

## Article

# Does Foreign Direct Investment Affect Tropospheric SO<sub>2</sub> Emissions? A Spatial Analysis in Eastern China from 2011 to 2017

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Received: 7 February 2020; Accepted: 31 March 2020; Published: 4 April 2020



**Abstract:** Air pollution has attracted much attention worldwide. Sulfur dioxide (SO<sub>2</sub>) is a major air pollutant in cities and affects human health seriously. The purpose of this paper is to examine how foreign direct investment affects SO<sub>2</sub> emissions and whether the pollution haven hypothesis exists in eastern China. On basis of the detailed data, we performed the spatial autocorrelation analysis and the spatial regression analysis. The results show that an increase in the foreign direct investment in a city is associated with a decline in SO<sub>2</sub> emissions in the same city, indicating that the pollution haven hypothesis does not hold in eastern China. But the spillover effect of the foreign direct investment is positive, indicating that a larger foreign direct investment in neighboring cities tends to raise SO<sub>2</sub> emissions in the local city.

**Keywords:** sulfur dioxide; foreign direct investment; pollution haven hypothesis; spatial dependence

## 1. Introduction

Air pollution has become a serious problem worldwide and has raised considerable concerns in China. Sulfur dioxide (SO<sub>2</sub>) is regarded as a major air pollutant in cities, on account of its negative effects on human health and ecosystem [1]. Many theories have guessed how foreign direct investment (FDI) could affect SO<sub>2</sub> emissions. Among them, the pollution haven hypothesis [1–3] and pollution halo hypothesis [4] are most famous. The pollution haven hypothesis suggests that FDI may worsen the environment and then lead to an increase in SO<sub>2</sub> emissions [5]. For example, in order to attract more foreign investment, developing countries tend to increase the exploitation of natural resources, lower environmental standards, and then produce products that are prone to cause pollution. Thus, developing countries are becoming “pollution havens” for developed countries. Conversely, the pollution halo hypothesis believes that FDI is good for the environment [4]. It is clear that there are two opposite opinions about the impact of FDI on SO<sub>2</sub> emissions. Our paper aims to figure out how FDI affects SO<sub>2</sub> emissions and whether the pollution haven hypothesis or the pollution halo hypothesis is valid. Figuring out this impact is important, because the government can use this information to formulate appropriate policies of investment, balancing the economic development against environmental protection.

The Yangtze River Delta region is located in eastern China. Few researchers have studied it using a spatial analysis method so far. That is a contribution and a highlight of our paper. This paper presented a series of analysis to find out how FDI affects SO<sub>2</sub> emissions in the Yangtze River Delta, using a spatial analysis method. Experiments were performed and we obtained some useful results. The reason why we focus on eastern China is that, eastern China, especially the Yangtze River Delta, is a quite important economic region in China. It is the richest area and the main manufacturing base in China. It is also the region with the strongest technological innovation capability and with the fastest internationalization process.

The second highlight of our paper is that we used the concept of the direct and indirect effects. In ordinary panel models, the impact of explanatory variable on dependent variable can be got according to the coefficient of the corresponding term. But in spatial panel models, we could not do so. We should use the direct and indirect effects. The reason is that the impact actually should be modeled as a set of partial differential equations. Direct and indirect effects are concepts invented by LeSage et al. [6]. The theory of direct and indirect effects has been confirmed by many economist. For example, in the literature [7], Elhorst et al. give a detailed example using the direct and indirect effects to interpret the impact of household income on the crime rate. The third highlight of our paper is that we adopted the environmental Kuznets curve (EKC) model. EKC model was proposed by Grossman [8] to elucidate the relationship between environmental quality and economic growth. In addition, our data is from 2007 to 2017, which is the latest that can be obtained so far.

The remaining part of this paper is as follows. Section 2 gives the literature review. Section 3 presents the empirical hypothesis. Section 4 discusses the methods of spatial analysis. Section 5 contains the description of the data in the eastern China. The spatial analysis results are discussed in Section 6. Lastly, the conclusion and policy implications are presented.

## 2. Literature Review

Some studies have explored the impact of FDI on SO<sub>2</sub> emissions, and generated mixed findings. For example, Jie He [5] studied China's 29 provinces and found that the impact is very small. Lan et al. [9] tested China's provincial data and found that FDI did not reduce SO<sub>2</sub> emissions.

However, these studies used ordinary panel models and ignored the spatial impact from neighboring cities. Anselin et al. [10–12] hold that the result will be incorrect if spatial effects is ignored. Therefore, it is essential to use spatial analysis.

There are also a few studies that look at the effects of FDI on SO<sub>2</sub> emissions using spatial analysis. Zhu et al. [1] studied the impacts of FDI on SO<sub>2</sub> emissions in the Beijing-Tianjin-Hebei region located in northern China. They found that FDI has a positive impact on SO<sub>2</sub> emissions, and FDI in surrounding areas can also affect the SO<sub>2</sub> emissions of local cities. Liu et al. [4] studied the spatial impacts of FDI on SO<sub>2</sub> emissions in 285 Chinese cities from 2003 to 2014. They found that the inflow of FDI increases the SO<sub>2</sub> pollution.

However, these studies used the coefficients of corresponding terms to interpret the impacts. In the opinion of LeSage et al. [6,13], using the coefficients to interpret the impacts may lead to wrong conclusions. Thus, we use the direct and indirect effects to analyze the impacts in our paper.

## 3. Empirical Hypothesis

The Yangtze River Delta region has a friendly foreign investment environment. A lot of multinational corporations choose the Yangtze River Delta region as the home to their regional headquarters in mainland China. The China-Singapore Industrial Park is also located in the Yangtze River Delta region. Foreign companies may apply universal environmental standards which are more stringent than that in the host country. Besides, FDI can provide the Yangtze River Delta region with newer and cleaner technologies which may reduce pollutants emissions. Last, multinational corporations can bring their environmental management systems to local companies in the host country. Hence, the environmental performance in the host country will be greater with the infusion of FDI. Through the above analysis, we propose a hypothesis as follows:

**Hypothesis 1.** *In the same city, FDI depresses SO<sub>2</sub> emissions.*

In Yangtze River Delta, cities with a larger FDI may have more stricter environmental standards, and they may transfer the pollution to nearby cities in order to reduce the local pollution. Through the above analysis, we also propose the following hypothesis:

**Hypothesis 2.** *A larger FDI in neighboring cities raises SO<sub>2</sub> emissions in the local city.*

These two hypotheses will be examined using spatial analysis in our paper.

#### 4. Methods

In this section, we will introduce the spatial autocorrelation and spatial econometric models. Besides, both the spatial autocorrelation and the spatial panel models need a spatial weights matrix. Queen contiguity matrix means that the element  $w_{ij} = 1$  if two cities share a common border or vertex, and  $w_{ij} = 0$  if not. If we normalize the queen contiguity matrix so that the sum of the elements in each row is one, we will get a row-normalized queen contiguity matrix. In this paper, the spatial weights matrix is set to a row-normalized queen contiguity matrix, and both the spatial autocorrelation and the spatial panel models share the same spatial weights matrix.

##### 4.1. Spatial Autocorrelation

The analysis of spatial autocorrelation should be done before the spatial regression [14,15]. Spatial autocorrelation comprises global spatial autocorrelation and local spatial autocorrelation. Anselin et al. [10–12] have depicted the theory of spatial autocorrelation in detail and the following equations are quoted from them.

##### 4.1.1. Global Spatial Autocorrelation

The Moran's I statistic is usually chosen to measure global spatial autocorrelation and can tell us the extent to which values on neighboring locations are similar [16]. The Moran's I statistic is written as:

$$I = \frac{\sum_i \sum_j w_{ij} z_i z_j / S_0}{\sum_i z_i^2 / n}, \quad (1)$$

where  $z_i = x_i - \bar{x}$ ,  $w_{ij}$  is the spatial weight which is row-standardized,  $S_0 = \sum_i \sum_j w_{ij}$ , and  $n$  is the number of observations.

Usually, the Moran's I value is between  $-1.0$  and  $+1.0$  when spatial weights matrix is row-standardized. If the Moran's I value is positive, it indicates there exists a positive spatial autocorrelation. That is to say, high values are surrounded by high values, and low values are near low values. If the Moran's I value is negative, it indicates there exists a negative spatial autocorrelation. That is to say, high values are near low values. If the Moran's I value is about zero, it indicates there exists a random pattern.

##### 4.1.2. Local Spatial Autocorrelation

The Getis-Ord  $G_i$  statistic, a local indicator of spatial association (LISA), is often used to measure local spatial autocorrelation. The Getis-Ord  $G_i$  statistic is written as:

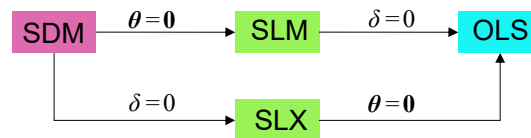
$$G_i = \frac{\sum_{j \neq i} w_{ij} x_j}{\sum_{j \neq i} x_j}, \quad (2)$$

in the usual notation.

From the values of the Getis-Ord  $G_i$  statistic, we can know the distribution of hot spots and cold spots.

##### 4.2. Spatial Panel Models

Elhorst et al. [7,13] have elaborated on the theory of spatial panel models and the following description of the theory are quoted from them. The spatial Durbin model (SDM) and its relationship to other simplified models are shown in Figure 1.



**Figure 1.** The relationships between the SDM and other models.

When considering spatial and time-period fixed effects, a typical non-spatial ordinary least squares (OLS) model can be written as:

$$y_{it} = \alpha + x_{it}\beta + \mu_i + \zeta_t + \varepsilon_{it} , \quad (3)$$

where  $y_{it}$  is the dependent variable in unit  $i$  in period  $t$ ,  $\alpha$  is the constant term,  $x_{it}$  denotes a vector of independent variables,  $\beta$  denotes a vector of unknown parameters,  $\mu_i$  denotes a spatial fixed effect,  $\zeta_t$  denotes a time-period fixed effect, and  $\varepsilon_{it}$  is the error term.

If we extend the OLS model with spatial interaction effects, the spatial Durbin model (SDM) can be written as:

$$y_{it} = \delta \sum_{j=1}^N w_{ij} y_{jt} + \alpha + x_{it}\beta + \sum_{j=1}^N w_{ij} x_{jt}\theta + \mu_i + \zeta_t + \varepsilon_{it} , \quad (4)$$

where  $w_{ij}$  is the spatial weight which is row-standardized,  $\delta$  is called spatial autoregressive coefficient,  $\sum_{j=1}^N w_{ij} y_{jt}$  denotes the interaction effect among the dependent variable of different units,  $\sum_{j=1}^N w_{ij} x_{jt}$  denotes the interaction effects among the independent variables of different units, and  $\theta$  denotes a vector of unknown parameters.

The spatial lag model (SLM) can be written as:

$$y_{it} = \delta \sum_{j=1}^N w_{ij} y_{jt} + \alpha + x_{it}\beta + \mu_i + \zeta_t + \varepsilon_{it} , \quad (5)$$

in the usual notation.

The spatial lag of X (SLX) model can be written as:

$$y_{it} = \alpha + x_{it}\beta + \sum_{j=1}^N w_{ij} x_{jt}\theta + \mu_i + \zeta_t + \varepsilon_{it} , \quad (6)$$

in the usual notation.

## 5. Data

### 5.1. Study Area

In eastern China, the Yangtze River Delta region is the most famous and important economic region. The Yangtze River Delta region comprises Jiangsu Province, Zhejiang Province, Anhui Province and Shanghai City. It is one of the most densely populated regions in China, making up one-sixth of the country's population. Meanwhile, the Yangtze River Delta region, as a major engine of China's economic growth, is one of the richest regions in China. The total economic output in the Yangtze River Delta make up a quarter of the gross domestic product of China. Local governments are sparing no effort to attract foreign investment in different kinds of fields.

The Yangtze River Delta region covers 41 cities in total. This paper selects 40 cities from 2011 to 2017 as samples. We exclude Zhoushan City because it is an island. The relevant data in our experiment come from the China City Statistical Yearbook [17], Shanghai Statistical Yearbook [18], Jiangsu Statistical Yearbook [19], Zhejiang Statistical Yearbook [20] and Anhui Statistical Yearbook [21]

in each year (Statement: The data that support the results of this research are available from the corresponding author upon request.).

## 5.2. Variables

The relevant variables and their indicators are selected as follows:

- SO<sub>2</sub> emissions: the indicator we select is the volume of industrial SO<sub>2</sub> emissions in each individual city. SO<sub>2</sub> is a common air pollutant in cities. Industrial activities can cause about 99% of SO<sub>2</sub> emissions. Such as, burning of fuel in factories, sulfuric acid production in chemical plants, and electric energy production in thermal power stations.
- Foreign direct investment: the indicator we select is the ratio of foreign capital actually utilized to the gross regional product (GRP) in each individual city. According to the pollution haven hypothesis and the pollution halo hypothesis, the FDI affects environmental pollution through complicated methods.

Other control variables are also added to the experiment, including:

- Economic income: the indicator we select is the per capita GRP in each individual city. According to the EKC theory proposed by Grossman [8], environmental pollution may have an inverted U-shaped relationship with per capita GRP. That is to say, during the initial phase, economic growth may lead to an environmental degradation, and afterwards economic growth may lead to an environmental improvement.
- Industrial structure: the indicator we use is the secondary industry as percentage to GRP in each individual city.
- Population size: the indicator we use is the annual average population in each individual city.

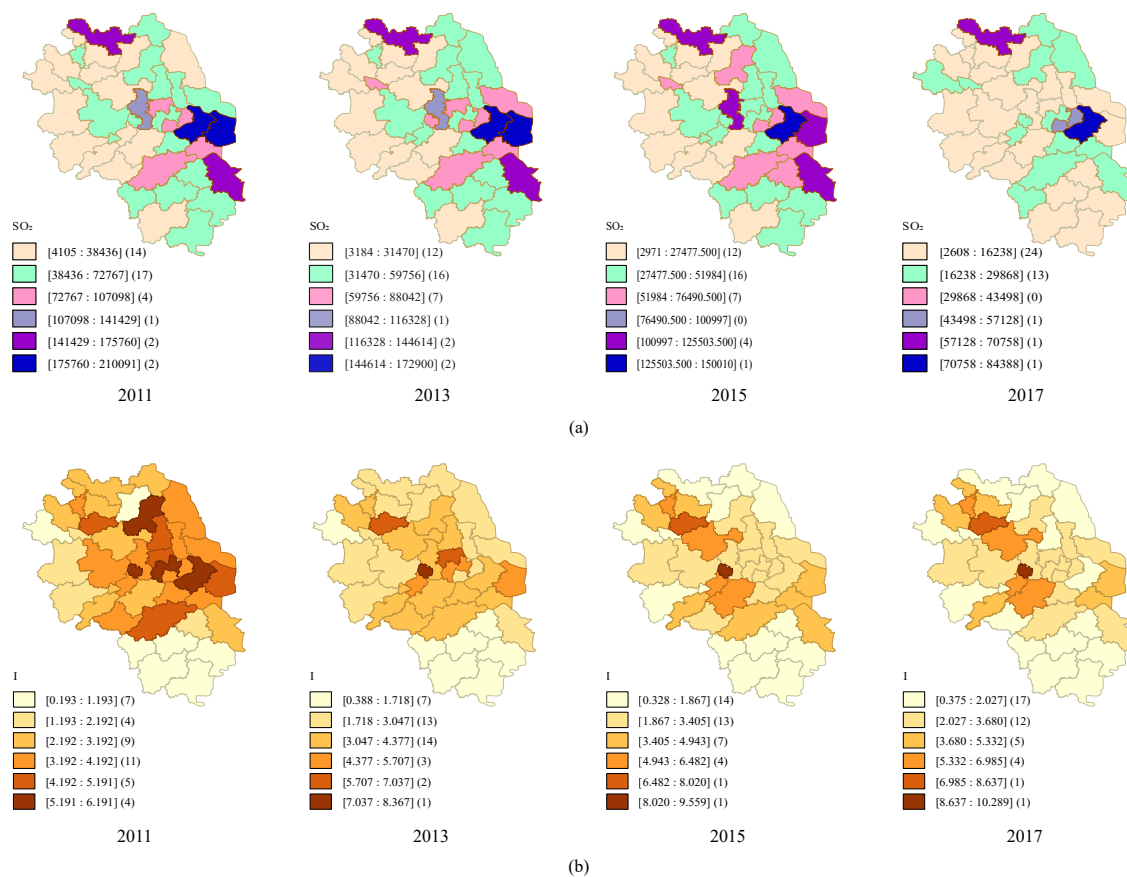
Definitions of all variables are depicted detailedly in Table 1, and descriptive statistics of all variables are reported in Table 2. Figure 2 illustrates the spatial distribution of SO<sub>2</sub> emissions and foreign direct investment in the Yangtze River Delta region from 2011 to 2017.

**Table 1.** Definitions of all variables.

Variable Symbol	Variable Name	Definition	Unit	Variable Type
SO <sub>2</sub>	Sulfur dioxide emissions	Volume of industrial sulfur dioxide emissions	ton	Dependent variable
I	Foreign direct investment	Foreign capital actually utilized as percentage to GRP	%	Core explanatory variable
G	Economic income	Per capita GRP in a year	RMB	Other control variable
S	Industry structure	Secondary industry as percentage to GRP	%	Other control variable
P	Population size	Annual average population	10,000 persons	Other control variable

**Table 2.** Descriptive statistics of all variables.

Variable	Observations	Mean	Std. Dev	Minimum	Maximum
SO <sub>2</sub>	280	44,303.314	38,890.120	2608	240,100
I	280	2.989	1.844	0.193	10.289
G	280	62,437.536	35,199.306	10,090	199,017
S	280	49.486	7.371	29.83	74.73
P	280	519.021	269.463	73.79	1453



**Figure 2.** Choropleth maps in Yangtze River Delta from 2011 to 2017. (a) SO<sub>2</sub> emissions, (b) foreign direct investment.

## 6. Results

### 6.1. Spatial Autocorrelation

#### 6.1.1. Global Spatial Autocorrelation

We calculated the global Moran's I of SO<sub>2</sub> emissions and foreign direct investment using Geoda [11]. The results can be seen in Table 3.

**Table 3.** Global spatial autocorrelation.

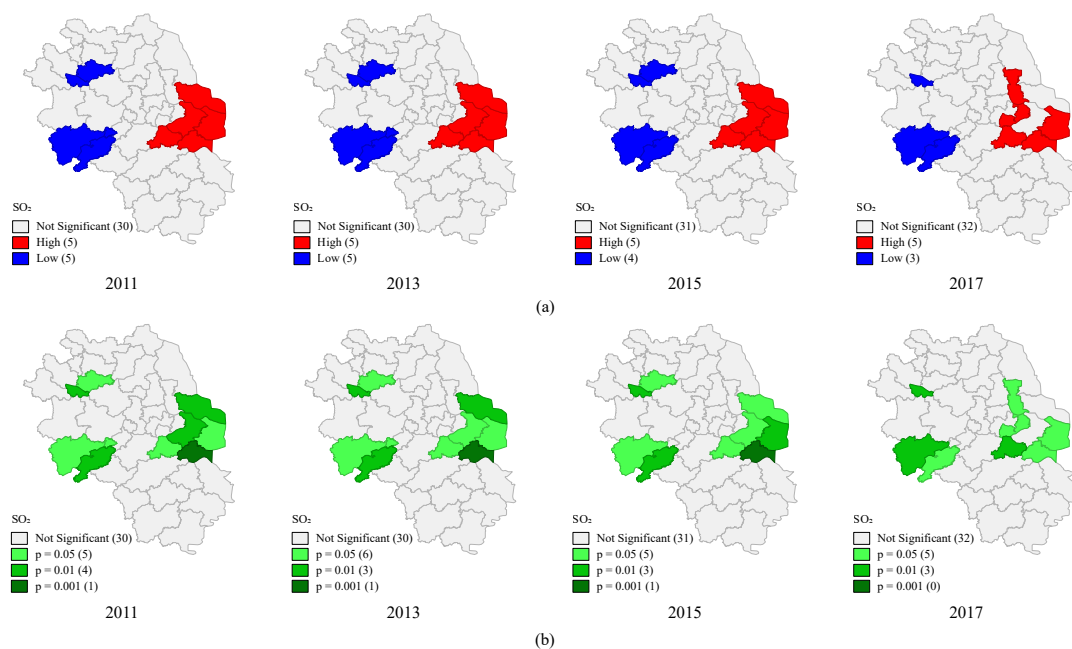
Year	SO <sub>2</sub>				I			
	Moran's I	z Value	p Value	sd	Moran's I	z Value	p Value	sd
2011	0.2386	2.8547	0.0050	0.0930	0.4700	5.0854	0.0010	0.0974
2012	0.2442	3.0080	0.0040	0.0903	0.3869	4.2388	0.0010	0.0972
2013	0.2415	2.8744	0.0040	0.0935	0.3356	3.7068	0.0030	0.0968
2014	0.2670	3.1791	0.0050	0.0928	0.3007	3.3943	0.0030	0.0951
2015	0.2111	2.5548	0.0110	0.0941	0.2840	3.2167	0.0060	0.0948
2016	0.2579	3.2536	0.0060	0.0875	0.2898	3.2746	0.0050	0.0949
2017	0.0845	1.2956	0.1010	0.0849	0.2927	3.3614	0.0040	0.0934

For the Global Moran's I statistic, the null hypothesis is that there is no spatial autocorrelation, in other words, the variable being analyzed is randomly distributed among the cities in Yangtze River Delta. As shown in Table 3, From 2011 to 2017, the Moran's I values of foreign direct investment are all positive, and the *p*-values are all less than 1%. It indicates that the null hypothesis should be rejected and the foreign direct investment in Yangtze River Delta has a significant positive spatial

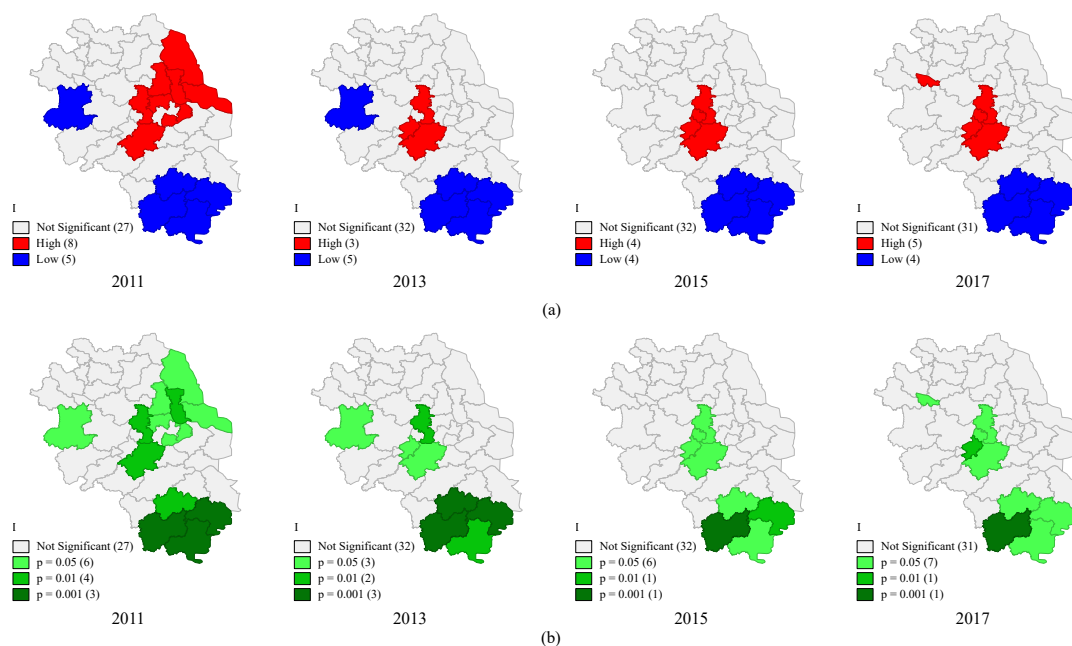
autocorrelation. That is to say, the values of foreign direct investment tend to cluster spatially. The Moran's I values of SO<sub>2</sub> emissions are all positive and the  $p$ -values are all less than 5% except for 2017, indicating a significant positive spatial autocorrelation. Apparently, these findings reveal the necessity of adopting spatial dependence models.

### 6.1.2. Local Spatial Autocorrelation

The Getis-Ord  $G_i^*$  statistic is a common local indicator of spatial association (LISA) measuring the local spatial autocorrelation [10,22]. We calculated the  $G_i^*$  values and drew the LISA maps using Geoda [11]. The LISA maps for SO<sub>2</sub> emissions can be seen in Figure 3 and the LISA maps for foreign direct investment are depicted in Figure 4.



**Figure 3.** LISA maps for SO<sub>2</sub> emissions in Yangtze River Delta. (a) cluster maps, (b) significant maps.



**Figure 4.** LISA maps for foreign direct investment in Yangtze River Delta. (a) cluster maps, (b) significant maps.

Figure 3 shows that there are at least about 5 hot spots and about 3 cold spots of SO<sub>2</sub> emissions in Yangtze River Delta. The hot spots are located in Shanghai City and the surrounding area, whereas the cold spots are around Anqing City. Figure 4 shows that there are at least about 3 hot spots and about 4 cold spots of foreign direct investment in Yangtze River Delta. The hot spots are located in Nanjing City and the surrounding area, whereas the cold spots are around Lishui City. These findings demonstrate the spatial association and further indicate the need for spatial dependence models.

### 6.2. Spatial Panel Models

Environmental Kuznets curve (EKC) model establishes a relationship between environmental pollution and economic development [8,23,24]. The EKC model contains a square term of income [3] and can be formulated as follows:

$$\ln(SO_2)_{it} = \alpha + \beta_2 \ln G_{it} + \beta_3 (\ln G_{it})^2 + x_{it} \beta + \mu_i + \zeta_t + \varepsilon_{it}, \quad (7)$$

in the usual notation.

Thus, we can extend the EKC model with the infusion of the terms of FDI and other control variables. Besides, through the analysis in the previous subsections, we know that the study also needs to take account of spatial association. Therefore, we can extend the EKC model in the form of SDM as:

$$\begin{aligned} \ln(SO_2)_{it} = & \delta \sum_{j=1}^N w_{ij} \ln(SO_2)_{jt} + \alpha + \beta_1 I_{it} + \beta_2 \ln G_{it} + \beta_3 (\ln G_{it})^2 + \beta_4 S_{it} + \beta_5 P_{it} + \theta_1 \sum_{j=1}^N w_{ij} I_{jt} \\ & + \theta_2 \sum_{j=1}^N w_{ij} \ln G_{jt} + \theta_3 \sum_{j=1}^N w_{ij} (\ln G_{jt})^2 + \theta_4 \sum_{j=1}^N w_{ij} S_{jt} + \theta_5 \sum_{j=1}^N w_{ij} P_{jt} + \mu_i + \zeta_t + \varepsilon_{it}, \end{aligned} \quad (8)$$

where,  $i$  and  $t$  denote the data for the  $t$ -th year of the  $i$ -th city, respectively. The spatial weight  $w_{ij}$  is an element of row-normalized contiguity matrix.

Because of the difference in spatial dependence, the SLM model and the SEM model are also used. The form of SLM can be written in the following way:

$$\ln(SO_2)_{it} = \delta \sum_{j=1}^N w_{ij} \ln(SO_2)_{jt} + \alpha + \beta_1 I_{it} + \beta_2 \ln G_{it} + \beta_3 (\ln G_{it})^2 + \beta_4 S_{it} + \beta_5 P_{it} + \mu_i + \zeta_t + \varepsilon_{it}, \quad (9)$$

in the usual notation.

The form of SLX can be written in the following way:

$$\begin{aligned} \ln(SO_2)_{it} = & \alpha + \beta_1 I_{it} + \beta_2 \ln G_{it} + \beta_3 (\ln G_{it})^2 + \beta_4 S_{it} + \beta_5 P_{it} + \theta_1 \sum_{j=1}^N w_{ij} I_{jt} + \theta_2 \sum_{j=1}^N w_{ij} \ln G_{jt} \\ & + \theta_3 \sum_{j=1}^N w_{ij} (\ln G_{jt})^2 + \theta_4 \sum_{j=1}^N w_{ij} S_{jt} + \theta_5 \sum_{j=1}^N w_{ij} P_{jt} + \mu_i + \zeta_t + \varepsilon_{it}, \end{aligned} \quad (10)$$

in the usual notation.

### 6.3. Model Comparison

In this paper, the maximum likelihood (ML) method is used to estimate the spatial models. The estimation results are reported in Table 4 and the direct and indirect effects in Table 5. Three different spatial models are considered.

**Table 4.** Model comparison of the estimation results.

Variables	SDM	SLM	SLX
$W \cdot \ln SO_2$	6.304 *** (9.160)	6.022 *** (8.847)	-
$I$	-0.131 ** (-2.032)	-0.035 (-0.656)	-0.047 ** (-1.963)
$\ln G$	-2.224 (-0.342)	-9.855 * (-1.859)	7.304 *** (3.008)
$(\ln G)^2$	0.082 (0.281)	0.426 * (-1.792)	-0.322 *** (-2.973)
$S$	0.018 (0.631)	0.014 (0.582)	0.001 (0.118)
$\ln P$	0.599 (0.870)	-0.526 (-0.837)	0.210 (0.807)
$W \cdot I$	0.318 ** (2.383)	-	0.048 (0.980)
$W \cdot \ln G$	-40.673 *** (-3.282)	-	1.655 (0.381)
$W \cdot (\ln G)^2$	1.855 *** (3.320)	-	-0.070 (-0.360)
$W \cdot S$	-0.062 (-1.233)	-	0.004 (0.195)
$W \cdot \ln P$	6.894 *** (3.022)	-	0.058 (0.071)
(Pseudo) $R^2$	0.0435	0.280	0.503
Log-L	295.8	280.0	1.792
AIC	-555.5935	-534.0869	30.41594

Notes: t-values are in parentheses; \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

**Table 5.** The estimated direct and indirect effects on sulfur dioxide.

Type	Variable	Value	z-Value	p-Value
Direct effects	$I$	-0.063	-2.46	0.014
	$\ln G$	5.097	2.04	0.041
	$(\ln G)^2$	-0.236	-2.12	0.034
	$S$	0.011	1.16	0.246
	$\ln P$	-0.829	-2.53	0.011
Indirect effects	$I$	0.028	1.29	0.197
	$\ln G$	2.991	1.39	0.165
	$(\ln G)^2$	-0.129	-1.35	0.176
	$S$	-0.003	-0.30	0.762
	$\ln P$	-0.583	-1.80	0.072

To further determine whether the SDM model can be simplified, we adopted the LR test and the Wald test. We compare the SDM model with the SLM model and the SLX model respectively. The purpose of the LR test and the Wald test are the same. We use both of them to verify the robustness of the outcome. The test results are reported in Table 6.

**Table 6.** LR and Wald test.

Model 1	Model 2	LR		Wald	
		$\chi^2$	p-Value	$\chi^2$	p-Value
SDM	SLM	31.51	0.000	23.73	0.000
SDM	SLX	588.01	0.000	83.91	0.000

As shown in Table 4, the log-likelihood (Log-L) value of SDM is greater than that of SLM and SLX, and the AIC value is less. Thus, the SDM model seems more suitable to describe the spatial dependence. The first row of Table 6 shows that the null hypothesis  $H_0: \theta = 0$  should be rejected when using the LR test or the Wald test. It means that SDM can not be simplified to SLM. In the same way, the second row of Table 6 shows that the null hypothesis  $H_0: \delta = 0$  should be rejected. It means that SDM can not be simplified to SLX as well. Thus, both tests show that the SDM model is more appropriate to describe the spatial dependence.

#### 6.4. Direct and Indirect Effects

Some coefficients in the estimation results reported in Table 4 seem not statistically significant, actually it does not matter. In the opinion of LeSage et al. [6,13], using the coefficients to interpret the

impacts may lead to wrong conclusions, because the coefficients in the SDM model do not express the effects of changes in the explanatory variables on SO<sub>2</sub> emissions. In fact, we should use the direct and indirect effects to assess the impacts. Direct and indirect effects are concepts invented by LeSage et al., and the detailed step-by-step mathematical proof can be seen in the book *Introduction to Spatial Econometrics* [6]. The change of an explanatory variable in a city will have an impact on the dependent variable in the same city. This impact is called a direct effect. The change of an explanatory variable in neighboring cities will have an impact on the dependent variable in the local city. This impact is called an indirect effect or a spillover effect.

From Table 5 we can see that the direct effect of FDI ( $I$ ) is negative and statistically significant, indicating that a larger FDI tends to reduce SO<sub>2</sub> emissions. This result supports Hypothesis 1. It also supports the pollution halo hypothesis and reject the pollution haven hypothesis. As shown in Table 5 and Table 4, the direct effect of FDI is about  $-0.063$  and the coefficient estimate of FDI is about  $-0.131$ . It indicates that the feedback effect is about  $0.068$  and nearly equals to  $-51.9\%$  of the coefficient estimate. However, the indirect effect of FDI is positive and significant, suggesting that a larger FDI in neighboring cities tends to raise SO<sub>2</sub> emissions in the local city. This result also supports Hypothesis 2. One possible explanation for this phenomenon is that Cities with a larger FDI may have more stricter environmental standards, and they may transfer the pollution to nearby cities in order to reduce the local pollution.

Turning to Table 5, the direct effect of income ( $\ln G$ ) is positive and statistically significant ( $p < 0.05$ ), and the direct effect of  $(\ln G)^2$  is negative and also statistically significant. Thus, it suggests that the relationship between economic income and SO<sub>2</sub> emissions shows an inverted U-shape. It demonstrates the existence of EKC relationship. The direct effect of  $\ln G$  is about  $5.097$  and  $(\ln G)^2$  is about  $-0.236$ . In this case, the EKC trajectory has a critical point at around  $G = 48,958.526$  RMB. It indicates that when per capita GRP in a year is less than  $48,958.526$  RMB, the value of SO<sub>2</sub> emissions is monotonic increasing, and when per capita GRP in a year is greater than  $48,958.526$  RMB, the value of SO<sub>2</sub> emissions is monotonic decreasing. Thus, raising the income is a good way to improve the environment.

From Table 5 we can see that the direct and indirect effects of industrial structure ( $S$ ) are not statistically significant. It indicates that the secondary industry is not the main cause of increased SO<sub>2</sub> emissions. One possible explanation for this phenomenon is that the effort of industrial upgrading in the Yangtze River Delta region has achieved good results.

## 7. Conclusions

This paper has examined the extent to which FDI can affect the SO<sub>2</sub> emissions in the Yangtze River Delta region, a vital economic region in eastern China. Previous studies have hardly touched on this region using spatial analysis, and that is the contribution of our paper. On basis of the detailed data collected from 40 cities in the Yangtze River Delta region, we performed the spatial autocorrelation analysis and the spatial regression analysis. The results of the spatial autocorrelation analysis show that the FDI and SO<sub>2</sub> emissions in the Yangtze River Delta both have a significant positive spatial autocorrelation and tend to cluster spatially. The results of the spatial regression analysis prove the existence of the pollution halo hypothesis and reject the pollution haven hypothesis. Besides, a larger FDI in neighboring cities raises SO<sub>2</sub> emissions in the local city.

Our findings have some policy implications as follows.

(1) The results show that larger FDI tend to reduce SO<sub>2</sub> emissions. So it can dispel the worries that the infusion of foreign investment will pollute the environment. Foreign enterprises could be encouraged to set up factories in Yangtze River Delta and bring in the advanced production technologies, realizing the transition from traditional mode to advanced mode.

(2) The results show that larger FDI in neighboring cities tend to raise SO<sub>2</sub> emissions in the local city. So the governments in Yangtze River Delta could not only be concerned about the local pollution, but also join hands with each other to reduce the pollution. They could have meetings together to talk

about formulating regulations and try to reach an agreement. They could also unite to supervise the pollution dumping and avoid the transfer of pollution.

(3) When introducing the foreign investment, the governments in Yangtze River Delta also need to carefully formulate the standards of environmental protection. It is essential to set a maximum value of pollution emissions and try to achieve the goal of energy conservation and emission reduction.

The conclusions above also have some limitations. For example, we do not take the trade war into consideration. Further work are required to better understand the extent to which trade war can affect the SO<sub>2</sub> emissions. In addition, we could also take advantage of satellite remote sensing techniques to monitor and analyze the SO<sub>2</sub> content in the future research.

**Author Contributions:** Methodology, Y.Y.; data processing, Y.Y.; funding acquisition, W.H.; writing—original draft preparation, Y.Y.; writing—review and editing, W.H. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the National Natural Science Foundation of China (Grant No. 41574022, 41274028 and 41674035).

**Conflicts of Interest:** The authors declare no conflict of interest.

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