Spatial Effect of Carbon Emissions: A Perspective of China's External Economy by Spatial Econometric Model

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***Abstract*—China has grown into the world's largest trading and foreign capital inflows country since 2010s and committed to reducing carbon emissions by 40%-45% by 2020. As the environmental governance in China has been raised to a new height, the focus of this paper will be placed on China's foreign trade and investment from the perspective of external economic variables, and empirical investigation will be conducted into how it has impacted on carbon emissions, which is believed as exerting a spatial auto-correlation effect among the provinces, with the assistance of the spatial econometric model under panel data on 30 provinces in 2001-2016. As demonstrated by the results, carbon emissions per capita in China bears a clustering effect significantly according to the Moran's I statistics. Furthemore, the estimates of spatial Durbin model with spatial fixed effects indicate that the level of economic growth and export value tend to cause carbon emissions to increase within a specific region, but mitigate it in the adjacent regions. However, the level of inward foreign investment leads to an opposite result, indicating that local governments ought to make the most of the spatial spillover effects in economic growth from adjacent regions, and development of complementary industries with high efficiency & low carbon emission. Meanwhile, local governments are supposed to be proactive in guiding the inward foreign investment into high & new technology-intensive industries, making the market accessible to foreign investment and putting in place the "Negative List System" in the field of clean energy.**

***Index Terms*—Carbon emissions, China's external economy, spatial econometric model.**

I. Introduction

Since the launch and enforcement of the reform and opening-up policy as well as joining the WTO, along with the market-oriented reform and the establishment of free trade zones, China's absorptive capacity of the inward foreign direct investment (FDI) and openness to the world market are maintaining a rapid yet steady momentum of growth.

Despite this, it started to undergo a series of structural transformations due to a continued weakening of external demands following the global financial crisis which occurred in 2007. On the one hand, as the population dividend comes to an end due to the aging population and rising labour cost, China has been increasingly reliant on those service-oriented industries rather than the manufacturing sector during the process of industrial structure optimization, which results in the reduction of dependence on foreign trade and export growth (Fig. 1).

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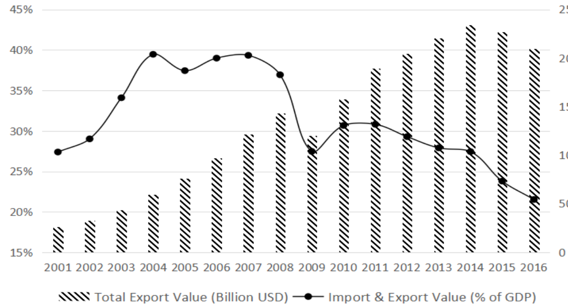

Fig. 1. China's trade dependency.
Source: China Statistical Yearbook (2001-2016).
Note: The figures of left axis is “Total Export Value (Billion USD)”, while right axis is “Import & Export Value (% of GDP)”..

Meanwhile, China's share of the world's FDI was merely 1% in 1991. At present, comparatively, China has grown into a country that attracts the most foreign investment for over 20 years (Fig. 2). Historically, it first overtook the United States to become the world's largest foreign capital inflows destination in 2014, and then maintained growth to be as generous a capital exporter as the United States and Japan in the last century.

In addition, China's outward foreign investment flows reached US$ 145.67 billion in 2015, up 18.3% year-on-year, which also marked a historic breakthrough, and made China rank second in the world for the first time. As a result, the foreign investment of Chinese companies was propelled into a "Going out" era, which made China the world's largest overseas acquirer with increasing involvement in the development of various international standards.

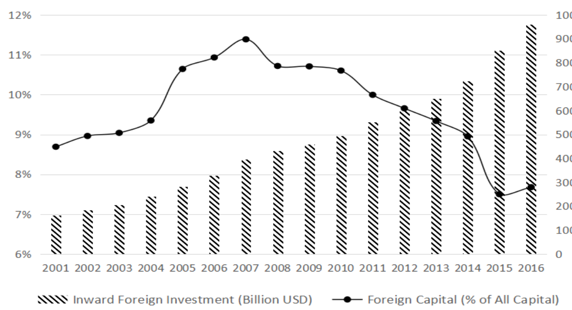

Fig. 2. Foreign direct investment in China..
Source: China Statistical Yearbook and China Industry Economy Statistical Yearbook (2001-2016)..
Note: The figures of left axis is “Inward Foreign Investment (Billion USD)”, while right axis is “Foreign Capital (% of All Capital)”.

On the other hand, China is among the world's most carbon-intensive countries following the accelerated process of urbanization and industrialization with relatively less attention paid to the environment. As a consequence, China has now ranked as the world largest greenhouse gas (GHG) emitter, overtaking the United States since 2006 and

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accounting for almost 30% of global carbon dioxide (CO2) emissions.

Considering that the transformation of socio-economic development has given rise to some severe environmental issues, China has pledged to reduce its carbon intensity by 40-45% starting from 2005 levels by 2020 in the 2010 Cancun Agreements and reiterated it during the UN Climate Change Summit in 2014. Moreover, China showed its determination to the world with the intention to peak CO2 emissions by 2030, cut down on CO2 emissions per unit of GDP by 60% to 65% from the 2005 level and increase the percentage of non-fossil fuels in its primary energy consumption to around 20%, etc, which were stated in its INDC (Intended Nationally Determined Contributions) submitted to the UNFCCC in 2015.

The environmental governance in China has been raised to a new height during the transformation of socio-economic development, especially for the emerging trend in the foreign trade and investment. Meanwhile, the relationship between these external economic variables and the environment was once characterized as the effects of "Carbon Leakage", that is, significant carbon emissions embodied in specific pollutant products through the trade activities, like primary metal and nonmetallic mineral, coal and petroleum [1]. Besides, the "Factor Endowment" and "Pollution Haven Hypothesis" - Developed countries transfer polluting industries restricted or prohibited by its own environmental regulations to those developing countries either with abundant resources or low degree of environmental preservation, during which environmental pollution transferred as well. Based on this, the present study will focus on China's foreign trade and investment from the perspective of external economic variables, and conduct an empirical investigation into how it will have impact on carbon emissions per capita for China, which is believed as having a spatial auto-correlation effect among the provinces, by applying the spatial econometric model under panel data on 30 provinces in 2001-2016.

II. Establishment of Model

Previously, scholars have made a substantial amount of effort on analyzing the influencing factors in carbon emissions and other forms of air pollution, with the focus primarily placed on different angles from Index Decomposition Analysis (IDA) methods, IPAT Equation to extended STIRPAT model involving theoretical and empirical research.

Before the proposal of the "Tobler's first law of geography" by American geographer Waldo Tobler, there had been one factor seriously overlooked in classical and neoclassical economics, which is "Space". For example, it has been discovered that there is spatial correlation or spatial dependence between the geographical units in regional environmental pollution. On the contrary, the spatial econometric analysis, which was first proposed by Paelinck and Klaassen in 1979, can make up for this drawback. Subsequently, Paul Krugman pioneered the "New Economic Geography" that introduced the element of "Space" into the econometric analysis in early 1990s. Later on, Anselin (1997), Elhorst (2001) and other scholars conducted in-depth research on introducing the relationship between regions into the traditional regression method through the space econometric analysis under a spatial data. Since then, LeSage and Pace extended the direct and indirect effect estimates to the spatial lag model and spatial Durbin model [2], and Elhorst suggested the corresponding procedures in operation for those latest researches [3].

A. Spatial Econometric Models

In the spatial econometric model, spatial correlation is mainly reflected in lag and error term of dependent variables. There are three basic models for panel data, namely, Spatial Lag Model (SAR), Spatial (Autoregressive) Error Model (SEM) and Spatial Durbin Model (SDM), which were expressed as equation (1), (2) and (3) respectively as follows. SAR assumes that the dependent variable bears spatial correlation with the dependent variable of adjacent units, whereas the dependent variable bears spatial correlation with the error term of adjacent units in SEM, which is largely dependent on the observed individual's characteristics (e.g., specific geographic location). In addition to the spatial correlation of dependent variable, if local explanatory variables bear spatial correlation with adjacent dependent variable, it is considered suitable for SDM.

$$\mathrm{y_{ij}} = \alpha + \rho \sum_{j=1}^{n} w_{\mathrm{ij}} y_{\mathrm{ij}} + (\beta_1 X_{\mathrm{i1}} + \ldots + \beta_{\mathrm{k}} X_{\mathrm{ik}}) + \varepsilon_{\mathrm{ij}} \tag{1}$$

$$\begin{aligned} \mathrm{y_{ij}} &= \alpha + \beta_1 X_{\mathrm{i1}} + \ldots \beta_{\mathrm{k}} X_{\mathrm{ik}} + \mu_{\mathrm{ij}} \\ \mu_{\mathrm{ij}} &= \theta \sum_{j=1}^{n} w_{\mathrm{ij}} \mu_{\mathrm{ij}} + \varepsilon_{\mathrm{ij}} \end{aligned} \tag{2}$$

$$\begin{aligned} \mathrm{y_{ij}} = \alpha &+ \lambda_1 \sum_{j=1}^{n} w_{\mathrm{ij}} y_{\mathrm{ij}} + (\beta_1 X_{\mathrm{i1}} + \ldots + \beta_{\mathrm{k}} X_{\mathrm{ik}}) \\ &+ \lambda_2 \sum_{j=1}^{n} w'_{\mathrm{ij}} (\beta_1 X_{\mathrm{i1}} + \ldots + \beta_{\mathrm{k}} X_{\mathrm{ik}}) + \varepsilon_{\mathrm{ij}} \end{aligned} \tag{3}$$

where *i* and *j* indicates area and time effect separately, *y* represents the endogenous dependent variable and *X* denotes exogenous explanatory variable with coefficients β. Meanwhile, ρ in equation (1) is the spatial auto-correlation coefficient of dependent variable ranging from -1 to 1, to describe the level of endogenous space interaction of dependent variables between local and its adjacent units. Similarly, θ in equation (2) refers to the spatial coefficient of error term, λ_1 in equation (3) indicates the spatial coefficient of dependent variable and λ_2 denotes a set of spatial coefficient of explanatory variables representing the level of space interaction between local explanatory variables with dependent variable of its adjacent unit. W is $NT*NT$ spatial weight matrix, and ε is disturbance term.

B. Spatial Weight Matrix

Spatial weight matrix is applied in order to satisfy the principle of "Spatial correlation will decrease while distance increases". The spatial weight matrix is basically classed into adjacency or distance standard, among which the matrix based on binary contiguity, (inverse) distance and economic distance are commonly utilized.

Considering of the statistical significance of spatial correlation in regional carbon emissions and the particularity of China's geographical conditions, this paper will conduct the spatial weight matrix based on inverse distance to illustrate the degree of spatial correlation from spatial unit *i* to *j*, with the geographical distance here is measured as distance between the capital cities of two regions. That is to say, the shorter the geographical distance, the higher the spatial correlation; the higher the geographical distance, and the lower the spatial correlation [4]. In addition, the spatial weight matrix will be standardized in the process of empirical estimation.

The spatial weight matrix based on inverse distance is expressed as equation (4), where *d* denotes the distance between spatial units.

$$W_{\mathrm{ij}} = \begin{cases} 1/d_{\mathrm{ij}} & \mathrm{i} \neq \mathrm{j} \\ 0 & \mathrm{i} = \mathrm{j} \end{cases} \tag{4}$$

C. Spatial Autocorrelation Test

Before the spatial econometric analysis is conducted, whether the spatial auto-correlation exists among the observing units will be validated in this study. The earliest spatial auto-correlation test can trace back to the Moran's I test proposed by Patrick Moran [5], and the calculation is as follows:

$$Moran\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\sum_{i=1}^{n}(x_i-\bar{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \tag{5}$$

where $S^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2$, $\bar{x} = \frac{1}{n}\sum_{i=1}^{n}x_i$, x_i represents observation value of i region, S^2 indicates sample variance, *n* refers to the total number of regions, and ω_{ij} denotes the spatial weight matrix.

The Moran's I index has a value range of [-1, 1]. When the value is in excess of 0, it indicates a positive spatial correlation between geographic units. Besides, if it is closer to 1, it suggests a closer spatial relationship, which means that, high value is adjacent to high value, and low value is adjacent to low value. On the contrary, when the value is closer to 0 or even less than 0, it indicates a weak or random spatial relationship between geographic units.

The Moran's I statistic calculated by Matlab 2017 is presented below (Table I). The null hypothesis of no spatial correlation is rejected at significance level of 0.01 in every single year, which implies that there is a significantly positive spatial correlation and "Matthew effect" feature in China's regional carbon emissions level, that is to say, carbon emissions per capita in China demonstrates a spatial dependence and clustering effect, rather than being randomly distributed. Therefore, the neglect of spatial factors will lead to deviation from model estimation to empirical conclusion.

TABLE I: ESTIMATES OF MORAN'S I STATISTIC

	Moran's I*	Z score
2001	0.349***	3.728
2002	0.368***	3.874
2003	0.349***	3.647
2004	0.361***	3.731
2005	0.372***	3.818
2006	0.364***	3.745
2007	0.349***	3.616
2008	0.325***	3.398
2009	0.306***	3.247
2010	0.281***	3.021
2011	0.258***	2.810
2012	0.266***	2.888
2013	0.302***	3.211
2014	0.302***	3.215
2015	0.285***	3.075
2016	0.271***	2.952

Note: 1) ***,**,* denote significance at the 1%, 5% and 10% levels respectively. 2) The null hypothesis of Moran's I test is that spatial auto-correlation does not exist.

Due to the limitations of Moran's I statistic in overall level, the local Moran scatter plot takes local variable and its adjacent spatial lag variable as horizontal and vertical axis respectively, which ends up being split into four quadrants to describe four types of spatial relationship. In this research, the first quadrant represents a region with high carbon emissions, which is surrounded by high carbon emissions region (HH). Similarly, HL is in the second quadrant, LL is in the third quadrant and LH is in the fourth quadrant respectively. Furthermore, as a result in Fig. 3 and Fig. 4, most of the regions in China at 2001 and 2016 are distributed in the first and third quadrants, exhibiting an explicit spatial correlation, namely spatial agglomeration effect or spatial externality of carbon emissions level. In contrast, a small number of other regions are distributed in the second and fourth quadrants, displaying a spatial anomaly effect. This is to say, carbon emissions per capita in China does not conform to random distribution. Instead, it shows a spatial correlation and clustering effect, which gives rise to the necessity to further apply spatial econometric models to the discussion around the spatial effect of regional carbon emissions in China.

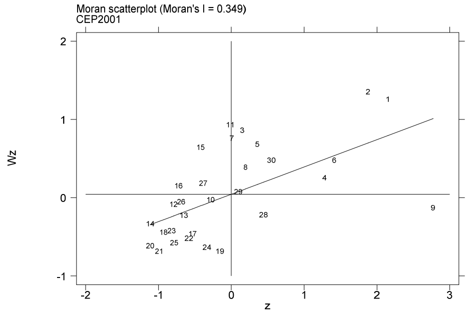

Fig. 3. Local Moran scatter plot in 2001.
Note: The figures means specific province in China.

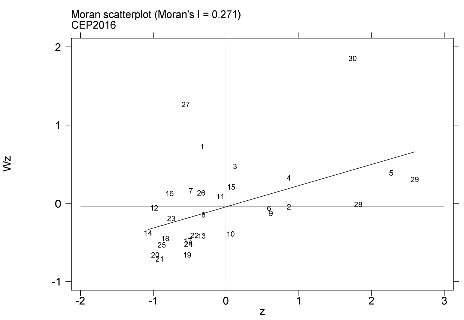

Fig. 4. Local Moran scatter plot in 2016.
Note: The figures means specific province in China.

III. Variable and Data

In this study, "Carbon Emissions Per capita" (CEP) and "Real GDP Per capita" (RGDPP) will be selected as surrogate variable for environmental pollution and level of economic growth respectively. Meanwhile, "Total Export Value" (EV) is employed to assess the foreign trade level containing significant carbon leakage, and "Ratio of Import & Export Value to GDP" (TRA) is used to indicate foreign trade dependence. Similarly, "Inward Foreign Investment" (FI) and "Export Value of Foreign Enterprises" (FEV) are applied to indicate the level of foreign capital utilization, while "Ratio of Foreign Capital to Total" (FC) shows dependence on foreign capital (Table II).

The calculation of carbon emissions is written as:

$$CE_{\mathrm{i}} = \sum_{\mathrm{i}}^{n} EC_{\mathrm{i}} * CEF_{\mathrm{i}} \tag{6}$$

where i represents eight kinds of energy like coal, oil and natural gas, CE_i (ton) stands for "Carbon Emissions", EC_i (10^4tce) denotes "Regional Energy Consumption" that is converted to standard coal referred from "China Energy Statistics Yearbook" in 2001-2016, and CEF_i (ton/tce) indicates "Carbon Emission Factor" that is calculated as average value from "2006 IPCC Guidelines for National Greenhouse Gas Inventories". Meanwhile, variables in this study are taken as logarithmic form, which is capable to avoid the heteroscedasticity in estimation process to some extent.

TABLE II: Variable Definitions and Descriptive Statistics

Variables	Abbreviation	Unit	Description	Mean	Std.Dev.	Minimum	Maximum
Dependent Variable	CEP	kg/per	Carbon Emissions Per capita	1767.924	950.014	0.347	5162.218
Explanatory Variables	RGDPP	Yuan/per	Real GDP Per capita*	21397.620	14810.360	2845.382	83286.230
	EV	Billion USD	Total Export Value	450.882	1010.227	1.623	7453.096
	TRA	%	Ratio of Import & Export Value to GDP	31.349	36.812	1.347	187.498
	FC	%	Ratio of Foreign Capital to Total	9.635	8.910	0.123	40.056
	FI	Billion USD	Inward Foreign Investment	823.172	1348.650	6.481	8799.000
	FEV	Billion USD	Export Value of Foreign Enterprises	228.461	546.206	0.007	3572.925

Source: China Energy Statistical Yearbook, China Industry Statistical Yearbook, China Statistical Yearbook on Environment (2001 - 2016).
Note: 2000 as the base year in real GDP Per capita.

IV. Empirical Estimates

Moran's I index is employed for the purpose of checking the existence of global spatial correlation of variable under the OLS (Ordinary Least Squares) estimation. Nevertheless, it is incapable to provide information for model selection in spatial regression analysis [6]. Therefore, the LM (Lagrange multiplier) test in standard and robust form, Wald and LR (likelihood ratio) tests are performed in this paper based on maximum likelihood estimation, which is also involved to avoid bias and inconsistency under the OLS estimation.

A. Test in Non-Spatial Panel Model

In terms of individual effects when the non-spatial panel data model is constructed by OLS estimation in Table III, it can be classed into random and fixed effects model, which can be determined by performing the Hausman test. Herein, Stata 15 is used to demonstrate that the fixed effects model has unique advantages with 1% statistical significance. Meanwhile, Baltagi indicated that when sample is selected from a specific individual, rather than being taken from the population on a random basis, it is appropriate to choose fixed effects model [7]. Additionally, as the spatial units in this paper are deliberately selected from 30 provincial and municipal administrations in China, it is unlikely that the random sampling problem arises. Therefore, the fixed effects model will be adopted properly in following analysis.

Furthermore, the fixed effects model can be further classified into spatial or time fixed effects, where the former refers to effects caused by geographical features which is invariant during time, and the latter refers to factors as regional policies and technological changes during time. In contrast, all models will be estimated based on the non-fixed effects, spatial fixed effects, time fixed effects and spatial-time fixed effects respectively in this paper. Consequently, the Real GDP Per capita (RGDPP) and Inward Foreign Investment (FI) have positive and negative coefficient towards carbon emissions per capita respectively within the region with statistical significance under all of the non-fixed and fixed effects models (Table III).

In addition to the spatial auto-correlation test by Moran's I index above, the LM test is conducted in standard and robust form to validate statistical significance and to provide information for model selection between the spatial lag and spatial error model [8]. The null hypothesis of two exerts no spatial lag effects and no spatial error effects respectively. As revealed by the results shown in Table III, null hypothesis of standard LM test for spatial lag model (LMLAG) and spatial error model (LMERR) in all models are rejected statistically significant, which suggests the existence of spatial auto-correlation once again. Furthermore, the null hypothesis of robust LM test for spatial lag model (R-LMLAG) in no fixed effects model is accepted, whereas robust LM test for spatial error model (R-LMERR) is rejected, indicating the relatively significance of the spatial error model so far [9].

TABLE III: ESTIMATIONS OF NON-SPATIAL PANEL DATA MODEL

Sample: 30 provinces of China (2001-2016)
Dependent Variable: logCEP
Observation: 480

	No fixed effects	Spatial fixed effects	Time fixed effects	Spatial and time fixed effects
logRGDPP	0.055***	0.055***	0.049***	0.048***
logEV	0.015	0.014	0.130***	0.146***
logTRA	5.686***	5.498***	-0.579	-1.411
logFC	-39.586***	-39.410***	7.189	9.468
logFI	-0.225***	-0.218***	-0.224***	-0.222***
logFEV	-0.199***	-0.204***	0.029	0.021
intercept	1010.265***			
R2	0.416	0.409	0.538	0.532
Hausman test*	49.75***			
LMLAG*	481.106***	489.015***	90.301***	87.233***
R-LMLAG	0.705	0.646	11.848***	12.783***
LMERR	610.197***	616.991***	205.635***	201.425***
R-LMERR	129.795***	128.622***	127.183***	126.975***

Note: 1) ***,**,* denote significance at the 1%, 5% and 10% levels respectively. 2) The null hypothesis of Hausman test is that the preferred model is random effects. 3) The null hypothesis of Lagrange multiplier test is that the sample has no spatial effect.

B. Estimates of Spatial Panel Model

Moreover, as indicated by LeSage and Pace, if the spatial lag or spatial error model is adopted based on the LM test, then spatial Durbin model (SDM) needs to be considered [2]. In Table IV, the spatial Durbin model is constructed first and then Wald and LR test is performed, of whose the null hypothesis is whether SDM can be simplified into SLM or SEM respectively. As a result, SDM with spatial fixed effects is identified as the most suitable spatial model due to the Wald and LR statistics, along with the R2 (Coefficient of Determination). Besides, some scholars indicated that SLM and SEM ignore the spatial auto-correlation effect of explanatory variables, which can easily lead to inconsistent and biased estimates. Therefore, the fixed effects of spatial Durbin model will be involved in this paper.

Specifically, Real GDP Per capita (RGDPP) and Total Export Value (EV) have a coefficient of 0.056 and 0.168 to carbon emissions per capita respectively within region, whereas Inward Foreign Investment (FI) holds a coefficient of -0.296 at 1% significance, which suggests that 1% increase in economic growth per capita, export value and inward foreign investment will lead to an increase of 0.056%, 0.168%, and a decrease of 0.296% in carbon emissions per capita respectively. Among the results, the relationship between Real GDP Per capita (RGDPP) and Inward Foreign Investment (FI) with carbon emissions are consistent with those in non-spatial panel model.

Meanwhile, what is important is that Real GDP Per capita (RGDPP) and Total Export Value (EV) have a spatial coefficient of -0.054 (W*logRGDPP) and -0.183 (W*logEV) to carbon emissions per capita respectively towards adjacent regions. In comparison, Inward Foreign Investment (FI) turns to 0.296 (W*logFI) at 5% significance, indicating that 1% increase in GDP per capita and export value within region has a transmission effect that leads to a 0.054% and 0.183% decrease of carbon emissions per capita in the adjacent regions. Likewise, 1% increase in local foreign investment is conducted to enhance 0.296% carbon emissions per capita towards the adjacent regions. It can be judged that economic growth with a higher level of dependence on foreign trade tends to exacerbate local carbon emissions but reduce the level in the adjacent areas. However, a marginal increase of foreign investment is demonstrated to mitigate local carbon emissions but cause the environment to deteriorate in the adjacent regions.

TABLE IV: ESTIMATIONS OF SPATIAL PANEL DATA MODEL (SDM)

Sample: 30 provinces of China (2001-2016)
Dependent Variable: logCEP
Observation: 480

	No fixed effects	Spatial fixed effects	Time fixed effects	Spatial and time fixed effects*
logRGDPP	0.056***	0.056***	0.057***	0.057***
logEV	0.169***	0.168***	0.163***	0.158***
logTRA	-1.629	-1.609	-1.602	-1.432
logFC	9.939*	10.908*	10.465*	11.185*
logFI	-0.294***	-0.296***	-0.298***	-0.299***
logFEV	0.055	0.059	0.047	0.053
W*logRGDPP	-0.054***	-0.054***	-0.053***	-0.054***
W*logEV	-0.195**	-0.183**	-0.142	-0.116
W*logTRA	3.259	2.975	1.799	0.525
W*logFC	-16.096*	-16.394*	-8.869	-7.142
W*logFI	0.297***	0.296***	0.288***	0.293***
W*logFEV	-0.100	-0.115	-0.065	-0.087
W*dep.var.	0.876***	0.876***	0.752***	0.744***
intercept	202.340***			
R2	0.866	0.869	0.864	0.867
LogL	-3544.545	-3539.620	-3528.339	-3521.966
Wald test*		278.120***	169.145***	170.709***
LR test*		13.855**	12.003*	12.906**

Note: 1) ***,**,* denote significance at the 1%, 5% and 10% levels respectively. 2) Wald test for spatial Durbin model against spatial lag model. 3) LR test for spatial Durbin model against spatial error model.

V. CONCLUSION

In this paper, the focus is placed on China's foreign trade and inward investment as a perspective of external economic variables, and attempt is made to conduct an empirical investigation into how it will impact on the level of carbon emissions in China, which exhibits spatial auto-correlation among regions, by constructing spatial econometric model under panel data of 30 provinces in 2001-2016.

As revealed by the results, regional carbon emissions level in China exerts an explicit effect of spatial auto-correlation due to the Moran's I statistic and local Moran scatter plot showing statistical significance. Additionally, the spatial coefficients of local carbon emissions per capita in SLM, SEM and SDM all suggest a positive correlation towards the adjacent regions, indicating that the improvement or deterioration of environment has a positive transmission effect towards the surrounding areas, and the environmental policies on "pollution transfer" industries or "free riding" behaviors are supposed to be treated as priority for every local government. Meanwhile, the improvement of integrated environmental management is inseparable from regional environmental cooperation in China, through the economic and legal means of implementation, like the establishment of environmental compensation mechanism, pollution permits trading system, and a unified environmental laws on the prevention and control of pollution under supervision by the central government.

More specifically, the estimates of China's foreign trade and inward investment activities are manifested in the spatial fixed Durbin model. Both Real GDP Per capita (RGDPP) and Total Export Value (EV) show a positive coefficient to local carbon emissions per capita, but shift into negative value in the adjacent regions. On the contrary, Inward Foreign Investment (FI) is demonstrated to bear a negative correlation to local carbon emissions per capita but shift into positive in the adjacent regions, which means that a higher level of economic growth and heavier dependence on export commodities trade will boost industrial development with a higher level of emissions within region, but activate spillover effects in technology, and agglomerate innovation & human capital with cluster effect to form low-carbon industries in surrounding areas. On the contrary, foreign corporations relying on advanced cleaning technologies and capital investment in the process of inward investment, lead to a mitigated impact on environment within the host region (Pollution halo hypothesis). Nevertheless, the development of local high-tech and environmental protection industries will produce the crowding out effect on low end industries with high pollution & low efficiency to the adjacent regions (Pollution paradise hypothesis). It was discovered that local governments ought to be proactive in guiding the inward foreign investment into high & new technology fields and low carbon industries, making the market accessible to foreign investment and implementing the negative list system in clean energy. Meanwhile, in order to mitigate the carbon emissions efficiently, local governments should make the most of spatial spillover effects in economic growth from the adjacent regions, like the transportation infrastructure, human capital, industrial agglomeration and development of complementary industries, with further strengthened trade relations between regions.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

ZHIGUANG Song conducted and managed entire work, including data collecting and analysis, conducting of research model and interpretation, as well as reviewing of this paper.

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