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Spillover effects of economic globalization on CO_2 emissions: A spatial panel approach☆

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ABSTRACT

This paper investigates the spatial effects of economic globalization on CO_2 emissions in a panel of 83 countries over the period 1985–2013. We apply the spatial panel method to address the problems of spatial dependency and the spillover effect among neighboring countries. First, the estimation results verify the existence of the spatial correlations in CO_2 emissions across nations. Second, we find that the indirect effect of economic globalization on CO_2 emissions is so significantly negative to overcome the positive direct effect, which implies a negative and significant total effect, so our results suggest that being surrounded by highly globalized countries has a positive effect on the environmental quality. Finally, we also find strong evidence for the inverted-U shaped EKC relationship between CO_2 emissions and income.

1. Introduction

With the dizzying-speed development of global economic integration and trade freedom, followed by the growth of global economy, people attach greater weight to how such trends will influence the environment. Economic globalization usually refers to the process by which different economies become more and more integrated and concurrent with increasing economic globalization, and there has been much research into its consequences. A recent work by Dreher et al. (2008) summarizes some findings on the influences of globalization on economic growth, government spending and within-country inequality. Little is known, however, about the effects of globalization on environment.

Even though there has been many published papers on the effects of globalization on environment in recent years, there are still many aspects of this concept that need further scrutiny. For instance, their understanding of the relationship between globalization and carbon dioxide (CO_2) emissions is highly partial. Previous studies tend to measure the incidence of economic globalization using the degree of trade openness (Jorgenson and Givens, 2014; Li et al., 2015; Le et al., 2016). From a policy perspective, the association between trade openness and CO_2 emissions is undoubtedly relevant, but trade openness is not an adequate measure to capture the incidence of other aspects of economic globalization, such as the extent of capital controls, the spread of technology, and knowledge beyond borders. Therefore, ignoring these factors, while centering exclusively on trade openness, can adversely affect our perception of the link between economic globalization and CO_2 emissions. In addition, sharp opposing views on the impact of trade openness on CO_2 emissions are widespread. There are arguments in favor of positive impact of trade openness on CO_2 emissions. For instance, a number of studies have found that increased openness can worsen environmental quality. The reason is that increased international trade compels governments to lower production costs within their jurisdiction by neglecting to enact or enforce laws to protect the environment (Drezner, 2000). This view of the influence of trade openness on the environment is consistent with Managi and Kumar (2009) and Kellenberg (2009). However, the proponents hold that, based on the theories of international trade and environmental economics, trade liberalization can bring economic benefits that can be distributed in a manner to protect the environment. Moreover, lowering barriers to trade and foreign investment encourages firms to transfer environmental/green technologies and management systems from countries with stricter environmental standards to countries, which lack access to environmental capabilities and technologies (Christman and Taylor, 2001). Meanwhile, the globalized information and knowledge have made it possible for the public to be more aware of ecological issues and this has generated greater mobilization. This view is empirically supported by a larger number of studies. Antweiler et al. (2001) find that trade openness is associated with reduced pollution as proxied by SO_2 concentrations. A more recent study by Zhang et al. (2017a); Zhang et al.

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(2017b) also reports that trade openness negatively and significantly affects emissions in 10 newly industrialized countries. However, there are still other studies find that the impact of trade on environmental quality is varied by the level of income. Specially, Le et al. (2016) demonstrate that trade openness has a benign effect on the environment in high-income countries, but a harmful effect in low and middle income countries.

Another drawback of the existing studies is that when examining the relationship between globalization and CO_2 emissions (Lim et al., 2015; Shahbaz et al., 2016), they fails to take the spatial dependence into account. Spatial dependence refers to the phenomenon that one observation in a sample of cross sectional observations is dependent on other cross sectional observations. For example, if the economic growth rate is relatively high in one country, the neighboring regions may imitate its economic development model and industrial structural configuration, and thereby the environment quality of neighboring countries will be affected by the development and environment policies of this country. Therefore a well performing country may induce a positive economic impact on its neighboring countries and regions – the positive economic impact would arguably lead to higher CO_2 emissions in the neighboring countries.[1] Switching back to the discussion in environmental impacts of economic globalization, the traditional panel econometric techniques, like fixed/random effects and GMM method, would lead to biased estimations because of ignoring the spatial correlations. More specifically, they only obtain the direct effect of economic globalization on CO_2 emissions, but fail to get the indirect (or spatial spillover) effect of economic globalization on CO_2 emissions. Here the indirect effects mean the effects brought by the neighboring country's economic globalization. In recent years, a growing body of environmental literature has estimated the determinant of CO_2 emissions using spatial econometric models to control for spatial dependence (see, Zhao et al., 2014; Kang et al., 2016; Meng and Huang, 2017; Meng et al., 2017).

This paper aims to overcome this omission in the literature, and to provide a comprehensive analysis of the relationship between economic globalization and CO_2 emissions. To achieve this goal, first, we use the KOF index of economic globalization constructed by Dreher (2006). The KOF index of economic globalization is based on eight variables associated with different dimensions of economic integration (see Appendix Table A1 for more detail), and this aggregate index distinguishes between the different aspects of economic integration, which allows us to adopt a broader perspective than existing studies. Second, we use the recently developed spatial panel data model to explore the influence of economic globalization on CO_2 emissions, and a comparative analysis between the non-spatial panel model and spatial panel model is conducted to validate the spatial spillovers effects of variables in order to provide more rigorous references for policymakers.

The rest of this paper is organized as follows. In the next Section, we present the theoretical framework of the model and the data. Section 3 introduces the spatial econometric method and testing procedures. The estimation results and discussions are showed in Section 3.1. Finally, Section 4 concludes this paper and provides some policy suggestions.

[1] In our earlier manuscript, we argued that, as a result of the high flowability of CO_2 emissions, CO_2 emissions in world may probably have strong spatial effects, which imply that CO2 emissions are a flow variable. An anonymous referee kindly reminds us that there is a distinct difference between flow and fund resources. A fund resource has a fixed stock amount over a certain time period. A flow resource is characterized by a continuous stream over a period of time. The referee suggest that CO_2, as a greenhouse gas emission, is better considered as being a fund resource, i.e., CO_2 is emitted from a particular location, and then enters the upper atmosphere (almost immediately) where the gas accumulates over time. It is for this reason that CO_2 emissions are fairly unique. After carefully searched and read corresponding literature about this issue, we totally agree with the referee, and argue that the spatial spillovers are being driver by the underlying integration of the economies rather than the flowability of CO_2 emissions.

2. Theoretical framework of the model and data

2.1. Theoretical framework of the model

In this paper, we explore the factors that influence global CO_2 emissions within the STIRPAT model framework (Dietz and Rosa, 1997). The basic form of the STIRPAT model is

$$I_{it} = aP_{it}^{b}A_{it}^{c}T_{it}^{d}e_{it}, \tag{1}$$

where I denotes the environmental impact, P, A, T denote population, affluence, and technology, respectively. a denotes the constant terms. b, c and d are the estimated parameters. e denotes the random disturbance. Using natural logarithms, the STRIPAT model can be converted to a convenient linear specification for panel estimation

$$\ln I_{it} = a_0 + b\ \ln P_{it} + c\ \ln A_{it} + d\ \ln T_{it} + \ \ln e_{it}. \tag{2}$$

The above basic model analyses the impacts of population (P), economic development (A) and industrial structure (T) on the environmental impact but ignores other important factors influencing CO_2 emissions, e.g. economic globalization. To further analyze the effect of economic globalization on the environment, we add economic globalization in Eq. (2), Moreover, according to the EKC hypothesis, the environmental quality is a function of GDP and square of GDP. Thus, we modifies the STIPAT model by adding economic globalization and the square of GDP to the set of factors, resulting in

$$\begin{aligned}\ln(CO_{2it}) = a_0 + b\ \ln(pop_{it}) + c\ \ln(pgdp_{it}) + d\ \ln(pgdp_{it})^2 + e\ \ln(indus_{it}) + \\ f\ \ln(glob_{it}) + gCV_{it} + \mu_i + \varepsilon_{it},\end{aligned} \tag{3}$$

where $glob$ denotes economic globalization. Specifically, CO_2 denotes carbon dioxide emissions per capita (henceforth denoted as CO_2 emission or simply emission); pop is total population; $pgdp$ is GDP per capita. Following Dietz and Rosa (1997), total population and GDP per capita measure the impact of demographic and economic factors. $Indus$ stands for industrial structure (expressed as proportion of the added value of industry to GDP); $glob$ represents economic globalization; μ_i is the individual fixed effect, which controls for all space-specific time-invariant variables that if omitted could potentially bias the coefficient estimates; $\varepsilon$is the standard error term and CVmeans the control variable suggested in previous studies on the determinants of CO_2 emissions. Here, we add urbanization level in our model, as it is typically associated with increased economic activity resulting in high energy consumption, which accelerates the emission of CO_2 (Martínez-Zarzoso and Maruotti, 2011; Adams and Klobodu 2017).

2.2. Data

We use a balanced panel sample of 83 developed and developing countries over the period 1985–2013. Appendix B provides the list of sample countries. One reason for limiting our sample to 83 countries was the availability of reliable data on various indicators, specifically for the data of industrial structure (expressed as proportion of the added value of industry to GDP).[2] The dependent variable is CO_2 emissions (metric tons per capita) and proxies for overall environmental pollution in a country. GDP per capita, population, urbanization and industrialization level are obtained from World Development Indicators (WDI), while economic globalization indices are taken from the KOF globalization index of globalization prepared at the Swiss Federal

[2] As the data of industrial structure (expressed as proportion of the added value of industry to GDP) is missing for some developed countries, such as USA and UK (only available after 1990), and the period of our study is from 1985 to 2013, so our sample do not include these countries.

Table 1
Summary statistics.

Variables	Mean	Std. dev	Max	Min	Skewness	Kurtosis
$\ln CO_2$	0.144	1.736	3.606	−4.480	−0.411	2.189
lngdp	8.039	1.514	11.425	4.880	0.227	2.167
lnpop	16.003	1.911	21.031	11.067	−0.165	3.177
lnurban	3.793	0.581	4.605	1.653	−0.956	3.504
lnindus	3.307	0.424	4.349	1.203	−0.599	3.804
lnglob	3.838	0.429	4.578	2.037	−0.884	4.138

Institute of Technology (Dreher, 2006), and this index takes values between 0 and 100 with higher values suggesting more globalization. Details about the definition and sources of all variables are provided in Appendix A (Table A2), and Table 1 summarizes the descriptive statistics for our variables.

3. Methodology

3.1. Spatial econometrics model

Tobler's First Law of Geography (Tobler, 1970) states that all attributed values of indicators on a geographic surface are related to one other, but closer indicators are more strongly related than the more distant ones. Based on this theory, no region is isolated. Omitting the spatial correlations in an econometric analysis when variables are spatially correlated would lead to bias (Anselin 1988). Maddison (2006) argues that the spatial relationship incorporated in the data would cause potential spatial autocorrelation problem. Since the importance of spatial dimensions, spatial models are widely used in empirical studies, and especially in environmental literature,[3] typical examples include Maddison (2006), Apergis (2016) and Luo et al. (2017), just to name a few. Accordingly, this paper aims to contribute to the strand of the literature that attempts to examine the effects of economic globalization on CO_2 emissions by the augmented STIRPAT model using spatial economic models.

Following Elhorst (2012), there are mainly three kinds of spatial econometrics models: Spatial Lag Panel Model (SLM), Spatial Error Panel Model (SEM), and Spatial Durbin Panel Model (SDM). The SLM model hypothesizes that the value of the dependent variable observed at a particular location is partially determined by a spatially weighted average of neighboring dependent variables. That is, CO_2 emission in region i is influenced by CO_2 emission of neighboring regions because of the spillover effects. The SLM model is specified as

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \mathbf{x}_{it}\boldsymbol{\beta} + \mu_i + \varepsilon_{it}, \tag{4}$$

where y_{it} is CO_2 emissions per capita for country i at time t ($i = 1, \cdots, N$; $t = 1, \cdots, T$). $\sum_{j=1}^{N} w_{ij} y_{jt}$ represents the endogenous interaction effects of the dependent variable y_{it}.

with the dependent variables y_{jt} in neighboring countries, namely, the weighted average of neighboring CO_2 emissions; the parameter ρ is the spatial autoregressive coefficient, which measures the strength of contemporaneous spatial correlation between one region and other geographically proximate regions; In this paper, it indicates the influence of carbon emissions of the nearby regions on this region; $\mathbf{x}_{it}$ is an matrix of the independent variables, which include *gdp* per capita, population size, industrial structure, urbanization level, and economic globalization; $\boldsymbol{\beta}$are vectors of unknown parameters to be estimated;

[3] An excellent survey on the determinants of emissions using spatial panel data approach is given in the recent study by Burnett, Bergstrom & Dorfman (2013). This section borrows heavily from this reference, and interested readers should consult it for further detail.

Table 2
Statistical tests of spatial autocorrelation by Moran's I.

Year	Moran's I	Year	Moran's I
1985	0.5050***	2000	0.5021***
1986	0.5074***	2001	0.5048***
1987	0.4981***	2002	0.5064***
1988	0.4849***	2003	0.5164***
1989	0.4876***	2004	0.5038***
1990	0.4975***	2005	0.5024***
1991	0.4903***	2006	0.4871***
1992	0.4812***	2007	0.4932***
1993	0.4767***	2008	0.5038***
1994	0.4851***	2009	0.4903***
1995	0.4985***	2010	0.4897***
1996	0.5016***	2011	0.4916***
1997	0.5014***	2012	0.4891***
1998	0.5079***	2013	0.4863***
1999	0.5065***	average	0.5055***

Note: *** denotes significance at the 1% level, respectively. The null hypothesis is no global spatial autocorrelation.

The error term, ε_{it}, is assumed to be independently and identically distributed with a zero mean and variance σ^2. w_{ij} is the element of spatial weight matrices.

The SEM model includes interaction effects among the error terms. This model is applied to a situation where the regional interaction effects are caused by the omitted variables that affect both the local and neighboring regions, which is specified as

$$\begin{aligned} y_{it} &= \mathbf{x}_{it}\boldsymbol{\beta} + \mu_i + \varphi_{it} \\ \varphi_{it} &= \lambda \sum_{j=1}^{N} w_{ij}\varphi_{jt} + \varepsilon_{it} \end{aligned} \tag{5}$$

where φ_{it} is the spatially autocorrelation error term. λ denotes the spatial autocorrelation coefficient of the error term, which measures the effects of residuals of adjacent regions on residuals of the local region. The other parameters are the same as the above mentioned. The difference between the parameter ρ and λ lies in the way how the spatial dependence is introduced into the regression equation.

LeSage and Pace (2009) suggest integrate SLM and SEM to form the comprehensive spatial Durbin model. The panel SDM model can be expressed as follows

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \mathbf{x}_{it}\boldsymbol{\beta} + \mu_i + \sum_{j=1}^{N} w_{ij}\mathbf{x}_{jt}\boldsymbol{\gamma} + \varepsilon_{it}, \tag{6}$$

where $\boldsymbol{\gamma}$ is a vector of spatial autocorrelation coefficient of explanatory variables. The other parameters are the same as the above mentioned.

To decide which model better suits the data, we follow the specification tests outlined by Elhorst (2012). Firstly, we estimate traditional panel data models and apply likelihood ratio (LR) test to examine fixed effects. Then, we employ Lagrange Multiplier (LM) tests (LMLAG and LMERR) and their robustness (Robust-LMLAG and Robust-LMERR) to examine whether the spatial lag model or the spatial error model is more appropriate to describe the data than a model without spatial interaction effects. Secondly, if the non-spatial panel model on the basis of these LM tests is rejected in favor of the spatial panel model, then we further use the Wald test and LR test to decide which spatial panel data model is more appropriate. We first estimate the SDM model and then test the hypotheses $H_0 : \gamma = 0$ and $H_0 : \gamma + \rho\beta = 0$ by Wald test and LR test. The first hypothesis examines whether the SDM model can be simplified to the SLM model, and the second hypothesis whether it can be simplified to the SEM model (Burridge, 1981). If both of null hypothesis are rejected, then the SDM model best describes the data. Therefore, the SDM is a more generalized form comparing with SLM and SEM model. Whereas, a related statistical test is needed to carry out to judge whether the SDM is applicable to the specific regression analysis.

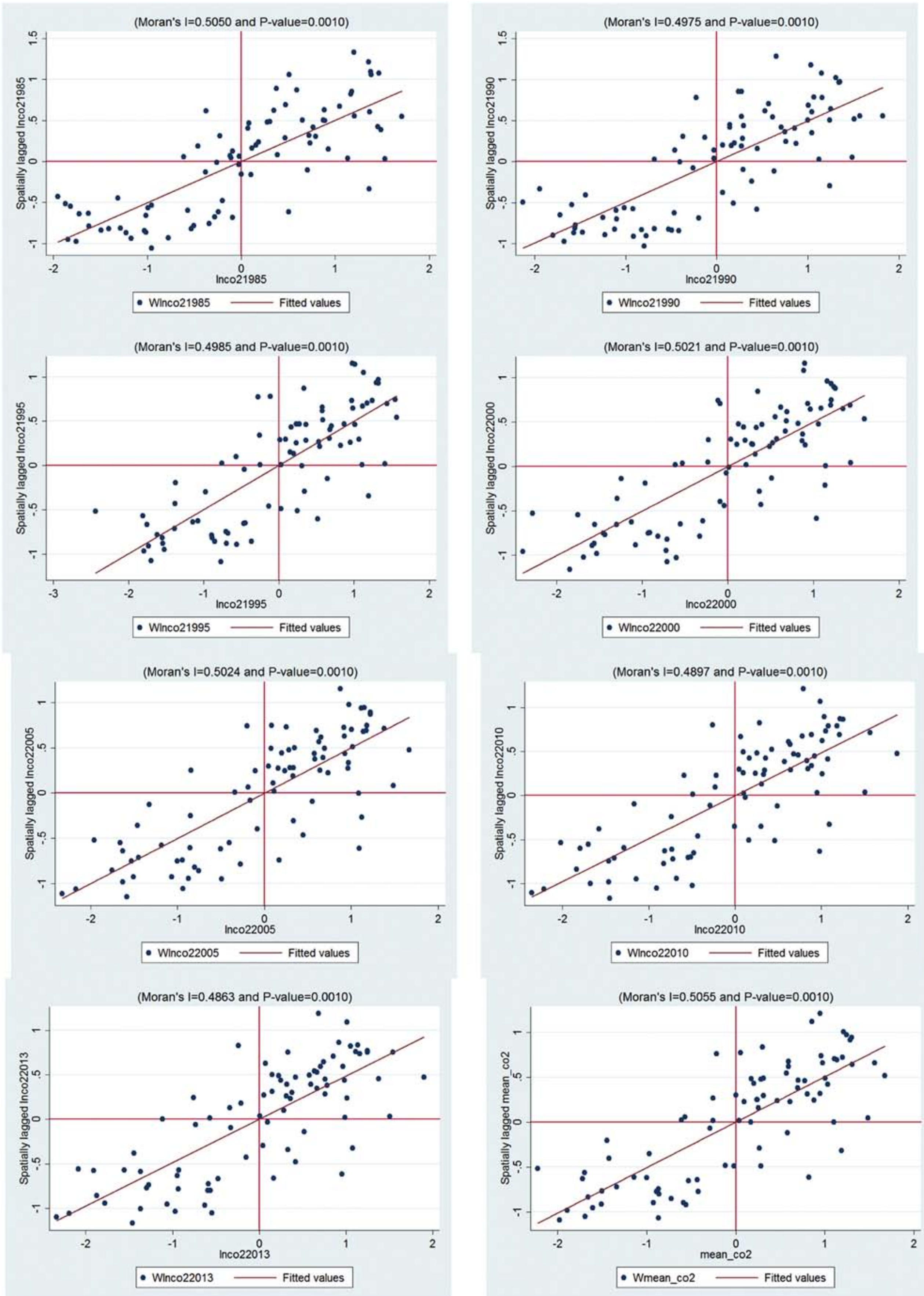

Fig. 1. Moran' I scatter plot of CO_2 emissions.

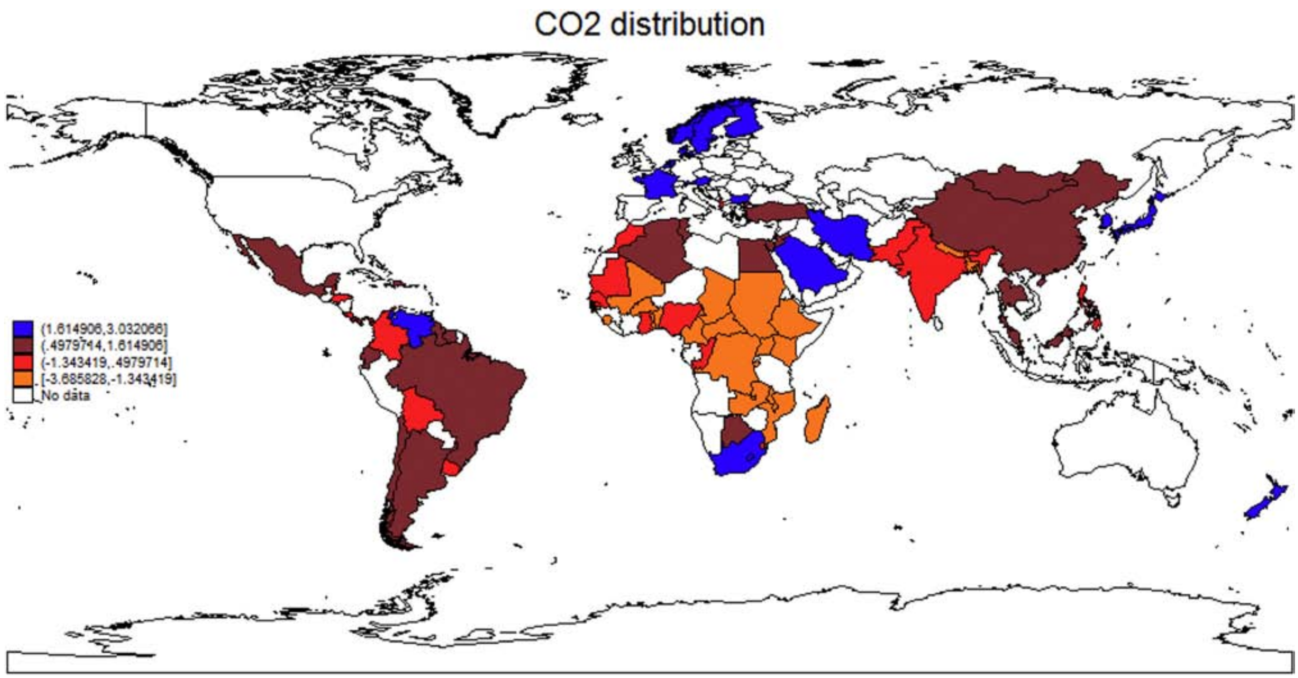

Fig. 2. Spatial distribution of CO_2 emissions. Notes: the arithmetic average (1985 to 2013) of the logarithm of CO_2 emission per capita is used. The class breaks correspond to quantiles of the distribution of the index.

In spatial econometrics model, another important consideration is how to specify the spatial weighting matrix, as different matrices capture different channels of spillovers (LeSage and Fischer, 2008; Corrado and Fingleton, 2012). In this paper, we use the inverse squared distance matrix.[4] This matrix assumes that neighboring relations are nonlinear and decline quicker than proportionally to the distance. Moreover, to check the robustness of the estimation results, we have also tested an alternative spatial weights matrix. Consistent with the previous literature, we normalize the matrix according to row standardization to interpret the spatial spillover effects as an average of all neighboring countries.

3.2. Estimation strategy and model interpret

The standard Ordinary Least Squares (OLS) estimation is often applied to estimate the spatial regression models, but it tends to lead to biased (for SLM model) or inefficient (for SEM model) estimator due to the introduction of spatial weight matrix. There are three commonly used methods to estimate models that include spatial interaction effects: the Maximum Likelihood (ML) estimator and the Quasi Maximum Likelihood Method (QML), the Instrumental Variable (IV) or Generalized Moment Method (GMM), and the Markov Chain Monte Carlo Method (MCMC). For a more detailed discussion of the methods, please see Elhorst (2010). An estimator based on the ML is commonly encountered in the existing studies (Fingleton and Gallo, 2008). In this paper, the ML estimation procedure is subsequently adopted.

Due to the spatial correlation in the spatial regression models, LeSage and Pace (2009) point out that the coefficients of the explanatory variables in the regression model cannot accurately reflect the marginal effect. For example, when the spatial lags of the dependent variable and independent variables are present in a model, the true total effect on a dependent variable (here $\ln(CO_{2it})$) of a unit change in an explanatory variable (i.e., $\ln(pop_{it})$) - that is, the true partial derivative of the expected value of $\ln(CO_{2it})$ with respect to $\ln(pop_{it})$ is not the same as the regression coefficient $\hat{b}$; it also captures spatial linkages and simultaneous feedback passing through the dependence system, which can be separated into a direct (own-region) effect and an indirect (spatial spillover) effect.

The proper interpretation of the marginal effect is rewritten the spatial Durbin model in terms of individual cross-sections. And then taking expectations

$$E(Y_t) = (I_n - \rho W)^{-1}\mu + (I_n - \rho W)^{-1}(X_t\beta + WX_t\gamma), \tag{7}$$

where I_n is an $n \times n$ identity matrix and the spatial multiplier matrix $(I_n - \rho W)^{-1}$ is equal to

$$(I_n - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots.$$

Therefore, the matrix of partial derivatives of the dependent variable in the different units with respect to the kth explanatory variable in the different units at a particular point in time t is

$$\left[\frac{\partial E(Y)}{\partial x_{1k}} \cdots \frac{\partial E(Y)}{\partial x_{Nk}}\right]_t = \begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_1)}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(y_N)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_N)}{\partial x_{Nk}} \end{bmatrix}_t = (I_n - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12}\gamma_k & \cdots & w_{1n}\gamma_k \\ w_{21}\gamma_k & \beta_k & \cdots & w_{2n}\gamma_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\gamma_k & w_{n2}\gamma_k & \cdots & \beta_k \end{bmatrix}$$

The above matrix can be denoted by $S = \frac{\partial E(Y)}{\partial x_k} = (I_n - \rho W)^{-1}C$.

Thus, the average direct impacts on Y of a unit change in x_k can be obtained as the average of the diagonal elements of matrix S, the average total impacts could be calculated by averaging over all regions the sum of the rows (or columns) of matrix S, and average indirect impacts (spillover effects) are obtained as a difference between the total and direct impacts. Formally,

[4] In the standard estimation and testing approaches, the weights matrix is taken to be exogenous. While it is reasonable to assume so when we use the contiguity matrix or the inverse distance matrix, it may be invalid to assume such exogeneity when the weights measure"socioeconomic" distance (Anselin and Bera 1998). We sincerely thank an anonymous referee for pointing out this issue.

Table 3
Cross section dependence of the variables.

Variables	lnCO_2	lngdp	lnglob	lnpop	lnurban	lnindus
CD-test	60.01***	164.38***	175.74***	269.08***	208.35***	4.73***

Notes: The CD-test performs the null hypothesis of cross-sectional independence. The test statistical follows the normal standard distribution N (0, 1). *** denotes significant at the 1% level.

$$\text{Total effects: } \overline{M}(k)total = \tfrac{1}{n}\sum_{i,j}^{n}\frac{\partial E(y_i)}{\partial x_{kj}} = \frac{1}{n} l_n'[(I_n - \rho W)^{-1}C]l_n;$$

$$\text{Direct effects: } \overline{M}(k)direct = \tfrac{1}{n}\sum_{i}^{n}\frac{\partial E(y_i)}{\partial x_{ki}} = \frac{1}{n} trace[(I_n - \rho W)^{-1}I_n\beta];$$

Indirect effects: $\overline{M}(k)indirect = \overline{M}(k)total - \overline{M}(k)direct$.

In models containing spatial lags of independent or dependent variables, interpretation of the parameters becomes richer and more complicated (LeSage and Pace, 2009). Firstly, the parameter estimates in the nonspatial model represent the marginal effect, whereas the coefficients in the spatial Durbin model do not. For this purpose, one should use the direct and indirect effects estimates to interpret the model. Meanwhile, one should note that the direct effects of the explanatory variables are different from their coefficient estimates. Direct effects estimates measure the impact of changing an independent variable on the dependent variable of a spatial unit. This measure includes feedback effects that arise as a result of impacts passing through neighboring units (e.g., from region i to j to k) and back to the unit that the change originated from (region i). Secondly, the indirect effects, known as spatial spillover, measure the impact of changing an independent variable in a particular unit on the dependent variable of all other units, or the impact of changing an independent variable in other units on the dependent variable in particular unit (LeSage and Pace, 2014). LeSage and Pace (2009) and Elhorst (2010) point out that the estimated indirect effects of the independent variables should eventually be used to examine the hypothesis as to whether or not spatial spillovers exist, rather than the point estimate of the spatially lagged dependent variable or the point estimates of the spatially lagged independent variables.

4. Empirical results

4.1. Spatial autocorrelation test

The Moran's I index is used to test the extent of spatial autocorrelation. A positive Moran's I value with statistical significance indicates spatial clustering and a negative and significant Moran's I value indicates spatial dispersion across the sample countries (Anselin and Florax 1995). Using data on CO_2 emissions per capita in 83 countries, we calculate the Moran'I index value for each year from 1985 to 2013, as well as the averaged values. As can be seen from Table 2, the Moran's I index is consistently positive and are statistically significant at the 1% level. This means that air pollution in world exhibits significant positive spatial autocorrelation. It is important to note that the global Moran's I test has a certain limitation. This test can only be used to describe the average degree of correlation overall. If there is a positive spatial autocorrelation in some countries and a negative spatial autocorrelation in others, then the influences will offset each other, in which case the Moran's I index may tend to 0 and show non-spatial autocorrelation. For this reason, to further test the spatial dependence, we conduct a Moran's I scatter plot for year 1985, 1990, 1995, 2000, 2005, 2010, 2013, and the averaged mean are reported in Fig. 1. The statistical significance of the Moran's I index values suggest that general econometrics methods that does not compensate for spatial dependency can yield possibly biased estimators. Meanwhile, combined with the spatial distribution of CO_2 in Fig. 2, we can also draw the conclusion that countries with similar CO_2 emissions tend to cluster, especially that countries with similar values tend to be neighbors. Consequently, we test whether the spatial econometrics models are better than general econometrics and chose the appropriate model to analyze the impact factors of CO_2 emissions in the following steps.

4.2. Panel unit root and cointegration tests

In order to properly specify the models described in the previous section, we begin with a preliminary analysis of the variables. We first test for the existence of non-stationarity in the variables, and subsequently for the existence of a cointegration relationship in the specifications. If all the variables are cointegrated, the error term follows a stationary process. Thus, the regression analyses based on long-term relationships are not spurious and it is possible to proceed with panel data models. It is noteworthy that only 82 countries (except Singapore) are used in panel unit root, panel cointegration test, and cross-sectional dependence test. The reason is that urbanization level has no within variation for Singapore and it cannot be used to test. For coherence, we choose the data of 82 countries for all variables.

First, we perform the cross-sectional dependence (CD) test for the variables to further examine whether spatial dependence across countries exists (Pesaran, 2004). The CD test does not require the specification of a spatial weighting matrix. The results are reported in Table 3. The null hypothesis that the variables are cross-sectional independent is clearly rejected for all variables, highlighting the importance of taking into account the spatial dependence across countries in this context.

Next, we perform the panel unit root tests using the approaches of LLC (Levin et al. 2002), IPS (Im et al. 2003), Breitung (Breitung, 2000), and CIPS (Pesaran, 2007). The first three approaches are the first-generation unit root tests that ignore cross-sectional dependence. The CIPS, the cross-sectionally augmented IPS, is the second-generation unit root tests that assume cross-sectional dependence of panel data.

Table 4
Panel unit root tests.

Variable		LLC	IPS	Breitung	CIPS
lnCO_2	Level	−2.7129***(0.0033)	−3.0711***(0.0011)	1.1895(0.8829)	−2.606254*
	First difference	−27.6531***(0.0000)	−34.4095***(0.0000)	−4.5454***(0.0000)	−5.329562***
lngdp	Level	0.3055(0.6200)	1.2738(0.8986)	0.8861(0.8122)	−2.21343
	First difference	−17.5418***(0.0000)	−21.4849***(0.0000)	−5.3152***(0.0000)	−3.992205***
lnglob	Level	0.9087(0.8182)	0.5603(0.7124)	1.9722(0.9757)	−2.592147*
	First difference	−26.6891***(0.0000)	−30.1242***(0.0000)	−5.8025***(0.0000)	−4.867352***
lnpop	Level	−0.9515(0.1707)	−4.9234***(0.0000)	1.6218(0.9476)	−2.5129
	First difference	−6.3511***(0.0000)	−9.2222***(0.0000)	−1.5956*(0.0553)	−2.7018***
lnurban	Level	−0.8681(0.1927)	−5.9139***(0.0000)	−0.8481(0.1982)	−2.02138
	First difference	−2.3710***(0.0089)	−6.6378***(0.0000)	−0.3926(0.3473)	−2.187867**
lnindus	Level	−3.5813***(0.0002)	−4.5795***(0.0000)	0.7686(0.7789)	−2.415316
	First difference	−31.5173***(0.0000)	−32.2228***(0.0000)	−6.6237***(0.0000)	−4.815889***

Notes: ***,**, and * denote a significance of 1%, 5% and 10%, respectively. The critical values of CIPS in level are −2.59, −2.65, and − 2.77 for 10%, 5%, and l% level, respectively. The critical values of CIPS in the first difference are −2.08 −2.16, and −2.30 for 10%, 5%, and l% level, respectively.

Table 5
Panel cointegration test.

	$lnCO_2$
Alternative hypothesis: common AR coefs. (within-dimension)	
Panel v-statistic	−4.412
Panel rho-statistic	4.388
Panel PP-statistic	−13.27
Panel ADF-statistic	−10.37
Alternative hypothesis: individual AR coefs. (between-dimension)	
Group rho-statistic	7.311
Group PP-statistic	−14.24
Group ADF-statistic	−11.82

Notes: All test statistics are distributed N(0,1), under a null of no cointegration.

Because the CIPS test produces accurate results in the presence of cross-sectional dependence, we prefer the second-generation unit root test to first-generation ones. Results for all the tests are reported in Table 4. The results show that after first differencing, all our variables are stationary at 1% level of significance. It is thus necessary to test for panel cointegration.

Third, we perform the panel cointegration tests using the Pedroni cointegration tests (Pedroni, 1999, 2004). We first compute the mean of the series across panels and subtract this mean from the series before we perform the panel cointegration test. Levin et al. (2002) suggest this procedure to mitigate the impact of cross-sectional dependence. The evidence suggests that we can reject the null of no cointegration using any statistics (see Table 5). Therefore, we explore the long-run relationship in the next subsection.

4.3. Spatial econometric regression results

To decide which model is more appropriate, following Elhorst (2012), we conduct the models without spatial interaction effects and perform the corresponding (robust) LM lag and LM error tests for the two spatial econometric estimators. Table 6 presents the estimation results for the non-spatial panel data models: pooled OLS only, fixed effects only, time-period fixed effects only and both spatial fixed effects and time-period fixed effects, respectively. We perform the LR test to investigate the null hypothesis that the spatial effects and time-period effects are jointly insignificant. The null hypothesis that the spatial fixed effects are jointly insignificant is rejected at the 1% significance level (5131.7137, 83 degrees of freedom, $P < 0.01$). However, the null hypothesis that the time fixed effects are jointly insignificant is not rejected (25.0091, 29 degrees of freedom, $P = 0.7487$). Thus, these results justify the panel data model with spatial fixed effects.

Table 7
Results of Spatial Durbin models.

	Spatial fixed effect model		Spatial random effect model	
	Coefficients	t values	t values	
ρ	0.0971***	3.45	0.0966***	5.10
lngdp	1.796***	6.84	1.700***	5.00
lngdp2	−0.0677***	−3.71	−0.0576***	−2.69
lnglob	0.0285	0.83	0.0168	0.72
lnpop	−0.455***	−12.00	−0.0340	−0.33
lnurban	0.0532*	1.88	0.116	1.50
lnindus	0.203***	4.89	0.192***	4.47
W*lngdp	1.553***	2.63	1.495***	2.74
W*lngdp2	−0.0906***	−2.70	−0.0853**	−2.53
W*lnglob	−0.148***	−3.82	−0.124***	−3.81
W*lnpop	0.838***	14.62	0.177***	4.21
W*lnurban	−0.579***	−3.34	−0.388	−1.38
W*lnindus	0.128**	2.26	0.164*	1.89
R^2	0.4722		0.4663	
Hausman test	39.647(0.0002)			

Notes: Numbers in the ( ) represent p values, and ***, **, * imply 1%, 5% and 10% level of significance, respectively.

To examine the spatial dependence, we employ Lagrange Multiplier (LM) tests and their robustness to examine whether non-spatial panel data models ignore the spatial interaction effects of data or not. The results are presented at the bottom part of Table 6. For the LM tests, the null hypothesis of no spatially lagged dependent variable and the null hypothesis of no spatially autocorrelated error term are strongly rejected at the 1% significance level in all model specifications. Regarding the results of their robustness tests, the null hypothesis of no spatially autocorrelated error term can be rejected at the 1% significance level in all model specifications, while the null hypothesis of no spatially lagged dependent variable cannot be rejected in the two-way fixed effects model. Apparently, these results imply that there exists spatial dependence among the data, which is consistent with the results of Moran's I index.

We next turn to choose which spatial econometric model is more appropriate. We first estimate both fixed and random effects of the spatial Durbin model so as to ascertain the robustness of our conclusions. The results for the fixed effects and the random effects models are quite similar in term of sign. We employ the Hausman test to test the random effects model against the fixed effects model. The results

Table 6
Estimation results of non-spatial panel model.

	Pooled OLS	Spatial fixed effects	Time-period fixed effects	Spatial and time-period fixed effects
lngdp	3.079***	1.986***	3.083***	1.883***
	(29.49)	(15.99)	(29.43)	(13.19)
lngdp2	−0.129***	−0.0776***	−0.130***	−0.0693***
	(−21.48)	(−10.18)	(−21.55)	(−7.35)
lnglob	0.0997**	0.0104	0.183***	0.0256
	(2.24)	(0.35)	(3.67)	(0.83)
lnpop	0.0473***	−0.00781	0.0548***	0.0646
	(6.21)	(−0.18)	(6.94)	(0.92)
lnurban	−0.0577	0.150**	−0.0539	0.170***
	(−1.64)	(2.40)	(−1.53)	(2.62)
lnindus	0.553***	0.174***	0.530***	0.173***
	(14.50)	(7.10)	(13.61)	(6.83)
intercept	−18.74***	−11.69***	−19.09***	−12.67***
	(−44.25)	(−16.47)	(−43.97)	(−12.17)
R2	0.8706	0.4534	0.8709	0.4587
LogL	−2282.19	281.84	−2272.21	293.64
LM spatial lag	164.4846[0.000]	19.0151[0.000]	158.5308[0.000]	16.7729[0.000]
LM spatial error	68.4874[0.000]	16.2807[0.000]	68.2584[0.000]	35.3301[0.000]
Robust LM spatial lag	122.2187[0.000]	7.3061[0.007]	114.9999[0.000]	2.5141[0.113]
Robust LM spatial error	26.2215[0.000]	4.5717[0.033]	24.7275[0.000]	21.0713[0.000]

Notes: Numbers in the ( ) and [] represent t-stat values and P values, respectively, and ***, **, * imply 1%, 5% and 10% level of significance, respectively.

Table 8
Direct, indirect and total effects.

	Direct effects		Indirect effects		Total effects	
	Coefficients	t values	Coefficients	t values	Coefficients	t values
lngdp	1.820***	7.54	1.913***	2.86	3.733***	8.57
lngdp2	−0.0690***	−4.01	−0.108***	−2.90	−0.176***	−8.75
lnglob	0.0249	0.71	−0.160***	−3.78	−0.135***	−2.78
lnpop	−0.440***	−11.29	0.865***	15.32	0.425***	6.79
lnurban	0.0430*	1.68	−0.630***	−3.32	−0.587***	−3.27
lnindus	0.207***	4.87	0.163**	2.39	0.370***	3.59

Notes: ***, **, * imply 1%, 5% and 10% level of significance, respectively.

(39.647, $P = 0.0002$) indicate that the random effects model must be rejected. To test the hypothesis whether the spatial Durbin model can be simplified to the spatial error model, the Wald test is used. The hypothesis that the spatial Durbin model can be simplified to the spatial error model is rejected (Wald test: 88.2435, $P = 0.0000$). Similarly, the LR test is used to test the hypothesis that the spatial Durbin model can be simplified to the spatial lag model and the result rejects the null hypothesis (LR test: 77.0696, $P = 0.0000$). These results imply that both the spatial error model and the spatial lag model should be rejected in favor of the spatial Durbin model.

The results for the spatial Durbin model are reported in Table 7. It is noteworthy that the spatial autocorrelation parameter ρ is statistically significant at 1% level, indicating the existence of spatial dependence presented in the data. The results suggest that an increase in CO_2 emissions of neighboring countries would cause the rising of CO_2 emissions in the country. The coefficient of GDP per capita is positive while the squared term carries a negative sign. These results show that an inverted-U EKC relationship for CO_2 emissions is supported. The coefficients of industrial structure are significantly positive at the 1% level. This indicates that a higher share of the added value of industry to GDP would contribute to higher CO_2 emissions. These results are broadly in line with our prediction because the development of industry is associated with energy consumption. The coefficient of urbanization is significantly positive at the 10% level. All else being equal, higher urbanization increases CO_2 emissions. The coefficient of the population size variable indicates that everything else equal, more populated countries are associated with lower emissions. This conclusion seems puzzling at a first glance since it is usually believed that more population leads to more energy consumption direct or indirectly and hence more CO_2 per capita. One possible explanation, as suggested by Zheng et al., (2014), is that population size is associated with some agglomeration force that could improve the production efficiency which leads to a reduction in CO_2 emission per capita. For economic globalization, however, we observe that its parameter estimate is positive but not statistically significant, suggesting globalization in one country has no impact on CO_2 emission per capita to this country.

It is noteworthy that the coefficients of the SDM model do not directly reflect the marginal effects of the corresponding explanatory variables on the dependent variable (LeSage and Pace, 2010), we thus report the direct, indirect, and total effects of the independent variables (see Table 8). In our study, the direct effect represents an impact, due to changes in the independent variable(s) on CO_2 emissions, at a particular country. The indirect effect represents an impact due to changes in independent variable, in other locations, on the local CO_2 emissions. The total effect is simply the sum of the direct and indirect effects.

The coefficients of the direct effects are in line with the results provided in Table 8. We can observe that the direct effects of the explanatory variables are different from their coefficient estimates. The reason is the feedback effects that arise as a result of impacts passing through neighboring countries and back to the countries themselves. These feedback effects are partly due to the coefficient of the spatially lagged

Table 9
Direct, indirect and total effects.

	Direct effects		Indirect effects		Total effects	
	Coefficients	t values	Coefficients	t values	Coefficients	t values
8-nearest spatial weight matrix						
lngdp	1.790***	10.53	2.524***	5.86	4.313***	15.70
lngdp2	−0.0661***	−4.83	−0.139***	−5.84	−0.205***	−17.41
lnglob	0.0202	0.42	−0.251***	−4.24	−0.231***	−2.63
lnpop	−0.148*	−1.78	0.593***	6.89	0.445***	3.38
lnurban	0.132***	2.03	−0.808***	−4.45	−0.676***	−5.03
lnindus	0.171***	5.34	−0.0555	−0.93	0.116	1.39
the contiguity spatial weights matrix based on the distance						
lngdp	1.737***	8.12	2.259***	4.10	3.996***	11.68
lngdp2	−0.0639***	−4.04	−0.122***	−3.96	−0.186***	−12.10
lnglob	0.0160	0.39	−0.147***	−3.68	−0.131***	−3.33
lnpop	−0.223***	−4.07	0.530***	9.00	0.306***	3.11
lnurban	0.117**	2.13	−0.733***	−2.90	−0.616***	−3.00
lnindus	0.189***	4.76	0.0385	0.91	0.228***	2.89

Notes: ***, **, * imply 1%, 5% and 10% level of significance, respectively.

dependent variable, and partly due to the coefficient of the spatially lagged value of the explanatory variable itself. For example, the direct effect of GDP is 1.820 and its coefficient estimate 1.796 its feedback effect is equal to 0.0240.

Interesting results emerge from the indirect effects. For GDP per capita, the spillover effect amounts to 1.913. An interpretation of this coefficient is that an increase economic development in all neighboring countries increases CO_2 emissions in the local country. A similar result is found with the industrial structure, i.e., the spillover effect amounts to 0.163. For population size, the spillover effect amounts to 0.865. This means that an increase in population size in all neighboring regions increases CO_2 emissions in the local country and overcomes the negative direct effect of population size implying a positive (and significant) total effect (0.425). The estimation of the indirect spillover effect related to urbanization level is significantly negative and overcomes the positive direct effect of urbanization implying a negative (and significant) total effect (−0.587). The indirect effect coefficients suggest that being surrounded by highly urbanization countries has a positive effect on the environmental quality. The indirect effects from all the variables (except industrial structure) are relatively large, compared to the direct effect estimates.

As regarding for our key explanatory variable, economic globalization, our results indicate that the direct effect is positive but statistically insignificant. The indirect effect of economic globalization is significantly negative and overcomes the positive direct effect implying a negative (and significant) total effect. The result suggests that being surrounded by highly globalization countries has a positive effect on the environmental quality. Furthermore, CO_2 is a global pollutant, and the impacts of global pollutants cannot be internalized by a single economy as there is no specific region which shows their impacts (Miah et al., 2010). Accordingly, the "free-rider" phenomenon may exist.[5] As globalization induced by environmental policy differences can be harmful for the environment if it systematically shifts polluting industry from countries with tough regulation to countries with weak regulation. This is particularly worrisome in the case of global pollutants, because such globalization can imply that efforts to reduce CO_2 emissions can be undermined if globalization simply induces a shifting of polluting industry to countries without emission regulations. In the context of climate change, this is referred to as carbon leakage.

To show the robustness of results to specifications of the spatial weight matrix, we employ the following spatial weight matrices. One is a binary matrix of the eight nearest neighbour, where the weight

[5] We sincerely thank an anonymous referee for pointing out this issue.

Table 10
Results of Spatial durbin models.

	Spatial fixed effect model		Spatial random effect model	
	Coefficients	t values	t values	
ρ	0.0965***	3.22	0.0981***	4.06
lngdp	1.744***	7.13	1.825***	6.86
lngdp2	−0.0639***	−3.73	−0.0654***	−3.85
lnglob	0.0414	1.06	−0.0178	−0.43
lnurban	0.106***	6.39	−0.0617*	−1.82
lnindus	0.199***	4.56	0.178***	5.18
W*lngdp	1.642***	2.92	1.597**	2.36
W*lngdp2	−0.0953***	−2.95	−0.0903**	−2.19
W*lnglob	−0.159***	−4.00	−0.0910*	−1.72
W*lnurban	−0.680***	−5.52	−0.328	−1.42
W*lnindus	0.108*	1.77	0.145*	1.77
R2	0.4716		0.4663	
Hausman test	26.3580 (0.0057)			

Notes: Numbers in the ( ) represent p values, and ***, **, * imply 1%, 5% and 10% level of significance, respectively.

Table 11
Direct, indirect and total effects.

	Direct effects		Indirect effects		Total effects	
	Coefficients	t values	Coefficients	t values	Coefficients	t values
lngdp	1.770***	7.90	1.998***	3.03	3.767***	8.56
lngdp2	−0.0653***	−4.05	−0.112***	−3.06	−0.177***	−8.43
lnglob	0.0379	0.97	−0.170***	−3.87	−0.132**	−2.55
lnurban	0.0950***	5.83	−0.736***	−5.40	−0.641***	−4.88
lnindus	0.202***	4.57	0.143**	2.00	0.345***	3.23

Notes: ***, **, * imply 1%, 5% and 10% level of significance, respectively.

$w_{ij} = 1$ if the country j is within the eight-nearest neighbour of the country i and $w_{ij} = 0$ if otherwise. The other spatial weight matrix defines countries to be neighbour if the distance between their centroids is <1750 miles (Maddison, 2006). Results for direct, indirect, and total effects are reported in Table 9. The results show that different spatial weight matrices give broadly the same estimates of direct, indirect and total effects. It is noteworthy that the two spatial weight matrices are sparser (most of its elements are zero), thus spillover and total effects become somewhat less significant (i.e., industrial structure).

Besides, we also explore whether the results are changed when ruling out population explanatory variable and expressing the main variables as population weighted values.[6] The rationale behind of this model is that it factors out the impacts of population on each of these variables. That is to say, it allows us to conclude that the direct effects of the main variables on CO_2 emissions per capita when setting the model in this way. The coefficients of spatial Durbin model are reported in Table 10, and Table 11 shows the results of the direct, indirect, and total effects calculated based the regression coefficients of the SDM in Table 10. For all the independent variables, the changes are tiny whether in term of significance or magnitude, which further confirms our main findings are robust with model specification.

These results highlight the importance of taking account of the spatial dependence to assess the determinants of CO_2 emissions. Indeed, without that we only consider internal effect of policies whereas it seems that external (indirect) effects could be at least as large.

5. Conclusions and policy implications

While economists have been analyzing how globalization affects CO_2 emissions for decades, their understanding of the link between globalization and CO_2 emissions is highly partial, and little attention has been paid to examine this issue using a spatial panel data model approach. The main contribution of this paper is thus to explore the effects of globalization, measured by the KOF index of economic globalization constructed by Dreher (2006), on CO_2 emissions for 83 countries using the Spatial Durbin Model. Empirical results verify the existence of the spatial correlations in CO_2 emissions across nations, specifically, we find the direct effect of economic globalization on CO_2 emissions is positive but statistically insignificant. However, the indirect effect of economic globalization is negative and highly statistically significant, and overcomes the positive direct effect implying a negative and significant total effect. In addition, our results also provide strong evidence in support of the income–CO_2 emissions EKC hypothesis, implying the inverted U-shaped curved relationship between GDP and CO_2 emissions.

Based on the empirical findings of this study, we can draw some important policy implications as follows. First, from the regional and national perspective, spatial spillover effects of the dependent variable and independent variables have a positive significant effect on both of the local and surrounding countries. Therefore, policymakers and international organizations should not only focus on the profit of local country but also consider the influence on surrounding countries. They shall pay particular attention to the spatial implications derived from a greater degree of economic integration with the rest of the world. Second, stronger international cooperation is crucial for energy conservation and emissions reduction. Meanwhile, the central government should also make some legislative and administrative moves to foster energy conservation awareness. Finally, since the industrial structure has a significantly positive impact on CO_2 emissions, and the significant difference in economic and social development across nations, there should be enough differentiations in environmental policies in different countries. For example, as the developing countries are still in the stage of development, they have much stronger motivation to introduce industry especially heavy and chemical industries that would foster GDP growth rate more rapidly. However, because the environment is more fragile in these countries, more stringent measures should be taken to restrain the high-pollution industries in developing countries.

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Appendix A

A.1. List of countries

Albania, Algeria, Argentina, Austria, Bangladesh, Belize, Benin, Bhutan, Bolivia, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Chile, China, Colombia, Congo, Costa Rica, Cyprus, Democratic Republic of the Congo, Denmark, Dominican Republic, Ecuador, Egypt, Ethiopia, Fiji, Finland, France, Ghana, Guinea-Bissau, Guyana, Honduras, India, Iran (Islamic Republic of), Japan, Jordan, Kenya, Kiribati, Korea Republic of, Madagascar, Malawi, Malaysia, Mali, Malta, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Mozambique Nepal, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Panama, Philippines, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Singapore, South Africa, Sudan, Suriname, Swaziland, Sweden, Thailand, Togo, Trinidad and Tobago,

[6] We sincerely thank an anonymous referee for giving us much good advice on model specification.

Tunisia, Turkey, Uganda, Uruguay, Vanuatu, Venezuela, Zambia.

Table A1
Components of the KOF Index of economic globalization.
Source: http://globalization.kof.ethz.ch/media/filer_public/2017/04/19/variables_2017.pdf

Economic globalization	Indices and variables	Weights
1 Actual flows		50%
	1.1 Trade (percent of GDP)	21%
	1.2 Foreign Direct Investment, stocks (percent of GDP)	28%
	1.3 Portfolio Investment (percent of GDP)	24%
	1.4 Income Payments to Foreign Nationals (percent of GDP)	27%
2 Restrictions		50%
	2.1 Hidden Import Barriers	22%
	2.2 Mean Tariff Rate	28%
	2.3 Taxes on International Trade (percent of current revenue)	26%
	2.4 Capital Account Restrictions	24%

Table A2
Variable definitions and sources.

Variables	Definition	Unit	Source
CO_2	Energy-related CO_2 emissions	ton	WDI (2016)
Economic globalization	The KOF index of economic globalization	–	Dreher (2006)
GDP per capita	GDP divided by population at the end of the year	US in constant 2010	WDI (2016)
Population size	Total Population	people	WDI (2016)
Industrialization level	Percentage of the added value of industry in GDP	percent	WDI (2016)
Urbanization level	Percentage of the urban population in the total population	percent	WDI (2016)

Notes: All the data are annually over 1985–2013. WDI: World Development Indicators.

References

Adams, S., Klobodu, E.K.M., 2017. Urbanization, democracy, bureaucratic quality, and environmental degradation. J. Policy Model 39 (6), 1035–1051.
Anselin, L., 1988. Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. Geogr. Anal. 20 (1), 1–17.
Anselin, L., Bera, A.K., 1998. Spatial dependence in linear regression models with an introduction to spatial econometrics. Stat. Tex. Mon. 155, 237–290.
Anselin, L., Florax, R.J., 1995. Small sample properties of tests for spatial dependence in regression models: some further results. New Directions in Spatial Econometrics. Springer, Berlin Heidelberg, pp. 21–74.
Antweiler, W., Copeland, B., Taylor, S., 2001. Is free trade good for the environment? Am. Econ. Rev. 91 (4), 877–908.
Apergis, N., 2016. Environmental Kuznets curves: new evidence on both panel andcountry-level CO_2 emissions. Energy Econ. 54, 263–271.
Breitung, J., 2000. The local power of some unit root tests for panel data. Advances in Econometrics. vol. 15. Nonstationary Panels, Panel Cointegration, and Dynamic Panels (JAI).
Burnett, J.W., Bergstrom, J.C., Dorfman, J.H., 2013. A spatial panel data approach to estimating US state-level energy emissions. Energy Econ. 40, 396–404.
Burridge, P., 1981. Testing for a common factor in a spatial autoregression model. Environ. Planning A 13 (7), 795–800.
Christmann, P., Taylor, G., 2001. Globalization and the environment: Determinants of firm self-regulation in China. J. Inter. Bus. Stu. 32 (3), 439–458.
Corrado, L., Fingleton, B., 2012. Where is the economics in spatial econometrics? J. Reg. Sci. 52 (2), 210–239.
Dietz, T., Rosa, E.A., 1997. Effects of population and affluence on CO_2 emissions. Proc. Natl. Acad. Sci. 94 (1), 175–179.
Dreher, A., 2006. Does globalization affect growth? Evidence from a new index of globalization. Appl. Econ. 38 (10), 1091–1110.
Dreher, A., Gaston, N., Martens, P., 2008. Measuring globalization – Gauging its consequences. Springer, New York.
Drezner, D.W., 2000. Bottom feeders. For. Policy 122 (1), 64–70.
Elhorst, J.P., 2010. Applied spatial econometrics: raising the bar. Spat. Econ. Anal. 5 (1), 9–28.
Elhorst, J.P., 2012. Dynamic spatial panels: models, methods, and inferences. J. Geogr. Syst. 14 (1), 5–28.
Fingleton, B., Le Gallo, J., 2008. Estimating spatial models with endogenous variables, a spatial lag and spatially dependent disturbances: finite sample properties. Pap. Reg. Sci. 87 (3), 319–339.
Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. J. Econ. 115 (1), 53–74.
Jorgenson, A.K., Givens, J.E., 2014. Economic globalization and environmental concern: a multilevel analysis of individuals within 37 nations. Environ. Behav. 46 (7), 848–871.
Kang, Y.Q., Zhao, T., Yang, Y.Y., 2016. Environmental Kuznets curve for CO_2 emissions in China: a spatial panel data approach. Ecol. Indic. 63, 231–239.
Kellenberg, D.K., 2009. An empirical investigation of the pollution haven effect with strategic environment and trade policy. J. Int. Econ. 78 (2), 242–255.
LeSage, J.P., Fischer, M.M., 2008. Spatial growth regressions: model specification, estimation and interpretation. Spat. Econ. Anal. 3 (3), 275–304.
LeSage, J., Pace, R.K., 2009. Introduction to Spatial Econometrics. CRC Press, Boca Raton.
LeSage, J.P., Pace, R.K., 2010. Spatial econometric models. In Handbook of applied spatial analysis. Springer, Berlin, Heidelberg, pp. 355–376.
LeSage, J.P., Pace, R.K., 2014. The biggest myth in spatial econometrics. Dent. Econ. 2 (4), 217–249.
Le, T.H., Chang, Y., Park, D., 2016. Trade openness and environmental quality: International evidence. Energy Policy 92, 45–55.
Levin, A., Lin, C.F., Chu, C.S.J., 2002. Unit root tests in panel data: asymptotic and finite-sample properties. J. Econ. 108 (1), 1–24.
Lim, S., Menaldo, V., Prakash, A., 2015. Foreign aid, economic globalization, and pollution. Policy. Sci. 48 (2), 181–205.
Li, Z., Xu, N., Yuan, J., 2015. New evidence on trade-environment linkage via air visibility. Econ. Lett. 128, 72–74.
Luo, G., Weng, J.H., Zhang, Q., Hao, Y., 2017. A reexamination of the existence of environmental Kuznets curve for CO_2 emissions: evidence from G20 countries. Nat. Hazards 85 (2), 1023–1042.
Maddison, D., 2006. Environmental Kuznets curves: a spatial econometric approach. J. Environ. Econ. Manag. 51 (2), 218–230.
Managi, S., Kumar, S., 2009. Trade-induced technological change: analyzing economic and environmental outcomes. Economic Modelling 26 (3), 721–732.
Martínez-Zarzoso, I., Maruotti, A., 2011. The impact of urbanization on CO_2 emissions: evidence from developing countries. Ecol. Econ. 70 (7), 1344–1353.
Meng, L., Huang, B., 2017. Shaping the relationship between economic development and carbon dioxide emissions at the local level: evidence from spatial econometric models. Environ. Resour. Econ. https://doi.org/10.1007/s10640-017-0139-2 (Forthcoming).
Meng, B., Wang, J., Andrew, R., Xiao, H., Xue, J., Peters, G.P., 2017. Spatial spillover effects in determining China's regional CO_2 emissions growth: 2007–2010. Energy Econ. 63, 161–173.
Miah, M.D., Masum, M.F.H., Koike, M., 2010. Global observation of EKC hypothesis for CO_2, SO_x and NO_x emission: a policy understanding for climate change mitigation in Bangladesh. Energy Policy 38 (8), 4643–4651.
Pedroni, P., 1999. Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxf. Bull. Econ. Stat. 61 (S1), 653–670.
Pedroni, P., 2004. Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. Economic Theory 20 (3), 597–625.
Pesaran, M.H., 2004. General Diagnostic Tests for Cross Section Dependence in Panels. Cambridge Working Papers in Economics.
Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econ. 22 (2), 265–312.
Shahbaz, M., Solarin, S.A., Ozturk, I., 2016. Environmental Kuznets curve hypothesis and the role of globalization in selected African countries. Ecol. Indic. 67, 623–636.
Tobler, W.R., 1970. A computer movie simulating urban growth in the Detroit region. Econ. Geol. 46 (Sup 1), 234–240.
Zhang, Q., Yang, J., Sun, Z., Wu, F., 2017a. Analyzing the impact factors of energy-related CO_2 emissions in China: what can spatial panel regressions tell us? J. Clean. Prod. 161 (10), 1085–1093.
Zhang, S., Liu, X., Bae, J., 2017b. Does trade openness affect CO_2 emissions: evidence from ten newly industrialized countries? Environ. Sci. Pollut. Res. 24, 17616–17625.
Zhao, X., Burnett, J.W., Fletcher, J.J., 2014. Spatial analysis of China province-level CO_2 emission intensity. Renew. Sust. Energ. Rev. 33, 1–10.
Zheng, X., Yu, Y., Wang, J., Deng, H., 2014. Identifying the determinants and spatial nexus of provincial carbon intensity in China: a dynamic spatial panel approach. Reg. Environ. Chang. 14 (4), 1651–1661.