ADVANCING EARTH AND SPACE SCIENCE

Earth's Future

RESEARCH ARTICLE
10.1029/2021EF002331

Key Points:

- Local effects of foreign direct investment on emissions are positive, while spatial spillover effects are negative
- The coexistence of the "Pollution Haven" and "Pollution Halo" theories in a country is examined
- Results help promote collaborative emission reduction across regions with trade

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Citation:
Lin, H., Wang, X., Bao, G., & Xiao, H. (2022). Heterogeneous spatial effects of FDI on CO_2 emissions in China. *Earth's Future*, *10*, e2021EF002331. https://doi.org/10.1029/2021EF002331

Received 20 JUL 2021
Accepted 28 DEC 2021

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Heterogeneous Spatial Effects of FDI on CO_2 Emissions in China

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Abstract As the world's largest CO_2 emitter, China's emission reduction is the key to mitigating global climate change. Global investment capital, as a significant influencing factor of emissions, greatly contributes to China's economic growth and stimulates frequent interprovincial trade since the reform and opening. However, the spatial correlation of foreign investment and CO_2 emissions across Chinese provinces is rarely considered. This paper explores the role of foreign direct investment (FDI) in emission reduction in China during 2004–2015 using the spatial Durbin economic models with two-way fixed effects. Then, the partial differential equations decomposition of the local and spatial spillover effects is conducted for capturing the marginal effects of influencing factors. Results show that FDI contributes to emission reduction for the whole country, whereas interprovincial transmission and intra-provincial transmission show significant heterogeneity. Specifically, FDI increases emissions in host areas, while FDI provides positive environmental externalities to adjacent areas through spatial spillovers. Our findings provide a new perspective to explain the coexistence of the "Pollution Haven" and "Pollution Halo" theories in a country. Also, the exploration of spatial spillover effects of FDI on emissions can provide a reference for other countries with rising trade and investment flows to promote collaborative emission reduction.

1. Introduction

Global climate change has far-reaching impacts on human societies and environment, such as more frequent extreme weathers, rising sea levels, and reductions in agricultural production (Diaz & Moore, 2017; Manoli et al., 2016; Xiao, Zhao, et al., 2021; Xiao, Zhou, et al., 2021). According to the World Bank, in 2019, CO_2 emissions in China exceeded 10,200 Mt, which constituted 27.9% of total emissions in the world (World Bank, 2015). As the largest CO_2 emitter of the world, China's efforts in reducing emissions play a critical role in mitigating global climate change and its negative impacts (Guan et al., 2021). China highlighted its emission peak and neutrality resolutions at the Climate Ambition Summit and aimed to peak CO_2 emissions before 2030 and achieved carbon neutrality before 2060 (Xiao, Zhao, et al., 2021; Xiao, Zhou, et al., 2021). One reason for the increasing CO_2 emissions of China can be the rapid economic development since the reform and opening up in 1978. After that, an increasing amount of global investment capital inflow to China, which become one of the key factors for Chinese economic growth. According to the United Nations Conference on Trade and Development's report on Investment Trends and Policies Monitors, China has become the world's largest recipient of foreign direct investment (FDI) since 2014 and surpassed the United States for the first time since 2003 (United Nations, 2015). However, with the rapid economic growth benefited from FDI, China's environmental change problem has become increasingly concerning (Pan et al., 2017; Wu et al., 2018). Therefore, as China continues to attract global investment, exploring the impacts caused by FDI, an important driving factor for economic growth, on CO_2 emissions will be of great significance to mitigate global climate change.

The "Pollution Haven" and "Pollution Halo" are two contradictory hypotheses that are used to explain the impacts of FDI on the environment. "Pollution Haven" hypothesis believes that due to the close correlation between a country's per capita income and environmental stringency, openness is also a good opportunity for developed countries to migrate high-carbon industries to other countries (usually, developing countries, such as China), and therefore lead to more serious pollution in developing areas (Mody et al., 1995). On the contrary, the "Pollution Halo" theory suggests that the foreign capitals bring advanced technology to the host country, making related production processes cleaner, and further improve environmental quality (Zarsky, 1999). The empirical findings of FDI on emission reduction differ significantly by area and time even from the same perspective; and even within the same country or the same period, the findings can differ at each level. For example, findings from Lee and Yu (2012), Liu, Hao, and Gao (2017), and Nasir et al. (2019) support the "Pollution Haven" hypothesis, while some studies argue that multinationals engaging in FDI can contribute to a reduction in local CO_2 emissions by bringing advanced technologies to the host countries (Xu et al., 2019; Zhu et al., 2016). Indeed, there is no consensus on whether the direct impact of FDI on CO_2 emissions is in line with the "Pollution Haven" hypothesis or the "Pollution Halo" hypothesis (Xie et al., 2020). In general, previous studies are generally in favor of the "Pollution Haven" hypothesis, or "Pollution Halo," or neither of them. However, whether these two hypotheses can exist simultaneously in a country is still unknown, which sets barriers for better understand the role of FDI in mitigating the CO_2 emissions of China.

Apart from the controversial impacts of FDI on CO_2 emissions, the existing studies are mainly conducted the empirical studies of FDI on emissions by treating the research economy independently (Sung et al., 2018). However, previous studies have suggested that there is frequent trade across China's regions and the foreign investment in local areas can be associated with the neighboring areas by labor, energy, technology, and capital flows (Xie et al., 2020; Zhang et al., 2018). Few studies explored the spatial spillover effects of FDI on CO_2 emissions across Chinese provinces. Ignoring the spatial correlation of FDI and CO_2 emissions would lead to a biased estimation of the impact of FDI on CO_2 emissions, which is not beneficial for promoting collaborative emission reduction.

To fill these two gaps, this study first explores the spatial spillover effects of FDI on shaping the emission patterns of Chinese provinces from 2004 to 2015 based on spatial econometric methods. Then, the partial differential equations (P.D.E.) decomposition is applied to yield the local effects, spatial spillover effects, and total effects of variables. The decomposition results not only highlight the spatial externalities of FDI on CO_2 emissions across Chinese provinces but provide a new perspective to explain potential coexistence of "Pollution Haven" and "Pollution Halo" hypothesis. Many pollutants may be associated with FDI, and different industries' production activities generate different pollutants. Our proposed research framework can be applicable to study the local and spatial spillover effects of FDI on other pollutants. Also, our results provide a basis for other countries with increasing trade and investment flows to promote interactive policy making across regions to reduce emissions.

2. Literature Review and Related Hypotheses

2.1. Literature Review

The empirical literature focusing on the relationship between FDI and CO_2 emissions can be grouped into two classes: micro-level studies and macro-level studies. The former usually utilize industrial-level or firm-level panel data, and the latter often use time-series data. Based on the empirical findings of FDI on emissions, some support "Pollution Haven" theory, while others support "Pollution Halo," and the rest indicates that the role of FDI in CO_2 emissions is still unclear.

At the macro level (country level), there are studies that in favor "Pollution Haven" hypothesis, or "Pollution Halo," or neither of them. Using multivariable time series analysis methods, such as Autoregressive Distributed Lagged (ARDL) analysis, Vector Error Correction Model (VECM)-cointegration method, and Granger causality test, the "Pollution Haven" hypothesis was verified in many developed countries (Hoffmann et al., 2005, Jorgenson, 2009; Xing & Kolstad, 2002), BRIC countries (Brazil, Russia, India, and China; Pao & Tsai, 2011; Zakarya et al., 2015), Middle East (Al-Mulali & Sab, 2012), the Gulf Cooperation Council countries (Al-Mulali & Tang, 2013), Malaysia (Lau et al., 2014), Turkey (Seker et al., 2015), Ghana (Solarin et al., 2017), South and Southeast Asian (Behera & Dash, 2017), France (Shahbaz et al., 2018), and China (Zhang & Zhang, 2018). In contrast, there are researches outlined negative relationships between FDI and CO_2 emissions in many countries, such as ASEAN five countries (Chandran et al., 2013; Zhu et al., 2016), Vietnam (Tang & Tan, 2015), China (Zhang & Zhou, 2016), Tunisia and Morocco (Hakimi & Hamdi, 2016), and several developing and developed countries (Amri, 2016). Besides, there is study that neither supports the "Pollution Haven" theory nor the "Pollution Halo" theory. Using cointegration theory and Granger causality test, Zhang (2011) found that the environmental influence of FDI is limited in China.

At the micro level (industrial or firm-level), researchers focus on the environmental effects of FDI within a country using panel data. Some researchers' opinions coincide with the "Pollution Haven" theory, attributing FDI inflows as one of the driving factors of carbon transformation. Using city-level panel data, Lan et al. (2012)

established fixed and random effects panel data models, and find that CO_2 emissions is positively related to FDI in low human capital cities. Ren et al. (2014) estimated the impacts of FDI and other openness factors on CO_2 emissions through two-step GMM, and the result suggested that large FDI inflows had made the environment worse in China. Zhou et al. (2018) confirmed that FDI played a negative role in environmental quality in China. Besides China, positive relationships between FDI and air pollutions were also evidenced in Mexico (Waldkirch & Gopinath, 2004) and South Korea (Chung, 2014). On the contrary, a considerable number of scholars hold optimistic attitudes toward FDI and regarded it as environmental-friendly, which coincided with the "Pollution Halo" theory. Zheng et al. (2010) found that FDI reduced air pollutions using panel OLS model. Zhang and Zhou (2016) applied the STIRPAT model, and evidenced that FDI was an important contributor in CO_2 emission reduction in China. Jiang et al. (2018) analyzed the cross-border renewable energy intensity convergence in China and believed that more FDI inflows led to lower CO_2 emissions because of technology transfer and knowledge spillovers. Different from those above results which have clear conclusions, there is an empirical study finding that FDI's role is unclear. Liu et al. (2018) extended FDI's impact from CO_2 emissions to a wide range of environmental pollution, and revealed that FDI inflows had distinct effects on different pollutants, and it was hard to say the exact influence of FDI on the environment.

The above evidence does provide us with a valuable basis for further research on the relationship between FDI and CO_2 emissions. Nevertheless, there are limitations of them: (1) the controversial roles of FDI in emission reduction presented by existing studies make the role of FDI in mitigating the CO_2 emissions of China unclear. Whether these two hypotheses can exist simultaneously in a country is still unknown; (2) as reviewed, most of the existing studies primarily conducted the empirical studies of FDI on emissions by treating the country, industry, or firms independently, and very few studies have pay attention to the spatial feature (Chuai et al., 2012; Huang et al., 2009; Wang & Teng, 2013). To fill these two gaps, we examined the possibility of co-existence of "Pollution Halo" and "Pollution Haven" in China. Also, the spatial spillover effects of FDI on shaping the emission patterns across Chinese provinces using spatial econometric tools were investigated (Anselin, 2013; LeSage & Pace, 2010).

2.2. Literature Review and Research Hypotheses

Hypothesis 1. *FDI has significant impacts on CO_2 emissions in both local regions and neighboring regions, but the directions of effects are opposite.*

As reviewed in Section 2.1, the role of FDI in emission reduction is debatable. Both positive and negative relationships between FDI and CO_2 emissions are empirically evidenced. Regarding the controversy toward FDI's impact on environment, we intuitively assume that the opposite roles of FDI can be found at different spatial levels, that is, the local effect and spatial spillover effect of FDI are both significant but opposite in sign.

Hypothesis 2. *At the nationwide level, FDI reduces CO_2 emissions.*

As reviewed in Section 2.1, at the macro level, both positive and negative impacts of FDI are found in the literature. Therefore, without loss of generality, we assume that FDI for the whole country will help reduce CO_2 emissions. It should be noted that this hypothesis is not a statistical null hypothesis, but just a value-neutral hypothesis. We do not have any expectations for the impact of FDI's in total effect. In the model, the (statistical) null hypothesis for the coefficient of FDI is that "FDI does not affect CO_2 emissions." If the coefficient of FDI is significantly negative in the empirical results, FDI is considered to reduce emissions; if it is significantly positive, FDI is considered to increase emissions.

3. Methodology and Data

3.1. Variables and Data

Provincial panel data of China from 2004 to 2015 is used for empirical analysis. The variables description and data sources are listed in Table 1. The dependent variable is the CO_2 emissions in 30 provinces of China from 2004 to 2015, as is constructed by Shan et al. (2018). This dataset excludes Taiwan, Hong Kong, Macao, and Tibet due to the lack of CO_2 emissions data.

Table 1
Descriptions of the Variables

Variables	Definition	Unit	Data sources	Related studies
Total CO_2 emissions	Energy-related (17 fossil fuels in 47 sectors) and process-related emissions (cement production) CO_2 emissions	Mt	Shan et al. (2018)	
Foreign direct investment (FDI)	Total investment of foreign-invested enterprises	Million US dollars	NBSC	Jiang et al. (2018) and Shahzad et al. (2020)
Population (P)	Population at the end of year	10,000 people	NBSC	Wang et al. (2012), Zhang and Lin (2012), Zhang and Zhou (2016), Bhattacharya et al. (2017), Liu et al. (2018), Yang et al. (2018), Vélez-Henao et al. (2019), and Miao et al. (2019)
Trade openness (Trade)	The sum of imports and exports within given regions	Thousand US dollars	General Administration of Customs, China	Zhang et al. (2018), Doğan et al. (2019), Ahmad and Khattak (2020), and Shahzad et al. (2020)
Economic level (GDP) and its square value	GDP per capita	RMB	NBSC	Grossman and Krueger (1991), Holtz-Eakin and Selden (1995), Cole et al. (1997), Cole (2003), Liu, Xiao, et al. (2017), Jiang et al. (2018), Doğan et al. (2019), Neagu (2019), Arminen and Menegaki (2019), and Ahmad and Khattak (2020)
Renewable energy intensity (REI)	Renewable energy use divided by GDP	kg/RMB	Calculated using data from China Energy Statistical Yearbook and NBSC	Bhattacharya et al. (2017), Neagu and Teodoru (2019), and Shahzad et al. (2020)
Energy structure (ES)	The share of coal consumption in total energy consumption	%	Calculated using data from China Energy Statistical Yearbook	Liu, Xiao, et al. (2017), Wu et al. (2018), Zheng et al. (2019)
Share of services sector (SV)	The share of the service sector value added in GDP	%	Calculated using data from NBSC	Liu, Xiao, et al. (2017), Jiang et al. (2018), Wang et al. (2019), Ma and Cai (2019)
Share of industry sector (IND)	The share of the industry sector value added in GDP	%	Calculated using data from NBSC	Poon et al. (2006), He (2009, 2010), Lu et al. (2017), Du et al. (2018), Zhang et al. (2018)
R&D expenditure (RD)	R&D expenditure for industrial enterprises above designated size	10 thousand RMB	NBSC	Fernández et al. (2018), Churchill et al. (2019), Petrović and Lobanov (2020), and Ahmad and Khattak (2020)
Human capital (HC)	Human capital level per capita of each province		Yuan and Zhao (2020)	Liu, Xiao, et al. (2017), Bano et al. (2018), Yao et al. (2020, 2021)

The main independent variable of interest is Foreign direct investment (FDI). As reviewed in Section 2.1, the role of FDI in emission reduction is still unclear, and thus we proposed two related hypotheses regarding the impact(s) of FDI on CO_2 emissions (see Section 2.2). We expect that the undecided empirical results of FDI in existing literature can be further evidenced and better interpreted from a spatial econometric perspective in this study. The FDI data utilized in this paper is from the National Bureau of Statistics of China (NBSC).

Motivated by the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model which serves as the benchmark regression framework (see Section 3.2.1), the following control variables are included: Population (P), Export and Import (TRADE), Economic growth (GDP) and its quadratic term, Renewable Energy Intensity (REI), Energy Structure (ES), Share of services sector (SV), Share of industry sector (IND), R&D expenditure (R&D), and Human Capital (HC). It is evidenced in the existing literature that the chosen variables play important roles in affecting emission reduction, and thus should be considered as control variables.

Population (P). In both the benchmark STIRPAT model (Dietz & Rosa, 1997) and the extended STIRPAT model (York et al., 2002), population size is one of the driving factors for environmental pollution. Besides, it has been evidenced in empirical studies (Miao et al., 2019; Wang et al., 2012; Zhang & Lin, 2012) that population size is positively correlated with air pollution.

Trade openness (TRADE). According to Doğan et al. (2019), trade openness increases the demand for eco-friendly products with higher quality and enables new technology transfer to countries. Due to the new technology transfers, CO_2 emissions can be reduced. Lots of studies evidenced similar results (Ahmad & Khattak, 2020; Shahzad et al., 2020; Zhang et al., 2018).

Economic growth (GDP) and Its quadratic term. In this paper, we use per capita gross domestic product (GDP) as a measure of economic growth. These terms are included in the independent variables to examine the environmental Kuznets curve (EKC) hypothesis (Grossman & Krueger, 1991; Selden & Song, 1994). See Holtz-Eakin and Selden (1995), Neagu (2019), and Arminen and Menegaki (2019) for more related empirical studies.

Renewable energy intensity (REI). It has been found that renewable energy utilization has an essential impact on air pollutions (Bhattacharya et al., 2017; Neagu & Teodoru, 2019; Shahzad et al., 2020). In this sense, the renewable energy intensity indicator in this paper is calculated by renewable energy consumption divided by GDP. Even energy consumption is related to CO_2 emissions by construction, however, directly using energy consumption as a molecular to compute energy intensity could have adverse consequences for econometric estimation in related contexts (Burnett et al., 2013; Itkonen, 2012; Jaforullah & King, 2017). Therefore, to avoid misleading econometric specifications, we use renewable energy consumption instead. The data of renewable energy consumption is from the China Energy Statistical Yearbook, and the data of GDP is from NBSC.

Energy structure (ES). Energy consumption structure is one of the driving forces for CO_2 emissions (Liu, Xiao, et al., 2017; Wu et al., 2016; Zheng et al., 2019). In this paper, energy structure is calculated based on the share of coal consumption in total energy consumption. Referring to Liu, Xiao, et al. (2017), energy consumption is made up of coal, coke, crude oil, petrol, kerosene, diesel, fuel oil, and natural gas; all of these energy products are converted into standard coal according to their conversion coefficients (0.7476, 0.9714, 1.4286, 1.4714, 1.4714, 1.4571, 1.4286, 13) given by Song and Guan (2015).

Share of service sector (SV). The role of the service sector in emission reduction is still ambiguous (Jiang et al., 2018; Ma & Cai, 2019; Wang et al., 2019). Liu, Xiao, et al. (2017) find a positive relationship between the proportion of tertiary industry and energy consumption in China, thereby leading to a positive linkage between the share of service sector and environmental pollutions.

Share of industry sector (IND). Industrial activities are one of the most important sources of air pollution in China (Du et al., 2018; He, 2009, 2010). The greater the proportion of the industrial sector in economic development, the higher the energy consumption, which in turn generates more pollution (Liu, Xiao, et al., 2017; Poon et al., 2006; Zhang et al., 2018).

R&D expenditure (RD). There are several studies in different countries over varying periods indicating that innovation plays a crucial role in the reducing CO_2 emissions (Churchill et al., 2019; Fernández et al., 2018; Petrović & Lobanov, 2020).

Human capital (HC). Educational level (human capital) is one of the important technical factors that can reduce emissions. Citizens with a higher level of education prefer the protection of the environment and try harder to save energy. They are more likely to apply this concept in their daily lives to reduce established energy consumption (Liu, Xiao, et al., 2017). Apart from the micro level, the role of human capital in emission reduction is also evidenced from a macro level (Bano et al., 2018; Yao et al., 2020, 2021). In this paper, we use the per capita human capital level of each province to measure human capital, with its data calculated by Yuan and Zhao (2020).

All nominal variables have been adjusted to remove the effects of inflation using CPI and PPI data from NBSC. The descriptive statistics for variables after taking logarithm are reported in Table A1.

Figure 1 displays the spatial distribution of CO_2 emissions and FDI inflow in the starting and ending years of our research. It can be seen from the coloring map that the amount of CO_2 emissions and FDI have significant spatial differences and agglomeration. For CO_2 emissions, most provinces in China had increased a lot from 2004 to 2015. The eastern China emitted much more than other areas in 2004, while 12 years later central and northeast regions contributed considerably higher emissions. For FDI, a "staircase" distribution is outlined: eastern China attracted the maximum FDI, followed by the central and western regions. During the sample period, the central region used more foreign capitals and developed relatively fast, whereas the staircase shape did not change. The above intuitive findings help to grasp the spatial distribution characteristics of the explained variables and variables of interest in this paper, and provide a basis for our economic modeling.

3.2. The Models

There are three steps of the modeling procedure. First, traditional OLS regressions are used to examine the overall effects of variables. In this step, the regression is based on the extended Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model, which will be introduced in Section 3.2.1. Second, based on the STIRPAT results, we establish spatial econometric models for further investigating the spatial effects of variables. Three alternative spatial econometric models are introduced in Section 3.2.2.1, with the model selection procedure given in Section 3.2.2.2. Third, because the coefficients of spatial models cannot reflect the marginal effects of variables (LeSage & Pace, 2010), this paper further adopts the P.D.E. approach to decompose the local, spatial spillover, and total effects for each independent variable. The P.D.E. method is introduced in Section 3.2.3.

3.2.1. The Extended STIRPAT Model

The first step of the modeling process is to analyze the overall contributions of various driving forces via a traditional panel data regression model. In environmental studies, the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model developed by Dietz and Rosa (1997) provides a theoretical basis for related research and is thus very widely used in environmental issues such as Zhang and Zhou (2016), Yang et al. (2018), and Vélez-Henao et al. (2019). The basic STIRPAT for cross-sectional setting is:

$$I_i = aP_i^b A_i^c T_i^d e_i \tag{1}$$

where i stands for the ith region (or provincial area, in this study); I, P, A, and T represent environmental impact, population, affluence, and technology, respectively; e_i is the error term.

For panel data, Equation 1 can be extended into:

$$I_{it} = aP_{it}^b A_{it}^c T_{it}^d e_{it} \tag{2}$$

where t represents time (year, in this study); a is a constant term; b, c, and, d represent coefficients that determine the effects of P, A, and T, respectively; and e_{it} is the error term.

The parameters a, b, c, and d can be estimated via OLS in a linear form by taking logarithms toward Equation 2, that is:

$$\ln I_{it} = a + b(\ln P_{it}) + c(\ln A_{it}) + d(\ln T_{it}) + e_{it}. \tag{3}$$

Equation 3 is the benchmark traditional regression used in the first step of our empirical analysis. The best way to understand this model is that it should be regarded as a framework indicating three dimensions contributing to environmental factors, and therefore one can incorporate more variables to refine the three dimensions represented by the letters P, A, and T in Equation 3 (York et al., 2002).

Based on York et al. (2002), Equation 3 can be extended into Equation 4 by including more independent variables shown in Table 1, as follows:

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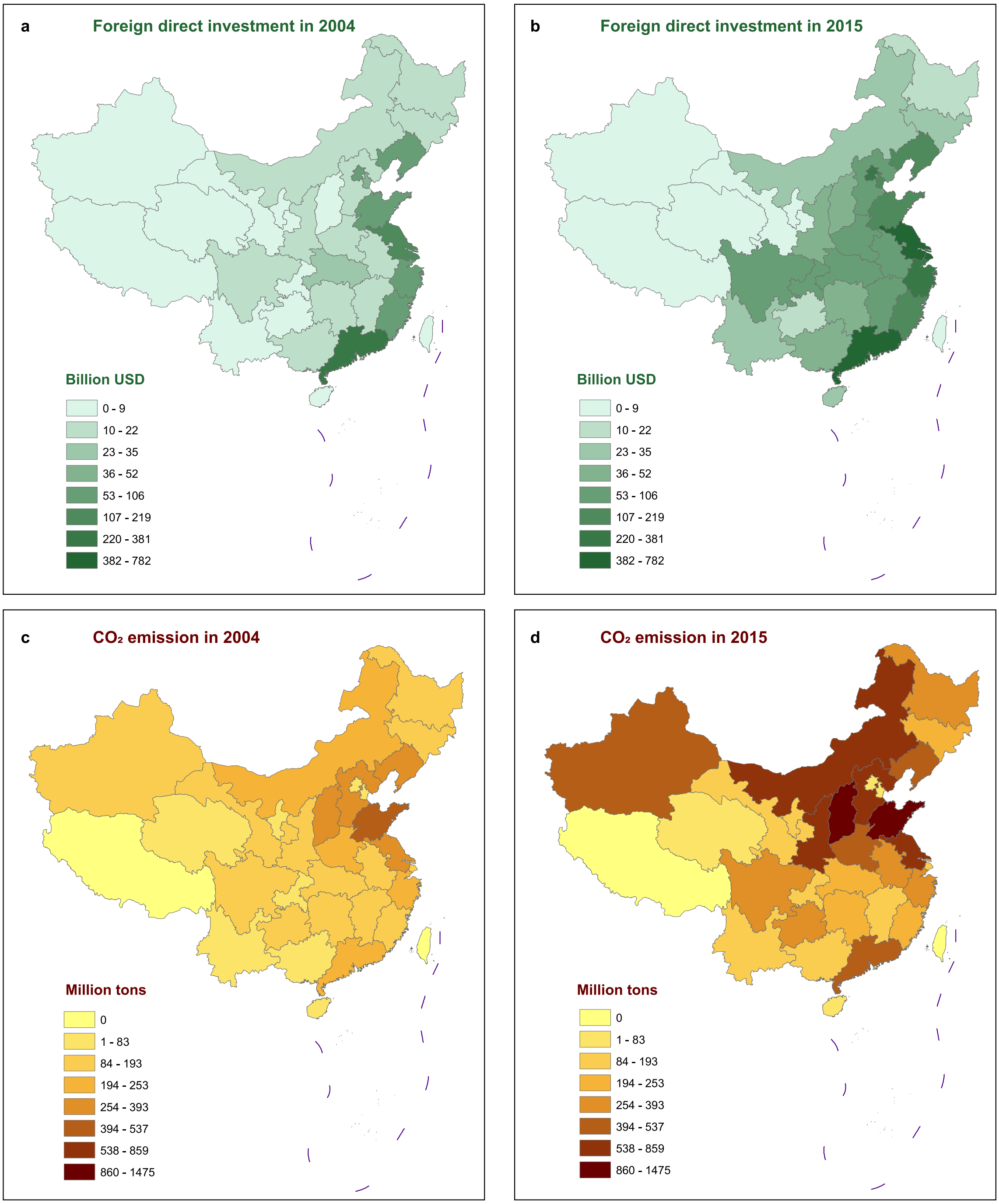

Figure 1. Spatial distribution of CO_2 emissions and foreign direct investment (FDI) in China.

$$\begin{aligned}\ln CO_{2it} = {} & a + b(\ln P_{it}) + c_1(\ln FDI_{it}) + c_2(\ln XM_{it}) + c_3(\ln GDP_{it}) + c_4(\ln GDP_{it})^2 \\ & + d_1(\ln REI_{it}) + d_2(\ln ES_{it}) + d_3(\ln SV_{it}) + d_4(\ln IND_{it}) + d_5(\ln RD_{it}) + d_6(\ln HC_{it}) + e_{it}. \end{aligned} \quad (4)$$

For dimension *I,* the environmental effect is defined as total CO_2 emissions of 30 provincial regions in China (Taiwan, Hong Kong, Macao, and Tibet are excluded due to the lack of data in these areas). The reasons for variable selection and related studies are introduced in Section 3.1.

3.2.2. The Spatial Econometric Methods

3.2.2.1. The Spatial Models

Based on the benchmark STIRPAT model, this paper further utilizes spatial econometric models to illustrate the local and spatial spillover effects of the independent variables. In literature, there are specifications for spatial panel models: the Spatial Autoregressive Model (SAR), the Spatial Error Model (SEM) and the Spatial Durbin Model (SDM), corresponding to different spatial interactions (Elhorst, 2014).

The first alternative model in this paper is SAR, which focuses on the modeling of the spatial lag of dependent variables. The panel SAR is expressed as:

$$Y_t = \rho W Y_t + X_t \beta + \alpha l_N + \mu + \eta_t l_N + \varepsilon_t \tag{5}$$

$$W_{ij} = \begin{cases} 1, & if\ i\ and\ j\ are\ adjunct \\ 0, & otherwise \end{cases} \tag{6}$$

where the subscript t represents time, N denotes the total number of regions, $\mathbf{Y}_t$ is an $N \times 1$ vector of the dependent variable, and $\mathbf{X}_t$ is an $N \times K$ matrix of independent variables given by the STIRPAT model in Equation 4. The error term ε_t is an $N \times 1$ vector where every element $\varepsilon_{it} \sim i.i.d \ \ N(0, \sigma^2)$. β is a $K \times 1$ coefficients vector. ρ stands for the spatial autoregressive coefficient indicating the spatial lag interaction. $\mathbf{l}_N$ means an $N \times 1$ vector with each entry equals to one. The $N \times 1$ vector $\boldsymbol{\mu}$ and the scalar η_t stand for spatial fixed effects and time fixed effects respectively. α is the intercept term. $\mathbf{W}$ is an $N \times N$ row-standardized spatial weight matrix that each element is defined as Equation 6 (In this paper, independent variables such as FDI, industrial structure, human capital, energy structure, and R&D are more affected by political and economic factors rather than physical geographic factors. Therefore, the 0–1 spatial weight matrix that involves administrative divisions is more applicable to this study). $\mathbf{WY}_t$ stands for the spatial lag of the dependent variable, that is, the endogenous interaction among dependent variables.

The second alternative model in this paper is SEM, which can be written as:

$$\boldsymbol{Y}_t = \boldsymbol{X}_t \boldsymbol{\beta} + \alpha \boldsymbol{l}_N + \boldsymbol{\mu} + \eta_t \boldsymbol{l}_N + \boldsymbol{u}_t \tag{7.1}$$

$$\boldsymbol{u}_t = \lambda \boldsymbol{W} \boldsymbol{u}_t + \boldsymbol{\varepsilon}_t \tag{7.2}$$

The SEM is based on such a modeling principle: besides independent variables, the dependent variable is also related to factors that are not included in the model (unobservable or unmeasurable factors), and those missing variables are spatially auto-correlated. As is put in Equations 7.1 and 7.2, λ represents the spatial autocorrelation coefficient, which indicates the interaction effects over error terms. $\mathbf{W}\boldsymbol{u}_t$ stands for the spatial lag of the error term. The error terms of Equation 7.2 ε_t is an $N \times 1$ vector where every entry $\varepsilon_{it} \sim i.i.d \ \ N(0, \sigma^2)$. The rest of the notations share the same meaning with SAR.

The third alternative model SDM includes both the spatial lag of the dependent variable (endogenous interaction effect) and independent or explanatory variables (exogenous interaction effect), and it can be expressed as:

$$\boldsymbol{Y}_t = \rho \boldsymbol{W} \boldsymbol{Y}_t + \boldsymbol{X}_t \boldsymbol{\beta} + W \boldsymbol{X}_t \boldsymbol{\theta} + \alpha \boldsymbol{l}_N + \boldsymbol{\mu} + \eta_t \boldsymbol{l}_N + \boldsymbol{\varepsilon}_t \tag{8}$$

where the parameter θ is a $K \times 1$ vector indicating the impact of peripheral independent variables on the local dependent variable. $\mathbf{WX}_t$ stands for the spatial lag of the independent variables, or the exogenous interactions among independent variables. The rest of the notations share the same meaning with SAR and SEM.

3.2.2.2. The Model Selection Procedure

According to Elhorst (2014), there are four steps for spatial model specification, that is, to make choices: (1) among different types (s) of fixed effects (spatial, time, or two-way); (2) between spatial models and non-spatial models; (3) between random effect and fixed effect; and (4) among different type(s) of spatial interaction effects (spatial lag, spatial error, or both).

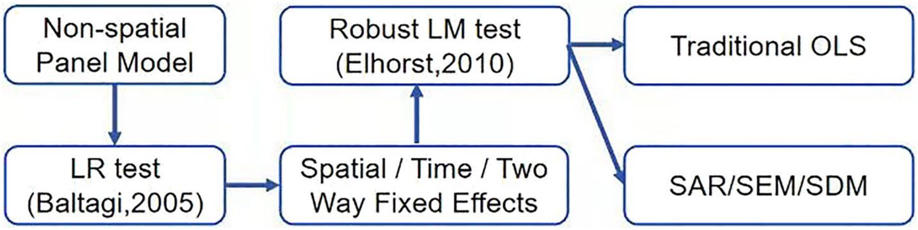

Figure 2. Model selection between traditional OLS and spatial models.

Based on the model selection procedure proposed by Elhorst (2014), this paper starts with the non-spatial OLS panel data regression. Then, the Likelihood Ratio (LR) tests are conducted to investigate which fixed-effect model fits the given data better (Baltagi, 2008). Based on that result, the robust Lagrange Multiplier (LM) tests are used to determine if the non-spatial model should be extended to a spatial econometric model (Elhorst, 2010). If the results of the LM tests suggest that the model should include spatial interaction(s), we then start from an SDM and use two Wald tests and two LR tests with null hypotheses ($H_0 : \theta = 0$) and ($H_0 : \theta + \rho\beta = 0$) to determine if the baseline SDM can be simplified to SAR or SEM (Burridge, 1981). For the choice between fixed effect and random effect, a Hausman test can be used (Lee & Yu, 2012). The above procedure can be summarized in two flow charts (see Figures 2 and 3) corresponding to the model specifications of non-spatial models and spatial models, respectively.

3.2.3. P.D.E. Decomposition for Local and Spatial Spillover Effects

Following Section 3.2.2, if SDM is eventually selected to be the best-fit model, one has to adopt the P.D.E. approach for further investigating the local (direct), spatial spillover (indirect), and total effects for the following two reasons.

First, different from traditional panel data models, the coefficients of SDM cannot represent the marginal effects of independent variables because both the spatial lags of dependent and independent variables coexist in the same model. For further investigating the marginal effects of each variable, it is necessary to adopt the P.D.E. approach (LeSage & Pace, 2010).

Second, the spatial econometric models can only offer either partial (the impacts of host or adjacent regions) or global (the impacts in terms of the whole country) results, but cannot provide both partial and overall impacts simultaneously. In this sense, P.D. E. decomposition can be applied to yield local effects, spatial spillover effects, as well as total effects at the same time.

According to LeSage and Pace (2010), Equation 8 can be rearranged as:

$$Y_t = (I - \rho W)^{-1}(\beta X_t + W X_t \theta) + (I - \rho W)^{-1}\varepsilon_t^* \tag{9}$$

ε_t^* is the new error term including fixed effects and ε_t in Equation 8. Deriving the **k**-th explanatory variable simultaneously on both the left and right sides of Equation 9, we have:

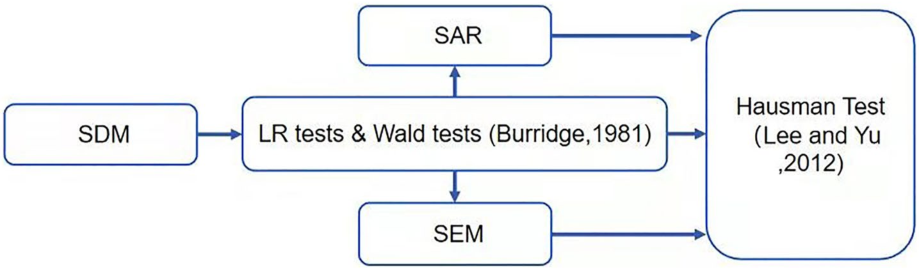

Figure 3. Model specification procedures among spatial panel models.

$$\begin{bmatrix} \frac{\partial Y}{\partial X_{1K}} & \cdots & \frac{\partial Y}{\partial X_{NK}} \end{bmatrix} = \begin{bmatrix} \frac{\partial Y_1}{\partial X_{1K}} & \cdots & \frac{\partial Y_1}{\partial X_{NK}} \\ \vdots & \ddots & \vdots \\ \frac{\partial Y_N}{\partial X_{1K}} & \cdots & \frac{\partial Y_N}{\partial X_{NK}} \end{bmatrix}$$

$$= (I - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & \cdots & w_{1N}\theta_k \\ w_{21}\theta_k & \beta_k & \cdots & w_{2N}\theta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}\theta_k & w_{N2}\theta_k & \dots & \beta_k \end{bmatrix} \tag{10}$$

The mean value of main diagonal elements in the right-hand matrix of Equation 9 is defined as the "local effect," or "direct effect," indicating the marginal effect of the **k**-th independent variable on the dependent variable within a region, which indicates to what extent local regions are influenced; the mean value of all the other elements is defined as "spatial spillover effect," or "indirect effect," reflecting the marginal effect of the **k**-th independent variable on the dependent variable in adjacent regions. The mean value of all elements of the matrix is defined as "total effect," which is equal to the sum of "local effect" and "spatial spillover effect" numerically.

All empirical processes in this paper can be done by using Matlab (Version R2017b), and the commands can be obtained from the package of LeSage (https://www.spatial-econometrics.com/) and Elhorst (https://spatial-panels.com/software/). The main code can be achieved by the script written by the authors of this paper.

4. Empirical Results

4.1. The Regression Models Results

Table 2displays the results of the traditional panel data regressions (the STIRPAT models) under different fixed effects settings, which provides a basic sketch of how FDI and other control variables affect CO_2 emissions without considering spatial effects. There are many consistent conclusions in the four regression results: population, energy structure, share of service sector, and share of industry sector are significantly positively correlated with CO_2 emissions; while R&D and human capital are significantly beneficial to emission reduction. The only variable that is significant but differs in sign among all alternative models is FDI. In pooled regression (Model 2-1) and time fixed-effect model (Model 2-3), FDI is negatively correlated with CO_2 emissions; while in spatial fixed-effect model (Model 2-2) and two-way fixed-effects model (Model 2-4), the sign of FDI is positive. In previous studies, some stated that FDI does provide cleaner productions (Jiang et al., 2018; Zhang & Zhou, 2016), some others found that FDI cannot reduce CO_2 emissions (Ren et al., 2014; Zhang & Zhang, 2018; Zhou et al., 2018), whereas several studies insisted that the role of FDI was unclear (Liu et al., 2018; Zhang, 2011). Our results also show the complexity of the role of FDI in emission reduction based on the traditional panel data regressions, and implies the need for further investigation. In this sense, if the complicated results on FDI can be integrated by using spatial methods, it will help navigate the complexity of the role of FDI in reducing emissions.

Based on the results of statistical tests in Table 2, two conclusions regarding model specification can be drawn. First, the two-way fixed-effects model (Model 2-4) outperforms the one-way fixed-effect models and the pooled model. According to the results of LR tests, the null hypotheses for "no spatial fixed effect" and "no time fixed effect" are rejected at 0.01 level and 0.05 level, respectively, which implies that both spatial and time fixed effects should be included in our model. That is, Model 2–4 outperforms others in terms of fixed-effect settings. Moreover, one additional piece of evidence for this conclusion is that the log-likelihood value of Model 2–4 is the largest among all alternative models. Second, the traditional non-spatial (the STIRPAT) model should be extended to a spatial panel data model. Given the answer to the first question, under the two-way fixed effects setting (Model 2–4), the robust LM tests for the spatial lag and the spatial error reject the null hypotheses at the significance level

Table 2
Empirical Results of Traditional Panel Data Models

Variables	Model 2-1 Pooled OLS	Model 2-2 OLS with spatial fixed effect	Model 2-3 OLS with time fixed effect	Model 2-4 OLS with spatial and time fixed effects
ln(P)	0.6776***	1.4636***	0.6829***	1.0904***
	(18.4216)	(5.5555)	(16.1984)	(3.6151)
ln(TRADE)	0.1431***	−0.0156	0.1505***	−0.0335
	(5.1696)	(−0.4576)	(5.0099)	(−0.9212)
ln(GDP)	0.2478	1.4224***	−0.0226	1.0648*
	(0.3705)	(2.8837)	(−0.0318)	(1.8995)
$[\ln(GDP)]^2$	0.0185	−0.0448*	0.0344	−0.0339
	(0.5562)	(−1.8371)	(0.9900)	(−1.4562)
ln(REI)	−0.0244	0.0082	−0.0323	0.0150
	(−0.5939)	(0.3613)	(−0.7844)	(0.6766)
ln(ES)	1.1244***	0.8992***	1.1400***	0.9050***
	(21.3516)	(13.9165)	(21.9044)	(13.5897)
ln(SV)	0.6549***	1.2657***	0.5176**	1.5084***
	(2.8596)	(4.6273)	(2.1302)	(5.2779)
ln(IND)	0.8604***	1.2083***	0.7683***	1.4691***
	(4.4242)	(4.4410)	(3.6026)	(5.0667)
ln(RD)	−0.2640***	−0.0730*	−0.2592***	−0.1054**
	(−5.3256)	(−1.6950)	(−5.1293)	(−2.2498)
ln(HC)	−1.6560**	−2.0440**	−1.7000**	−2.8094***
	(−2.1222)	(−2.2617)	(−2.0057)	(−2.6231)
ln(FDI)	−0.1250***	0.1221***	−0.1415***	0.1278***
	(−4.2868)	(3.6610)	(−4.6763)	(3.6634)
Intercept	−3.4016			
	(−1.0199)			
R^2	0.8944	0.8432	0.8831	0.4760
Adjusted R^2	0.8911	0.8387	0.8789	0.4610
FE R^2		0.9728	0.8977	0.9746
Sigma	0.0749	0.0192	0.0724	0.0180
Log-likelihood	−38.2134	206.0751	−32.5633	218.3234
LR-test joint significance spatial fixed effects	501.7734 ***			
LR-test joint significance time-period fixed effects	24.4965 **			
Robust LM test no spatial lag under two-ways fixed effects	5.4628 **			
Robust LM test no spatial error under two-ways fixed effects	7.0578 ***			

Note. *T* values are in parentheses. *Statistical significance at 10% level; **Statistical significance at 5% level; ***Statistical significance at 1% level.

of 0.05 and 0.01, respectively. These results indicate that the model should be extended into a spatial model by incorporating both spatial lag and spatial error.

Based on the model selection procedure in Figure 3, this paper examines whether SDM can be simplified to SAR or SEM via LR tests and Wald tests. The SDM estimation and related testing results are listed in Table 3.

The results of SDM under spatial fixed effect, time fixed effect, two-way fixed effects, and random effect are reported in Table 3, together with related testing results. According to those results, the two-way fixed effects

Table 3
Estimation and Tests Results of Spatial Durbin Panel Models

Variables	Model 3-1 Spatial Durbin Model (SDM) with spatial fixed effect	Model 3-2 SDM with time fixed effect	Model 3-3 SDM with spatial and time fixed effects	Model 3-4 SDM with random effect
ln(P)	0.5586	0.5352***	0.7274**	0.5839***
	(1.4811)	(10.9956)	(1.9749)	(7.8137)
ln(TRADE)	0.0029	0.2015***	−0.0175	0.0243
	(0.084)	(6.3264)	(−0.4776)	(0.7240)
ln(GDP)	1.0429*	−1.1817	1.4079**	0.3083
	(1.7193)	(−1.5993)	(2.3988)	(0.5912)
$[\ln(GDP)]^2$	−0.0337	0.0796**	−0.0501*	0.0056
	(−1.1959)	(2.2086)	(−1.8097)	(0.2197)
ln(REI)	0.0063	−0.0213	−0.0008	0.0063
	(0.3063)	(−0.5858)	(−0.0419)	(0.2743)
ln(ES)	0.8792***	1.0451***	0.8670***	0.8687***
	(13.7793)	(19.1050)	(13.9641)	(13.5839)
ln(SV)	1.2966***	0.3195	1.3360***	0.9859***
	(4.7662)	(1.2841)	(4.8953)	(3.6960)
ln(IND)	1.1851***	0.5323**	1.1337***	1.0509***
	(4.1691)	(2.3215)	(3.9415)	(4.1636)
ln(RD)	−0.0907**	−0.2254***	−0.0917**	−0.1037**
	(−2.1494)	(−4.7299)	(−2.0434)	(−2.3996)
ln(HC)	−0.6399	−0.2245	−0.6645	−0.1225
	(−0.562)	(−0.2707)	(−0.5817)	(−0.1093)
ln(FDI)	0.1279***	−0.0224	0.1360***	0.1308***
	(3.8451)	(−0.6020)	(4.0996)	(4.0243)
W*ln(P)	3.1296***	−0.2284*	2.6340***	0.1253
	(5.3256)	(−1.8164)	(4.0728)	(0.7320)
W*ln(TRADE)	−0.1025*	0.1055	−0.2130**	−0.1419**
	(−1.7192)	(1.3215)	(−2.5150)	(−2.4745)
W*ln(GDP)	3.4885***	−1.1170	4.2539***	−0.2405
	(3.4241)	(−0.8420)	(3.7765)	(−0.4275)
$W*[\ln(GDP)]^2$	−0.1563***	0.0391	−0.2063***	0.0213
	(−3.2673)	(0.6205)	(−3.8326)	(0.7686)
W*ln(REI)	−0.0929**	0.0229	−0.1078**	−0.0774
	(−2.1453)	(0.2830)	(−2.4542)	(−1.6108)
W*ln(ES)	0.3103**	0.4169**	0.5110***	0.1492
	(2.0066)	(2.4926)	(3.2475)	(0.9850)
W*ln(SV)	0.6065	0.2812	1.4504**	0.2847
	(1.1206)	(0.4527)	(2.1804)	(0.5706)
W*ln(IND)	−0.0611	0.9103	0.4782	0.1449
	(−0.0982)	(1.3678)	(0.6365)	(0.3012)
W*ln(RD)	−0.0171	−0.1548	−0.0118	0.0744
	(−0.2045)	(−1.3375)	(−0.0935)	(0.8447)

Table 3
Continued

Variables	Model 3-1 Spatial Durbin Model (SDM) with spatial fixed effect	Model 3-2 SDM with time fixed effect	Model 3-3 SDM with spatial and time fixed effects	Model 3-4 SDM with random effect
W*ln(HC)	−0.0349	4.6080**	−3.2921*	−0.2104
	(−0.0242)	(2.4606)	(−1.7466)	(−0.1421)
W*ln(FDI)	−0.3475***	−0.1183	−0.3499***	−0.1454**
	(−3.9042)	(−1.3574)	(−3.6309)	(−2.008)
Intercept		12.5020	−41.4702***	
		(1.6460)	(−4.9069)	
Rho	−0.1596**	−0.0842*	−0.1846**	−0.1276*
	(−1.9742)	(−1.6690)	(−2.0223)	(−1.8641)
R^2	0.9778	0.9222	0.9801	0.9718
Sigma	0.0152	0.0533	0.0136	0.0193
Log-likelihood	242.1074	15.7873	261.8158	143.6834
Wald test for no spatial lags		97.2746***		
LR test for no spatial lags		86.9805***		
Wald test for no spatial errors		95.3727***		
LR test for no spatial errors		84.4997***		
Hausman test (where random effects is preferred in H0)		51.8313***		

Note. T values are in parentheses. *Statistical significance at 10% level; **Statistical significance at 5% level; ***Statistical significance at 1% level.

SDM (Model 3-3) is the best-fitting model for our data, which can be justified and interpreted from the following two aspects.

First, given the setting of two-way fixed effects, the SDM cannot be simplified into SAR or SEM. Both LR tests and Wald tests suggest a rejection of H_0 for "no spatial lag" and "no spatial error," meaning that the spatial lags and spatial error do exist, and thus a reduction from SDM to a simpler model, such as SAR (which only incorporates spatial lags) or SEM (which only incorporates spatial errors), can loss illustrative meaning.

Second, the fixed-effects model outperforms the random effect model and one-way (only spatial or time) fixed-effect models in our study. The Hausman test result significantly rejects the null hypothesis at 0.01 level, which indicates that the fixed-effects model is better than the random effects model. Also, the two-way fixed-effects models yield greater R^2 and log-likelihood value than the random effect and one-way fixed-effect models, which provides in-sample hints that the two-way fixed-effects models fit the data better than other alternative models.

The two-way fixed effects SDM (Model 3-3) is eventually selected to be the best-fitting model means that: (1) each period and each area in our data set has its own feature, and thus one has to control both of these effects in order to investigate the spatial mechanism; (2) both direct and indirect channels work for the mechanism between carbon emission and its driven factors, and thus one must take the spatial lag of independent variables into consideration.

Compared with the traditional OLS regression (see Table 2), there are many new findings in the resulting two way-fixed effect SDM. First, the signs of population, energy structure, the share of service sector, and the share of industry sector are significantly positive; and RandD is significantly negative in sign. These results are consistent with Model 2–4. Second, the signs of the spatial lags of population, energy structure, and share of service sector are significantly positive; and the sign of the spatial lag of human capital is significantly negative. Third, the signs of ln(GDP) and W*ln(GDP) are significantly positive, while the signs of the squared value of GDP and its spatial lags are significantly negative (In Table 3, only when the spatial fixed effect is included in the model [Model 3-1 and Model 3-3], the spatial lag term of GDP is positively significant, while its squared term is negatively significant. Meanwhile, in the models without spatial fixed effects [Model 3-2 and Model 3–4], the Log-likelihood values

Table 4
Decompositions of the Local, Spatial Spillover, and Total Effects for All Variables

	Local effects		Spatial spillover effects		Total effects	
Variables	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
ln(P)	0.7003*	1.9281	2.3979***	3.8854	3.0982***	5.8774
ln(TRADE)	−0.0124	−0.3529	−0.1994**	−2.4915	−0.2117**	−2.2737
ln(GDP)	1.3590**	2.4346	3.8117***	3.6713	5.1707***	5.1352
$[\ln(GDP)]^2$	−0.0476*	−1.7888	−0.1868***	−3.7694	−0.2344***	−4.6347
ln(REI)	0.0013	0.0667	−0.0998**	−2.4341	−0.0985**	−2.1055
ln(ES)	0.8540***	13.5579	0.4119***	3.0470	1.266***	9.4021
ln(SV)	1.3136***	4.8265	1.2835**	2.0403	2.5971***	3.8108
ln(IND)	1.1320***	3.9577	0.4032	0.5763	1.5352**	1.9818
ln(RD)	−0.0921**	−2.1376	−0.0066	−0.0542	−0.0986	−0.7378
ln(HC)	−0.5793	−0.5064	−3.0669*	−1.6603	−3.6461**	−2.0263
ln(FDI)	0.1423***	4.2764	−0.3413***	−3.8932	−0.199**	−2.0982

Note. *Statistical significance at 10% level; ** Statistical significance at 5% level; ***Statistical significance at 1% level.

are much smaller than that of the models with spatial fixed effects [Model 3-1 and Model 3-3], meaning that the models without spatial fixed effects may not be appropriately specified. In other word, only when we run a "correct" model [the model with spatial fixed effect], can the EKC hypothesis be supported from the spatial perspective). Last but not least, ln(FDI) is significantly positive, while its spatial lags W*ln(FDI) is significantly negative.

Even though the above findings lay the foundation and offer important inspiration for the study, they may only provide a basic picture for the story. According to LeSage and Pace (2010), the coefficients of SDM can neither represent the marginal effects of independent variables nor can they yield the total effects. Therefore, one needs to further refer to the P.D.E. decomposition results for better understanding the roles of each driven factor in emission reduction in terms of their local effects, spatial spillover effects, and total effects.

4.2. The P.D.E. Decomposition Results

The direct (local) and indirect (spillover) effects are decomposed using P.D.E. Equation 10 and these results are shown in Table 4. FDI has significant impacts on CO_2 emissions in both local regions and neighboring regions, but the directions of effects are opposite (Table 4). The local effect of FDI is positive, while its spatial spillover effect is negative (Table 4). This result provides support for **Hypothesis 1**, and has important economic meanings: (1) from the local perspective, the positive direct effect means FDI increases emissions in host areas, which coincided with the "Pollution Haven" theory; (2) from the spatial spillover perspective, the negative indirect effect indicates that FDI will provide positive environmental externalities to neighboring areas and promote cleaner production, which is consistent with the "Pollution Halo" theory. The opposite signs in local and spatial spillover effects of FDI reconcile the controversy in existing research from a spatial perspective, which could be an increment of this paper. Based on the existing studies of FDI and CO_2 emissions, there could be some possible explanations (Pollution-Intensive Industry Transfer, Technology spillovers, and Industrial Agglomeration Effects) for the empirical results of the opposite local and spatial spillover effects for FDI, which will be discussed in Section 5. At the national level, the total effect of FDI is significantly negative, suggesting FDI can reduce emissions (Table 4). This result indicates that the spatial spillover effect dominates the local effect, and thus FDI reduces CO_2 emissions when considering the economy in each region as a whole. In this sense, our result does generally evidence the "Pollution Halo" theory for the whole country.

Table 4 also shows the signs of GDP and its squared value are in line with the environmental Kuznets curve (EKC) hypothesis. The EKC hypothesis implies an inverse U-shape curve between pollutions and per capita GDP (Grossman & Krueger, 1991; Selden & Song, 1995). In this study, the sign of ln(*GDP*) is significantly positive in local, spatial spillover, and total effects, while its quadratic term is significantly negative (Table 4). There are economic interpretations for these results: (1) the positive coefficients of ln(*GDP*) means that economic develop-

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ment is positively correlated with CO_2 emissions for both local and neighboring areas; and (2) the negative signs of the quadratic term indicate that the marginal effect of economic growth on CO_2 emission is diminishing. In this sense, our result provides evidence for the EKC hypothesis of China at both local and spatial spillover levels.

The determinants that increase emission include the share in coal consumption, population, and tertiary industrial structures in both local and adjacent areas. These results are consistent with some existing studies. To be specific, a larger share in coal consumption increases emissions in both local and adjacent regions, which is consistent with the empirical evidence of Liu, Xiao, et al. (2017), Wu et al. (2018), and Zheng et al. (2019). Agglomeration of the population can lead to higher emissions, which is consistent with many existing studies on population economics and regional economics (Bhattacharya et al., 2017; Vélez-Henao et al., 2019; Yang et al., 2018). For the positive local and spatial spillover effects of the development of service industry, they coincide with Lin and Zhang (2017), Liu, Xiao, et al. (2017), and Jiang et al. (2018). It can be interpreted that the efficiency of fuel consumption in China varies by region, and in most central and western regions, the fuel consumption in service sector is inefficient and therefore lead to high emissions (Lin & Zhang, 2017).

The factors that contribute to mitigating emission are the utilization of renewable energy in adjacent regions, trade openness in adjacent regions, human capital in adjacent areas, technological innovation in local regions, the share of secondary industry in local regions. For renewable energy intensity, it is an important factor for emission reduction in adjacent areas but has little impact on the FDI destination area, which is consistent with the existing evidence (Bhattacharya et al., 2017; Neagu & Teodoru, 2019; Shahzad et al., 2020) from a spatial perspective. In terms of trade openness, it can reduce emissions via spatial spillover channels, which is in line with Zhang et al. (2018), Doğan et al. (2019), and Shahzad et al. (2020). Also, human capital is one of the important factors that can reduce emissions via spatial spillover channels. Bano et al. (2018) and Yao et al. (2020) have outlined a positive relationship between education and emission reduction. It can be interpreted that citizens with a high level of education often want the protection of the environment and they try harder to save energy, and they are therefore more likely to apply this concept in their daily lives to reduce established energy consumption (Liu, Xiao, et al., 2017). For technological innovation, it has an important local effect for cleaner production, as many existing studies have found out (Ahmad & Khattak, 2020; Churchill et al., 2019; Petrović & Lobanov, 2020). As for the development of secondary industry, its positive local effect is consistent with some studies, such as Liu, Xiao, et al. (2017), Du et al. (2018), and Zhang et al. (2018).

Tables A2–A7 are used to demonstrate that the main results of this paper (that is, the conclusions drawn to the hypotheses proposed in Section 2.2) are robust to the reduction of variables expanded in the *T* dimension in the STIRPAT model. The results from Tables A2–A7 show that both local and spatial impacts of FDI on emissions have survived all robustness checks: in each Table, the local effect of FDI is significantly positive, while its spatial spillover effect and total effect are significantly negative, which means that **Hypothesis 1** and **Hypothesis 2** hold in these situations.

5. Discussion

This section discusses the potential mechanisms through which FDI affects CO_2 emissions in China. FDI will have a variety of impacts on the host economy and economies adjacent to it. The three main mechanisms are explained below.

5.1. Pollution-Intensive Industry Transfer

Pollution-Intensive Industry Transfer mechanism refers to the situation in which pollution-intensive FDI is more likely to be transferred from developed countries to developing countries. Many multinational corporations choose to locate their pollution-intensive industry or production stage in developing countries, such as China, due to high standards for cleaner production and stringent regulation in terms of environmental protection in their home country (Fu et al., 2021). In general, the existing literature documents a positive correlation between FDI and pollution across countries (Fu et al., 2021; Khan & Ozturk, 2020; Zhao et al., 2020). In addition, different regions in China are associated with different environmental regulation enforcements, which attract multinationals with more CO_2 emissions self-select into regions with weaker enforcements and softer punishments which includes new entries into these areas and transfers from other areas to these areas (An et al., 2021). This could explain the positive correlation between a region's FDI and its CO_2 emissions we find, that is, pollution heaven.

The position of China in the Global Value Chain could intensify the hypothesis of Pollution Haven we find. This is consistent with Hua et al. (2020) and Duan et al. (2021). Multinationals globally allocate their resources across countries, and they may invest in China to produce or assemble the components. These production-intensive-oriented FDI are mainly pollution-intensive, compared with more innovation-intensive tasks.

5.2. Technology Spillover

The technology spillover mechanism refers to the situation in which multinationals bring better technology to the local economy. This corresponds to the Pollution Halo hypothesis, which argues that foreign capital brings more advanced and cleaner technology to host countries and further improves the environment. Related discussions can be found in Ning et al. (2016), Wang et al. (2016), Luo et al. (2021) and Chen et al. (2022). An extensive body of research assesses the impact of competition from globalization on the productivity and organization of domestic firms, emphasizing the market reallocation or spillover effects of actual foreign competition. The pioneering work by Aitken and Harrison (1999) and Javorcik (2004), evaluates the effect of FDI on domestic firm productivity through productivity spillover. Specifically, Javorcik (2004) and many other papers show that multinational production generates positive spillovers via backward production linkage. Wang and Wang (2015) focus on China and they find that FDI can improve output, employment, and income in the local economy.

Our results also support that FDI could create greener production associated with more advanced technology, for regions that are closer to FDI destination regions. In other words, the technology spillovers of FDI contribute to emission reductions in FDI destinations and periphery areas.

5.3. Industrial Agglomeration Effects

Agglomeration mechanism refers to the situation in which multinational production emerges in clusters. Specifically, multinationals tend to locate themselves closer to other multinationals or domestic firms in the same or related industries to obtain better access to lower transport costs between input suppliers and final good producers, labor and capital-good market externalities, and technology diffusion, as is analyzed in detail in Head et al. (1999), Bobonis and Shatz (2007), and Alfaro and Chen (2014). The clustering of multinationals intensifies the production as well as CO_2 emissions in each region. On the one hand, active FDI tends to create huge demands of construction and transportation (Yang et al., 2021), which creates considerable emissions in the host area (the positive direct effect). On the other hand, the agglomeration of industries in a region will reduce the number of branches of industries (especially non-polluting enterprises) in non-agglomeration areas and thus promote cleaner production (the negative indirect effect). Regarding the agglomeration effects, one can refer to He and Mao (2020) and Pang et al. (2021) for further discussions.

The above three mechanisms could explain the different effects of FDI on CO_2 emissions. Pollution-Intensive Industry Transfer mechanism and Industrial Agglomeration Effects enhance the positive local effect, and Technology spillovers and Industrial Agglomeration Effect lead to a negative spatial spillover effect. The synthesized scheme makes our spatial empirical results reasonable: FDI can increase local CO_2 emissions (positive direct effect) and reduce CO_2 emissions in neighboring regions (negative indirect effect) simultaneously.

6. Conclusions, Implications, and Future Study

6.1. Conclusions

This paper aims to explore the role of FDI in emission reduction from a spatial perspective. Using the extended STIRPAT model and the spatial economic methods, this paper investigated the main drivers of CO_2 emissions in China over the period 2004–2015. Based on regression results, the PDE decomposition was utilized to investigate the local (direct) effects, spatial spillover (indirect) effects, and total effects of variables. The main findings are as follows: (1) the local effect of FDI is positive, indicating that more FDI in the host region will lead to an increase in CO_2 emissions in this area; (2) the spatial spillover effect of FDI is negative, suggesting that FDI will provide positive environmental externalities to adjacent regions and promote cleaner production; (3) in terms of the whole country, FDI can reduce CO_2 emissions; (4) the EKC hypothesis is supported from the local, spatial, and country levels; (5) a larger share in coal consumption can increase emissions in both local and adjacent regions.

Three mechanisms are proposed to explain the empirical findings of FDI. (1) Pollution-Intensive Industry Transfer: Multinational corporations from developed countries choose to locate their pollution-intensive industry or production stage in China, which increases CO_2 emissions in the FDI destination. (2) Technology Spillover: Multinationals bring better technology and generate positive spillover to domestic firms. The technology spillovers of FDI contribute to emission reductions in FDI destinations and periphery areas. (3) Industrial Agglomeration Effects: The clustering of multinationals intensifies the production as well as CO_2 emissions in each region but reduces the emissions in the whole country.

6.2. Policy Implications

Since China became the world's largest carbon dioxide emitter in 2006, its efforts to address climate change have received widespread attention. As China has pledged to achieve carbon peak by 2035 and carbon neutrality by 2060, the findings of this paper can contribute to achieving these goals of China effectively by considering the "trade-environment" linkage, thereby providing implications for solving the problem of global climate change.

First, environmental capacity should be considered by host counties when attracting foreign investments, which may offer a reversal mechanism for investor screening, thereby lowering the investment threshold for environmentally friendly multinational companies and leading to a much cleaner production globally. FDI has both significant local and spatial spillover effects and therefore policymakers should consider the environmental capacity of not only the target area but also the periphery regions. FDI deteriorates the local environment but brings technology spillover simultaneously; as such, it is better to guide foreign investments to areas with high environmental capacity. Thus, from a provincial perspective, it is suggested to introduce more FDI into areas where the environment is relatively strong (and the surrounding is relatively weaker) because those "high capacity" areas can "afford" negative environmental impact and simultaneously enjoy advanced technology. Meanwhile, from a nationwide perspective, the environmental capacity is supposed to be considered as a whole, so as to make it difficult for the entry of pollution producing enterprises, which can be seen as a global screening mechanism. Consequently, in the long run, they may be "compelled" to embrace a cleaner production.

Second, considering the fact that increasing greenhouse gases and climate warming are global issues, our findings imply the responsibility of foreign investors like China when being a foreign direct investor in other countries. In this sense, from the perspectives of global responsibility and the future of our earth, both local and spatial spillover effects of FDI are supposed to be taken into consideration of foreign investors. Specifically, as the initiator, advocate, and one of the most important participants of the "Belt and Road" Initiative, China is supposed to pay attention to environmental effects when investing in other countries. China is now playing the role of an important host country and rapidly developing home country simultaneously and can provide many experiences for emerging economies. If the CO_2 emissions in host countries are taken into consideration, it will contribute essentially to the "Green Economy" and global sustainable development.

Third, for the positive local effect, more efforts are supposed to be made to alleviate this impact, thereby contributing to the sustainable development of both the local economy as well as the whole earth. As FDI directly increases the CO_2 emissions in the local areas, the structure of FDI in China should be optimized in the long run. The government (especially local governments) can issue a variety of policies to promote clean technology research and development, such as reducing the tax burden of high-tech enterprises, encouraging investment in research and development and their equipment, encouraging the transformation of scientific and technological achievements. This policy implication may be especially applicable to some traditional energy-oriented regions.

6.3. Future Study

There are some limitations of this paper, which can be left for future empirical study.

First, in this paper, we do not analyze the effect of disaggregated industry-level FDI on CO_2 emissions. The emission patterns and production technology of different industries are heterogeneous. The future work could focus on how FDI of different industries affects CO_2 emissions. We could replicate our analysis using more disaggregated industry level or firm level FDI data to better evaluate their respective effect on emissions. Specific FDI policy recommendations can be provided with this result.

Second, in this paper, we mainly focus on the short-run effect. However, the effect of FDI on CO_2 emissions may take time to work and change over time. Therefore, the future studies may focus on how the effect of FDI on CO_2 emissions in the long run and how the spillover effects and correlations change over time. To further investigate the dynamic relationships among FDI, CO_2 emissions and other economic variables, time series analysis methods can be used, such as ARDL, BEKK, and GRACH-Copula approaches.

Third, in this paper, the regression model is based on three dimensions: Population (P), Affluence (A), and Technology (T). These three dimensions are treated equally in the regression. Nevertheless, in reality, the contributions of them may not be exactly the same. Thus, it would be interesting and of practical meaning to investigate: (1) what are the differences in the importance of the three dimensions in generating environmental pollution; and (2) how the relative propositions change over time. To address these issues, future study may utilize the max-linear competing factor model (see Cui & Zhang, 2018) and the max-linear regression model (see Cui et al., 2021).

Appendix:

Table A1
Descriptive Statistics of Variables

Variables	Obs	Mean	Std. Dev.	Min	Max
ln(CO_2)	360	5.3633	0.8291	1.7579	7.3485
ln(P)	360	8.1633	0.7514	6.2897	9.2918
ln(TRADE)	360	17.088	1.6439	13.1026	20.9711
ln(GDP)	360	10.1743	0.6643	8.3311	11.5727
$[\ln(GDP)]^2$	360	103.9571	13.4671	69.4072	133.9264
ln(REI)	360	−2.9790	0.3613	−5.4308	1.1765
ln(ES)	360	−0.1750	0.1775	−0.8329	0.5159
ln(SV)	360	−0.8993	0.1735	−1.2622	−0.2275
ln(IND)	360	−0.5269	0.1962	−1.6226	−0.5269
ln(RD)	360	4.1745	0.6528	1.5698	5.3700
ln(HC)	360	0.2301	0.0416	0.1260	0.3670
ln(FDI)	360	10.4623	1.4254	6.5511	13.5698

Table A2
Decompositions of the Local, Spatial Spillover, and Total Effects (Exclude Human Capital)

	Local effects		Spatial spillover effects		Total effects	
Variables	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
ln(P)	0.6245*	1.6657	2.4521***	3.9080	3.0766***	5.6625
ln(TRADE)	−0.0075	−0.2191	−0.1603**	−2.1435	−0.1677*	−1.8842
ln(GDP)	1.1674**	1.9679	3.2669***	3.1955	4.4344***	4.6793
$[\ln(GDP)]^2$	−0.0388	−1.3763	−0.1600***	−3.2781	−0.1988***	−4.1760
ln(REI)	0.0013	0.0653	−0.1046**	−2.5241	−0.1033**	−2.2119
ln(ES)	0.8709***	14.5477	0.4254***	3.0391	1.2963***	9.3038
ln(SV)	1.3181***	5.0357	1.0755*	1.7525	2.3936***	3.6296
ln(IND)	1.1520***	4.2050	0.2854	0.4082	1.4374*	1.8439
ln(RD)	−0.0907**	−2.0394	−0.0047	−0.0403	−0.0954	−0.7321
ln(FDI)	0.1303***	3.9151	−0.4003***	−4.5173	−0.2700***	−2.8653

Note. * Statistical significance at 10% level; ** Statistical significance at 5% level; *** Statistical significance at 1% level.

Table A3
Decompositions of the Local, Spatial Spillover, and Total Effects (Exclude Human Capital and R&D)

	Local effects		Spatial spillover effects		Total effects	
Variables	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
ln(P)	0.7320**	2.0225	2.4665***	3.9497	3.1985***	5.8785
ln(TRADE)	−0.0290	−0.8750	−0.1936***	−2.8023	−0.2226***	−2.7191
ln(GDP)	1.3331**	2.3526	2.7353***	2.8772	4.0684***	4.6346
$[\ln(GDP)]^2$	−0.0441	−1.6172	−0.1317***	−2.8541	−0.1758***	−3.8446
ln(REI)	0.0045	0.2250	−0.1038**	−2.4358	−0.0993**	−2.0511
ln(ES)	0.8460***	13.7080	0.4468***	3.1967	1.2927***	9.2496
ln(SV)	1.2852***	4.7555	1.2272**	2.0559	2.5124***	3.8027
ln(IND)	1.1054***	3.9476	0.5291	0.8240	1.6345**	2.2110
ln(FDI)	0.1558***	5.4355	−0.3828***	−4.5525	−0.2270***	−2.5866

Note. *Statistical significance at 10% level; **Statistical significance at 5% level; ***Statistical significance at 1% level.

Table A4
Decompositions of the Local, Spatial Spillover, and Total Effects (Exclude Human Capital, R&D, and Share of Industry Sector)

	Local effects		Spatial spillover effects		Total effects	
Variables	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
ln(P)	0.4393	1.2642	2.2258***	3.4039	2.6651***	4.9368
ln(TRADE)	0.0265	0.8460	−0.1475**	−2.5659	−0.1210*	−1.7761
ln(GDP)	1.6242***	2.7627	3.5253***	3.6783	5.1495***	5.7114
$[\ln(GDP)]^2$	−0.0513*	−1.8228	−0.1807***	−3.8856	−0.2320***	−4.9774
ln(REI)	0.0005	0.0228	−0.0846*	−1.8965	−0.0841	−1.6333
ln(ES)	0.8206***	13.0624	0.5098***	3.6053	1.3305***	9.1209
ln(SV)	0.3659***	2.6470	1.0696***	3.4971	1.4355***	4.0921
ln(FDI)	0.1428***	4.8011	−0.4206***	−4.7494	−0.2778***	−2.9934

Note. *Statistical significance at 10% level; **Statistical significance at 5% level; ***Statistical significance at 1% level.

Table A5
Decompositions of the Local, Spatial Spillover, and Total Effects (Exclude Human Capital, R&D, Share of Industry Sector, and Share of Services Sector)

	Local effects		Spatial spillover effects		Total effects	
Variables	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	t-value
ln(P)	0.3983	1.0808	1.8921***	2.7311	2.2904***	4.0304
ln(TRADE)	0.0401	1.2706	−0.1410**	−2.2020	−0.1008	−1.3245
ln(GDP)	1.4968**	2.5492	2.5795***	2.6627	4.0764***	4.5924
$[\ln(GDP)]^2$	−0.0528*	−1.8664	−0.1530***	−3.1830	−0.2057***	−4.3199
ln(REI)	0.0039	0.1833	−0.0868*	−1.8440	−0.0829	−1.4819
ln(ES)	0.8302***	12.8103	0.5082***	3.5062	1.3385***	9.1094
ln(FDI)	0.1473***	4.9751	−0.3666***	−4.0281	−0.2193**	−2.3116

Note. * Statistical significance at 10% level; ** Statistical significance at 5% level; ***Statistical significance at 1% level.

Table A6
Decompositions of the Local, Spatial Spillover, and Total Effects (Exclude Human Capital, R&D, Share of Industry Sector, Share of Services Sector, and Energy Structure)

	Local effects		Spatial spillover effects		Total effects	
Variables	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
ln(P)	0.6346	1.5667	−0.3633	−0.4185	0.2713	0.3398
ln(TRADE)	−0.0369	−0.9389	−0.2747***	−3.0985	−0.3116***	−2.9051
ln(GDP)	3.5077***	4.8480	3.1214**	2.3734	6.6290***	4.8863
$[\ln(GDP)]^2$	−0.1433***	−4.0764	−0.2103***	−3.0844	−0.3536***	−4.8307
ln(REI)	0.0273	1.0341	−0.1169*	−1.6549	−0.0897	−1.0861
ln(FDI)	0.1006***	2.6804	−0.6164***	−4.5479	−0.5158***	−3.4765

Note. * Statistical significance at 10% level; ** Statistical significance at 5% level; *** Statistical significance at 1% level.

Table A7
Decompositions of the Local, Spatial Spillover, and Total Effects (Exclude Human Capital, R&D, Share of Industry Sector, Share of Services Sector, and Renewable Energy Intensity)

	Local effects		Spatial spillover effects		Total effects	
Variables	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
ln(P)	0.3293	0.8996	1.9917***	2.9267	2.3210***	4.2521
ln(TRADE)	0.0393	1.2753	−0.1375**	−2.1703	−0.0981	−1.3184
ln(GDP)	1.3631**	2.3160	2.5158**	2.5404	3.8789***	4.2925
$[\ln(GDP)]^2$	−0.0473*	−1.6632	−0.1491***	−2.9971	−0.1964***	−3.9774
ln(ES)	0.8429***	13.8615	0.4689***	3.2682	1.3118***	8.7114
ln(FDI)	0.1513***	5.1443	−0.3526***	−3.7824	−0.2013**	−2.0605

Note. *Statistical significance at 10% level; **Statistical significance at 5% level; *** Statistical significance at 1% level.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The CO_2 emissions data utilized in this study can be constructed from Shan et al. (2018). The data of other variables can be obtained from National Bureau of Statistics of China. https://data.stats.gov.cn/easyquery.htm?cn=E0103.

Acknowledgments
Thanks are due to Ramiz Masroor, Igor Hernandez, Liz Wachs, Travis Atkinson, Turner Cotterman, Xingchi Shen, and other seminar participants at the Ph.D Day with their valuable advice to this paper and the International Trade, Finance, and Energy session of the 37th USAEE/IAEE North American Conference. Thanks are also due to Daoping Wang (Shanghai University of Finance and Economics) and Yiran Zhang (Capital University of Economics and Business) for their help and suggestions in revising this paper. Ge Bao is grateful to Fundamental Research Funds from University of International Business and Economics (Grant/Award Number: CXTD10-02).

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