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Carbon Dioxide Emissions, Urbanization Level and Industrial Structure: Empirical Evidence from North China

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Abstract: This paper aims to examine the nexus among carbon dioxide (CO₂) emissions, urbanization level and industrial structure in North China over the period 2004-2019, according to an expanded Cobb-Douglas production function. The panel econometric techniques are employed to complete the empirical analysis, including cross-sectional correlation test, panel unit root test, panel cointegration test and panel Granger causality test. The empirical results support the long-term equilibrium relationship among CO₂ emissions, urbanization level and industrial structure in North China, and the urbanization level contributes most to CO₂ emissions, followed by fossil energy consumption. Furthermore, the bidirectional causality between CO₂ emissions and urbanization level and unidirectional causality from industrial structure to CO₂ emissions are found in North China, indicating that urbanization level and industrial structure have significant impacts on CO₂ emissions. Finally, according to the empirical findings, several policy suggestions are proposed for the purpose of reducing CO₂ emissions in North China.

Keywords: carbon dioxide emissions; urbanization level; industrial structure; panel econometric techniques; North China

1 Introduction

In recent years, the world's climate has gradually warmed. We have experienced warm winters one after another, and some countries are experiencing an unprecedented crisis. The main cause of climate warming is the emissions of greenhouse gases, of which the most one is CO₂. China, a country with the largest CO₂ emissions in the world, will reach 27% of global CO₂ emissions in 2017. China is deeply aware of the urgency of reducing CO₂ emissions. To achieve the goal of low-carbon economic development, China submitted "strengthening action on climate change - China's national independent contribution" (hereinafter referred to as "national independent contribution") in 2015, publicly committed that its CO₂ emissions will reach the peak around 2030, and strive to reach the peak as soon as possible. On September 22, 2020, at the general debate of the 75th UN General Assembly, China proposed to enhance the national independent contribution, adopt more powerful policies and measures, strive to reach the peak of CO₂ emissions by 2030, and strive to achieve carbon neutrality by 2060. The research on CO₂ peaking in China is becoming more and more important and urgent. North China, including Beijing, Tianjin, Hebei, Shanxi and Inner Mongolia, is an important part of China's economy. In 2019, North China's GDP accounted for 13.85% of the total GDP of China, while carbon emissions in North China accounted for 21.78% of China's total. With the increase of CO₂ emissions, reducing the carbon emissions intensity in North China is very important for low-carbon development. Based on this, researching the relationship among carbon emissions and economic growth in the North of China can promote a benign transformation of economic growth patterns in this region. The early realization of a low-carbon economic development path will eliminate the link between carbon emissions and economic growth, and is of positive significance to China's energy conservation and emission reduction.

With the continuous expansion of global warming, extensive economic development mode is no longer applicable, which requires us to reduce energy consumption and improve utilization rate. Therefore, low-carbon economic development path has become the focus of the world. Regions such as Beijing, Tianjin and Hebei not only play an important

role in the geographical location but also a major impact on China's economic development. The integration of Beijing, Tianjin and Hebei has made this region more and more important. The planning of low-carbon economy for the whole region can truly solve the carbon emissions problems and make the region achieve sustainable development. It is worth noting that North China is a key area of China's urbanization and industrial restructuring, revealing that the urbanization and industrial restructuring in this region can significantly change China's economic development mode, improve the quality of economic development, and provide a demonstration effect for other regions to achieve low-carbon development. Therefore, this article explores the relationship between carbon emissions, urbanization levels and industrial structure in North China, and aims to provide a reference for formulating carbon emission reduction policies from the perspective of urbanization and industrial structure. In general, the main contributions of this article are:

(1) In previous studies on the link among carbon emissions and economic growth, the absolute value of each variable was often used as the research object, so that the results could only reflect the overall trend and could not further describe the internal relationship between variables. Therefore, this paper introduces relative variables such as carbon emission intensity, energy consumption structure and GDP per capita, and expands the traditional Cobb-Douglas production function, which can reveal the internal connection between carbon emissions, economic growth and energy consumption.

(2) According to panel data of five provinces in North China, this paper studies the relationship among the above three variables. At the same time, considering the relevant industrial and economic development status, this paper add industrial structure and urbanization rate into the model, which can truly reflect the relationship between carbon emissions, energy consumption and economic growth under the background of China's new normal economic development. Meanwhile, the empirical results provide a reference for the development of carbon reduction policy of urbanization and industrial structure perspective.

The rest of this article is organized as follows. The related literature is introduced in Section 2. Section 3 introduces the methods that this paper needs. Section 4 reports the data sources and empirical analysis. Finally, we summarize the conclusions and propose some policy proposes in Section 5.

2 Literature Review

Before studying the relationship between fossil energy consumption, industrial structure, urbanization rate, per capita GDP and carbon dioxide emissions in China, it is necessary to use the previous research results as references. A large amount of literature has analyzed the relationship between energy consumption and economic growth, depicting the nature character and the causal relationship. Kraft J and Kraft A (1978) were the earliest to study the relationship between economic growth and energy consumption and found a unidirectional causal link between GNP and energy consumption^[1]. However, Akarca A. T and Long T. V (1980), by changing the data interval to two years in the same date, found that no causation between GNP and energy consumption. Later, more and more scholars have begun to study the relationship between these two variables, and the results can be distinguished by four hypotheses:

(1) Growth hypothesis. This shows that there is a one-way causal relationship between energy consumption and economic growth, which shows that the economic system is an energy-dependent economy. In other words, increasing energy consumption will promote real GDP growth and more aggressive energy policies should be adopted to drive economic development. The empirical results of the literature (Wang Y et al. 2011; Vafaeirad M 2015; Chaudhry I S 2015) display a unidirectional causal link from energy consumption to economic growth.

(2) Conservation hypothesis. This shows that economic growth has a one-way causality to energy consumption, which means that the government issuance of energy conservation policies at the right moment can reduce energy consumption, but it will not affect the growth of real GDP. References (Narayan P K 2012; Qazi U 2021; Li Y et al.2020; Ozturk I 2010) point out the causal relationship between two variables.

(3) Neutrality hypothesis. This shows that changes in energy consumption have little or no impact on economic growth. Besides, economic development will not affect energy consumption. Thus, the policy of saving energy has no unfavorable

82 impact on economic development. The literature (Yakubu M M 2017; Oyaromade R 2014; Faisal et al.2016; Destek M A
83 2015) clearly pointed out that there is no causal relationship between economic growth and energy consumption.

84 (4) Feedback hypothesis. This indicates that energy consumption is likely have bidirectional causation with economic
85 growth, and the government should actively improve the efficiency of energy utilization. References (Wang S et al.2016;
86 Etokakpan M U 2020; Kahia M et al.2017; Amri F 2017) discover that these two variables maintained two-way causality.

87 According to the research above, we found that the relationship between energy consumption and economic growth
88 in different countries and regions is completely different. With the deepening of research, even in the same country, the
89 corresponding direction and causal relationship quit diversity. The main reason are: (1) Different economic development
90 methods and different industrial structures are significantly different in different countries or regions. (2) Different stages
91 of development in the same country adopt different energy and economic intervention measures, such as adjusting energy
92 consumption structure and adopting measures to reduce emissions and save energy. Therefore, the conclusions of different
93 periods are also different; and (3) Different techniques in modeling will also produce various conclusions.

94 Researchers have widely adopted Pedroni (1999; 2004) panel cointegration method to study the long-term relationship
95 between energy consumption and economic growth. J Li and L Chen (2018) used panel co-integration to study the
96 relationship between investment demand, Gross Domestic Product, population scale, electricity consumption and installed
97 electrical capacity for China during the 2004-2016 periods. Farhani (2013) studied the relationship between carbon dioxide
98 emissions, urbanization , GDP and energy consumption of 11 MENA countries using panel data method, and Farhani found
99 that more the sources of energy use and greater trade opening to the outside tend to cause more carbon dioxide emissions,
100 and the improvement in the level of urbanization in environmental functions has a positive impact on reducing pollution
101 levels. Catia Cialani (2017) using the panel unit root, cointegration and Granger causality to study the relationships among
102 per capita carbon dioxide emissions, GDP and international for 150 countries during the 1960-2008 period. The results
103 show that there is a two-way short-term causal relationship between international trade and GDP per capita. Eyup Dogan
104 and Alper Aslan (2017) used cross-sectionally dependent heterogeneous panel estimation techniques to explore the link
105 between carbon dioxide emissions, GDP, energy consumption and tourism in the EU and candidate countries during the
106 period of 1995-2011. Usama Al-mulai (2014) studied the relationship between consumption and GDP growth of nuclear
107 energy and carbon dioxide emissions of 30 major consumer of nuclear energy using Granger causality test and panel data
108 methods, and employing Granger causality test and panel data method. The results showed that the consumption of nuclear
109 energy plays a significant role in the growth of GDP but has make no difference on carbon dioxide emissions. MN Esfahani
110 and E Rasoulinezhad (2015) used group cointegration, FMOLS and DOLS groups and studied the relationship between oil
111 consumption, GDP and CO₂ emissions in the next 11 (N-11) countries from 1980 to 2013, and the results showed that there
112 is a long-term two-way relationship between GDP per capita oil consumption and CO₂ emissions. I Saleh and S Abedi
113 (2014) studied the link among carbon dioxide emissions and GDP using panel date and the Vector Auto-Regression Model
114 and found that a bidirectional causality relationship among carbon dioxide emissions and GDP for three groups of countries.
115 Kais Sadi and Ben Mbarek (2016) studied the relationship between factors such as carbon dioxide emissions and GDP per
116 capita during 1990-2013 period using Pedroni's method in nine developed countries.

117 Because of the problem of global warming is becoming more and more serious, many researchers in the study of the
118 relationship between energy consumption and economic growth has begun to consider carbon dioxide emissions. Recently,
119 experts conducted more in-depth studies by examining the relationship among industrial structure. For instance, Yuan Wang
120 studied the link between carbon dioxide emissions, energy use and urbanization in the Association of Southeast Asian
121 Nations countries (2016) BRICS (2016), and Bhat T A (2020) tudied the link between saving and economic growth, using
122 panel co-integration etc. These papers show that the results of causality between different countries are different, so a
123 unified energy policy will not be a good strategy for widespread implementation. Moreover, JLS Lim (2017) and Sulaiman
124 C (2017) employed different methods to analyze the relationship in Malaysia, and reached a similar conclusion: There is a
125 one-way relationship in CO₂ emissions to economic growth in the long run. In addition, for new EU member states and

candidate countries. The results show that there is a one-way causality from trade openness, energy consumption and urbanization to carbon dioxide emissions, from energy consumption, urbanization and GDP to trade (Kasman A 2015). Finally, for 14 MENA countries, Salari M (2021) using simultaneous-equation models for testing the relationship among carbon dioxide emissions and energy consumption, and found that there is a bidirectional causal relationship among these variables.

To better understand the relationship among industrial structure, energy consumption structure, urbanization rate, per capita GDP and CO₂ emissions, the production function of Cobb-Douglas is introduced in (Cobb C W et al.1928). This production function is used as a department model, with the research object as the department and the department output as the explanatory variable. The major control variables are energy consumption, industrial structure and population density playing an important role in the output. It also introduces other variables in the model that may affect the output. Based on the estimation of the model, the contribution of these input variables to output is analyzed, and the purpose of the study is achieved (Van G 2021). Ouyang (2017), Wang and Fang (2014) and Xu (2016) analyzed the influences of urbanization on carbon dioxide emissions and found a bi-directional causal relationship among carbon dioxide emissions, urbanization and energy consumption: specifically. There is a two-way positive causal link between urbanization and carbon dioxide emissions exists, and a same correlation exists in them. Khalid (2016) and Margarita (2016) explored the relationship among carbon dioxide emissions and tourism of Portuguese during 2000-2008 and found that tourism activity has an important effect to carbon intensity. Kofi Baah (2017) employed Johansen co-integration model for China during 1970-2014 period. The results show that there is a long-term N-shaped relationship between economic growth, carbon dioxide emissions and international tread, under the estimated Kuznet curve framework. The effects of land finance and land urbanization on CO₂ emissions were studied by Zhang and Xu (2017) and the literature found that the two variables significantly affect carbon dioxide emissions. There are many factors that affect CO₂ emissions, like: industrial structure, energy consumption structure, urbanization rate and per capita GDP, etc. However, most of the existing studies involve only a few of factors, which are not comprehensive. Moreover, there is not much research on the causality relationship between these variables. Therefore, a multivariable model based on Cobb Douglas production function is proposed in this paper. Because the panel data model can effectively solve the problem of sample shortage and consider time series data and cross-sectional data, it helps to correctly estimate the relationship between variables and improve the importance of model estimation (2012). For accurate comparison of the contribution of each variable to carbon dioxide emissions in the five provinces, including Hebei, Shanxi, Beijing, Inner Mongolia and Tianjin, we analyze causality and co-integration relationship between those variables in different provinces panel data model.

3 Methodology

3.1 Production Function Model

A single-sector economic model that considers CO₂ emissions, it is assumed that society as a whole has only one production department and one production function. On the basis of the traditional production function, the CO₂ emissions are introduced into the production function, and the concrete form of the model is expressed as follow:

$$Y = f(A(t), L_t, H_t, R_t, W_t) = A(t)L_t^\alpha H_t^\beta R_t^\gamma W_t^\varepsilon \quad (1)$$

where Y is the output value that is CO₂ emissions, L_t^α , H_t^β , R_t^γ and W_t^ε are the fossil energy consumption structure, industrial structure, urbanization rate, per capita GDP, respectively, and A, α , β , γ and ε are the constant values.

By changing the original variable in equation (1) to the following logarithmic equation, the effect of heteroscedasticity on the regression result can be prevented:

$$\ln Y = \ln A + \alpha L_t + \beta H_t + \gamma R_t + \varepsilon \ln W_t \quad (2)$$

where $\ln Y$ is the natural logarithm of the output, and $\ln A$ means the logarithm of total factor CO₂ emissions productivity, L_t is energy consumption structure, H_t stands for the logarithm industrial structure, R_t represent the

urbanization rate, $\ln W_t$ is the logarithm of per capita GDP, and $\alpha, \beta, \gamma, \varepsilon$ are the output elasticities.

If equation (2) considers individual factors and time series factors, the panel data model for each factor of production under the framework of the production function model can be derived from equation (3).

$$\ln Y_{it} = \ln A_i + \alpha_i L_{it} + \beta_i H_{it} + \gamma_i R_{it} + \varepsilon_i \ln W_{it} + \mu_{it} \quad (3)$$

where μ_{it} is the random error term. It is independent, satisfying the null hypothesis mean value and has the same variance of σ_μ^2 . means the number of cross-section, and t stands for time period.

There will be two cases. First, the equation (3) is a fixed effect model when the individual non-observation effects presented by $\ln A_i$ is the individual characteristics and do not change with time; Second, the equation (3) is a random effect model, when $\ln A_i$ is a random variable and conforms to a specific distribution.

3.2 Cross-sectional Dependence Test

Neglecting the cross-section data correlation will lead to low efficiency and invalid test statistics. Hence, before a series of empirical analysis is carried out, it is necessary to test whether the cross-sectional is dependence. The spatial error regression model can be expressed as follows:

$$y_{it} = X'_{it}\beta + u_{it}, \quad i=1,2,\dots,N, \quad t=1,2,\dots,T \quad (4)$$

where u_{it} means the regression error perturbation term with random individual effect. According to Anselin (1988), there are:

$$u_i = \mu + \varepsilon_t \quad (5)$$

$$\varepsilon_t = \lambda W \varepsilon_t + v_t \quad (6)$$

where $\mu = (\mu_1, \mu_2, \dots, \mu_N)$, $\mu \sim IIN(0, \sigma^2)$, $v'_t = (v_{t1}, v_{t2}, \dots, v_{tN})$, $v_{it} \sim IIN(0, \sigma_v^2)$, and v_t and μ are independent of each other. In formula (6), if $|\lambda| < 1$, W is a space weight matrix with all zero diagonal elements of $N \times N$ dimension, besides satisfies $(I_N - \lambda W)$ is a non-degenerate matrix.

Cross-sectional dependence test, that is, to check the correlation between the N cross-sections in the panel data. As long as two of the cross-sections are related, it is considered that there is cross-sectional dependence panel data. The null hypothesis of the cross-sectional dependent test can be expressed as below:

$$H_0: \rho_{ij} = \rho_{ji} = \text{cor}(u_{it}, u_{jt}) = 0, i \neq j \quad (7)$$

The alternative hypothesis is shown in Equation (8):

$$H_1: \rho_{ij} = \rho_{ji} \neq 0, i \neq j \quad (8)$$

The test statistics based on uncorrelated regression in Breush and Pagan (1980) is provided by:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2 \quad (9)$$

$$\text{where } \hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^T \hat{u}_{it} \hat{u}_{jt}}{(\sum_{i=1}^T \hat{u}_{it}^2)^{1/2} (\sum_{j=1}^T \hat{u}_{jt}^2)^{1/2}} \quad (10)$$

And $\hat{u}_{it}$ is the residual estimation of (10). Under the null hypothesis, the asymptotic distribution of the LM test statistics is a χ^2 distribution with $N(N-1)/2$ degrees of freedom. When $N < T$, this test is suitable for the case. When $N > T$, the following two methods can be used for testing.

Pesaran (2004) proposed a simple method to test the cross-section error, which is suitable for the case that the cross-section individuals N are relatively large and the time T is relatively small. The test is an average of the correlation coefficients of the residuals that obtained from the OLS regression, and the test statistics are as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \right) \quad (11)$$

Under the null hypothesis of uncorrelated, the asymptotic limit distribution of CD statistic is normal distribution. Besides Pesaran confirms the superior performance of this test in small examples and it is very suitable for our research.

3.3 Panel Unit Root Test

The unit root test should be carried out before the panel data regression analysis, which can avoid spurious regression. There are many methods of unit root test that including LLC test (Levin A et al. 2004), IPS test (Im, K.S 2003), Breitung (Breitung, J. 1999), Hadrid(Hadri, K 2000) and Carrion-i-Silvestre et al.(Lluís Carrion-i-Silvestre 2005). The LCC test method is as below:

$$\Delta y_{it} = a_i + \delta_i t + \gamma_i y_{i,t-1} + \sum_{t=1}^{p_i} \phi \Delta y_{i,t-1} + \xi_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T \quad (12)$$

We assume that ξ_{it} is independent distributed for all i , Δ represents the first order difference operator $(1-L)$. If $\gamma_i = 0$, then y_{it} contains the unit root, while if $\gamma_i < 0$, y_{it} is considered to be stationary. The null hypothesis of LLC and the alternative hypothesis of LCC are as follows:

$$H_0 : \gamma_1 = \gamma_2 = \dots = \gamma_N = 0 \quad (13)$$

$$H_1 : \gamma_1 = \gamma_2 = \dots = \gamma_N = \gamma < 0 \quad (14)$$

To test the null hypothesis H_0 and the alternative hypothesis H_1 , Levin and Lin suggest that we should make a regressing of Δy_{it} and $y_{i,t-1}$ for each i relative to the other variables in Equation (12) firstly and obtain residuals $\hat{e}_{it}$ and $\hat{v}_{i,t-1}$, respectively. Secondly, the regression estimate of Equation (15) is γ .

$$\hat{e}_{it} = \gamma \hat{v}_{i,t-1} + \xi_{it} \quad (15)$$

The t statistic for test $\gamma = 0$ is as follows:

$$t_\gamma = \frac{\tilde{\gamma}}{sd_{\tilde{\gamma}}} \quad (16)$$

Where the $\tilde{\gamma}$ is the least square estimate of Equation (15),

$$sd_{\tilde{\gamma}} = \hat{\sigma}_\xi \left[\sum_{i=1}^N \sum_{t=p_i+2}^T \tilde{v}_{i,t-1}^2 \right]^{-\frac{1}{2}} \quad (17)$$

$$\hat{\sigma}_\xi^2 = (NT)^{-1} \sum_{i=1}^N \sum_{t=p_i+2}^T (\tilde{e}_{it} - \tilde{\gamma} \tilde{v}_{i,t-1})^2 \quad (18)$$

$$\bar{p} = \frac{1}{N} \sum_{i=1}^N p_i, \quad \tilde{T} = (T - \bar{p} - 1) \quad (19)$$

The IPS test sets the alternative hypothesis to the following equation:

$$H_A^* : \text{at least one } i \text{ satisfies } \gamma_i < 0$$

This hypothesis broadens the strong assumption that Levin and Lin require Equation (12) to be homogeneity under the alternative hypothesis. Therefore, the IPS test cannot use mixed data, and the ADF unit root test should be performed for each individual in the N cross-sections, respectively.

The Hadri test is similar to time series KPSS test. H_0 : none of the sequences in the panel data contain unit roots. Considering the back-end residual sequence of the original panel data, define the LM statistic, which contains two types of statistics: drift term and trend term. The formula is as follows:

$$LM_1 = \frac{1}{N} \left[\sum_i \left[\sum_t S_i(t)^2 / T^2 \right] / f_0 \right] \quad (20)$$

$$LM_2 = \frac{1}{N} \left[\sum_i^N \left[\sum_t S_i(t)^2 / T^2 \right] / f_{i0} \right] \quad (21)$$

where $S_i(t) = \sum_{s=1}^t \hat{u}_{it}$ is the residual accumulated function, f_0 is the residual spectral density when the frequency is 0. Considering cross-section heterogeneity, LM_2 is chosen as a test statistic.

Under the condition of H_0 , the asymptotic distribution of the statistic $Z = \sqrt{N}(LM - \xi)/\varsigma$ is the normal distribution.

3.4 Panel Co-integration Test

Only after the unit root test indicates that the series is stable can the panel co-integration test be performed by Pedroni [22] co-integration test theory. The theory holds that cross-sectional independence is related to different individual effects. It is used as below:

$$\Psi_{it} = \alpha_{it} + \delta_i t + \gamma_{1i} L_{it} + \gamma_{2i} K_{it} + \gamma_{3i} H_{it} + \gamma_{4i} R_{it} + \gamma_{5i} W_{it} + \varepsilon_{it} \quad (22)$$

where $t = 1, 2, \dots, T$ represents the time period, $i = 1, 2, \dots, N$ represents the country or region in the panel date. The parameter α_{it} is the likelihood of fixed effects and δ_i is the deterministic trends in specified- country or specified-region, ε_{it} means the estimated residual, which is a departure from long-term relationships. When some variables are expressed in the form of natural logarithms, the parameters $\gamma_{1i}, \gamma_{2i}, \gamma_{3i}, \gamma_{4i}, \gamma_{5i}$ in Equation (12) can be interpreted as elastic coefficients. In order to test the null hypothesis that there is no co-integration, that is, $\rho_i = 1$, the later unit root test of the residuals is expressed as follows:

$$\varepsilon_{it} = \rho_i \varepsilon_{it-1} + \omega_{it} \quad (23)$$

Pedroni proposed two co-integration test sets [21-22]. The method of panel testing based on internal dimension includes panel ρ -statistic, v -statistic, ADF-statistic and PP-statistic. These statistics use the auto-regressive coefficients of different countries or regions to estimate the unit root test of the residuals. Statistics take the common time and the heterogeneity of countries or regions into account. The group test based on the between dimension method includes group PP-statistic, group ADF-statistic and group ρ -statistic. These statistics based on the average of the auto-regressive coefficients for each group. In the panel, the auto-regressive coefficient is related to the unit root test of the residuals for each country or region. These seven statistics are asymptotically standard distributions. When Pedroni test shows that there is co-integration relation among variables, fixed effect estimation and causality test can be carried out.

3.5 Panel Causality Test

Engle and Granger proposed that an un-directional or a bi-directional Granger Causality will exist in two variables if there is co-integration between the two variables in the long term. Besides, Granger causality test is widely applied in studying causality between variables. In the case of time series, Granger defines the causal relationship between two economic variables X and Y as follows: under the past information contains variables X and Y conditions, the prediction result of variable Y is better than that conducting the past information of Y alone, that is, the variable X can help us explain the future change of the variable Y , so X is considered as the Granger cause of Y . This paper uses Granger model to analyze the causal relationship between time series:

$$y_t = \alpha_0 + \sum_{i=1}^m \alpha_i y_{t-i} + \sum_{i=1}^m \beta_i x_{t-i} + \varepsilon_t \quad (24)$$

$$x_t = \alpha_0 + \sum_{j=1}^n \alpha_j y_{t-j} + \sum_{j=1}^n \beta_j x_{t-j} + \varepsilon_t \quad (25)$$

The equation (26) represents the null hypothesis of the tests, that is, X is not the Granger cause of Y . If equation (26) is rejected, we can conclude that X Granger caused Y . Meanwhile, it can be concluded that Y Granger caused X when formula (27) is rejected:

$$H_o : \beta_i = 0, i = 1, 2, \dots, m \quad (26)$$

$$H_o : \beta_j = 0, j = 1, 2, \dots, n \quad (27)$$

4 Data and Empirical Analysis

4.1 Data Source and Descriptive Statistics

This paper adopts panel data of North China, including Hebei, Shanxi, Beijing, Tianjin, and Inner Mongolia, over the period of 2004-2019. The model proposed in this paper involves five variables, namely, fossil energy consumption (Fes), industrial structure (S), urbanization rate (Ur), per capita GDP (pcGDP) and CO₂ emissions (CE). We obtained these data from the website of China National Bureau of Statistics. In order to avoid drastic fluctuations in the data and eliminate the heterodyne phenomenon in the time series, some variables are transformed in the nature logarithmic series, such as lnCE and lnpcGDP. At the same time, the coefficient of the logarithmic model can represent the elasticity of the variable.

The summary statistics of lnCE, Ur, S, lnpcGDP and Fes are presented in Table 1. The mean of CO₂ emissions ranges from 4.73 in Beijing to 6.25 in Shanxi. As for the per capita GDP, Shanxi has the lowest per capita GDP, whereas Beijing has the highest. Based on the urbanization rate, which is defined as the ratio of urban population to the total population, Beijing has the highest urbanization rate, while Hebei is the lowest in the panel. In realizing industrial structure, which is displayed by the proportion of the added value of the secondary industry to GDP, Hebei has the highest industrial structure because there are many heavy industrial enterprises in Hebei, and Beijing has the lowest industrial structure among five provinces. Regarding the fossil energy consumption, Shanxi has the highest ratio, whereas Beijing has the lowest in North China.

Table1 Summary statistics of time series variables

	Variable	Mean	Median	Maximum	Minimum	S.D
North China	lnCE	5.60222	5.61730	6.73723	4.36990	0.78545
	Ur	0.59515	0.53595	0.86500	0.26220	0.18607
	S	0.45814	0.50539	0.58622	0.19738	0.11083
	lnpcGDP	3.53101	3.69861	5.02108	1.62187	0.91146
	Fes	0.68443	0.74011	0.96710	0.12146	0.23264
Beijing	lnCE	4.72664	4.75615	4.87396	4.53505	0.11804
	Ur	0.83787	0.84700	0.86500	0.77640	0.02846
	S	0.25679	0.24445	0.32555	0.19738	0.04023
	lnpcGDP	6.93703	6.93294	7.16415	6.69938	0.16999
	Fes	0.31791	0.32471	0.46124	0.12146	0.10155
Tianjin	lnCE	4.87364	4.86277	5.27839	4.36990	0.32638
	Ur	0.77330	0.76770	0.82640	0.72020	0.03673
	S	0.52029	0.52151	0.55213	0.46584	0.02487
	lnpcGDP	4.02475	4.10635	5.02108	2.79589	0.76104
	Fes	0.56234	0.54824	0.71215	0.39250	0.10017
Hebei	lnCE	6.31048	6.43459	6.73730	5.58642	0.41510
	Ur	0.40074	0.41076	0.51330	0.26220	0.07717
	S	0.51403	0.51978	0.54343	0.48268	0.01942
	lnpcGDP	5.83782	5.83197	5.88926	5.78263	0.03812
	Fes	0.75144	0.74011	0.87474	0.69345	0.05934
Shanxi	lnCE	6.24596	6.31063	6.55757	5.61223	0.28786

	Ur	0.44989	0.44571	0.55030	0.35060	0.06301
	S	0.52131	0.53457	0.58622	0.40687	0.04926
	lnpcGDP	2.96725	3.12562	3.90000	1.62187	0.79291
	Fes	0.89984	0.89850	0.91725	0.88604	0.01071
Inner Mongolia	lnCE	5.85437	6.09040	6.52609	4.72471	0.66681
	Ur	0.51394	0.50930	0.60300	0.42820	0.06082
	S	0.47831	0.50098	0.55973	0.37851	0.06531
	lnpcGDP	3.39281	3.56917	4.61202	1.77605	1.01522
	Fes	0.89063	0.88440	0.96710	0.81440	0.04737

Prior to empirical analysis, a correlations test should be conducted on the panel data. The results of correlations test for the panel data are listed in Table 2. As shown in the table, the test results, at 1% level of significance or 10% level of significance, reject the null hypothesis. Therefore, there is a statistical correlation between variables.

Table 2 Correlations for the panel data set (p values in parentheses)

	LnCE	LnpcGDP	S	Ur	Fes
LnCE	1.0000				
LnpcGDP	-0.6218 (0.0000)***	1.0000			
S	0.6046 (0.0000)***	-0.2147 (0.0559)*	1.0000		
Ur	-0.6914 (0.0000)***	0.7259 (0.0000)***	-0.5551 (0.0000)***	1.0000	
Fes	0.6317 (0.0000)***	-0.6289 (0.0000)***	0.7013 (0.0000)***	-0.8568 (0.0000)***	1.0000

Notes: * Denotes 10% level of significance; *** Denotes 1% level of significance.

4.2 Results of Cross-sectional Dependence Test

The results of Pesaran cross-sectional dependence test are listed in Table 3. As shown in the table, the test results, at 5% level of significance, accept a null hypothesis with no cross-sectional dependence. Therefore, the first-generation unit root tests including Im, Pesaran and Shin W-stat (IPS) test, Levin, Lin & Chu (L.L&C) *t*-test, Phillips-Perron Fisher (PP-Fisher) test and Augmented Dickey Fuller-Fisher (ADF-Fisher) test can be used to test the stationary of different variables.

Table 3 Pesaran cross-sectional dependence test results.

Cross-Sectional Dependence Test	Pesaran's Test of Cross-Sectional Independence	p-Value
Pesaran cross-sectional dependence test	-1.790	0.0735**

Notes: ** Denotes 5% level of significance.

4.3 Results of Panel Unit Root Test

It is necessary to check the stationary of these variables before the panel co-integration is used to test the long-term relationship between the fossil energy consumption, industrial structure, urbanization rate, per capita GDP in the five provinces of North China. The commonly used methods of unit root test are Im, Pesaran and Shin W-stat (IPS) test, Levin, Lin & Chu (L.L&C) *t*-test, Phillips-Perron Fisher (PP-Fisher) test and Augmented Dickey Fuller-Fisher (ADF-Fisher) test. Obviously, from the results of the unit test in Table 4, it can be seen that these variables are not stationary in level forms.

Table 4 Panel data unit root test results (p-values in parentheses)

Form	Variable	LLC	IPS	ADF-Fisher	PP-Fisher	Conclusion
Level	LnCE	2.46140 (0.9931)	2.72231 (0.9968)	2.22710 (0.9943)	6.60561 (0.7621)	Non-stationary
	LnpcGDP	4.21713 (1.0000)	5.10981 (1.0000)	0.77700 (0.9999)	7.64333 (0.6636)	Non-stationary
	S	3.61775 (0.9999)	4.73665 (1.0000)	4.59892 (0.9163)	1.70636 (0.9981)	Non-stationary
	Ur	-1.95382 (0.0254)**	-1.04417 (0.1482)	12.9137 (0.2285)	4.69817 (0.9104)	Non-stationary
	Fes	1.86711 (0.9691)	2.69557 (0.9965)	4.90453 (0.8975)	10.1427 (0.4281)	Non-stationary
First Difference	ΔLnCE	-2.69812 (0.0035)***	-1.95910 (0.0251)**	20.7872 (0.0226)**	21.1765 (0.0199)**	Stationary
	ΔLnpcGDP	-4.03324 (0.0000)***	-1.79299 (0.0365)**	20.8073 (0.0225)**	32.4461 (0.0003)***	Stationary
	ΔS	-4.68804 (0.0000)***	-1.83457 (0.0333)**	17.8950 (0.0568)**	21.3395 (0.0188)**	Stationary
	ΔUr	-1.67630 (0.0468)**	-1.36916 (0.0855)*	14.4950 (0.1516)	13.5496 (0.1945)	Stationary
	ΔFes	-5.53667 (0.0000)***	-4.11200 (0.0000)***	34.6729 (0.0001)***	35.7699 (0.0001)***	Stationary

Notes: * Denotes 10% level of significance; ** Denotes 5% level of significance; *** Denotes 1% level of significance.

In general, differenced methods can be further used for non-stationary sequences to determine the stationary of those variables. ΔLnCE, ΔLnpcGDP, ΔS, ΔUr, ΔFes represent those variables at the first difference. From the Table 4, it can be seen that the unit root test statistic of all variables exceeds the critical value at 10% level and all these variables are stationary at the first difference, indicating that the null hypothesis that there is a unit root is rejected.

4.4 Panel Co-integration Test Results

Because all variables are stationary in the first difference, the Pedroni [22] test can be used to test the panel co-integration. The Pedroni method constructs seven statistics to test the residuals for each province in the group based on the mean value of the single auto-regressive coefficient related to the unit root. From the results in Table 5, among the seven statistics, four are significant at the level of 5%, revealing that the co-integration relationship exists among the examined variables. Moreover, Kao test and Johansen test are employed to test the co-integration relationship for robust, and the results also support the conclusion that there is a co-integration relationship among the examined variables.

Table 5 Panel co-integration tests results of five provinces in North China

Pedroni residual co-integration test		
Test Statistics	Statistics	Prob.
Panel v-Statistic	-0.366215	0.6429
Panel rho-Statistic	1.197785	0.8845
Panel PP-Statistic	-1.681520	0.0463**
Panel ADF-Statistic	-1.664685	0.0480**
Group rho-Statistic	2.289475	0.9890

Group PP-Statistic	-3.605421	0.0002***		
Group ADF-Statistic	-2.050062	0.0202**		
Kao co-integration test				
ADF	-4.785527	0.0000***		
Fisher-type Johansen co-integration test				
Hypothesized	Fisher Statistic			
No. of CE(s)	Trace test	Prob.	Max-eigen test	Prob.
None	68.61	0.0000***	38.60	0.0000***
At most 1	37.02	0.0001***	24.46	0.0065***
At most 2	18.18	0.0429***	18.09	0.0534***
At most 3	8.351	0.5946	7.081	0.7177

Notes: * ** *** Denote the rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

4.5 Model form Determination

There are two main methods to detect the fixed effect and the random effect, named likelihood ratio (LR) test and Hausman test. The LR test is used to test the fixed effect, and the Hausman test is used to test the random effect. Before estimating the contributions of the fossil energy consumption, industrial structure, urbanization rate and per capita GDP to CO₂ emissions, LR test and Hausman test are used to determine the model is the random effect or fixed effect.

Table 6 is the effect test results, from which it can be seen that the cross-section F statistic is larger than the critical value, revealing that the null hypothesis that the fixed effect is redundant can be reject, that is, it is reasonable to introduce the fixed effect. Because the cross-section random statistic of Hausman test is larger than the critical value, it can reject the null hypothesis that the random effect is irrelevant to explanatory variables at the 5% level of significance. In the same way, the model should be a fixed effect model based on the estimation coefficient of the fixed effect and the random effect as well as the variance values after the difference. Then an F -test will be used to select model, including the variable parameter model, the variable intercept model and the contest parameter model. From these models, we can get three different values of the sum squared residual values, which are set to S_1 , S_2 and S_3 . The F -test value can be obtained by calculating the equation (28) and equation (29). If $F_1 > F_{1,\alpha}$, the null hypothesis is rejected, which means that the panel data model is not a variable intercept model. If $F_2 > F_{2,\alpha}$, the null hypothesis is rejected, which means that the panel data model is not a constant parameter model:

$$F_1 = \{(S_2 - S_1) / [(N-1) \times K]\} / \{S_1 / [N \times T - N \times (K+1)]\} \quad (28)$$

$$F_2 = \{(S_3 - S_1) / [(N-1) \times (K+1)]\} / \{S_1 / [N \times T - N \times (K+1)]\} \quad (29)$$

where S_1 is the variable parameter model residual sum of squares, S_2 is the variable intercept model residual sum of squares, S_3 is the sum of the residual squares of the invariant parametric model, N is the number of sections, K is the number of variables, and T is the number of periods. In this paper, $N=5$, $K=4$, $T=16$, so $(N-1) \times K=16$, $(N-1) \times (K+1)=20$, $N \times T - N \times (K+1)=55$.

Table 6 Panel data model effect test results

LR test results		
	Statistic	Prob.
Cross-section F	74.760141	0.0000***
Hausman test results		
	Chi-Square Statistic	Prob.
Cross-Section Random	299.040563	0.0000***

Variable	Fixed	Random	Var(Diff.)	Prob.
LnpcGDP	0.234444	0.811250	0.003951	0.0000***
S	2.398829	-5.187013	0.539484	0.0000***
Ur	2.960566	0.066332	0.106724	0.0000***
Fes	-0.402448	0.555015	0.088323	0.0013***

Notes: *** Denote the rejections of null hypothesis at 1% significance levels

Table 7 is the results of F -test. F_1 rejects the null hypothesis, indicating that the panel model is not a variable intercept model, and F_2 rejects the null hypothesis, indicating that the panel model is not a constant parameter model. In summary, the panel model should be a variable-parameter model, that is, a fixed effect variable parameter model.

Table 7 F-test results (p-values in parentheses)

S1	S2	S3	F1	F2
0.240369	0.875686	4.563935	9.0856 (0.0000)***	49.4648 (0.0000)***

Notes: *** Denote the rejections of null hypothesis at 1% significance levels

4.6 Panel Data Model Estimation

According to the above results, we can set up a variable parameter model with fixed effect involving the fossil energy consumption, industrial structure, urbanization rate, per capita GDP in the five provinces of North China. Table 8 is the estimated results of the model. From which it can be seen that the R^2 and the adjusted R^2 are 0.9951 and 0.9929, respectively. Besides, the F statistic is significant and each coefficient is positive and significant at the 10% significance level. Therefore, this model has the advantages of significant, high goodness of fit and good model effect. From the estimated results of the model, we can know that:

(1) In five provinces of North China, except for Inner Mongolia, the urbanization rate makes the largest contributed to CO_2 emissions, followed by the industrial structure. The level of urbanization in Inner Mongolia has a negative impact on CO_2 emissions, mainly because of the reduction of the negative environmental impacts through the improvement of technology and the reform of industrial structure. The per capita GDP variable is the natural logarithm, and its coefficient can be interpreted as elasticity. The results showed that a 1% increase in GDP per capita actually increased CO_2 emissions in Beijing, Tianjin, Hebei, Shanxi and Inner Mongolia by -0.18%, -0.25%, 0.05%, 0.16%, 1.14%, respectively. It can be seen from the data that the economic development in Beijing and Tianjin can help reduce CO_2 emissions. It is because Beijing and Tianjin are mainly developing low-carbon economies such as tertiary industry. In other provinces, especially Inner Mongolia, the economy is relatively backward, and in order to develop the economy, more fossil fuels with high carbon emissions are consumed. From the impact of industrial structure on CO_2 emissions, expect Beijing, other provinces are positive, among which Hebei is the highest, and Inner Mongolia is the lowest, because Hebei mainly relies on the secondary industry to develop economy, while Inner Mongolia's economy is underdeveloped, resulting that the proportion of the added value of the secondary industry to GDP is low.

(2) In general, in the provinces where economic growth relies on heavy industry or underdeveloped provinces, the contribution of fossil energy consumption to the growth of CO_2 emissions is relatively large. Among them, the contribution rates of Shanxi and Hebei are the highest, because Shanxi and Hebei mainly use fossil energy to develop the economy. A 1% increase of the fossil energy consumption in these two province increases CO_2 emissions by 5.15% and 7.45%, respectively.

Table 8 The estimated results of the variable parameter model with fixed effect (p-values in parentheses)

Variables	Beijing	Tianjin	Hebei	Shanxi	Inner Mongolia
LnpcGDP	-0.184666	-0.252950	0.045949	0.159132	1.141293

	(0.0529) *	(0.0503) *	(0.0415) **	(0.0964) *	(0.0000) ***
S	-2.527673 (0.0114) **	3.258304 (0.0546) *	4.800726 (0.0001) ***	2.238717 (0.0110) **	0.399838 (0.0260) **
Ur	6.105563 (0.0334) **	14.31894 (0.0341) **	4.905273 (0.0597) *	8.385134 (0.0344) **	-8.456532 (0.0030) ***
Fes	0.524540 (0.0386) **	0.109423 (0.0884) *	5.146342 (0.0962) *	7.453247 (0.0823) *	0.531132 (0.0620) *
C	0.859413	-6.814882	1.82401	-5.377967	5.664071
R2	0.995068	Adjusted R2	0.992916	F-statistic	462.3686 (0.0000)***

Notes: * ** *** Denote the rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

In order to verify the effectiveness of establishing panel data model, the autocorrelation and heteroscedasticity tests need to be performed. In this study, the Wooldridge test is used to test whether there is a correlation between different variable, and the Modified Wald test method is used to check the heteroscedasticity of the different variables. The results are listed in Table 9, showing that there is no sequence correlation and heteroscedasticity, indicating that the model's estimation results are valid.

Table 9 Autocorrelation and heteroscedasticity test results (p-values in parentheses)

Test Type	Test Method	Statistic
Autocorrelation test	Wooldridge test	3.321 (0.1425)
Heteroscedasticity test	Modified Wald test	8.76 (0.1190)

4.7 Panel Granger Causality Test Results

Table 10 reports the panel Granger causality test results. The contents of which contain asterisks means that the null hypothesis should be rejected at a specified level of significance. In Tianjin, for example, when the null hypothesis is “LnpcGDP does not Granger Cause LnCE”, the *F*-test corresponding *p*-value is 0.01 which is less than 0.05. Therefore, the null hypothesis should be rejected, implying that per capita GDP does Granger cause CO₂ emissions. From the results listed in Table 10, we can get the following findings:

(1) From the results of the Granger causality test in the relationship between CO₂ emissions and urbanization rate, there is a unidirectional causality running from urbanization rate to CO₂ emissions in the five provinces, meaning that urbanization rate does Granger cause CO₂ emissions. Therefore, the change of urbanization rate will have an impact on CO₂ emissions. Besides, there exists bi-directional causal relationship between CO₂ emissions and urbanization rate in Beijing and Tianjin.

(2) From the results of the Granger causality test in the relationship between CO₂ emissions and per capita GDP, there is a bidirectional causality between per capita GDP to CO₂ emissions in the Tianjin, Hebei and Shanxi, indicating that the feedback hypothesis that CO₂ emissions and per capita GDP are interrelated and mutually complementary emerges. Therefore, the policy of developing the economy and increasing the per capita GDP will have an impact on the emissions of CO₂, and the management of CO₂ emissions will also have an impact on economic development. In Inner Mongolia, there is a unidirectional causality running from per capita GDP to CO₂ emissions, supporting the growth hypothesis, that is to say, with the increase of per capita GDP in Inner Mongolia, CO₂ emissions will increase. Additionally, Beijing is mainly based on the third industry to develop the economy, and its industry belongs to the low carbon industry, so there is no causal relationship between per capita GDP and CO₂ emissions.

(3) Except for Hebei and Beijing, there is a unidirectional relationship between fossil energy consumption and CO₂ emissions. Because Beijing as a developed area with more service industries, its development is mainly based on electric power, and fossil energy consumption is relatively low. Therefore, there is no causal relationship between fossil energy

consumption and CO₂ emissions in Beijing. In Tianjin, Hebei, and Shanxi, there is a unidirectional relationship from CO₂ emissions to industrial structure, which means CO₂ emissions can promote the adjustment of industrial structure in these provinces.

(4) From the whole region of North China, there are bi-direction causalities between CO₂ emissions and per capita GDP, and between CO₂ emissions and urbanization rate. Besides, the unidirectional causal relationships from fossil energy consumption to CO₂ emissions and from industrial structure to CO₂ emissions are found, revealing that fossil energy consumption and industrial structure have significant influences on CO₂ emissions in North China.

Table 10 Results of Granger causality tests (p-values in parentheses)

Null Hypothesis	Beijing	Tianjin	Hebei	Shanxi	Inner Mongolia	North China
LnpcGDP does not Granger Cause LnCE	0.98818 (0.4093)	6.12997 (0.0209)**	5.47498 (0.0278)**	3.06865 (0.0964)*	3.77584 (0.0645)*	9.42479 (0.0003)** *
LnCE does not Granger Cause LnpcGDP	5.06632 (0.9363)	5.96870 (0.0224)**	9.58697 (0.0059)** *	3.46694 (0.0765)*	5.55442 (0.5928)	4.13813 (0.0203)**
Fes does not Granger Cause LnCE	0.49467 (0.6254)	0.56397 (0.5878)	2.93316 (0.1045)	1.03915 (0.3926)	1.19854 (0.3456)	10.6013 (0.0001)** *
LnCE does not Granger Cause Fes	0.14616 (0.8660)	4.37885 (0.0470)**	5.69709 (0.0251)**	4.86519 (0.0370)**	6.66724 (0.0167)**	0.29003 (0.7492)
S does not Granger Cause LnCE	0.08017 (0.9236)	0.81149 (0.4742)	0.07144 (0.9316)	0.16196 (0.8529)	2.80225 (0.1132)	4.47315 (0.0151)**
LnCE does not Granger Cause S	1.51918 (0.2701)	5.76465 (0.0245)**	6.09861 (0.0212)**	4.21023 (0.0512)*	0.42433 (0.6666)	1.91107 (0.1561)
Ur does not Granger Cause LnCE	12.18178 (0.0026)**	10.94885 (0.0039)**	6.67948 (0.0167)**	3.42330 (0.0784)*	3.00803 (0.0999)*	13.9660 (0.0000)** *
LnCE does not Granger Cause Ur	6.77116 (0.0160)**	8.31398 (0.0090)**	2.94618 (0.1037)	0.50370 (0.6204)	0.05593 (0.9459)	10.15619 (0.0049) ***
Fes does not Granger Cause LnpcGDP	0.46363 (0.6432)	0.33945 (0.7209)	1.88487 (0.2071)	11.2426 (0.0036)** *	0.22543 (0.8025)	0.38226 (0.6838)
LnpcGDP does not Granger Cause Fes	2.15123 (0.1723)	8.04270 (0.0099)** *	0.41506 (0.6723)	8.80355 (0.0076)** *	6.15488 (0.0207)**	0.06942 (0.9330)
S does not Granger Cause LnpcGDP	0.80540 (0.4767)	1.97251 (0.1948)	0.37596 (0.6969)	2.99672 (0.1006)	1.81168 (0.2182)	5.02806 (0.0093)** *
LnpcGDP does not Granger Cause S	12.7091 (0.0024)** *	4.60446 (0.0420)**	3.13706 (0.0925)*	6.57866 (0.0173)**	0.32774 (0.7288)	6.27785 (0.0032)** *

Ur does not Granger Cause LnpgGDP	1.01445 (0.4006)	1.21191 (0.3419)	6.04704 (0.0216)**	0.48501 (0.6309)	2.47257 (0.1394)	0.80983 (0.4494)
LnpgGDP does not Granger Cause Ur	1.25366 (0.3309)	3.11088 (0.0940)*	0.24697 (0.7863)	2.69804 (0.1208)	21.6700 (0.0004)** *	0.22170 (0.8018)
S does not Granger Cause Fes	0.75053 (0.4995)	1.28933 (0.3218)	0.49909 (0.6229)	1.98950 (0.1925)	6.73755 (0.0163)**	0.11159 (0.8946)
Fes does not Granger Cause S	0.87298 (0.4503)	7.74971 (0.0110)**	1.51612 (0.2707)	7.58513 (0.0117)**	0.24263 (0.7895)	1.79494 (0.1743)
Ur does not Granger Cause Fes	0.00102 (0.9990)	3.43762 (0.0778)*	1.34397 (0.3085)	2.59740 (0.1287)	4.30505 (0.0488)**	0.22391 (0.8000)
Fes does not Granger Cause Ur	0.84314 (0.4617)	1.51819 (0.2703)	1.34832 (0.3075)	0.13179 (0.8782)	0.86967 (0.4515)	3.48275 (0.0366)**
Ur does not Granger Cause S	2.33202 (0.1528)	3.93288 (0.0592)*	8.66108 (0.0080)**	7.28835 (0.0131)**	1.02554 (0.3970)	1.63503 (0.2029)
S does not Granger Cause Ur	4.00355 (0.0571)*	2.49891 (0.1370)	7.21363 (0.0135)**	0.49523 (0.6251)	2.05464 (0.1841)	0.23175 (0.7938)

Notes: * ** *** Denote the rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

5 Conclusion and Policy Implications

China has made great achievements in economic development over the past decades, but the CO₂ emissions are becoming more and more serious. Under such circumstances, China has promised to substantially reduce carbon emissions in the next 30 years. Therefore, it's necessary exploring the nexus between CO₂ emissions, fossil energy consumption, industrial structure, urbanization rate and per capita GDP in North China, including Beijing, Tianjin, Hebei, Shanxi and Inner Mongolia. In this article, the above objectives were accomplished by collecting relevant data from 2004 to 2019 and using panel econometric analysis techniques.

The results of the cross-sectional dependence test suggested that there was no cross-sectional dependence across the panel. The unit root test results clearly indicated that all variables were non-stationary at the level but stationary at their first different. Then, we employed Pedroni's panel co-integration test, Kao co-integration test and Fisher-type Johansen co-integration test to conduct panel cointegration test, showing that all variables were cointegrated in the long run. On this basis, the LR test method and the Hausman test method were used to determine the form of the model. After the panel data model was established, the contribution of various factors to CO₂ emissions was analyzed by studying the coefficient of each variable in each province. According to the model estimation results, the urbanization rate contributed most to CO₂ emissions, followed by the fossil energy consumption. Finally, the panel Granger causality test revealed that there existed bi-directional causal relationships between CO₂ emissions and urbanization rates in Beijing and Tianjin, and unidirectional causal relationships from CO₂ emissions to urbanization rates in other regions. In addition, there existed unidirectional causal relationship from industrial structure to CO₂ emissions in North China, reverse causalities in Tianjin, Hebei and Shanxi and no causality in Beijing and Inner Mongolia.

Based on the empirical results, several policy recommendations are put forward. Firstly, China should reduce fossil energy consumption and develop sustainable energy source. The proposal of energy saving and emission reduction policy is mainly from the issue of CO₂ emissions caused by fossil energy combustion. According to the Granger causality results, it is known that this problem should be paid attention in North China, especially in Shanxi. Therefore, we must reduce the use of fossil fuels and focus on developing clean and renewable energy like wind energy and solar energy. Through these measures, we can not only reduce CO₂ emissions in North China, but also achieve green GDP growth. The results of

Granger causality showed that there was a causal relationship between the per capita GDP and CO₂ emissions in North China except Beijing, so the growth of green GDP will help to weaken this causality and make the North China's economy develop sustainably. Secondly, we must constantly improve energy efficiency and promote industrial structural upgrading. Some provinces, such as Hebei and Shanxi, mainly rely on heavy industry to develop the economy. We should promote the reform of the industrial structure, and increase the proportion of the tertiary industry, which will help to reduce the emission of CO₂. Besides, the government should improve energy saving technology, and incite thermal power generation to achieve cleaner production. Finally, in the five provinces of North China, we should focus on improving the urbanization rate, and at the same time, we should also consider the actual bearing capacity of the region so as to achieve the goal of rational development, which is also conducive to reducing CO₂ emissions.

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