Analysis of the Current Carbon Emission Intensity and Influencing Factors in the Beijing-Tianjin-Hebei Region

Empirical Analysis Based on County-level Panel Data from 2013 to 2019

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Abstract

Beijing Tianjin Hebei region is the economic center of the north of China. Therefore, using county-level panel data to analyse the carbon emission of Beijing Tianjin Hebei region is important to achieve the dual carbon goal. According to the energy consumption and NPP / VIRRS nighttime light data from 2013 to 2019, we calculate the carbon dioxide emission quantity and the carbon dioxide emission intensity. We constructed he STIRPAT model with individual and time double fixed effects, using the instrumental variable method, then searched possible factors affecting the regional carbon emission intensity at county level.

The results show that: firstly, the total carbon emission of Beijing, Tianjin and Hebei showed a downward trend from 2013 to 2019. However, the reduction rates of the three provinces vary significantly. Beijing has the fastest carbon emission reduction rate, followed by Tianjin, and then Hebei Province. Secondly, for elements affecting carbon emissions, it can be seen that the regional population ($\ln POPU$), the degree of industrial upgrading ($SENI$) and the proportion of secondary industry in the regional GDP ($pSEC$) are significantly negatively correlated with the regional carbon emission intensity. Lastly, the economic development level and industrial structure of Beijing, Tianjin and Hebei are quite different, the factors affecting carbon emission intensity are also different.

Therefore, the government should develop the regional industrial structure of Beijing, Tianjin and Hebei, establish a reasonable carbon tax collection system and build an effective carbon emission trading market.

Keywords: carbon emission intensity; STIRPAT model; Instrumental variable method

1 Introduction

In agrarian societies, humans primarily utilized carbohydrates, while in the current industrial society, humans predominantly rely on hydrocarbons. The process of economic development has been accompanied by the emission of substantial greenhouse gases, particularly carbon dioxide (CO_2). This has led to the worsening of the greenhouse effect in recent years. Faced with the severe challenges of climate issues, there is an urgent need for humanity to transform its economic development paradigm, aiming for long-term economic sustainability by fostering a clean, efficient, and green economy. [13] The issue of carbon emissions is one that concerns the right to development of regions. China, as the world's largest developing country, is currently at a crucial period of transitioning its economy to a higher-quality level. Consequently, the establishment of an efficient, clean, and sustainable green economic development model is the path China must follow for economic growth. To demonstrate its commitment as a major player in global environmental matters, General Secretary Xi Jinping, during the 75th United Nations General Assembly debate, proposed that China would take more robust measures to control carbon emissions in the process of its economic development. He also came up with the "Dual Carbon Goals" of "peaking carbon emissions by 2030" and "achieving carbon neutrality by 2060."

The Beijing-Tianjin-Hebei region (Jing-Jin-Ji Region) serves as the development center of northern China. Throughout its historical development, while the Jing-Jin-Ji region has achieved rapid economic growth, it has also faced severe environmental challenges. Particularly, Hebei Province's economic development has not been sufficiently comprehensive, and there exists plenty of heavy industries characterized by low returns, high energy consumption, and high emissions. Therefore, conducting research on carbon emissions in the Jing-Jin-Ji region holds significant importance for achieving the "Dual Carbon Goals."

Currently, the academic community have conducted extensive research on carbon emissions, covering various aspects such as exploring the factors influencing carbon emissions, examining the pathways through which these factors affect emissions, evaluating the policy effectiveness of government carbon reduction policies, constructing carbon emissions trading markets, and assessing the welfare costs of carbon taxation. However, most of these studies have utilized panel data at the provincial or municipal levels, potentially overlooking the heterogeneity at the county-level units. Additionally, when selecting the dependent variable, many researchers have used regional total carbon emissions as the main focus. While this measure is useful for analyzing the issue of peaking carbon emissions, relying solely on it for policy formulation may not be entirely equitable. Because larger provincial-level administrative units often have a higher total carbon emissions. Therefore, this paper will first investigate the spatial and temporal evolution characteristics of carbon emissions and emissions intensity in the Beijing-Tianjin-Hebei Region. Subsequently, at the county-level scale, we will construct a STIRPAT model, establish time and spatial fixed-effects models, and utilize instrumental variable methods to analyze the factors influencing carbon emissions intensity in the Beijing-Tianjin-Hebei Region.

The following sections of this paper will be developed from the following parts. The second part provides a critical review of the existing research findings and analytical methods used by scholars regarding the factors influencing carbon emissions. The third part introduces the construction of the dependent variable "carbon emissions intensity (CE) ", the independent variables, and the development of an STIRPAT model with individual and time double fixed effects. The fourth part presents the changes in carbon dioxide emissions and emissions intensity in the Beijing-Hebei-Tianjin region from 2013 to 2019, along with the baseline regression results of the STIRPAT model and the results using instrumental variable methods. To ensure the credibility of the model, the fifth part conducts robustness tests and heterogeneity analysis. Finally, in the sixth part, we get the conclusions and further discussion. Then we present several policy recommendations for addressing carbon emissions issues in the Beijing-Hebei-Tianjin region.

2 Conceptual Definition and Related Literature

Carbon dioxide emissions (carbon emissions) encompass both human emissions in production activities and emissions from humans and other organisms in the process of living. Currently, scholars use two main categories of indicators to reflect the current status of carbon emissions. Most scholars use total carbon dioxide emissions as their research focus, while some researchers use carbon emission intensity (i.e., the carbon emissions corresponding to the unit GDP output

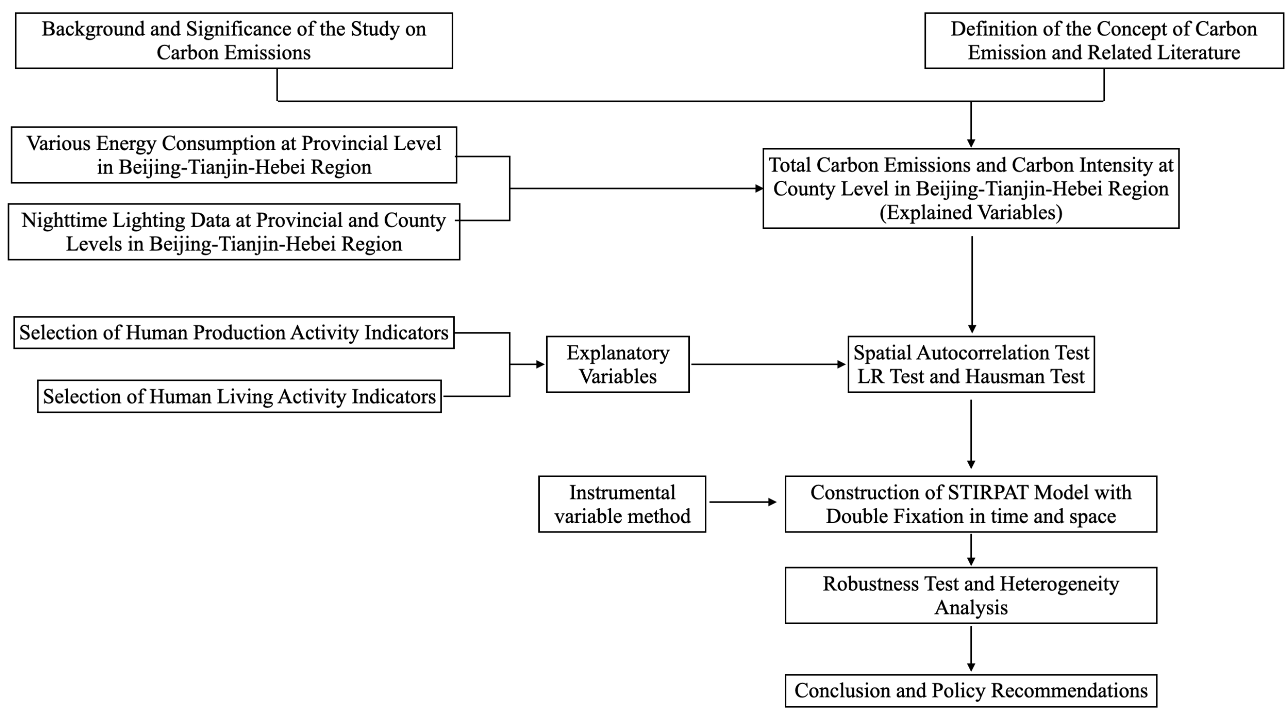

Figure 1: Research Approach

of a certain region over a certain period) as their research focus. Below, we will introduce and summarize the research findings and methods of these scholars.

2.1 Factors Influencing Regional Carbon Emissions

In terms of factors influencing regional carbon emissions, scholars have conducted extensive research.

From the perspective of the overall industrial structure in a certain area, the concentration of the primary and secondary industries tends to promote an increase in carbon emissions, while an increase in the concentration level of the tertiary industry is favorable for reducing carbon emissions (Gong Xinshu et al., 2022) [14]. Most scholars generally agree that the more important the secondary industry is in the local economy, the higher the carbon emissions tend to be (Mo Huibin et al., 2021) [15]. However, the carbon emission efficiency of various industries within the industrial sector differs. Factors contributing to these differences include the proportion of heavy industry in the value-added of the secondary industry, the proportions of specific industries within the heavy industry sector, the production technologies employed by enterprises within each industry, energy consumption intensity, energy consumption structure, and others (Lin Xueqin et al., 2021) [16].

Regarding the relationship between industries, scholars' opinions vary. For instance, Liu Zhihua et al. (2022) found that the advancement of industrial structure sophistication can reduce the carbon emission intensity in local area [17]. Xie Yunfei's (2022) research on "industrial digitalization" and "digital industries" also supports this viewpoint [18]. However, Zhang Yan et al. (2022) argued that the impact of improving industrial coordination on reducing carbon emissions is not significant [19]. Zhao Liping and Li Yuan (2018) [20] suggested that the impact of industrial structure on carbon emissions weakens gradually with the increase in urbanization levels.

From a mechanistic perspective, technological innovation and industrial structural upgrades mutually promote each other and influence intermediary variables, facilitating the achievement of carbon reduction goals. Enhancing energy utilization efficiency is an important transmission pathway for both factors to influence carbon reduction (Yin Yinggang, 2021) [21]. Energy structure also plays a partial intermediary role in promoting carbon reduction through green finance.

Regional carbon emissions are also influenced by the economic scale and quality of the region. Ahmed et al. (2019) [1] considered regional economic growth and the development of the regional financial industry to be among the most important factors affecting global carbon emissions. Generally, larger regional economies tend to have higher total carbon emissions (Mo Huibin et al., 2021) [15]. Regions with better economic quality tend to have more companies adopting green production technologies and lower carbon emission levels. However, some scholars argue that this issue should be discussed in both the short and long term. For example, Raggad (2020) suggested that in the short term, increased economic output is achieved through increased input factors and a doubling of production scale, with little improvement in labor productivity, thus leading to increased carbon emissions in the short term [2]. In the long term, there exists technological transformation. This implies a change in the production function, or furthermore in the type and quantity of input factors, factor utilization, and the time required to produce a unit of product. Such changes may lead to an increase or decrease in carbon emissions. Zhang Lifeng (2021) also believed that economic development levels and technological levels have a positive impact on carbon emissions, but this impact diminishes over time [22].

The population size and living quality of residents in a region are important factors influencing regional carbon emissions. Latief et al. (2021) found a causal relationship between population size and energy consumption in a certain region [3]. Larger populations are often associated with higher regional carbon emissions (Zhang Lifeng, 2021) [22], and this trend becomes more significant when the proportion of young population, the quality of life of residents, and the development of supporting infrastructure are higher (Mo Huibin et al., 2021) [15]. Zhang Yunhui et al. (2022) [23], when conducting spatial econometric analysis of carbon emissions in 30 provincial-level administrative regions across the country, found a clear inverted U-shaped relationship between income disparity and carbon emissions. Income disparity promotes economic agglomeration, which in turn affects carbon emissions.

Furthermore, formal and informal environmental regulations also play crucial roles in regulating regional carbon emissions. A series of policies aimed at promoting local economic sustainability, issued by the governments of resource-based cities, can increase government support for existing enterprises, encouraging them to choose energy-efficient, low-carbon, and environmentally friendly policies. This helps optimize the industrial structure, improve people's living standards, and ultimately has a positive impact on reducing carbon emissions (Zhang Yan et al., 2022) [19]. Yin Yinggang (2021) [21] also think that the level of regional openness, government tax systems and intensity, and the level of public services can influence regional carbon emissions. However, some scholars argue that the impact of formal environmental regulations is limited. For example, Li Jing et al. (2021) [24] found that the impact of environmental regulations on carbon emission intensity exhibits a double-threshold inverted U-shaped feature, with the threshold variable needing to exceed a certain threshold to show significant changes. Therefore, in addition to formal environmental regulations issued by the government, we cannot ignore the important role of a series of informal environmental regulations in the process of carbon reduction.

Zeng Sheng et al. (2021) [25] argued that green investment has a "U-shaped" or "N-shaped" impact on high-quality economic development and has an "inverted U-shaped" or "inverted N-shaped" impact on carbon emissions.

In addition to the above factors, it should be noted that different regions have different geographical locations, temperature climates, development stages, and resource endowments. Therefore, various factors influencing carbon emissions have distinct temporal and spatial heterogeneity in terms of their impact intensity and even direction. Thus, we cannot generalize the impact of these factors across all regions (Li Zekun et al., 2021) [26] (Zhang Yan et al., 2022).

2.2 Methods Used to Study Carbon Emissions

This section introduces the methods and econometric models that scholars have employed to study carbon emissions. Overall, scholars generally calculate the carbon emissions of various fossil fuels based on the carbon emission factors and coefficients listed by the Intergovernmental Panel on Climate Change (IPCC) in 2006. Some scholars also believe that there is a positive correlation between nighttime light brightness and carbon emissions in a region, using DMSP/OLS stable nighttime light data and NPP/VIIRS imagery to derive indicators measuring carbon emissions quantities (Du Haibo et al., 2021) [27] (Mo Huibin et al., 2021) [15] (Zhang Yan et al., 2022) [19].

Due to the externality of carbon emissions, scholars often use spatial econometric models to analyze the factors influencing carbon emissions and their magnitudes. The following summarizes the methods scholars have used to investigate carbon emissions:

2.2.1 Spatial Econometric Methods for Studying Carbon Emissions

Carbon emissions are often associated with spatial spillover effects. Zhou Yanfan et al. (2021) [28] conducted spatial econometric analysis of agricultural carbon emissions in 168 counties in Hebei Province and found significant positive spatial spillover effects of agricultural carbon emissions at the county scale. Spatial spillover effects and boundary effects jointly affect agricultural carbon emissions. Therefore, regional industrial upgrading has a positive externality, leading to a reduction in carbon emissions in surrounding areas (Yu Zhiwei et al., 2022) [29]. Mo Huibin et al. (2021) [15] argued that high carbon emission regions and low carbon emission regions have different spatial effects. High carbon emission regions exhibit spillover effects, while low carbon emission regions exhibit lock-in effects, with spillover effects being more significant. Lin Xueqin et al. (2021) [16] studied industrial carbon emissions in the Beijing-Tianjin-Hebei region and found that the differences in industrial carbon emission efficiency between cities are gradually decreasing, with high carbon emission areas increasingly exhibiting a strip-like spatial distribution. Therefore, regional integration is conducive to reducing the carbon emission intensity of the entire region. However, Li Ai (2021) [31] found that the Beijing-Tianjin-Hebei urban agglomeration has a stable network compared to the Yangtze River Delta and Pearl River Delta urban agglomerations.

Therefore, scholars often use spatial econometric methods to examine the spatial distribution of carbon emissions and the impact of various influencing factors on carbon emissions in a certain region. They first conduct exploratory spatial analysis by calculating Moran's I and Anselin Local Moran's I cluster tests to determine whether there is spatial correlation between carbon emissions in various cities in a region. If spatial correlation exists, an appropriate spatial econometric model is selected for further analysis. Based on this, Yu Zhiwei et al. (2022) [29] and Li Jing et al. (2021) [24] proposed that the relationship between industrial structure and carbon emissions is not linear but has a threshold effect. They combined regional economic development level and technological innovation ability as threshold variables and constructed a dynamic spatial Durbin model based on Hansen's method for regression.

2.2.2 STIRPAT Model for Analyzing Environmental Pollution Issues

The STIRPAT model is a classic nonlinear model for analyzing the degree of environmental pollution and its influencing factors. It is often combined with spatial econometric models and other environmental theories and is widely applied to carbon emission issues. The model posits that the degree of environmental pollution is influenced by a series of factors such as socioeconomic development level, production technology, regional population, etc., and these factors exhibit a nonlinear relationship with environmental pollution. Based on the STIRPAT model and the Environmental Kuznets Curve (EKC) hypothesis, Zhang Yunhui et al. (2022) [23] established a spatial Durbin model. Controlling for fixed effects in the model is also a common practice. Li Jing et al. (2021) [24] found that China's regional carbon emission intensity exhibits "temporal inertia." Xu Weixiang et al. (2022) [32], in order to study the transfer and dynamic evolution of carbon emissions, combined spatial lag effects with the traditional spatial Markov chain.

2.2.3 Literature Summary

Carbon emissions are a matter concerning the right to regional development. Through the review of literature in the preceding sections, it can be seen that scholars generally use the "total carbon emissions" of a region as the dependent variable when studying factors influencing carbon emissions. However, existing research shows that factors such as regional GDP, population size, and the quality of people's lives also influence total carbon emissions. Therefore, it is fairer and more reasonable to use "carbon emission intensity" considering regional GDP as the dependent variable. Additionally, when analyzing carbon emission intensity, population size should also be included in the consideration.

Furthermore, because micro-scale statistical data are not comprehensive, most scholars' research on carbon emissions is still limited to the provincial and municipal panel analysis. In studies of carbon emissions in the Yangtze River Basin, some scholars have noticed the correlation between nighttime light data and the intensity of human activities, and have used nighttime light grid data to estimate carbon emissions at a smaller scale. However, such estimates for the Beijing-Tianjin-Hebei region are still lacking. Therefore, this study will comprehensively consider factors related to both production and living and, in conjunction with nighttime light data, analyze carbon emission intensity at the county level in the Beijing-Tianjin-Hebei region. The following hypotheses are proposed:

Hypothesis 1: The greater the intensity of human living activities and the more dispersed the activity distribution, the higher the carbon emission intensity.

Hypothesis 2: The greater the intensity of human production activities, especially in the secondary industry, the higher the carbon emission intensity.

Hypothesis 3: Factors influencing carbon emission intensity exhibit regional variations, and the factors affecting carbon emission intensity in Beijing, Tianjin, and Hebei Province differ from each other.

3 Research Design

In this section, we will first explain the construction of the dependent variable indicator, followed by an explanation of the selected independent variables and their data sources. Finally, we will introduce the construction of the STIRPAT model with individual and time-fixed effects. Due to the lack of statistical data for some county-level administrative regions, this study uses data from 165 county-level administrative regions in the Beijing-Tianjin-Hebei region for the years 2013 to 2019.

3.1 Explained Variable: Calculation Method and Data Source for Carbon Emissions

Carbon emissions refer to the emissions of carbon dioxide (CO2). In this study, "carbon emission intensity," which represents the amount of carbon emissions per unit of GDP, is used as the dependent variable. The logarithm of this variable is taken as the dependent variable. Since data from the "China Energy Statistical Yearbook" only provide statistics at the provincial level, which is not precise enough for carbon emission research in the Beijing-Tianjin-Hebei region, and because municipal-level statistical data are partially missing, night-time light data can be used to reflect the intensity of production and living activities in a certain area. Therefore, this study adopts a method similar to that used by Du Haibo (2021) to estimate carbon emissions data at the county level, combining night-time light data from the Beijing-Tianjin-Hebei region from 2013 to 2020 with regional organic energy consumption. The general estimation method is as follows:

First, estimate the carbon emissions for each provincial-level administrative region based on the consumption of various energy sources over the years.

Then, use ArcGIS to calculate the grid brightness between provinces.

Finally, calculate the ratio of total carbon emissions to light brightness for provincial-level administrative regions, and multiply it by the light brightness of each county-level administrative region. Since production technology improves year by year in each province and energy efficiency increases year by year, this estimation is conducted annually by province. The calculation method is explained in detail below.

3.1.1 Calculation of Provincial-Level Carbon Emissions

This study draws on the method for calculating carbon emissions from energy activities as outlined in the "2006 IPCC Guidelines for National Greenhouse Gas Inventories." Currently, the primary source of energy for electricity generation is organic compounds, so carbon emissions can be roughly estimated by the types and quantities of fuel burned. The drawback of using this method is that it overlooks the combustion conditions of organic fuels and the carbon residues in the residues. Therefore, this method can only provide a rough estimate of carbon emissions for a given country or region. However, it has the advantage of being a simple and quick calculation method. The basic idea for the calculation is that "the level of carbon emissions estimation is equal to the carbon

$$CE = CEF \times AL \tag{1}$$

where CE represents the estimated carbon emissions (Carbon Emission), CEF(Carbon Emission Factor) represents the carbon emission factor, and CAL (Carbon Activity Level) represents the level of carbon emission activities. Following the method referenced from Su Yongxian [33], the calculation formula for carbon dioxide emissions in this paper is as follows:

$$CE = \frac{44}{12} \times \sum_{i=1}^{8} CEF_i \times CAL_i \tag{2}$$

Where "i" represents the type of energy. The types of energy included in this study and the corresponding carbon emission factors for each type of energy are shown in the table below:

Table 1: Energy Sources and Carbon Emission Factors

Energy Source	Carbon Emission Factor
Coal	2.53
Coke	2.69
Crude Oil	2.76
Petrol	2.20
Paraffin	2.56
Diesel Oil	2.73
Fuel Oil	2.26
Natural Gas	2.09

Data Source: Carbon Emission Factor Inventory and Coefficients released by IPCC in 2006.

According to the table 1, the calculated total carbon dioxide emissions for Beijing, Tianjin, and Hebei provinces from 2013 to 2019 are shown in table 2. Overall, from 2013 to 2019, all three regions showed a decreasing trend in total carbon emissions, but there were significant differences in their carbon reduction rates. Beijing had the fastest carbon reduction rate, with an average annual reduction of 6.93% in carbon dioxide emissions compared to the previous year. Tianjin followed, with an average annual reduction of 3.16% in carbon dioxide emissions compared to the previous year. Hebei province had the slowest carbon reduction rate, with an average annual reduction of 0.43% in carbon dioxide emissions compared to the previous year.

Table 2: Total Carbon Dioxide Emissions (in ten thousand tons) and Emission Reduction Rate in the Beijing-Tianjin-Hebei Region from 2013 to 2019

Province	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**Emission Reduction Rate**(%)
Beijing	10422.3	10306.3	8913.3	7788.3	7259.4	6964.5	6775.8	6.93
Tianjin	22552.9	21548.1	20548.0	19133.5	18547.4	18784.2	18602.9	3.16
Hebei	109546.2	103664.4	108572.8	107912.2	106643.5	107612.7	106769.3	0.43

3.1.2 Estimating County-Level Carbon Dioxide Emission Intensity Using Nighttime Light Data

In this paper, we first imported the nighttime light data image [34] into ArcMap 10.7 and used raster processing tools to extract the total brightness values of nighttime lights for each provincial-level administrative region and county-level administrative region. To enhance precision, we applied Lambert projection to the Beijing-Tianjin-Hebei region. We then calculated the total carbon emissions for each county-level administrative region using the following formula:

$$CE_{it}^{j} = CE^{j} \times \frac{\text{County } i \text{ Nighttime Light Intensity}}{\text{Province } j \text{ Nighttime Light Intensity}} \tag{3}$$

The estimated results for provincial-level carbon emission intensity are shown in table 3.

Table 3: Descriptive Statistics of Carbon Emission Intensity in the Beijing-Tianjin-Hebei Region from 2013 to 2019

Year	**Samples**	**Min**	**Max**	**Mean**	**Standard Deviation**
2013	150	0.27	23.62	5.92	4.03
2014	150	0.24	15.47	5.29	3.42
2015	150	0.17	101.7	6.01	8.65
2016	150	0.12	17.37	4.74	3.25
2017	150	0.09	26.24	5.27	4.41
2018	150	0.07	24.64	5.49	4.28
2019	151	0.05	24.04	5.08	3.84

3.2 Selection of Explanatory Variables and Data Sources

Human activities primarily influence carbon emissions through production and daily life. Therefore, factors affecting carbon emissions can be comprehensively considered from these two aspects. Based on previous research, carbon emissions from production activities depend on various factors such as local industrial structure and the technologies used in production. The secondary industry is the sector with the most significant impact on carbon emissions among the three industrial sectors. Therefore, this paper selects the total production value of the secondary industry, the proportion of the secondary industry in GDP, and the level of industrial upgrading to measure how industrial structure affects carbon emissions. Foreign direct investment is selected as an indicator of technological proficiency, reflecting how human production activities influence carbon emissions.

Factors affecting carbon emissions resulting from human daily activities are primarily determined by two aspects: the population size of the region and the quality of life of the residents in that region. The year-end resident population serves as an indicator of regional population size, while per capita GDP serves as an indicator of the quality of life of residents. Data for these variables were sourced from various statistical yearbooks, including the "China Statistical Yearbook," "Hebei Economic Yearbook," "China Urban Statistical Yearbook," statistical yearbooks of various cities, and statistical bulletins of various cities over the years. To eliminate the impact of price levels on the data, price adjustments were made using 2013 as the base year, and missing data were supplemented with averages. To eliminate the impact of exchange rates, data denominated in U.S. dollars were converted to Chinese yuan based on the annual average exchange rate between China and the United States. Detailed explanations of these indicators are provided below.

3.2.1 Per Capita GDP (pGDP)

Per capita GDP refers to the ratio of the total value of all final products and services produced by both domestic and foreign nationals residing in a certain country or region during a specific period (usually one year) at current market prices to the population. In this paper, per capita GDP for each county is used to assess the income and consumption levels of local residents.

3.2.2 Year-End Resident Population

Regarding the impact of population factors on carbon dioxide emissions, the research findings of domestic and international scholars are not consistent. For example, in the series of studies by York et al. (2003) [4] on the relationship between human activities and environmental threats, they found that the level of economic development in a region is one of the most significant factors, while the population size of the region is the most important factor affecting environmental threats other than carbon dioxide. On the other hand, Latief et al. (2021) [3] found a causal relationship between population size and energy consumption in certain regions. This may be due to the unique characteristics of different regions. Areas with large populations often have more advanced infrastructure and better consumer channels, which can lead to an increase in carbon dioxide emissions. At the same time, the provision of infrastructure and services may also have economies of scale, which could lead to a reduction in carbon dioxide emissions. Therefore, this paper selects population size as one of the explanatory variables.

3.2.3 Value Added by the Secondary Industry and the Proportion of the Secondary Industry in GDP

The secondary industry is one of the categories in the three-sector classification in China and can be broadly divided into two parts: industry and construction. Compared to the primary industry (agriculture, forestry, and fishing) and the tertiary industry (services), the secondary industry, especially heavy industry, often involves substantial consumption of fossil fuels in the production process, resulting in more carbon dioxide emissions. In certain cities within Hebei Province, such as Tangshan, coal mining and steel production are pivotal industries.

When considering the impact of the secondary industry on carbon emissions intensity, two aspects need to be taken into account. Firstly, it is the proportion of the value added by the secondary industry in the local GDP. A higher proportion indicates that a larger proportion of GDP is contributed by the production of the secondary industry, which could potentially lead to higher carbon emissions intensity. Secondly, it is the overall scale of the local secondary industry. Since industries in the supply chain are interrelated, a larger scale of the local secondary industry may require a larger scale of upstream and downstream industries, which could also result in higher carbon dioxide emissions. Therefore, this paper selects value added by the secondary industry and the proportion of the secondary industry in GDP as two indicators for explaining carbon emissions intensity.

3.2.4 Foreign Direct Investment

Foreign direct investment (FDI) refers to productive investment activities conducted by foreign companies, other economic organizations, or individuals after obtaining approval from the Chinese government. Foreign direct investment not only brings technology and capital to the region but also promotes green economic development in the area.

3.2.5 Degree of Industrial Upgrading

The industrial structure measures the characteristics of an area's industrial composition. The Beijing-Tianjin-Hebei region exhibits a clear hierarchical industrial structure. Due to Beijing and Tianjin being directly administered municipalities with relatively small administrative areas, the proportion of the primary industry is extremely low. Beijing, being the capital, has also witnessed the migration of industrial enterprises, transitioning into a post-industrial phase. Tianjin's economic growth is driven by both the secondary and tertiary industries. In contrast, Hebei Province has a relatively low proportion of the tertiary industry, with a higher share of the secondary industry, particularly in lower-level sectors of the production chain, such as raw material supply, and heavy industries with high pollution and energy consumption. These heavy industries are a significant source of income for Hebei Province.

Considering that the industrial structure involves multiple sectors, individual county-level administrative regions may only represent a portion of the industrial chain. Therefore, this study employs the ratio of the tertiary industry to the secondary industry at the level of prefectural cities corresponding to each county-level administrative region to reflect the degree of industrial upgrading in the local area.

Below is a summary of variable symbols and explanations:

Table 4: Symbols and Explainations

Symbols	**Explanation**	**Mean**	**Standard Deviation**	**Max**	**Min**
$\ln pCE$	Logarithmic value of average carbon emission intensity (CE)	1.38	0.838	4.62	-1.12
$\ln POPU$	Logarithm of regional year-end resident population	4.07	0.99	17.86	5.68
$\ln tSEC$	Logarithm of regional secondary GDP	13.47	1.47	17.87	5.68
FDI	Foreign investment in the city where the county-level administrative region is located as a share of GDP	0.01	0.01	0.11	0.00
$SENI$	Degree of industrial sophistication	2.42	15.16	187.29	0.46
$pSEC$	Ratio of value added of secondary industry to the region's GDP in that year	3.914	2077.35	0.00	75.96

4 Build the Fixed-Effect STIRPAT Model

The STIRPAT model is built on the theoretical foundation of Human Structural Ecology and evolved from the IPAT model for studying issues related to environmental change and social development.

The IPAT model was originally proposed by Ehrlich and Holdren (1971), where I represents the impact on the environment, serving as the dependent variable in the model. P, A, and T represent population, affluence, and technology levels, respectively, and they are all independent variables. The model formula is expressed as follows:

$$I = P \times A \times T \tag{4}$$

The IPAT model is based on the assumption that the three variables mentioned above have equal elasticity coefficients in their impact on the environment, which may not be entirely accurate in real-world situations. To address this limitation, scholars have improved the IPAT model and introduced the STIRPAT model, as shown below:

$$I = aP^{\beta_1}A^{\beta_2}T^{\beta_3}e \tag{5}$$

Taking the logarithm of both sides of the equation, we obtain:

$$\ln a = \ln \beta_1 \ln P + \beta_2 \ln A + \beta_3 lnT + lne \tag{6}$$

Rearrange this equation,

$$\ln I = \gamma + \beta_1 \ln P + \beta_2 \ln A + \beta_3 \ln T + \varepsilon \tag{7}$$

where $\gamma = \ln a$, $\varepsilon = lne$.

Compared to the IPAT model, this model can analyze the network effects of various human factors affecting the environment, covering policy, social, and cultural factors. Therefore, it has been widely applied in empirical research in such fields, and carbon emissions research is one of them.

4.0.1 Spatial Autocorrelation Test

Previous research by scholars has shown that carbon emissions often exhibit spatial spillover effects, and the most common method for testing this is by calculating the Moran's Index. If this index is significant, it indicates the presence of spatial autocorrelation, and in the subsequent analysis, a spatial weight matrix needs to be established to create a spatial econometric model. If the Moran's Index is positive, it suggests positive spatial autocorrelation, and if it is negative, it indicates negative spatial autocorrelation. Conversely, if the Moran's Index is not significant, this does not imply that the indicator exhibits spatial autocorrelation. In this study, we conducted a test on the spatial scale of county-level carbon emission intensity, and the calculation formula is as follows:

$$Moran'I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{8}$$

The calculated results of Moran's I for county-level carbon emission intensity from 2013 to 2019 are shown in the table below.

Table 5: Spatial Autocorrelation Tests(2013-2019)

Year	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Moran's I	-0.010	-0.007	0.024	0.022	0.002	-0.013	0.288
	(-0.101)	(0.006)	(0.832)	(0.778)	(0.231)	(-0.165)	(0.774)

It can be observed that at the county level, the calculated Moran's I for all the years is not statistically significant, indicating the absence of spatial autocorrelation in carbon emission intensity at the county level. Therefore, this study does not employ spatial econometric analysis.

4.0.2 Hausman Test and LR Test

To further explore which model, random or fixed effects, should be used to analyze carbon emission intensity, this study conducted the Hausman test and LR test on panel data. As shown in the test results in the table below, both indicators correspond to statistically significant test values. Therefore, this study chooses to establish a fixed effects model.

In summary, the constructed model takes the following form:

Table 6: Test Result

Test Method	**Statistical Value**	**Degree of Freedom**	**Significance**
Hausman Test	144.19	6	0.00
LR Test	2157.25	142	0.00

Where CE represents carbon emission intensity, X represents a series of explanatory variables affecting carbon emission intensity. $X_{it} = \{\ln pGDP_{it}, \ln POPU_{it}, \ln tSEC_{it}\}$, $Y_{it} = \{FDI, SENI, pSEC\}$. And i represents different county-level administrative units, and t represents the year.

5 Empirical Results

5.1 The carbon dioxide (CO2) emission situation in the Beijing-Tianjin-Hebei region.

5.1.1 2013-2019 Carbon Dioxide Emission Total Change

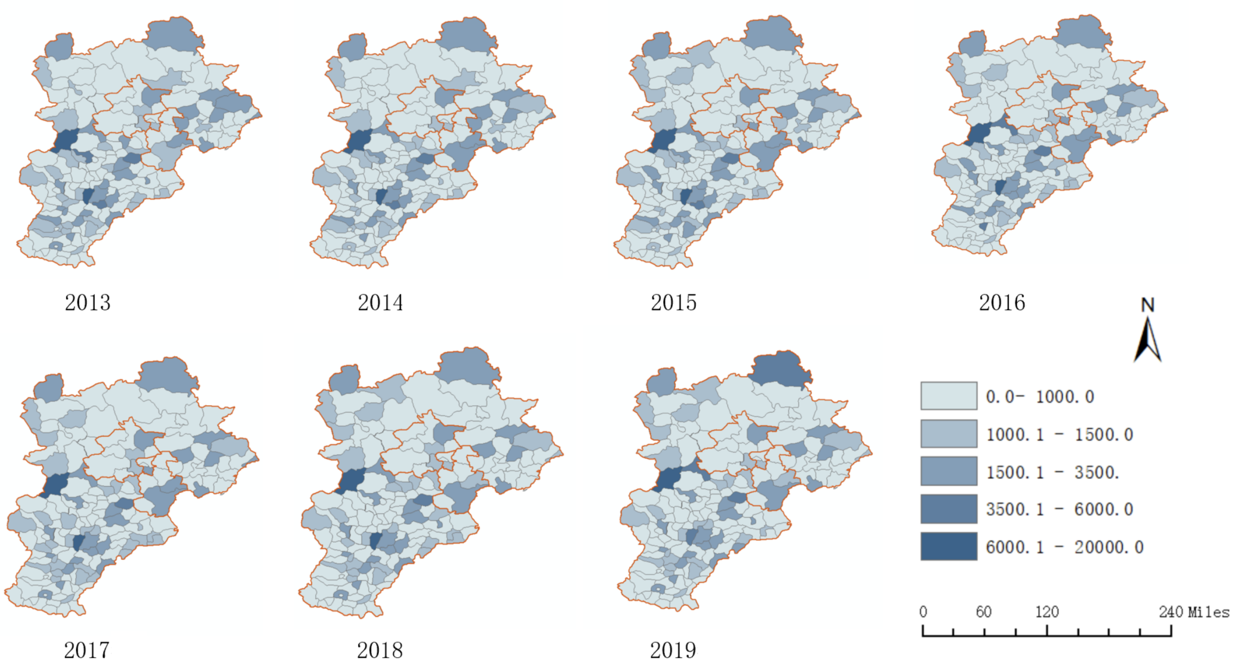

Figure 2: Carbon Dioxide Emission Total in the Beijing-Hebei-Tianjin region from 2013 to 2019

Note: The green portion represents missing GDP data for the respective region.

As shown in the above figure, there are significant differences in the total carbon dioxide emissions among different regions within the Beijing-Hebei-Tianjin region. Among them, Chengde Weichang County, Zhangjiakou Kangbao County, Laiyuan County in Baoding, Tianjin, and Tangshan consistently have higher total carbon dioxide emissions.

5.1.2 2013-2019 Carbon Dioxide Emission Intensity Change

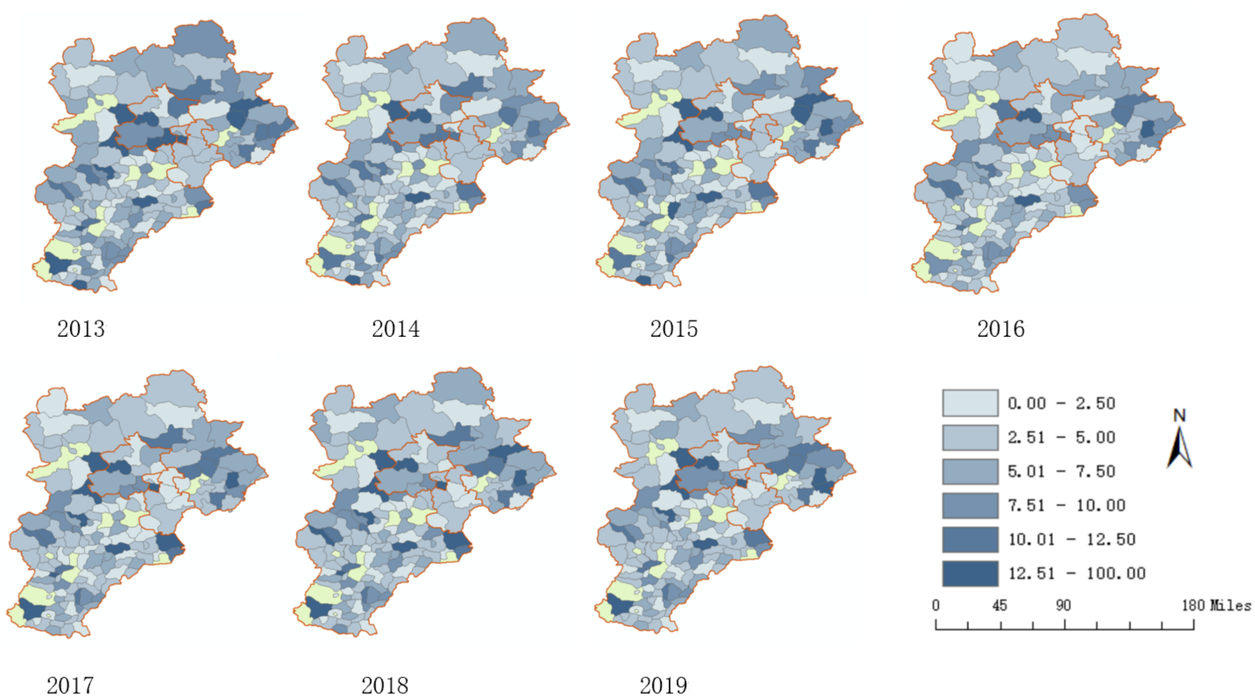

Figure 3: Carbon Dioxide Emission Intensity in the Beijing-Hebei-Tianjin region from 2013 to 2019

The green portion represents missing GDP data for the respective region.

As shown in the figure above, overall, the carbon dioxide emission intensity in the Beijing-Tianjin-Hebei region varies significantly among different areas. Luanan County in Tangshan, Mancheng County in Baoding, Changping District in Beijing, and Wu'an City under Handan have been areas with relatively high carbon dioxide emission intensity in recent years.

5.2 County-Level Fixed Effects STIRPAT Model Benchmark Regression Results

The regression results of the fixed-effects STIRPAT model are presented in the following table.

Table 7: Benchmark Regression Results

Variable	**β coefficient**	**t-Value**	**Significant**
$\ln pGDP$	-0.94	-29.51	0.00
$\ln tSEC$	0.01	0.62	0.53
$\ln POPU$	-0.99	-25.23	0.00
FDI	-0.37	-0.39	0.693
$SENI$	-0.00	-2.60	0.01
$pSEC$	-0.00	-25.22	0.00
c	15.07	30.20	0.00
F		119.57	
R^2		0.954	

From Table 7, it can be observed that the F-value of this regression model is 119.5714, confirming the effectiveness of this regression equation. The adjusted R-squared value is 0.9541, indicating that the regression curve estimated by this model fits the sample points quite well.

5.3 The regression Result using Instrumental Variable Method

In the analysis of carbon emissions, we cannot ignore the potential endogeneity issues. The main reasons for endogeneity problems in the model arise from the bias in the random sample selection, omitted explanatory variables, and mutual causality. In the analysis of carbon emissions, the increase in per capita income provides people with more opportunities to choose green high-tech products, encourages people to purchase higher-quality products, such as energy-efficient appliances, leading to a reduction in carbon emissions. Moreover, the market demand for such products further stimulates innovation in low-carbon production technologies within enterprises, resulting in a decrease in carbon emission intensity. Therefore, there is likely an endogeneity problem in the model. To investigate this issue, the results of the test are shown in the table below, confirming the existence of endogeneity. In this study, it is believed that the income level of a region is related to the local government's education expenditure, but the fiscal budget's education expenditure is not directly related to carbon emission intensity. Therefore, the annual fiscal budget expenditure on education in each county-level administrative region may serve as an instrumental variable to explain per capita GDP. Below is the test for this variable.

This study also controls for time effects and individual effects. Research by Sun Shengmin et al. (2017) indicates that, when controlling for both fixed effects, most endogeneity issues are often explained by virtual variables generated by fixed effects. Therefore, finding a strong instrumental variable is challenging. Zhu Shunquan et al. (2019) suggest that the weak relevance of instrumental variables can be determined by the first-stage F-value obtained in 2SLS regression. If the first-stage F-value is greater than 10, it can be considered that there is no problem with weak instrumental variables. Regarding whether the selected instrumental variables are exogenous for the original model, Sun Shengmin et al. (2017) propose the idea of using a "semi-simplified regression" test. If a variable is added to the original equation, and the results show that the coefficient of that variable is not significant, it indicates that the variable can be used as an instrumental variable for the model. At this point, the form of the STIRPAT model regression equation in this study is as follows:

$$\ln CE_{it} = a \ln X_{it} + \xi Y_{it} + \mu_{it} + \lambda_{it} + \varepsilon_i \tag{9}$$

$$\ln pGDP_{it} = \delta_i + \beta_i lnEDU + \epsilon_i \tag{10}$$

In this study, the natural logarithm of the government's annual education expenditure in each county-level administrative region (lnEDU) is used as an instrumental variable. The results of the 2SLS regression and semi-simplified regression are shown in the table below. It can be observed that in the 2SLS regression, the first-stage F-value is 45.015, which is greater than 10. Additionally, in the semi-simplified regression, the regression coefficient of "lnEDU" is not statistically significant. Therefore, it can be concluded that lnEDU can be used as an instrumental variable.

Table 8: Results of Instrumental Variable Regression and Semi-Simplified Regression

Explainary Variable	**Carbon Emission Intensity**	
	2SLS Regression	**Semi-Simplified Regression**
$\ln tSEC$	0.012	0.012
	(1.066)	(1.041)
$\ln POPU$	-1.102**	-1.014**
	(-3.058)	(-26.212)
FDI	-0.137	-0.103
	(-0.144)	(-0.110)
$SENI$	-0.001	-0.001*
	(-1.812)	(-2.245)
$pSEC$	-0.005**	-0.004**
	(-3.041)	(-26.524)
$\ln pGDP$	-1.062**	-0.973**
	(-2.974)	(-30.729)
$\ln EDU$		-0.007
		(-0.248)
c	16.714**	15.524**
	(3.244)	(27.081)
Adjusted R^2	0.9578	0.9683
F value of the 1st stage	45.015	

From the regression results above, it can be observed that three indicators, namely population size (lnPOPU), industrial sophistication level (SENI), and the proportion of the secondary industry in the local GDP (pSEC), tend to be associated with lower carbon emissions intensity. This relationship may be due to the fact that in the context of county-level administrative divisions, a higher population often implies higher population density in the area. Compared to dispersed residential areas, high-density population clusters are advantageous for the government to provide centralized infrastructure services such as winter heating. This helps reduce the carbon emissions intensity in the region. The negative correlation between the proportion of the secondary industry value added in GDP and carbon emissions intensity suggests that a region can reduce carbon emissions during the production process of the secondary industry by improving technological efficiency. The negative correlation between industrial sophistication and carbon emissions intensity indicates that regional governments can adjust the industrial structure of the region reasonably by increasing the value added of the tertiary industry, thus reducing the proportion of value added from the secondary industry, ultimately lowering carbon emissions intensity.

6 Robustness Testing and Heterogeneity Analysis

Ensuring model stability and differentiating differences among different samples are crucial aspects of research. Therefore, in the following sections, this paper will conduct robustness testing on the model by adding new explanatory variables and analyze the spatial and temporal heterogeneity of carbon emissions through regression analysis in different regions and years.

6.1 Robustness Testing: Adding Explanatory Variables

In model construction, it is common to omit explanatory variables, which can lead to model instability. Per capita GDP at the regional level reflects the residents' quality of life from the income perspective. However, residents in different regions have different consumption patterns in their production activities, and therefore, "disposable income" to some extent reflects residents' daily consumption levels. Therefore, this paper adds the natural logarithm of "urban residents' disposable income" as a new variable to the original model and conducts regression analysis using the 2SLS method to test the robustness of the model. The regression results are shown in the table below. It can be seen that at the 0.1 significance level, after adding the new explanatory variable, the significant explanatory variables in the original model remain significant, and the newly added explanatory variable "lnINCOME," similar to per capita GDP, is significantly negatively correlated with carbon emissions intensity. This further supports the notion that an increase in residents' income leads to a reduction in carbon emissions intensity. Therefore, it can be considered that this model is robust.

Table 9: Robustness test regression results (Explanatory Variables: Logarithm of per Capita Carbon Emissions)

Variable	**β coefficient**	**t-Value**	**Significant**
$\ln tSEC$	0.015	1.351	0.177
$\ln POPU$	-1.020	-3.349	0.001
$SENI$	-0.001	-2.575	0.010
$pSEC$	-0.004	-3.329	0.001
FDI	-0.988	-0.785	0.433
$\ln pGDP$	-0.984	-3.253	0.001
$\ln INCOME$	-1.257	-3.464	0.001
c	28.319	3.786	0.000
Adjusted R^2		0.959	
F value of the 1st stage		42.833	

6.2 Heterogeneity Analysis: Regression Analysis for the Three Provinces in the Beijing-Tianjin-Hebei Region

The economic development levels in the three provinces of the Beijing-Tianjin-Hebei region vary significantly. Therefore, the carbon emission intensities of county-level administrative regions in different provinces may exhibit distinct characteristics. In order to further investigate these characteristics, this study conducted separate regressions for Beijing Municipality, Tianjin Municipality, and Hebei Province. The results are presented in the table below.

Table 10: 2SLS Regression Results for Different Provinces

Explainary Variable	**Carbon Emission Intensity** ($\ln pCE$)		
	Beijing	Tianjin	Hebei
$\ln pGDP$	-0.8919**	13.275**	-0.788**
	(-3.4243))	(0.196)	(-3.570)
$\ln tSEC$	-0.385	0.008	
	(0.113)	(-0.201)	(0.803)
$\ln POPU$	-2.454**	2.736	-0.818**
	(-3.560)	(0.201)	(-3.668)
FDI	-88.200	-3.473	-7.531
	(-2.155)	(-0.319)	(-3.796)
$SENI$	-0.011*	-1.251	0.107**
	(2.125)	(-0.311)	(3.026)
$pSEC$	0.630	4.507	-0.004**
	(0.686)	(0.274)	(-3.570)
c	14.905	-35.791	14.096**
	(0.898)	(-0.191)	(33.545)
F value of the 1st stage	17.447	30.431	57.736
Adjusted R^2	0.874	0.275	0.970

From the table above, it can be observed that the factors influencing carbon emission intensity vary among different provinces in the Beijing-Tianjin-Hebei region.

For Beijing Municipality, the level of industrial upgrading is positively correlated with carbon emission intensity, while per capita GDP, population size, and foreign direct investment are negatively correlated with carbon emission intensity. This may be attributed to Beijing's efforts to alleviate non-capital functions by relocating a large number of industrial enterprises and focusing its economy on the tertiary service sector. An increase in the level of industrial upgrading implies that the tertiary sector in Beijing is shifting toward larger-scale, higher-quality development, which may lead to increased energy demand by businesses and, consequently, higher carbon emission intensity. Meanwhile, the limited land area of Beijing, coupled with the growth in per capita GDP and population size, signifies Beijing's transition into a post-industrial era and the development of a high-quality green economy, resulting in a decrease in carbon emission intensity. An increase in foreign direct investment is conducive to the introduction of advanced and environmentally friendly production technologies, further reducing carbon emission intensity.

For Tianjin, none of the variables are statistically significant. Therefore, the estimation for Tianjin Municipality through the 2SLS regression method is not accurate.

The situation in Hebei Province is similar to that of Beijing Municipality. Additionally, an increase in the proportion of the second industry's value-added in the local GDP has a negative impact on carbon emission intensity. Currently, Hebei Province is undergoing an economic transformation, with the tertiary sector's share in the economy continuously increasing, resulting in a relatively lower proportion of the second industry in GDP. This negative correlation suggests that Hebei Province's development of the service industry is still in the early stages of high energy consumption, contributing to an increase in carbon emission intensity.

7 Conclusion and Policy Recommendations

In the above, this article discusses the changing trends of total carbon dioxide emissions and carbon dioxide emission intensity in the three provinces of Beijing, Tianjin and Hebei from 2013 to 2019. The county-level carbon dioxide emission intensity was estimated through nighttime light data, and a fixed-effect STIRPAT model was established to further explore the factors affecting the carbon dioxide emission intensity of each county-level administrative unit.

7.1 Main Conclusions

In summary, the following conclusions can be drawn:

Conclusion 1: During the period of 2013-2019, the total carbon emissions of the three regions of Beijing, Tianjin and Hebei all show a decreasing trend. However, the carbon emission reduction rates of the three regions vary greatly, with Beijing having the fastest carbon emission reduction rate, followed by Tianjin, and Hebei Province having the slowest carbon emission reduction rate. Both the total carbon emissions and the intensity of carbon emissions are regionally heterogeneous.

Conclusion 2: From the perspective of factors affecting carbon emissions, it can be learnt that the regional population (lnPOPU), the degree of industrial sophistication (SENI) and the proportion of the value-added of the secondary industry in the GDP of the region (pSEC) are significantly negatively correlated with the regional carbon emission intensity.

Conclusion 3: As the level of economic development and the respective industrial structures of Beijing, Tianjin and Hebei provinces are quite different, the factors affecting carbon emission intensity are also different. For Beijing, industrial upgrading is positively related to carbon intensity, while population size, foreign investment and regional GDP per capita are negatively related to carbon intensity. In Hebei Province, the proportion of the secondary industry in the local GDP is also significantly affected.

7.2 Policy Recommendations

China has set ambitious targets of reaching carbon peak by 2030 and achieving carbon neutrality by 2060. Due to the limitations of technological advancements in short time, the initial phase of achieving these goals will primarily rely on the utilization of existing advanced technologies to enhance energy efficiency and control emissions from carbon sources. However, in the long term, fundamental changes in technology are expected, with renewable energy technologies gradually maturing and gradually replacing fossil fuels (Song Guojun, 2021) [35].

Nevertheless, scholars have found that achieving both interim and long-term targets by 2030 and 2060 may be challenging through spontaneous technological transformations driven solely by market forces. Research by Stan et al. (2021) [37] analyzed the role of industries in carbon emissions reduction across 30 provincial-level administrative regions in China (excluding Hong Kong, Macao, and Tibet). They concluded that achieving carbon neutrality by 2030 will require more than just improving energy efficiency and relying on market-driven green technology advancements. It will necessitate government intervention and macroeconomic control measures, such as implementing carbon taxes, establishing a rational carbon emissions trading system, and enhancing the carbon emissions market (Shu Langen, 2021) [36].

Based on these considerations, this paper presents the following policy recommendations.

Suggestion 1: Optimize the Industrial Structure in the Beijing-Tianjin-Hebei Region

The industrial structure, particularly the proportion and quality of the secondary industry, significantly impacts carbon emissions in the Beijing-Tianjin-Hebei region. Therefore, governments at all levels in this region, especially those of Beijing and Hebei Province, should focus on promoting capital-intensive development, intensify efforts to introduce advanced technologies, and especially, in the case of Hebei Province, continue to facilitate the transition of local industries towards a high-quality green industrial structure. Additionally, there should be further optimization of production technologies in Hebei to enhance the agglomeration of the tertiary industry and the collaboration and division of labor in the industrial chain. This will promote the development of high-tech industries, improve energy utilization efficiency, and gradually replace traditional fossil fuels with clean and environmentally friendly new energy sources.

Governments should also further improve the infrastructure for improving residents' quality of life, encourage green consumption by residents, and promote eco-friendly and thrifty living.

Suggestion 2: Establish a Rational Carbon Taxation Mechanism

Carbon taxation directly affects market transaction prices, resulting in rapid effects. However, government imposition of carbon taxes may distort market price mechanisms, causing inefficiencies. Therefore, while carbon taxes can help achieve short-term emission reduction goals more effectively, a comprehensive carbon emissions trading market needs to be established for long-term objectives. The latter would involve measures such as industrial transfers and rationalizing industrial structures to further enhance the role of carbon emissions trading in emissions reduction (Shi et al., 2021; Jiang and Sheng, 2021).

Suggestion 3: Create an Effective Carbon Emissions Trading Market

According to the Coase Theorem, external problems can be internalized through well-defined property rights, and this can be achieved through market mechanisms. China began exploring and experimenting with carbon trading from 2005 onwards. After participating in international CDM projects and establishing carbon emissions trading pilot programs, China has entered the third phase of establishing carbon emissions trading pilots nationwide. Therefore, scholars have engaged in extensive discussions regarding the establishment of carbon emissions trading markets.

Concerning the effectiveness of carbon trading markets, studies have shown varying results. Guo (2022) used the difference-in-differences method to study carbon emissions trading pilot policies and demonstrated their effectiveness. She also argued that pilot policies could further promote the development of green economies and improve their efficiency. However, Wang (2021) found that pilot policies significantly influenced emission reduction but did not significantly promote local economic development. Most scholars agree that the "National Resource-Type City Sustainable Development Plan (2013-2020)" has significantly reduced carbon emissions in resource-dependent cities (Zheng et al., 2022; Cui, 2017).

In terms of carbon trading mechanism design, some scholars have suggested reducing the total allocation of carbon emission quotas, decreasing the allocation of free carbon emission quotas, and raising carbon emission trading prices to further achieve emission reduction goals. However, such actions may also inhibit local economic development to some extent.

Regarding carbon trading market price signals, many factors can influence carbon emission trading market prices. These factors include the use of clean energy in existing industries, the prices of non-clean energy, the advancement of carbon emission reduction technologies, the macroeconomic and financial environment, climate conditions, and manufacturers' price expectations for carbon emission quotas. Peng (2021) further studied the impact pathways of various factors and argued that carbon emission trading prices are formed through the combined effects of "total quantity-trading mechanism," "carbon taxation mechanism," and "project offset mechanism." The trading of carbon emission rights encourages enterprises to innovate their technologies and production standards. Carbon emission trading prices serve as market signals, and higher prices imply higher opportunity costs for carbon emissions, resulting in more significant emission reduction effects (Wei et al., 2021).

Carbon emissions and carbon emission trading policies also have cross-border spillover effects between regions, known as "local-neighbor" transmission. Therefore, regional carbon emission control requires cooperation between governments. Governments can facilitate regional industrial structure rationalization and further enhance it, reduce local dependence on traditional energy resources, encourage the use of clean energy, promote the advancement of green technologies, and improve energy efficiency. Enhanced collaboration and complementarity among regions in terms of industry, together with the shared development of green economies, are crucial. It is essential to recognize that regional carbon emissions control is a complex and systemic project that involves multiple stakeholders, including governments, businesses, and households. Achieving carbon reduction goals requires collaborative efforts from all members of society. The "Beijing-Tianjin-Hebei Regional Integration" presents an opportunity to advance cooperation among regional governments on carbon emissions issues, and it calls for the joint efforts of diverse stakeholders to contribute to carbon reduction (Wang, 2015).

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