FDI, Economic Growth and China's Carbon Emission Intensity: An Empirical Study Based on Spatial Panel Econometric Model

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Abstract. With the expansion of China's foreign investment and rapid economic growth, China's carbon emissions are also increasing year by year. Using spatial panel econometric model and data from 30 provinces in China from 1995 to 2015, this paper studies the relationship among FDI, economic growth and carbon emissions in China. The results show that there is no significant positive correlation between FDI and carbon emissions in China, and there is a significant positive correlation between economic growth and carbon emissions. Finally, based on the empirical results, this paper proposes corresponding policy recommendations.

1. Introduction
Since the reform and opening up, the introduction of a large number of foreign capital has played a significant role in promoting economic growth and expanding trade. Over the past decade, China has been the second largest foreign-funded economy and the largest developing economy. FDI has become one of the main ways to increase China's GDP. According to the UNCTAD report, the total amount of global foreign direct investment (FDI) in the first half of 2018 fell by 41%, but the scale of China's FDI attraction increased by 6% against the trend, making China the largest FDI inflow country in the world[12]. However, China has been implementing the extensive mode of growth since the reform and opening up, which has brought increasingly serious environmental pollution problems. While the economy is growing rapidly, CO₂ emissions are also increasing rapidly. As China becomes the world's largest emitter of CO₂, under the framework of the Paris Agreement, the Chinese government has clearly stated that by 2030, the emission of CO₂ should reach its peak and strive to reach its peak as soon as possible. According to statistics, China's carbon intensity in 2017 is about 46% lower than that in 2005, initially reversing the momentum of rapid carbon emission growth. However, with the increasing scale of investment, China still faces enormous pressure to reduce emissions. To achieve emission reduction targets, China must fully coordinate the relationship between FDI importation and environmental pollution, and solve the contradiction between economic growth and CO₂ emissions.

Throughout the relevant research results at home and abroad, scholars have three different views on the impact of FDI on energy conservation and emission reduction: one is based on the "pollution paradise" hypothesis [1]. Anderw K Jorgenson used panel data of 39 developing economies from 1975 to 2000 to construct a fixed-effect regression model to test the impact of FDI on energy conservation and emission reduction. The empirical test of the environmental effects of developing economies proves that FDI increases the carbon dioxide emissions of developing economies[2]. Ren and Yang
use the data of imported FDI and CO₂ emission intensity from China to analyze that the CO₂ emission intensity will increase continuously with the introduction of FDI from China[3]. One is based on the "pollution halo" effect[4]. Omri, Nguyen and Rault used panel data from 54 countries in the world from 1990 to 2011 to study the relationship among carbon emission intensity, economic growth and FDI. They believe that FDI can help to reduce the global carbon emission intensity, because it provides an important impetus for industrial development, including technology transfer, pipeline[5]. By establishing simultaneous equations to verify the interaction between FDI and economic growth and the impact of FDI on the environment, Huang Qing used industrial pollution data of 217 cities in China from 2003 to 2006 to make an empirical test. The results show that FDI is beneficial to the treatment of industrial pollution and the improvement of environmental conditions in China[6]. Another is based on the environmental Kuznets curve theory. Selden and Song studies show that FDI has an inverted U-shaped relationship with pollution, that is, the initial stage of foreign direct investment will bring a series of environmental problems, but when the investment reaches a certain scale, the improvement of residents' income level will generate demand for high environmental quality, which will lead to a higher environmental quality. FDI and environmental pollution showed a flat state and eventually decreased [7]. It can be seen that FDI is a "double-edged sword".

In summary, scholars have carried out a lot of in-depth studies on the carbon emission effects of FDI, but most of them use time series data or traditional panel data, while the literature based on Spatial Panel econometric model is still relatively scarce. However, in practice, CO₂ emissions between adjacent regions are strongly spatial dependent. Due to the influence of economic development level, technological level, energy endowment and other factors, CO₂ emissions in a region will be affected by adjacent regions. Therefore, considering the economic and geographical attributes of FDI and CO₂ emission data, this paper uses the spatial panel econometric model to make an empirical analysis of the relationship between them.

2. Variable Selection and Data Sources

2.1. Estimation of Carbon Emission Data

Based on the carbon emission estimation method of the IPCC (2006) emission inventory, this paper estimates the carbon intensity of 21 years in China's 30 provinces from 1995 to 2015. Nine energy emission indicators, such as coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas and electricity, are selected. The calculation method is shown in Formula (1).

\[ C = \sum_{i=1}^{9} C_i = \sum_{i=1}^{9} E_i \times SCC_i \times CEF_i \]  

Among them, \( C \) represents carbon emission measurement; \( i \) represents various energy sources; \( E_i \) represents energy consumption, which is derived from the energy terminal consumption data in the China Energy Statistics Yearbook; \( SCC_i \) is the benchmark coal factor for various energy sources; and \( CEF_i \) provides the carbon emission factor for IPCC (2006).

2.2. Selection of Independent Variables

Based on theoretical and literature studies, this paper chooses three sets of explanatory variables: foreign direct investment level, economic development level and other control variables. Foreign direct investment level is expressed by the actual amount of FDI used by each region, and the data are converted into RMB by the average exchange rate of that year. Economic development level is expressed by the per capita GDP of each region. Taking 1995 as the base period, the corresponding price index is used to mitigate the impact of price fluctuations. The control variables include urbanization level, technological level and industrial structure. The explanations of specific variables
are shown in Table 1. All data come from China Statistical Yearbook and provincial and Municipal Statistical yearbooks.

Table 1. Descriptive statistics of variables

| Variable | Variable Interpretation                          | Sample Size | Average Value | Standard Deviation | Maximum Value | Minimum Value |
|----------|-------------------------------------------------|-------------|---------------|--------------------|---------------|---------------|
| CO2      | CO₂ Emissions                                   | 630         | 20458.15      | 19522.8            | 252           | 154882        |
| FDI      | Actual Utilization of Foreign capital           | 630         | 27900.19      | 38841.17           | 41            | 225732        |
| PGDP     | Per Capita Actual GDP                           | 630         | 16284.6       | 13816.95           | 1814          | 76248         |
| UL       | Urbanization Rate (2014 Edition)                | 630         | 44.56984      | 16.7599            | 14            | 90            |
| IS       | the Proportion of Secondary Industry Output Value to GDP | 630      | 14246.97      | 34053.39           | 43            | 269944        |
| TL       | Three Patent Application Authorization Quantities | 630         | 45.18571      | 7.930468           | 20            | 60            |

Note: The results of variables in this table have not been logarithmically transformed, and will be in logarithmic form in empirical research.

3. Establishment of Spatial Panel Measurement Model

3.1. Spatial Lag Model

Spatial Lag Model (SLM) mainly explores whether each variable has spillover effect in a region. If there are real regional spatial autocorrelation among variables, such as regional economic factors flow, innovation diffusion, technology spillover, the following models can be set up:

\[ y_t = \alpha + \rho Wy_t + x_t \beta + \mu_t \]

\( \beta \) reflects the influence of independent variables on dependent variables, and \( Wy_t \) mainly measures the external spillovers of adjacent areas in geographical space.

3.2. Spatial Error Model

If there is an error perturbation term in the spatial dependence between variables to measure the impact of the error impact of the dependent variables in the adjacent area on the observed values in the region, the following model can be set up:

\[ y_t = \alpha + x_t \beta + \mu_t + \lambda W \mu_t + \epsilon_t \]

\( \beta \) reflects the influence of independent variables on dependent variables, \( \mu_t \) is the random error term vector, \( \epsilon_t \) is the random error vector of normal distribution, \( \lambda \) is the spatial error coefficient of the dependent variable vector, which measures the direction and extent of the observation value \( y \) of the adjacent region affecting the observed value \( y \) of the region.

3.3. Determination of Spatial Weight Matrix

In the model above, spatial effect factors are introduced into econometric research, so spatial interaction needs to be expressed by spatial weight matrix \( W \). There are many methods to determine spatial weight matrix \( W \). The most common weight matrix is 0-1 matrix and geographical distance weight matrix. In theory, compared with 0-1 matrix, geographic distance matrix should be a more scientific and ideal index in the test of spatial effects. However, in practical research, the actual statistical data of socio-economic distance is difficult to obtain, and the calculation of weights in the model is exogenous, so the method of geographic distance matrix is difficult. This paper uses 0-1
weight matrix. 0-1 matrix is based on adjacent criteria. \( W_{ij} \) is:

\[
W_{ij} = \begin{cases} 
1 & \text{When region } i \text{ and region } j \text{ are adjacent;} \\
0 & \text{When region } i \text{ and region } j \text{ are not adjacent.}
\end{cases}
\]

\( m = n \) or \( m \neq n \). Because of its symmetry and simplicity of calculation, the matrix is most commonly used, and is suitable for estimating the impact of geospatial effects.

4. Empirical Analysis

4.1. Correlation Test

After taking spatial dependence into account, it is necessary to test spatial dependence before establishing a model for analysis and research. The most commonly used method is the Moran's I index method. Moran's I is defined as follows:

\[
Moran's \quad I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (Y_i - \overline{Y}) (Y_j - \overline{Y})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}
\]

(4)

Among them, \( S^2 = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \overline{Y})^2 \), \( \overline{Y} = \frac{1}{n} \sum_{i=1}^{n} Y_i \), \( Y_i \) represents the observed value of carbon emission intensity in the \( i \)th region, \( j \) is the total number of regions and \( W_{ij} \) is the spatial weight matrix.

If the Z value of the normal statistics of Moran's I is greater than the critical value of the normal distribution function at 0.01 level of 1.96, it shows that the intensity of carbon emissions in China has a significant positive correlation in the geospatial distribution. Conversely, it means negative correlation. The global Moran index I of carbon emission intensity from 1995 to 2015 calculated by Stata software is all positive, and Z value passes the significance test of 1% level. The calculation results are shown in Table 2, which shows that the carbon emission intensity of China's provinces is not completely random, but has obvious spatial autocorrelation. This suggests that consideration of the impact of FDI on China's carbon emissions should consider spatial dependence.

| Year | I    | z (I) | p    | Year | I    | z (I) | p    | Year | I    | z (I) | p    | Year | I    | z (I) | p    |
|------|------|-------|------|------|------|-------|------|------|------|-------|------|------|------|-------|------|
| 1995 | 0.196| 2.073 | 0.038| 2002 | 0.312| 3.15  | 0.002| 2009 | 0.304| 3.158 | 0.002| 2010 | 0.331| 3.358 | 0.001|
| 1996 | 0.198| 2.09  | 0.037| 2003 | 0.304| 3.075 | 0.002| 2010 | 0.331| 3.358 | 0.001| 2011 | 0.341| 3.417 | 0.001|
| 1997 | 0.285| 2.867 | 0.004| 2004 | 0.308| 3.128 | 0.002| 2011 | 0.341| 3.417 | 0.001| 2012 | 0.328| 3.323 | 0.001|
| 1998 | 0.254| 2.594 | 0.009| 2005 | 0.326| 3.37  | 0.001| 2012 | 0.328| 3.323 | 0.001| 2013 | 0.313| 3.484 | 0    |
| 1999 | 0.277| 2.825 | 0.005| 2006 | 0.291| 3.095 | 0.002| 2013 | 0.313| 3.484 | 0    |
| 2000 | 0.23 | 2.423 | 0.015| 2007 | 0.279| 2.989 | 0.003| 2014 | 0.292| 3.297 | 0.001| 2015 | 0.297| 3.276 | 0.001|
| 2001 | 0.272| 2.806 | 0.005| 2008 | 0.314| 3.239 | 0.001|       |      |       |      |

4.2. Selection of Models

Firstly, the traditional panel model is tested. Because the test results of LM on SLM model and SEM model partly reject the original hypothesis, the model has spatial effect. In order to judge which model of SLM and SEM is more in line with objective reality, we can generally test LMERR, LMLAG and R-LMERR, R-LMLAG in two Lagrange Multiplier forms. Anselin and Florax (1995) proposed the following criteria: If LMLAG is more significant than LMERR in spatial dependence test, and R-LMLAG is significant while R-LMERR is not significant, SLM model can be judged to be more
suitable; on the contrary, if LMERR is more significant than LMLAG in statistical results and R-LMERR is significant while R-LMLAG is not, SEM model can be judged to be more suitable. In this paper, the cross-sectional data of 2005, 2010 and 2015 are used to select the model. Table 3 shows that the SEM model is more suitable than the SLM model.

Table 3. LM test statistics for 2005, 2010 and 2015

|       | LMerror | R-LMerror | LMLag | R-LMLag |
|-------|---------|-----------|-------|---------|
| 2005  | 7.895   | 3.036     | 4.914 | 0.055   |
| 2010  | 5.92    | 3.46      | 2.691 | 0.231   |
| 2015  | 2.93    | 0.931     | 2.088 | 0.09    |

In addition, the spatial panel model includes the spatial fixed effect model and the spatial random effect model. Which model should be applied should be tested by Hausmann test. The Hausmann statistics of SLM model is -17.55, and that of SEM model is -23.66. Both of them are negative. Therefore, the original assumption of random effect can be accepted and random effect model should be selected.

4.3. Empirical Results Analysis

In this paper, the traditional mixed panel model, SLM model and SEM model are used for quantitative regression analysis. The results are shown in Table 4. Among them, the estimated value of the spatial autoregressive coefficient is 0.3968152, and the estimated value of the spatial autoregressive coefficient of the error term is 0.4401847. Both of them are significant at the level of 1%, indicating the existence of the spatial autoregressive effect. Combined with the previous analysis, this following analysis is mainly based on the estimation results of the SEM model. After introducing spatial effects, the regression coefficient of FDI is positive, but not significant, indicating that there is a positive correlation between FDI and carbon emissions. Following the theoretical framework of Grossman and Krueger (1992), FDI can indirectly affect CO₂ emissions from economic scale, industrial structure and technological effects. The regression coefficient of per capita GDP is positive and significant, indicating that there is a positive correlation between economic growth and carbon emissions, and there is obvious spatial and geographical attributes. Economic growth in various regions deteriorates the local environment, increases carbon emissions, and also affects the environmental conditions of surrounding areas. The regression coefficient of urbanization level is positive and significant, indicating that the promotion of China's urbanization strategy is not conducive to reducing carbon emissions. The regression coefficient of technology level is negative, but not significant. The reason is that the introduction and absorption of energy-saving and environment-friendly technologies will help reduce carbon emissions, but the high energy consumption of heavy industry will increase carbon emissions in the process of industrialization in China. The regression coefficient of industrial structure is positive and significant, which indicates that the development of secondary industry with industry as the main factor will lead to the continuous increase of carbon emissions, and the transformation and upgrading of industrial structure will help reduce carbon emissions.

Table 4. Spatial econometric test results

|       | OLS | SLM | SEM |
|-------|-----|-----|-----|
| lnFDI | -0.112691*** (-5.16) | 0.0067881 (-0.15) | 0.0299466 (-0.89) |
| lnPGDP| -0.1720952** (-2.37) | 0.3268966 (-2.09) | 0.6502083*** (-4) |
| lnUL  | -0.0320247 (-0.28) | 0.2185659 (-2.02) | 0.3209764*** (-2.32) |
| lnTL  | 0.4738121*** (-18.17) | 0.0021591 (-0.04) | -0.0310513 (-0.47) |
| lnIS  | 2.21495*** (-19.15) | 0.6909843*** | 0.5343607** (-2.14) |

Note: The values in parentheses are t-test values.
5. Conclusion and Suggestion

5.1. Conclusions
Based on panel data of 30 provinces in China from 1995 to 2015, this paper uses SLM and SEM models to measure the carbon emission intensity of China by FDI and economic growth. The results show that: (1) China's carbon emission intensity has obvious agglomeration effect, and is not completely random distributed, which indicates the impact factors of local carbon emission intensity will also affect the carbon emission intensity of other regions; (2) FDI has no significant positive impact on carbon emissions. The "pollution halo" hypothesis is not established in China. FDI mainly indirectly affects the carbon emission intensity in China from three conveniences: scale, structure and technological effects. The specific impact mechanism of each channel is different, and further research is needed; (3) at present, the impact of economic growth on China's carbon emission intensity is positively correlated, because environmental pollution has lagging effect and stock characteristics, and the role of economic growth in promoting carbon emission reduction will not be realized in the short term; (4) the use of heavy industry technology will bring a lot of carbon emissions. However, as China enters the later stage of industrialization, the industrial structure will be transferred from the secondary industry to the tertiary industry. Carbon emissions will show obvious restraint characteristics, but at the same time, the promotion of urbanization will increase carbon emissions.

5.2. Suggestions
Based on the above conclusions, the following suggestions are put forward: (1) the Chinese government should strengthen the screening and control of FDI investment industry, guide the inflow orientation of FDI industry, strengthen the supervision of foreign-funded enterprises, and introduce high-quality and high-income foreign investment in a targeted manner; (2) China should accelerate the transformation and upgrading of industrial structure, vigorously develop the tertiary industry, strengthen upgrading and transformation of high-pollution and high-emission industries, adopt new environmental protection technologies brought about by foreign investment, and promote technological transformation and innovation; (3) China should increase the popularization of "coal to gas", reduce the exploitation rate of natural resources such as coal and improve the efficiency of resource utilization; (4) China should advocate energy conservation and emission reduction, encourage and support the construction of energy-saving and environmental protection industries, encourage the use of clean and renewable energy sources, and cultivate the concept of low-carbon consumption of the people to avoid the continuous deterioration of the environment.

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