} C_{ij}^t - \sum_{i=1}^{36}\sum_{j=1}^{18} C_{ij}^0 = \sum_{i=1}^{36}\sum_{j=1}^{18} W_{ij}\ln\left(\frac{C_{ij}^t}{C_{ij}^0}\right)$$

In order to observe the changes in carbon emissions between years, in the upper right corner of each variable in the formula, those labeled with 0 indicate the base period, and those labeled with t indicate the reporting period, noting $W_{ij} = \frac{C_{ij}^t - C_{ij}^0}{\ln C_{ij}^t - \ln C_{ij}^0}$, W_{ij} as the weighting function.

$$\Delta C = \sum_{i=1}^{35}\sum_{j=1}^{17} \mathrm{W}_{ij}\ln\left(\frac{C_{ij}^0}{C_{ij}^t}\right)$$

$$= \sum_{i=1}^{35}\sum_{j=1}^{17} \mathrm{W}_{ij}\ln\left(\frac{P^t \times ED^t \times IS_i^t \times EI_i^t \times ES_{ij}^t \times r_{ij}^t}{P^0 \times ED^0 \times IS_i^0 \times EI_i^0 \times ES_{ij}^0 \times r_{ij}^0}\right)$$

$$= \Delta C_p + \Delta C_{ED} + \Delta C_{IS} + \Delta C_{EI} + \Delta C_{ES} + \Delta C_r$$

After the deformation of the above formula, finally, the incremental factor changes in carbon emissions are decomposed into sub-factors including several influences such as changes in total population capacity, changes in the level of economic development, and changes in the industrial structure.

3.3. Carbon peak trend mutation prediction modeling

The Mann-Kendall mutation point test is a statistical method used to study trends and changes in data. When predicting carbon peaking in a region, this method can be used to analyze carbon emissions data for a region to determine if there is a change in carbon emissions trends. By testing the significance of the trend, it is possible to determine the point in time at which carbon peaks and predict future carbon emission trends. The method has high accuracy in determining the timing and effect of carbon peaking, and can provide an important reference for policy makers. At the same time, the method can also be used for trend analysis in other fields, such as climate change and water resource management.

In this paper, the conditional judgment function and Mann-Kendall trend test are used to construct a comprehensive judgment model to determine the energy carbon peaking status. The flow chart of its judgment model is shown in Figure (11). Firstly, the total energy carbon emissions are calculated by using the city's basic energy data, and if the peak carbon emissions appear within the last 5 years, it is judged as not reaching the peak. At the same time, according to the international standard of "historical carbon dioxide emission peak judgment", the region is required to reduce carbon emissions by at least 10% within 5 years after the peak of carbon emissions. On the other hand, considering that it takes a period of time to test the authenticity of the peak after the city's energy carbon emissions have reached the peak, insufficient data will also affect the accuracy of the Mann-Kendall trend test. If the peak occurs outside 5 years, the Mann-Kendall trend test is used to determine the energy carbon peak status. If the results show that there is a significant downward trend in carbon dioxide emissions after the peak year, the city can be recognized as having completed carbon peaking; conversely, if there is no significant trend in carbon emissions, the city is judged to be in a plateau period. The platform period refers to the period after the city's carbon emissions reach the peak at a certain point in time, the carbon emissions may fluctuate within a certain range and then step into a steady decline phase, and the period before there is a significant downward trend is called the platform period. During the platform period, carbon emissions may still rise due to economic factors, extreme weather and other natural factors, making it difficult to judge whether or not the goal of carbon peaking has been accomplished. Therefore, it is necessary to take into account the per capita carbon emissions, GDP carbon intensity and other factors to predict the future trend of carbon emissions in the city, and to propose more stringent emission reduction measures and more aggressive emission reduction targets to accomplish the carbon peak at an early date.

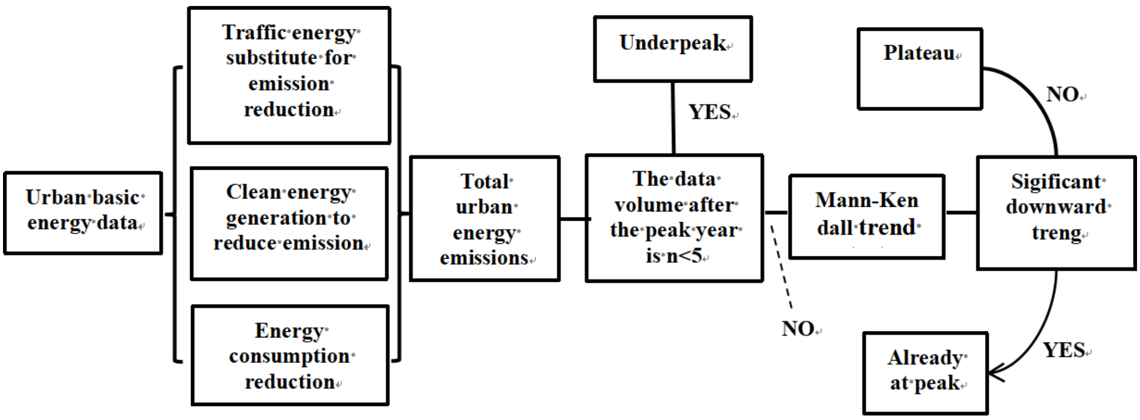

Figure 1. Energy Carbon Peak M-K Mutation Point Prediction Process

First of all, we need to analyze, this time using Mann-Kendall (M-K) trend test to analyze the trend of carbon emissions in Beijing-Tianjin-Heidi, M-K trend test method is a non-parametric statistical test method, the difference between the traditional parametric test method is that the variables in the method can not obey the normal distribution . It is assumed to be a time series variable, n is the length of the time series, and the M-K method defines the statistic S:

$$S = \sum_{k=1}^{n-1}\sum_{j=k+1}^{n} \mathrm{sgn}\left(x_j - x_k\right)$$

where S is the M-K trend test statistical variable, x_j、x_k is the corresponding measured value in years j and k, respectively, and $k > j$, while

$$\operatorname{sgn}(x_j - x_k) = \begin{cases} 1, x_j - x_k > 0 \\ 0, x_j - x_k = 0 \\ -1, x_j - x_k < 0 \end{cases}$$

$$Var(S) = \frac{n(n-1)(2n+5)}{18}$$

$$Z = \begin{cases} \frac{S+1}{\sqrt{Var(S)}}, S > 0 \\ 0, S = 0 \\ \frac{S-1}{\sqrt{Var(S)}}, S < 0 \end{cases}$$

Where Var(S) is the variance of S and Z is the statistical test value. For the bilateral hypothesis, when $-Z_{1-a/2} \le Z \le Z_{1-a/2}$, the original hypothesis is accepted, that is, the series is not considered to have passed the trend test, and the trend of change is not obvious; when $Z < Z_1 / 2$, the series passes the trend test, and there is a significant downward trend: and similarly, when $Z > Z_{10} / 2$, the series is considered to have passed the test and there is a significant upward trend. a is the given level of significance, which is usually taken to be 0.05, i.e., the 95% confidence interval, and the corresponding Z value is ±1.96 at this confidence level. The value of z at this confidence level is ±1.96.In addition, this work will apply the M-K method of variance point detection to process the carbon emission time series in the Beijing-Tianjin-Hebei region to analyze and determine the emergence of variance points.

3.4. Improved vector autoregressive modeling

In this paper, the structural vector autoregressive (SVAR) model is used to give the impulse response function a more reasonable economic significance by restricting the identification conditions of the model to a certain extent so that the customer service does not reflect the deficiencies of the relevant structures at the same time.

The general $VAR(p)$-model is as follows.

$$y_t = \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + Hx_t + \varepsilon_t$$
$$t = 1, 2, \cdots, T$$

where y_t is the column variable of the endogenous variable in dimension k, x_t is the column variable of the exogenous variable in dimension d, p is the order of lags, and T is the number of samples. the $k*k$-dimensional matrix $\phi_1, \cdots, \phi_p$ and the $k*d$-dimensional matrix H are the coefficient matrices to be estimated. ε_t is the k-dimensional regressive column variable.

The basic form of the k-element p-order SVAR model is.

$$A_0 y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t$$

where X is the main diagonal Y element of the square matrix of 1, reflecting the structural relationships of the same cycle.

The general VAR model for the k-element and p-order is.

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t$$

After the transfer, write as follows.

$$A(L) y_t = \varepsilon_t$$

$$A(L) = I - A_1 L - A_2 L^2 - \cdots - A_p L^p$$

Eq. is the parameter matrix polynomial for the lag operator L.

Simultaneous multiplication of both sides of Eq. by the $k*k$-order A matrix yields.

$$AA(L) y_t = A\varepsilon_t$$

$$E(u_t) = 0, E(u_t u_t^T) = I_k$$

Eq. is an SVAR-type model.

The model uses the lag order to control the parameters to be estimated. The lag order p cannot be too large, resulting in too few degrees of freedom to give accurate results. At the same time, it cannot be too small to reflect the dynamic characteristics between variables well. For this study, the object is the Beijing-Tianjin-Hebei region.

3.5. Indicator construction and variable setting

Green GDP (GGDP) is an indicator of domestic output that takes the environment into account, also known as environmentally adjusted domestic output (EDP). GGDP calculates gross domestic product while taking into account the negative impacts of economic activity on the environment, including natural resource consumption and energy consumption and pollutant emissions. GGDP takes into account the negative impacts of economic activity on the environment, including natural resource depletion, energy consumption, and pollutant emissions, while calculating gross domestic product (GDP), hence the term "green" GDP.GGDP is academically defined as EDP, as opposed to "domestic ecological output" (GEP), which is a measure of ecological services. GGDP is academically defined as EDP, as opposed to "domestic ecological output" (GEP), which calculates ecological services. The method of accounting for this indicator can vary from country to country and region to region, but generally takes into account the characteristics of environmental resources and the environmental costs of economic activities and tries to incorporate them into the calculation.The adoption of GGDP can provide a more comprehensive assessment of a region's economic health, and can help policymakers to better protect the environment and sustainable development in the pursuit of economic growth. GGDP, abbreviated as Green GDP, is a new type of economic indicator that measures the environmental impact of production and consumption in a country or region.

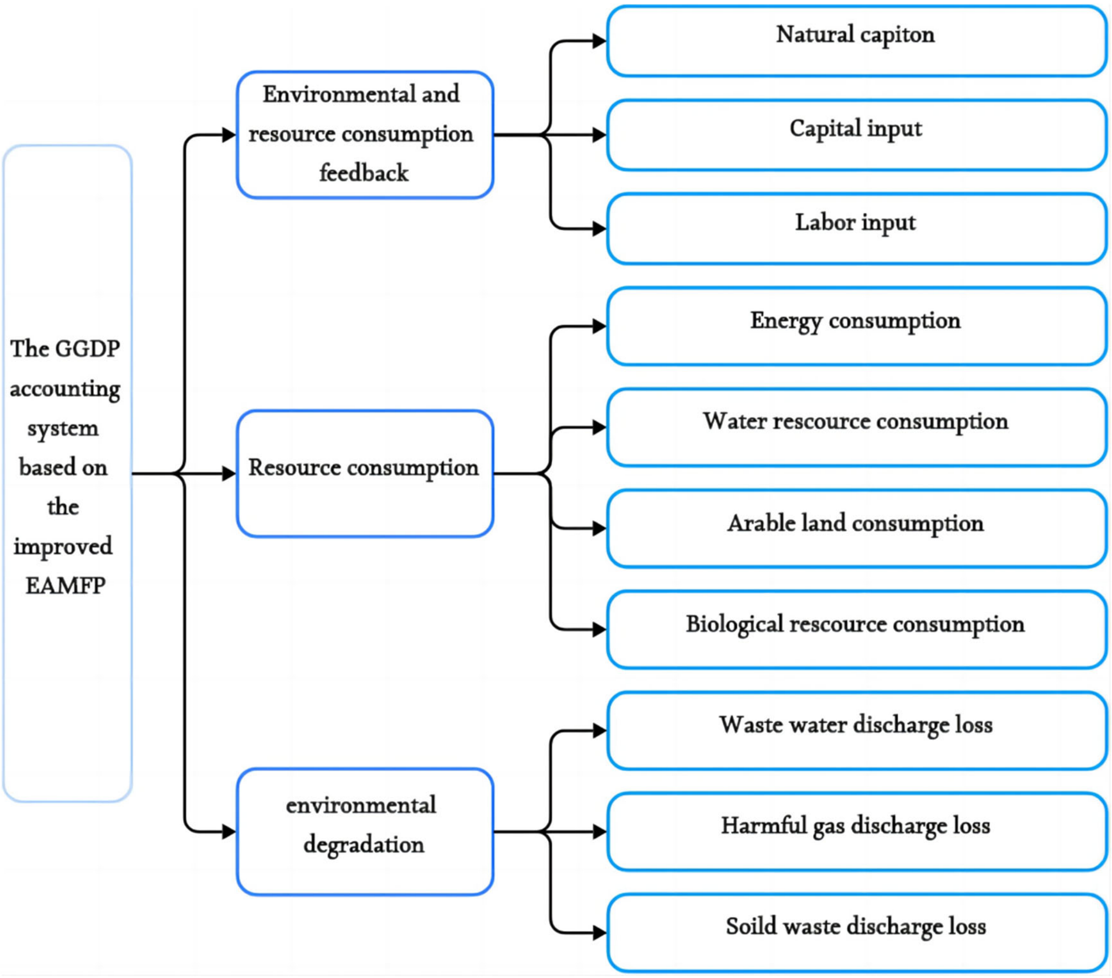

Figure 2. Improved GGDP accounting system in the Beijing-Tianjin-Hebei region

Note: LL is the consumption of arable land and LL_s is the price per unit of arable land consumed.

$$GGDP = GDP - (EDE + RCV) + EAFMP * (EDE + RCV)$$

$$RCV = WD * WD_s + LL * LL_s + EL * EL_s$$

$$EDE = WW * WW_s + NG * NG_s + SW * SW_s$$

A review of the data shows that one ton of water is worth \$4.564, one ton of energy is worth \$718, it costs \$7.5 to treat one ton of hazardous gases, \$44 to treat one ton of wastewater and \$285.7 to treat one ton of solid waste. This gives the total value of resource consumption and total environmental degradation expenditures for each country separately.

The basis for studying the carbon emission reduction in Beijing-Tianjin-Hebei is the measurement of carbon emissions. Inventory method, measurement method and physical balance method are the most common carbon emission measurement methods in the world at present. Among them, the inventory method has better applicability, is practical and easy to operate, and is the method proposed by the United Nations Intergovernmental Panel on Climate Change (IPCC).

$$\mathrm{CE}^n = \sum_{i=1}^{n} \mathrm{E}_i \times \mathrm{LCV_i} \times \mathrm{CC_i} \times COR_i \times \frac{44}{12}$$

E_i denotes the consumption of energy type i, LCV_i denotes the average low-level heating value of energy type i; CC_i denotes the carbon content per unit of calorific value; COR_i denotes the rate of carbon oxidation during fuel combustion; and i denotes the types of energy sources: coal, coke, crude oil, gasoline, kerosene, diesel oil, gas oil, and natural gas.

4. Empirical Analysis

4.1. Accounting results of GGDP and carbon emissions in the Beijing-Tianjin-Hebei region

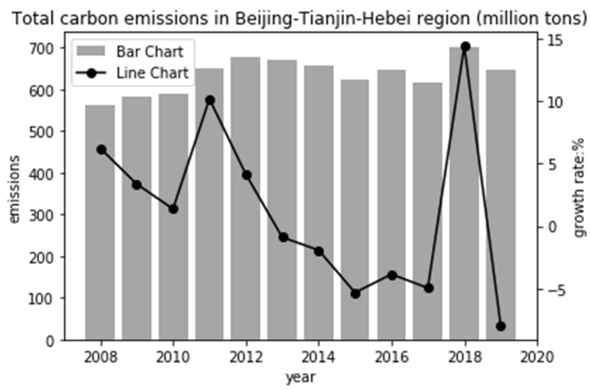

Figure 3. Total Carbon Emissions and Growth in the Beijing-Tianjin-Hebei Region, 2008-2019

As can be seen in Figure 3, the total carbon emissions in the Beijing-Tianjin-Hebei region show a phased change, with the smallest carbon emissions in 2008, at 563 million tons, and the largest carbon emissions in 2018, at 702 million tons. The total carbon emissions in the Beijing-Tianjin-Hebei region showed a growth trend from 2008-2012, from 563 Mt to 677 Mt. The total carbon emissions in the Beijing-Tianjin-Hebei region showed a brief decline from 2013-2015, from 671 Mt to 623 Mt, a reduction of 7.13%, a decline which on the one hand, may be very much related to China's economic slowdown, and on the other hand, may be associated with the The total carbon emissions rose to 647 Mt in 2016, compared with a 4.99% decrease in the Beijing-Tianjin-Hebei region in 2017. Carbon emissions in the Beijing-Tianjin-Hebei region as well as the year-on-year growth rate both reached a maximum in 2018, with a growth rate of 14.04%, while carbon emissions in the Beijing-Tianjin-Hebei region showed a significant decrease in 2019, with a decrease of 7.95%.

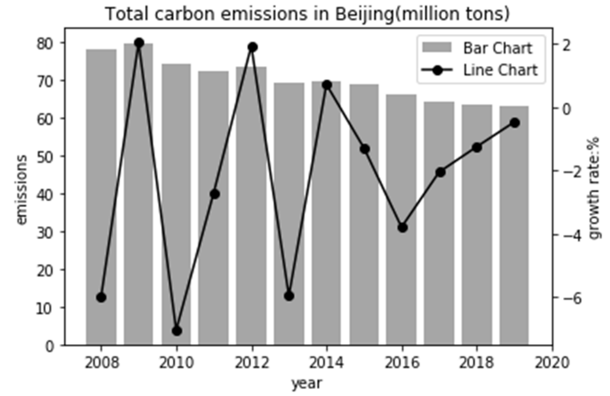

Figure 4. Total Carbon Emissions and Growth in Beijing, 2008-2019

Carbon emissions are different in Beijing, Tianjin and Hebei. Among them, carbon emissions from energy consumption are relatively small in Beijing. Meanwhile, Beijing's carbon emissions as a whole are slowly declining in fluctuation. From 2014 to 2019, Beijing's carbon emissions always declined, but at a slower rate, from 69 million tons to million 63 tons. This shows that the implementation of the relevant energy adjustment policies introduced by Beijing is better, and the control of carbon emissions is better and effective.

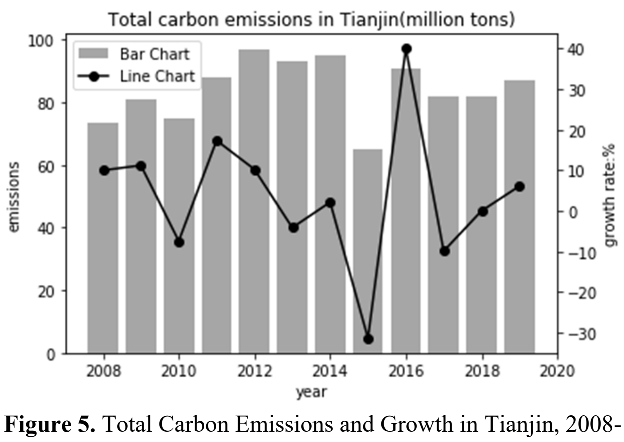

Figure 5. Total Carbon Emissions and Growth in Tianjin, 2008-2019

Unlike Beijing, Tianjin's carbon emissions are growing, peaking in 2012 at 97 mt. After 2013, Tianjin's carbon emissions fluctuate and decline, with the largest drop in 2015, from 95 mt in 2014 to 65 mt in 2015, a 31.34% decrease. 2016 onwards shows another growth trend, and by 2019 carbon emissions are 87 million tons. The reason for this is that Tianjin is still dominated by industrial development, with more carbon emissions.

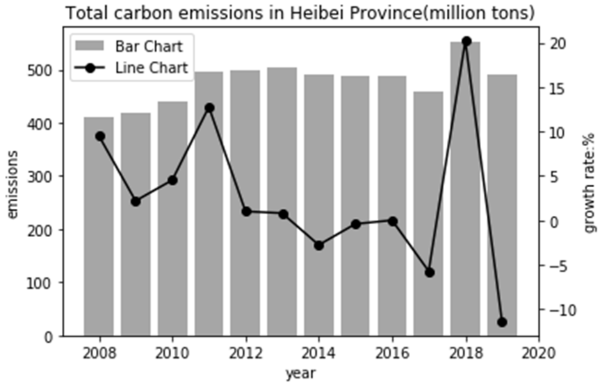

Figure 6. Total Carbon Emissions and Growth in Hebei Province, 2008-2019

Compared with Beijing and Tianjin, Hebei Province has the largest carbon emissions, accounting for more than 70% of the total in the Beijing-Tianjin-Hebei region, which is inseparable from the natural conditions of Hebei Province. Influenced by the natural conditions and other factors, Hebei Province is dominated by heavy chemical industrial industries such as iron and steel, coal and cement, which has resulted in a high-consumption and high-pollution development mode in Hebei Province. Carbon emissions in Hebei Province also show phased changes, as can be seen in Figure 5, from 2008 to 2013, the total carbon emissions in Hebei Province increased year by year, from 411 million tons to 508 million tons, an increase of 24%. after 2014, carbon emissions in Hebei Province showed a downward trend, falling to 488 million tons in 2015. The decline may have a lot to do with the slowdown of China's economic growth on the one hand, and on the other hand, it may be related to the coal decapacitation policy pursued by the government of China 2022 Issue 6 22 Regional Economies.In 2018, the carbon emissions of Hebei Province to the maximum value of 553 megatonnes.

Beijing, Tianjin and Hebei provinces are all economically important regions in China, but also face the challenge of high carbon emissions. Beijing is a political, cultural and technological center, with carbon emissions mainly from transportation, industry and energy consumption, amounting to 290 million tons of carbon dioxide equivalent in 2019. Tianjin, a port and economic center, has carbon emissions mainly from industry, transportation and energy consumption, amounting to 160 million tons in 2019. Cities in Hebei province also have high carbon emissions, mainly from industry and transportation, with 120 million, 110 million, 44 million, 45 million and 52 million tons of carbon dioxide equivalent in Shijiazhuang, Tangshan, Qinhuangdao, Handan and Xingtai, respectively. Traditional industries with high energy consumption and pollution are one of the main causes of carbon emissions in the region. Therefore, reducing carbon emissions has become key to China's national development strategy, especially in these important regions.

4.2. Carbon Peak Prediction and Influencing Factors in Beijing-Tianjin-Hebei Region under GGDP Accounting System

4.2.1. Carbon Emission Projections for the Beijing-Tianjin-Hebei Region

In this paper, the improved STIRPAT model proposed by Sun Jie (2022) was used to analyze and predict China's peak carbon emissions , with:

$$\ln C = a + b\ln P + C\ln R + d\ln J + f\ln I + g\ln S$$

Where: C is the total carbon emissions; P is the population size; R is the contribution of GGDP to GDP; J is the industrial structure, which is expressed as the share of industrial value added; I is the energy structure; S is the energy intensity; a is a constant term; and b、c、d、f、g is a logarithmic constant term.

According to the model proposed by Sun Jie scholars, the first linear regression analysis was carried out, and the results showed that the VIFs of the five independent variables were greater than 10, and there was the problem of multiple covariance among the independent variables, so in order to obtain stable regression coefficients, P、R、J、I、S was taken as the independent variable, and C was the dependent variable.

From the results of the analysis, it can be seen that when the five independent variables and carbon emissions as the dependent variable are analyzed in ridge regression analysis, there is R2=0.975 at k=0.040, which indicates that the five independent variables can explain the reason for 97.5% of the changes in carbon emissions. Carrying out the F-test there is a model that passes the test (F=62.839, P=0.000**<0.01) and the model equation is:

$$\ln C = 2.374 + 0.867\ln P + 0.132\ln R + 0.573\ln J + 0.368\ln I - 0.136\ln S$$

In this paper, by setting three development scenarios and analyzing the prediction of the rate of change of each indicator under different scenarios, calculating the predicted values of the independent variables under the three scenarios and bringing the predicted values of the independent variables into the formula, the predicted values of the carbon emissions in each year under different scenarios are found as shown in Table 5, and the trend of the carbon emissions in the different scenarios of the three regions of Beijing-Tianjin-Hebei is shown in Figs. (8) (9) (10):

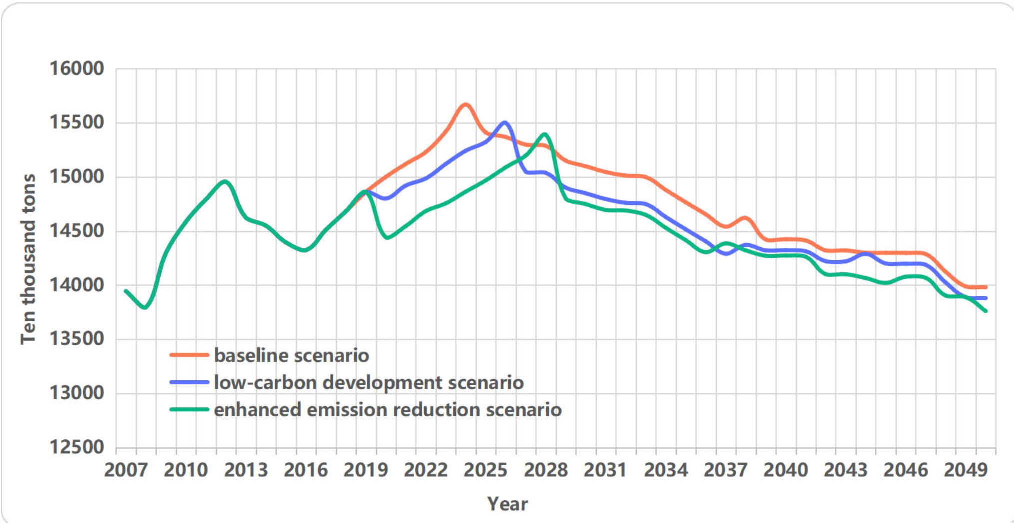

Figure. 7. Projections of carbon emission dynamics in Beijing under multi-scenarios

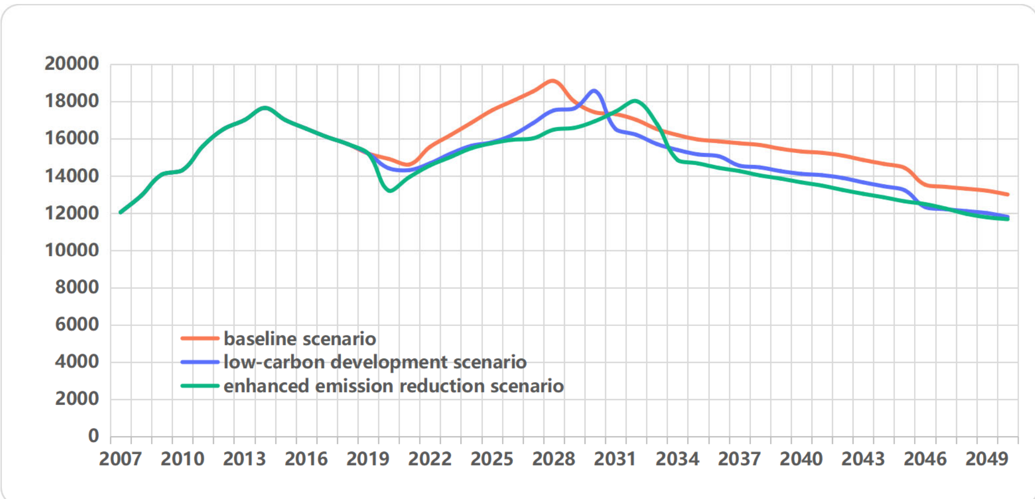

Figure 8. Carbon Emission Dynamics Projections for Tianjin under Multiple Scenarios

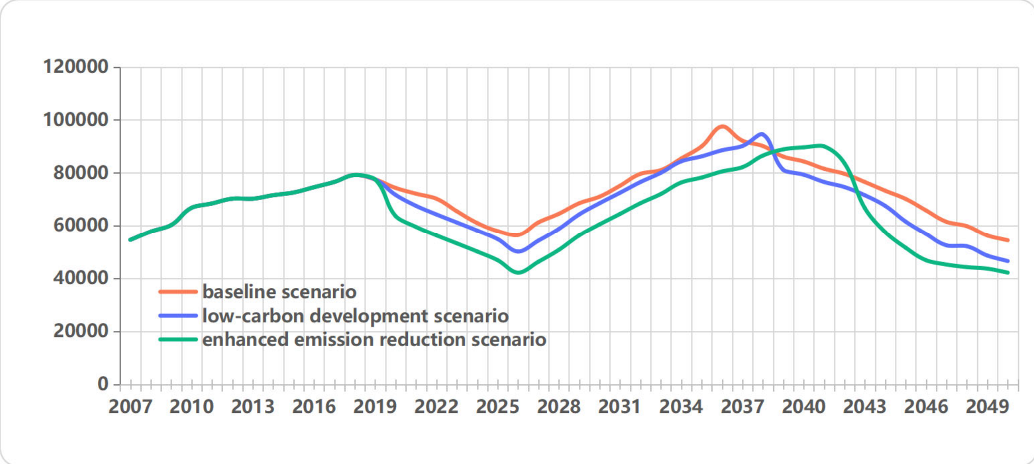

Figure 9. Projections of carbon emission dynamics under multi-scenarios in Hebei Province

Looking at the projected carbon emission trends in the Beijing-Tianjin-Hebei region, we can see that: the horizontal coordinates of the temporal distribution of carbon emissions in Beijing under the baseline scenario, low-carbon development scenario, and enhanced emission reduction scenario are 2024, 2026, and 2028, respectively; the horizontal coordinates of the temporal distribution of carbon emissions in Tianjin under the baseline scenario, low-carbon development scenario, and enhanced emission reduction scenario are 2028, 2030, and 2032, respectively; and the horizontal coordinates of the temporal distribution of carbon emissions in Hebei Province under the baseline scenario, low-carbon development scenario, and enhanced emission reduction scenario are 2036, 2038, and 2041, respectively.

4.2.2. M-K test for carbon peaking in Beijing-Tianjin-Hebei region based on carbon emission projection data

This work will also apply the M-K method of variance point detection to process the time series of carbon emissions in the Beijing-Tianjin-Hebei region to analyze and determine the emergence of variance points, the theoretical framework of which is as follows:

Assume that the time series of carbon emissions in the Beijing-Tianjin-Hebei region is $x_1, x_2, \cdots, x_n$, and m_i denotes the cumulative number of the i th sample $x_n > x_j \left(1 \le j \le i\right)$. Define the statistics as follows:

$$d_k = \sum_{i=1}^{k} m_i, 2 \le k \le n$$

d_k is the mutation point test statistic variable, and the mean and variance of d_k are defined under the assumptions of stochastic independence of the original series, etc., respectively:

$$E\left(d_k\right) = \frac{k\left(k-1\right)}{4}$$

$$Var\left[d_k\right] = \frac{k\left(k-1\right)\left(2k+5\right)}{72}, 2 \le k \le n$$

Normalize d_k to get:

$$UF_k = \frac{\left(d_k - E\left(d_k\right)\right)}{\sqrt{Var\left(d_k\right)}}$$

Where UF_k is the standardized form of d_k, and the probability α_1 can be obtained by calculating and checking the table. At a certain level of significance α_0, $\alpha_1 > \alpha_0$, when the original hypothesis is accepted, the trend of the series is not obvious changes; $\alpha_1 < \alpha_0$, the original hypothesis is rejected, at this time, it is indicated that the series has a large trend.All the UF_k 's obtained by the calculation will form a curve, and the reliability test will show whether there is a tendency to change or not. After the sequence is processed in reverse order, the method is used again, and the above calculation process is repeated, and the calculated value is multiplied by -1 to get UB_k. Similarly, UB_k will form another curve. If the intersection point of the two curves UF_k and UB_k is within the confidence interval, then this point is the beginning of the variation point. Bring in the Beijing-Tianjin-Hebei carbon emission time series data.

4.2.3. Beijing-Tianjin-Hebei Region Carbon Peak Test Results and Analysis

Based on the measurement and prediction of carbon emissions in the Beijing-Tianjin-Hebei region, a map of the predicted trend of regional carbon emissions drawn under the baseline scenario, the low-carbon development scenario and the enhanced emission reduction scenario is derived, and a test map of carbon emission mutation points under the three scenarios in the Beijing-Tianjin-Hebei region is derived:

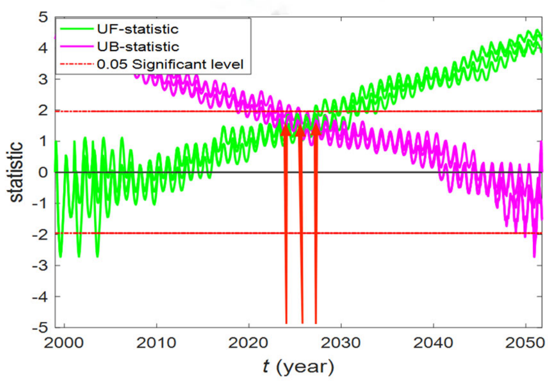

Figure 10. Carbon Emission Mutation Points in Beijing

As can be observed from the M-K test plot of carbon emissions in Beijing, the horizontal coordinates of the temporal distribution of carbon emissions in the baseline scenario, low-carbon development scenario, and the enhanced emission reduction scenario are 2024, 2026, and 2028, respectively, after conducting the M-K test on the projected data based on the carbon emissions of Beijing, and the M-K test image shows that the intersection point of the UF_k and UB_k curves is within the confidence interval. The M-K mutation point test image shows that the intersection of the x and y curves is within the confidence interval, and it can be judged that Beijing's carbon emission peak point is not in the plateau period, indicating that after the peak year, Beijing's carbon emission has a significant downward trend, and it can be judged to have completed the carbon peak. It can be judged that Beijing will be able to reach its peak carbon emissions before 2030, and if Beijing actively adopts low-carbon policy recommendations and carries out enhanced emission reduction measures, the peak carbon emissions will be reached earlier.

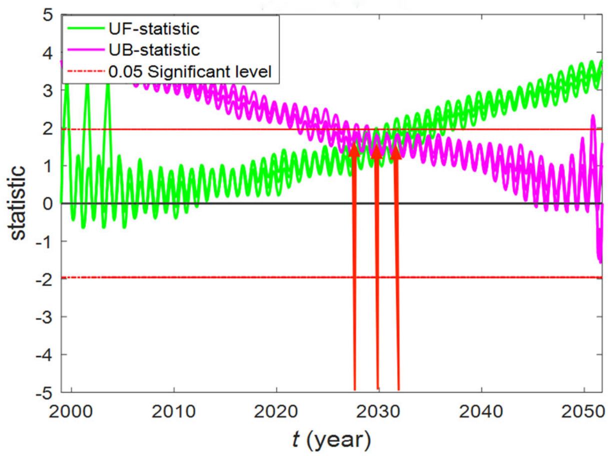

Figure 11. Carbon emission mutation points in Tianjin

From the M-K test chart of Tianjin's carbon emission mutation points, it can be observed that the horizontal coordinates of the time distribution of Tianjin's carbon emissions under the baseline scenario, low-carbon development scenario and enhanced emission reduction scenario are 2028, 2030 and 2032, respectively, and the intersection of the curves is within the confidence interval, as shown in the M-K test image. It can be determined that the peak point of Tianjin's carbon emissions is not in the plateau period, indicating that after the peak year, Tianjin's carbon emissions have a significant downward trend, and it can be determined that the city completes the carbon peak. However, compared with the trend of Beijing's carbon emissions, the overall trend of Tianjin's carbon emissions is not optimistic, mainly because Tianjin still focuses on industrial development, which has more carbon emissions. If Tianjin wants to achieve the goal of carbon peaking by 2030, it needs to increase the implementation of enhanced emission reduction.

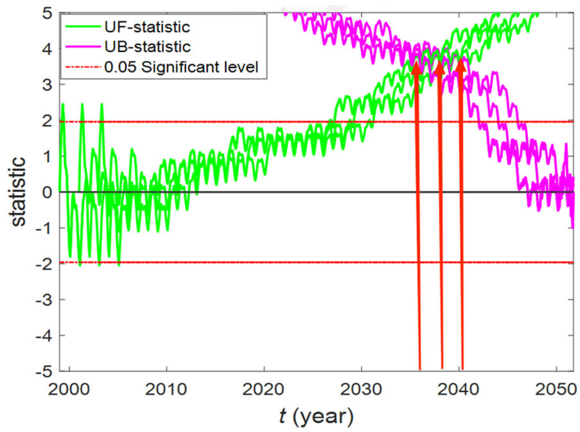

Figure 12. Carbon emission mutation points in Hebei Province

As can be observed from the M-K test plot of carbon emission mutation points in Hebei, the horizontal coordinates of the temporal distribution of carbon emissions in Hebei province under the baseline scenario, low-carbon development scenario, and enhanced emission reduction scenario are 2036, 2038, and 2041, respectively, after conducting the M-K test based on the projected data of carbon emissions in Hebei. However, the test image shows that the intersection of the UF_k and UB_k curves is not within the confidence interval, and it is determined that the peak of carbon emissions in Hebei Province is in the plateau period, i.e., after the carbon emissions in Hebei Province reach the peak in these three scenarios, the carbon emissions may fluctuate within a certain range, and then enter into a stable decline phase, and the period before the obvious downward trend does not occur is called the plateau period. During the plateau period, based on our consideration of the economic and natural factors of Hebei Province, we believe that carbon emissions in Hebei Province may still rise, and it is difficult to judge whether the target of carbon peaking has been achieved.

Based on our reading of the notice issued by the State Council on the Peak Carbon Action Program by 2030, we have made a preliminary estimation of the peak carbon emissions in the Beijing-Tianjin-Hebei region by 2030 under the current domestic policy scenarios for each of the municipal districts in the Beijing-Tianjin-Hebei region, taking into account our discussion of the peak carbon emissions in the Beijing-Tianjin-Hebei region in the study.

4.3. Decomposition of Influencing Factors of Carbon Emission in Beijing-Tianjin-Hebei Region under GGDP Accounting System

After understanding the trend of total carbon emissions from major industrial enterprises in the three regions, we used the LMDI additive decomposition model to decompose the factors of carbon emissions from major industrial enterprises from 2003 to 2017, and obtained the cumulative contributions of the population size effect, economic development level effect, industrial structure effect, energy intensity effect, the five major decomposition factors of GGDP, and the comprehensive change effect of major industrial enterprises in all years. The value. According to the trend of comprehensive change effect, it can be concluded that the cumulative effect of the factor of economic development level and population size has always been positive, and the cumulative effect of the factor of economic development level and population size "growth rate" is relatively stable, indicating that in general, the factor of economic development level and the factor of population size in the past years is "increasing row". The "increasing row" effect. However, because of the energy structure of industrial enterprises over the years, inhibit the regional carbon emission status, while in recent years, with the optimization of energy structure, the cumulative effect of the energy consumption structure factors have been in a state of "emission reduction" effect.

The cumulative effect of the industrial structure factor is the most fluctuating of the five factors, reaching the peak of the "emission increase" effect in 2006 and the "emission reduction" effect in 2017, and the cumulative effect of the industrial structure factor has been in the state of "emission reduction" effect in recent years. The cumulative effect of the industrial structure factor has been in the state of "emission reduction" effect in recent years.

Combined with the comprehensive effect, it can be seen that before 2012, the comprehensive effect of carbon emissions and the effect of the level of economic development in the Beijing-Tianjin-Hebei region had the same trend of change and were not very different from each other. That is to say, from 2003 to 2012, the factor of economic development level was the main factor for industrial enterprises in the Beijing-Tianjin-Hebei region to "increase their emissions. However, from 2013 onwards, the growth rate of carbon emissions from enterprises in the Beijing-Tianjin-Hebei region slowed down, and the other factors began to play a role, especially the energy intensity factor, which played an important role in the "emission reduction" effect, but at the same time, the economic development factor remained the main factor in the "emission increase" of industrial enterprises after 2013. The other factors are starting to play a role, especially the energy intensity factor, which plays an important role in "emission reduction".

In the following paper, we will analyze the year-by-year contribution values of five carbon emission factors, namely, population size factor, economic development level factor, industrial structure factor, energy intensity factor, and energy structure factor, in the Beijing-Tianjin-Hebei region from 2003 to 2017. For the population size factor and economic development level factor, population growth and economic development are the general trend, is the indispensable driving force for the historical wheel of social stability and development to move forward, we can't directly reduce carbon emissions by reducing the population and letting the rate of economic development drop to negative value.

(1) Analysis of the effect of industrial structure factors

The first stage was from 2004 to 2008, when the Beijing-Tianjin-Hebei region, especially Tianjin, became the node of China's largest industrial city in 2006, and the "shift" of the center of gravity of the industry made the industrial structure effect in the first stage show the effect of "increasing emissions". However, in 2007 and 2008, carbon emissions dropped significantly, during which time the country adopted a series of short-term emission reduction or even production shutdown measures for enterprises with high energy consumption and pollution and high emissions in the relevant areas in order to host the Beijing Olympics, making the contribution of the industrial structure effect negative in these two years.

The second stage is from 2009 to 2015, and it can be clearly seen that after the Olympic Games in 2009, the contribution value of industrial structure effect has a significant rebound. The third stage is from 2016 to now, thanks to the haze "raging" in 2015, the government introduced emission reduction policies and residents' awareness of environmental protection, the industrial structure has changed again, and the contribution value of the industrial structure effect has become negative, showing the "emission reduction" effect. The contribution value of industrial structure effect becomes negative, showing the effect of "emission reduction".

(2) Analysis of energy intensity factor effects

The most important aspect of energy consumption is energy intensity, which reflects the amount of energy consumed to generate a unit of GDP, with the less energy consumed generating a greater economic return and proving a higher utilization of energy.

5. Conclusion and Discussion

China's Beijing-Tianjin-Hebei region is one of the largest carbon emitters in the world, and carbon emissions are closely related to the economy. Using the improved GGDP accounting system based on EAMFP, it is found that Hebei's carbon emissions are significantly higher than those of Beijing and Tianjin, and emission reduction efforts need to be strengthened.GGDP is strongly correlated with CO2 emissions, and the scale of output is the main emission increase factor. Through the analysis of LMDI decomposition, STIRPAT model and SVAR model, it is recommended to strengthen the development of green finance, learn from the successful experience of carbon emission reduction, and implement measures according to local conditions, so as to promote carbon peaking and carbon neutrality in the Beijing-Tianjin-Hebei region, and to realize the sustainable development of the economy.

Against the backdrop of addressing climate change and realizing the goals of carbon peaking and carbon neutrality, China's Beijing-Tianjin-Hebei region faces the challenges of uneven carbon emissions and economic restructuring. This paper proposes to strengthen the publicity of the concept of green development, advocate low-carbon life, build a monitoring mechanism, and call on the government to transition from a "rough" to an "intensive" model. Scientific and technological progress is crucial to the promotion of carbon emission reduction, sustainable economic development and green finance. The multi-faceted development of finance can safeguard scientific and technological progress, cultivate technical talents, and strengthen green production to promote carbon emission reduction. However, the current development of green finance in Beijing-Tianjin-Hebei is insufficient and requires efficient allocation of funds, improvement of the development system, assistance to environmentally friendly enterprises, and attention to international trends. To this end, the carbon financial market should be built, communication and interoperability should be strengthened, and international experience should be drawn upon to promote improvements in the governance of carbon emission reduction. These initiatives will help to realize green and sustainable development, and will be useful for Beijing-Tianjin-Hebei and other regions.

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