The third-country effects of CO$_2$ emissions in BRI countries: A verification on China's impacts by spatial Durbin panel data model

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Abstract. Since the WTO accession in 2001, China's outward foreign direct investment (OFDI) and foreign trade have been leaping forward, especially reflected as the "One Belt & One Road" initiative (BRI), proposed in 2013, which has been its largest public product for international community thus far. On that basis, this study focuses on the third-country effects of carbon dioxide (CO$_2$) emissions in BRI related countries, and delves into its spatial interaction from rising impacts of China's global economic cooperation activities, with the economic & political distance from China as institutional factors, using spatial econometric method in a panel data of 60 BRI countries from 2007 to 2016. Accordingly, the empirical results first significantly reveal the existence of spatial autocorrelation for CO$_2$ emissions per capita in BRI countries by Moran's I test. Furthermore, according to the main estimated results of the spatial Durbin model with spatial fixed effects, China’s OFDI and imports to BRI countries exert third-country effects or spatial spillover effects; from the perspective of sustainability and emission reduction during BRI, China is required to launch more economic cooperation in emerging and low carbon industries with limited political claims. In response, BRI countries are supposed to develop its high tech and low carbon complementary industries with surrounding countries, so as to keep the CO$_2$ emissions at a low level.

1. Introduction

Since the WTO accession and the introduction of “Going Out” strategy in the new millennium, China’s outward foreign direct investment (OFDI) has increased on the whole, especially after the global economic & financial crisis which caused a period of deflation and recession in 2007. As suggested from the Statistical Bulletin of China's Outward Foreign Direct Investment (2016), China's OFDI flows in 2016 has reached $1961.5 billion, compared with only $27 billion in 2002 when this data started to be harvested, and ranked as the second largest world investor since 2015, making it as a truly capital exporting country (Fig. 1). In the meantime, since Asian Development Bank (2017) has reported $26 trillion or $1.7 trillion per year from 2016 to 2030 required for infrastructure to sustain growth and strike poverty in developing Asia-Pacific, when climate change mitigation and adaptation costs are incorporated, much room is still provided for China’s overseas investment persistently.
On that basis, the “Going out” strategy has been implemented since 2003, which was proposed to encourage its enterprises to invest overseas. The “One Belt & One Road” initiative (BRI) has been China’s largest public product for the international community thus far. It was officially proposed in 2013 as a national strategy, along with consecutive corresponding projects (e.g., the Silk Road Fund and Asian Infrastructure Investment Bank established in 2014), with the aim to strengthen China’s connectivity with the world, covering the relevant fields of commodity trade, (soft) infrastructure construction, intergovernmental communication, as well as cultural ties. The intercontinental network has currently covered 65 countries in Europe, Africa, Asia and China, linking $23 trillion gross domestic product (GDP) and 4.4 billion people in total; it is becoming the most promising economic cooperation corridor worldwide.

At the same time, since the WTO accession in 2001, remarkable achievements have been achieved in China's total trade as well, marking an increase from $509.65 billion in 2001 to $3684.92 billion in 2016, as well as an average annual growth rate of 14.10% (UN Comtrade). Thus, given that China is the world’s biggest trading nation and emitter, and when transboundary air pollution issue is critically impacting global emissions, how China’s economic cooperation activities have impacted global carbon dioxide (CO₂) emissions, from the perspective of spatial effects, is set as the research object of this study.

2. Literature Reviews

Overseas investment and international trade are the two critical aspects of global economic cooperation activities, and numerous researches have been conducted in relevant fields. Besides theoretical researches in foreign direct investment (FDI) and environment (e.g., the Limits-to-Growth theory, pollution haven hypothesis, as well as pollution halo hypothesis), the empirical studies on the perspective of spatial effects in this field have also provided crucial references. Coughlin and Segev (2000) pioneered the application of spatial econometric techniques to verify US's OFDI data in China and build a spatial lag model. It was reported that the spatial lag coefficients of economic size, labor productivity and coastal location display significant positive relation, suggesting that the US's OFDI in those relevant fields in a specific China’s province will be impacted and attracted by other spatial units, concluded as a positive spillover effect [1]. In contrast, for existing literatures that estimated the greenhouse gas emissions embodied in international trade, Wyckoff and Roop (1994) calculated the carbon emissions embodied in manufactured goods imported by the OECD countries; they reported...
that the carbon emissions embodied in its imports took up nearly 13% of total emissions [2]. More broadly, Peters and Hertwich (2008) employed the input-output data of 2001 to delve into the embodied carbon emissions in international trade among 87 countries. It was identified that carbon emissions embodied in international trade took up 1/4 of the world’s total emissions, of which China’s exports and imports carbon emissions respectively accounted for 24% and 7% of its domestic carbon emissions [3]. In the meantime, in terms of the role of institutional factors in cross-border investment and trade, especially displaying the association with China’s impacts, Kolstad and Wiig (2012) suggested that institutional quality of host country was negatively correlated with China’s OFDI, which is attracted to large markets (OECD countries), and to countries with large natural resources and poor institutions (non-OECD countries) combined [4]. To be specific, Cheung and Qian (2009) suggested that corruption and legal defects in Africa positively impacted China’s OFDI [5].

Thus, given that limited number of existing literatures in third-country effects for global CO\textsubscript{2} emissions, especially on the perspective of increasing impacts from China, as it is being the world’s emerging investor and largest trading nation, using spatial econometric methods. Accordingly, in the present study, the spatial Durbin econometric models that control spatial effects of both explained and explanatory variables will be employed to investigate the spatial autocorrelation of CO\textsubscript{2} emissions in BRI related countries, and the special emphasis is placed on the spatial intercorrelation from China’s overseas investment and foreign trade, as well as economic and institutional distance from China, on the basis of a macro data set for 60 BRI countries from 2007 to 2016.

3. Spatial Econometric Models

In accordance with the theory of spatial econometrics, the spatial interactions to the spatial variables primarily fall into three types. The first is Spatial Lag Model (SLM): Endogenous spatial interaction reflected in explained variables between a range of regions. Spatial Durbin Model (SDM) is the second: Spatial relationships not only originate from explained variables, but also from explanatory variables between various regions. The third is Spatial (Autoregressive) Error Model (SEM): Spatial interaction reflected in error terms, namely, spatial relationships are impacted by unobservable factors in various regions (i.e., specific geographic location) [6].

On that basis, the specific model settings of Spatial Lag Model (SLM), Spatial Durbin Model (SDM), and Spatial Error Model (SEM) are respectively expressed as Eq. (1), (2) and (3).

\begin{align}
\text{Eq. (1)} & \quad y_{ij} = \alpha + \rho \sum_{j=1}^{n} w_{ij} y_{j} + (\beta_{1} X_{i1} + \ldots + \beta_{k} X_{ik} ) + \varepsilon_{ij} \\
\text{Eq. (2)} & \quad y_{ij} = \alpha + \lambda_{1} \sum_{j=1}^{n} w_{ij} y_{j} + (\beta_{1} X_{i1} + \ldots + \beta_{k} X_{ik} ) + \lambda_{2} \sum_{j=1}^{n} w_{ij} (\beta_{1} X_{i1} + \ldots + \beta_{k} X_{ik} ) + \varepsilon_{ij} \\
\text{Eq. (3)} & \quad y_{ij} = \alpha + \beta_{1} X_{i1} + \ldots \beta_{k} X_{ik} + \mu_{ij} \quad \mu_{ij} = \theta \sum_{j=1}^{n} w_{ij} \mu_{ij} + \varepsilon_{ij}
\end{align}

Where i and j respectively denote the area and time effect; W refers to the spatial weight matrix reflecting the spatial relationship among geographic units; y indicates the explained variable; X represents a set of explanatory variables with coefficients \( \beta \). In the meantime, \( \rho \) and \( \lambda_{1} \) in Eq. (1) and (2) denote the spatial lag coefficients reflecting the spatial dependence between explained variables, \( \theta \) in Eq. (3) refers to the spatial error coefficient revealing the spatial interaction in random disturbance item, and \( \lambda_{2} \) in Eq. (2) represents the spatial lag coefficient of explanatory variables. Moreover, u represents the individual effect; \( \varepsilon \) is the random disturbance term.
4. Variables and Data

In this study, China’s investment and imports, as well as economic and institutional distance with China, will be used as the core explanatory variables to delve into the spatial intercorrelation of CO\textsubscript{2} emissions in BRI countries from China’s impacts. To be specific, China’s outward foreign direct investment stock (OFDI) originates from the Statistical Bulletin of China’s Outward Foreign Direct Investment, in which the stock of investment indicates the reserve at the end of the previous year. Likewise, China’s imports from BRI countries (IV) are referred from the UN Comtrade. The absolute economic (GDPB) and institutional (WGIB) distance between BRI countries and China are respectively measured as the GDP per capita in current prices and Worldwide Governance Indicators from the IMF and World Bank. Besides, the level of economic development, industrial and trade structure, along with the infrastructure level in BRI countries are expressed as the scale, structure and technique effect on the CO\textsubscript{2} emissions within the region, which are selected as GDP per capita in current prices (GDP) of a specific BRI country from IMF, ratio of manufacturing & construction value (IG), and trade value (TG) to GDP from World Bank, and ratio of individuals using the internet of population (IUI) from International Telecommunication Union (Table 1). In the meantime, the logarithm of all variables in the models will be adopted to linearize the estimation, as well as significantly eliminate the heteroscedasticity and reduce the singular value of data.

Table 1. Variable definitions and descriptive statistics

| Variables         | Abbreviation | Unit       | Description                                      | Abbreviation | Unit       | Description                                      |
|-------------------|--------------|------------|--------------------------------------------------|--------------|------------|--------------------------------------------------|
| Explained Variable| CO2P         | 10 kg/per  | CO\textsubscript{2} Emissions Per capita          |              |            |                                                  |
| Explanatory Variables | OFDI      | Million USD | China's Outward Foreign Direct Investment Stock | IG           | %          | Industry (Including Construction) Value Added (% of GDP) |
|                   | IV          | Hundred million USD | China's Import Value | TG           | %          | Trade Value (% of GDP)                           |
|                   | GDPB        | Thousand USD | GDP Gap (Absolute Value) | IUI          | %          | Individuals Using the Internet (% of Population) |
|                   | WGIB        | -          | Worldwide Governance Indicators Gap (Absolute Value) | GDP          | USD        | GDP Per capita (Current Prices)                  |

5. Empirical Estimation

In the following sections, a spatial weight matrix of inverse geographic distance is first built to calculate the Moran’s I index and delve into the spatial autocorrelation of CO\textsubscript{2} emissions in BRI countries. Subsequently, spatial panel data models are employed, and several corresponding statistical tests are conducted to explore the third-country effects of CO\textsubscript{2} emissions in BRI countries, in particular the rising impacts from China. Lastly, the conclusions and countermeasures are listed.

5.1. Spatial Weight Matrix

The selection of spatial weight matrix is primarily split into binary contiguity, (inverse) geographical distance, as well as economic distance standard. In the present study, as impacted by the features of air pollutants and availability of data, the spatial weight matrix based on inverse geographical distance (W) is built in Eq. (4), where d denotes the geographical distance between the capital cities of each location i, j. In this matrix, geographical distance criterion is referenced to determine the degree of spatial autocorrelation, namely, the lower the geographical distance, the higher the spatial autocorrelation will be; the larger the geographical distance, the less obvious the spatial autocorrelation will be [7].
Spatial Autocorrelation Test

Spatial autocorrelation measures the relationship between the variables at a range of regions separated by specified distance. Thus far, the Moran's I (1950) test and Geary (1954) test have been widely proposed by spatial econometricians to verify whether there is a spatial autocorrelation between variables, and the Moran's I test is calculated here as:

\[
W_{ij} = \begin{cases} 
1/d_{ij} & i \neq j \\
0 & i = j
\end{cases}
\]

(4)

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

(5)

Where \( S^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2 \); \( \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \); \( x_i \) denotes observation value of \( i \) region; \( S^2 \) represents sample variance; \( n \) indicates total number of regions; \( \omega_{ij} \) refers to spatial weight matrix.

The Moran's I index ranges from -1 to 1. At the value over 0, a positive spatial autocorrelation between geographic units is suggested, and if it is closer to 1, a closer spatial relationship will be reflected, namely, high values approximates high values, and low values approaches to low values. In contrast, when it is closer to 0 or even below 0, geographic units exhibit a weak or random spatial relationship. In this study, Moran's I statistics of \( CO_2 \) emissions per capita in BRI countries calculated by Matlab 2017 is listed in table 2, and the null hypothesis (No spatial autocorrelation) is rejected at the significant level of 1% in the observation period, suggesting that the level of \( CO_2 \) emissions among the BRI countries exhibits noticeable positive spatial autocorrelation, spatial aggregation effect or Matthew effect, i.e., the country with high/low level of \( CO_2 \) emissions can be spatially adjacent to high/low countries, rather than being randomly distributed, and spatial factors overlooked will cause deviations from model estimation to empirical conclusion.

Table 2. Moran's I statistics of \( CO_2 \) emissions per capita in BRI countries

| Year | Moran's I | Z score |
|------|-----------|---------|
| 2007 | 0.506***  | 5.589   |
| 2008 | 0.503***  | 5.489   |
| 2009 | 0.506***  | 5.567   |
| 2010 | 0.499***  | 5.449   |
| 2011 | 0.470***  | 5.137   |
| 2012 | 0.520***  | 5.782   |
| 2013 | 0.537***  | 6.000   |
| 2014 | 0.518***  | 5.758   |
| 2015 | 0.495***  | 5.455   |
| 2016 | 0.449***  | 4.955   |

a ***,**,* denote significance at the 1%, 5% and 10% levels respectively.

In addition, local Moran's I scatter plot outlined by Anselin et al. (1996) is employed to classify spatial autocorrelation into four types, consisting of an observation variable on the x-axis and its
spatially lagged variable on the y-axis [8]. Accordingly, there will be four types of local spatial relationships in four respective quadrants, namely, High-High (HH), Low-Low (LL), Low-High (LH) and High-Low (HL), i.e., countries located in the first and third quadrants display a positive spatial autocorrelation. In contrast, countries located in the second and fourth quadrants exhibit a negative spatial autocorrelation. As results in Fig. 2, BRI countries are primarily located in the first and third quadrants, suggesting an explicit positive spatial autocorrelation, particularly in the third quadrant. In other words, the level of CO$_2$ emissions among the BRI countries is not randomly distributed but exhibits a spatial dependence and clustering effect; most of the countries are densely concentrated in low CO$_2$ emissions regions from a per capita perspective.

Figure 2. Local Moran scatter plot of CO$_2$ emissions per capita in 2007 (left) and 2016 (right)

5.3. Estimations of Spatial Panel Data Model (SDM)

First, panel data estimation can be split into random and fixed effects model, as determined by the Hausman test (H$_0$: The preferred model is random effects). In this study, Stata 15 is utilized to demonstrate that the fixed effects model exhibits unique advantages at the 1% level of statistical significance. Thus, regional (spatial) and time fixed effects will be subdivided, and the former refers to the effects attributed to time-invariant geographical features in a range of regions, the latter represents the time-variant factors (e.g., governmental policies and technological variations). Next, Lagrange multiplier (LM) test (H$_0$: There is no spatial effect in the model) proposed by Burridge (1980) and Auselin (1988) will be employed to verify that whether the spatial interaction effect exits in spatial lag or error term [9]-[10]. In this study, it is ultimately indicated that the spatial error model has been relatively critical thus far. Furthermore, when LM test rejects the non-spatial effects hypothesis and the spatial lag or error model is appropriate, the feasibility of the spatial Durbin model (SDM) should be verified by Wald and likelihood ratio (LR) tests, covering vital spatial effects from explanatory variables overlooked by the other two models [10]-[11]. Accordingly, the null hypothesis of two tests is that the SDM can be simplified to the SLM or SEM, and the results generally reveal that the SDM with spatial fixed effects is more appropriate, by explicitly different statistical significance in three models, which is elucidated in the following section (Table 3).

To be specific, the spatial coefficient of explained variable (W*dep.var.) is 0.225 at 1% significance, empirically demonstrating a distinct spatial autocorrelation effect. Besides, foreign direct investment from China (OFDI), industry value added to GDP (IG), trade value to GDP (TG) and GDP per capita (GDP) suggest positive local coefficients respectively, at the significant level of 1% towards the CO$_2$ emissions per capita in the region, while the gap of Worldwide Governance Indicators (WGIB) displays a noticeable negative local coefficient. Furthermore, OFDI, gap of GDP (GDPB), IG and individuals using the internet (IUI) exhibit positive spatial coefficients, while China's import value (IV) and GDP have remarkable negative spatial coefficients.
Table 3. Estimations of spatial panel data model (SDM)

|                      | No fixed effects | Spatial fixed effects | Time fixed effects | Spatial and time fixed effects |
|----------------------|------------------|----------------------|--------------------|-------------------------------|
| logOFDI              | 0.044***         | 0.045***             | 0.042***           | 0.042***                      |
| logIV                | 0.210            | 0.130                | 0.223              | 0.119                         |
| logGDPB              | -9.188*          | -9.522*              | -18.006***         | -20.420***                    |
| logWGIB              | -3.021***        | -3.306***            | -2.679***          | -2.879***                     |
| logIG                | 8.518***         | 8.036***             | 7.846***           | 6.998***                      |
| logTG                | 2.159***         | 2.456***             | 2.003***           | 2.422***                      |
| logIUI               | -1.640*          | -1.618               | -2.523***          | -2.958**                      |
| logGDP               | 0.066***         | 0.067***             | 0.074***           | 0.077***                      |
| W*logOFDI            | 0.016            | 0.026**              | 0.012              | 0.016                         |
| W*logIV              | -0.583**         | -0.598**             | -0.394             | -0.543*                       |
| W*logGDPB            | 30.378***        | 41.813***            | 0.022              | 1.933                         |
| W*logWGIB            | 0.641            | 0.436                | 1.046              | 0.973                         |
| W*logIG              | 4.990**          | 6.756***             | 4.163*             | 4.392**                       |
| W*logTG              | -0.450           | -0.918               | -0.282             | -0.187                        |
| W*logIUI             | 6.977***         | 10.537***            | 3.505**            | 4.987**                       |
| W*logGDP             | -0.050***        | -0.063***            | -0.008             | -0.011                        |
| W*dep.var.           | 0.226***         | 0.225***             | -0.007             | -0.014                        |
| intercept            | -514.625***      |                     |                    |                               |

Observation          | 600              | 600                  | 600                | 600                           |

R2                   | 0.872            | 0.886                | 0.889              | 0.900                         |

LogL                 | -4364.330        | -4332.878            | -4318.724          | -4284.707                     |

Wald test            | 56.791***        | 12.594               | 15.668**           |                               |

LR test              | 36.109***        | 13.502*              | 16.319**           |                               |

a ***, ** denote significance at the 1%, 5% and 10% levels respectively.

6. Conclusions & Suggestions

This study primarily explores the third-country effects of CO₂ emissions per capita in BRI related countries, especially from the perspective of growing impacts of China, using spatial econometric models in a macro-level data set for 60 BRI countries from 2007 to 2016. Before the empirical estimation, the Moran’s I test and local Moran’s I scatter plot in inverse geographic distance standard are first conducted in this study, combined with the estimate of spatial coefficient of explained variable in table 3. As a result, the existence of spatial autocorrelation for the level of CO₂ emissions in BRI countries is empirically confirmed. It is therefore suggested that unilateral industrial and environmental policies, transfer of polluting industries and free-riding phenomenon should be avoided, whereas interregional joint prevention and control system among the observation areas should be adopted to effectively hinder the diffusion of CO₂ emissions. To be more specific, in the estimates of spatial Durbin model with spatial fixed effects:

1) Since China’s OFDI exhibits significantly positive local and spatial coefficients to BRI countries, along with a negative spatial coefficient in China’s imports, China should promote industrial structure and make investment mode more high efficiency & low carbon, (e.g., human capital, technology and innovation fields) in the process of global economic cooperation activities. Meanwhile, BRI countries are encouraged to maintain and develop low carbon industry complementarity with surrounding regions, so as to keep the CO₂ emissions at a low level.
2) In terms of the sustainable development and emission reduction, when W Gib and GDPB hold noticeable negative local and positive spatial coefficients respectively, it is implied that political claims with other non-economic & environmental purposes in the process of China’s overseas investment and foreign trade should be limited, especially for those countries exhibiting high political proximity with China. In the meantime, if lower economic distance between China and a specific BRI country suggests more complementary with higher emissions (e.g., resource-oriented countries such as Russia and Central Asia), that is, spatial crowding-out effects in economic cooperation. It indicates that BRI countries are supposed to promote the development in low-carbon energy and products, and maintain a friendly economic relation and cooperation with China. Otherwise, it should discover its industrial supplementary characteristic with surrounding countries driven by high tech and low carbon industries, in the view of sustainable development.

3) Finally, since the level of economic growth shows a positive local but negative spatial coefficients to CO₂ emissions of local and surrounding areas separately in this study, it suggests that local government of BRI countries should proactively exploit spillover effects from regional economic development and strengthen regional cooperation, so as to attract the technique effect in economic growth from adjacent areas to hinder CO₂ emissions in a larger scale.

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