A Spatial Dynamic Panel Analysis of the Environmental Kuznets Curve in European Countries

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Abstract

Previous studies in the environmental Kuznets curve have overlooked spatial interdependence and this could bias the estimates. This paper therefore addresses the issue of spatial interdependence in the environmental Kuznets curve by using panel data on European countries over the period 1961-2009. The results obtained from the spatial dynamic panel suggest a significant degree of persistence in the per capita CO_2 emissions in European countries over time. Furthermore, we have found that per capita CO_2 emissions in a nearby country lead to a domestic increase in per capita CO_2 emissions and overall, the results are robust irrespective of the concept of neighborhood.

Key words: Environmental Kuznets curve, spatial dynamic panel.

JEL classification: C21, O1, Q56.

1. Introduction

Human activities have contributed to the increase of carbon dioxide (CO_2) emissions, mainly due to deforestation and the burning of fossil fuels. The reduction of CO_2 emissions is now a major challenge facing many countries. Despite the attempts by many governments to restrain fossil fuel emissions, CO_2 emissions have been increasing. The CO_2 emissions (major greenhouse gas) seem to contribute to rising sea levels, reduced agricultural productivity and the spread of diseases.

The publication of the "Limits to Growth" (Meadows, et al., 1972) has spurred the debate on economic growth versus environmental degradation and this debate is still topical. Hence, researchers and policymakers have been interested in the relationship between economic growth and environmental quality. Some have argued that economic growth involves an increase of CO_2 emissions and that any efforts to curb the emissions will eventually slow down economic growth. On the contrary, others have considered economic growth as a panacea for environmental quality and they think that as countries experience growth, CO_2 emissions will increase at a decreasing rate (environmental Kuznets curve, thereafter EKC). Thus, there is a growing stream of works on the relationship between economic growth and environmental degradation. What comes out from this vast literature is that overall there is evidence of an inverse U-shaped EKC between environmental degradation and income per capita (Bengochea-Morancho, et al., 2001, Bhattarai and Hammig, 2001, Carson, et al., 1997, Lin and Liscow, 2013, Neumayer, 2004, Schmalensee, et al., 1998). However, Dijkgraff and Vollebergh (2000) used data from OECD countries from 1950 to 1992 and from 1960 to 1997 and they rejected the presence of a quadratic relationship between CO_2 emissions and income per capita respectively. Though, these works have been thorough, a major critique is the lack of integration of spatial interdependence in the relationship between economic growth and environmental degradation. Ignoring this spatial interdependence could lead to bias estimates and affect policy recommendations.

Spatial interdependence can be ascribed to the situation where observations on the dependent variable (or the error term) at one location are correlated with observations of the dependent variable (or the error term) at other locations. Apparently, spatial interdependence could exist in studying the link between economic growth and environmental degradation. There could be some strategic interactions or behavioral mimicry among governments. For instance in the case of CO_2 emissions, policymakers in country *A* could be reluctant to mitigate its levels of CO_2 emissions if neighboring countries are not curbing their own emissions. On the contrary, policymakers in country *A* could be encouraged to do so if nearby countries are doing the same. Thus, it seems likely that the policymakers of country *A* select their levels of CO_2 emissions but are also concerned with the levels of CO_2 emissions chosen by other countries. Therefore, data could exhibit spatial interdependence as emissions within a particular country are affected by the emissions from its neighboring countries. There are very few studies that integrate spatial interdependence in the EKC, but most of them leave out dynamic effects over time.

Rupasingha et al. (2004) explored the relationship between per capita income and toxic pollutants at the county-level in the United States (US) and found that ethnic diversity and spatial effects are important in understanding toxic pollution in US counties. They also found an inverted U-shaped curve for quadratic specification. However, incorporation of a cubic term for income revealed that toxic pollution eventually increases again as income continues to rise. Maddison (2006) used only two-year panel data from 136 countries on sulphur dioxide, nitrogen oxides, volatile organic compounds and carbon monoxide emissions and found that national per capita emissions of sulphur dioxide and nitrogen oxides are significantly influenced by the per capita emissions of neighboring countries. Burnett et al. (2013) used a spatial panel data from 1970 to 2009 on US state-level CO_2 emissions and found an inverted-U shaped relationship even after controlling for spatial interdependence in the data.

Though the above studies are interesting, there are however two main shortcomings. Firstly, the income per capita is treated as exogenous which is not accurate. There is simultaneity between CO_2 and income per capita. The increase of income per capita could increase the CO_2 emissions, and the increase of the CO_2 emissions could negatively affect crop production, people's health and productivity, thus reducing income per capita. Thus, the results from these studies could be biased if the estimates are plagued by endogeneity. Secondly, the CO_2 emissions could be persistent over time since the current levels of CO_2 emissions could be influenced by the past levels of CO_2 emissions. Studying dynamic models are of great interest since they allow for empirical modeling of dynamics while accounting for time-invariant country characteristics. As pointed by Bond (2002, p.1) : "even when coefficients on lagged dependent variables are not of direct interest, allowing for dynamics in the underlying process may be crucial for recovering consistent estimates of other parameters". Nevertheless, estimating spatial dynamic panel when there are many endogenous variables such as the lagged, spatial lag of dependent variable and other potential covariates could be tricky. To solve this issue, researchers (Bouayad-agha and Vedrine, 2010, Davies and Vadlammanti, 2013, Foucault, et al., 2008, Gassebner, et al., 2011, Madariaga and Poncet, 2007) tend to extend the Generalized Method of Moments (GMM) estimator proposed by Arellano and Bover (1991), Blundell and Bover (1998). Kukenova and Monteiro (2008) compared the performance of spatial maximum likelihood estimator (MLE), spatial dynamic MLE (Elhorst, 2005) spatial dynamic quasi-MLE (Yu, et al., 2008), Least square dummy variable, difference GMM as well as extended GMM in terms of bias, root mean squared error and standard-error accuracy via a Monte-Carlo and found that in order to account for the endogeneity of several covariates, spatial dynamic panel models should be estimated using extended GMM techniques. As noted by Elhorst (2012), applying GMM estimator to spatial dynamic panel rather traditional spatial maximum likelihood estimators is that the former could be used to instrument endogenous covariates other than the lagged and spatial lag of dependent variable. Madariaga and Ponce (2007) also pointed that another drawback of the MLE is that it does not control for the presence of measurement errors.

In this study, we model for spatial interdependence in the EKC using a spatial dynamic panel on European countries over the period 1961-2009. The results suggest a significant degree of persistence in the per capita CO_2 emissions in European countries over time. Furthermore, we find that per capita CO_2 emissions in a nearby country lead to a domestic increase in per capita CO_2 emissions and overall, the results are robust irrespective of the concept of neighborhood.

The paper is structured as follows. Section 2 considers a theoretical framework; Section 3 presents the econometric estimation and data used; Section 4 discusses the findings and Section 5 concludes the paper with some policy recommendations.

2. Theoretical framework

As earlier stated, in the case of CO_2 emissions, there could be some strategic interactions or behavioral mimicry among governments. We present here a simple theoretical model of spatial interdependence drew from Brueckner (2003), Franzese and Hays (2008). We consider two countries (A, B) with their respective utilities (U^A, U^B) and actions (P_A, P_B)

such as the chosen levels of CO_2 emissions. We assume that the two countries are neighbors. Due to cross-border spillover, *A*'s utility depends on its own action (P_A) and that of nearby country *B* (P_B), vice-versa. Thus, domestic welfare in each country depends on both countries' actions:

$$U^A = U^A(P_A, P_B); \quad U^B = U^B(P_B, P_A) \tag{1}$$

Such interdependence can be better expressed by the best-response functions for each country which gives a country best response to the choices of other countries:

$$P_A^* = Arg\max_{P_A} U^A(P_A, P_B) = R^A(P_B); \quad P_B^* = Arg\max_{P_B} U^B(P_B, P_A) = R^B(P_A) \tag{2}$$

Figure 1 illustrates these two response functions where the intersection at point *N* is the Nash equilibrium with the set of strategies that satisfies equation (2).

[Insert Figure 1 about here]

Hence, the government of country *A* (*B*) selects its own CO_2 emissions but the country's emissions are also directly affected by the levels of emissions chosen by other countries such as *B* (*A*). The slopes of these best-response functions indicate whether actions by *A* induce *B* to move in the same direction, making the policies implemented in *A* and *B* strategic complements, or in opposite directions as strategic substitutes. The best-response functions' slopes depend on the ratios of second cross-partial derivatives:

$$\frac{\partial P_A^*}{\partial P_B} = {-U^A_{P_A P_B}}\Big/{U^A_{P_A P_A}}; \quad \frac{\partial P_B^*}{\partial P_A} = {-U^B_{P_B P_A}}\Big/{U^B_{P_B P_B}} \tag{3}$$

Policies that are strategic complements imply that $U^{A,B}_{P_A P_B} > 0$. In other words, reaction functions slope are upward. Policies that are strategic substitute imply that $U^{A,B}_{P_A P_B} < 0$, suggesting that reaction functions slope are downward[1].

3. Econometric estimation and data

We use a panel data on European countries over the period 1961-2009. Two models are used in the study.

The first moeeedel ignores spatial interdependence in the EKC and considers the state dependence of CO_2 emissions. Thus, past levels of per capita CO_2 emissions could affect current levels of per capita CO_2 emissions. The estimated model is:

$$\mathrm{CO_2}PC_{it} = \psi \mathrm{CO_2}PC_{i,t-1} + X_{it}\beta + \lambda_i + \gamma_t + e_{it} \qquad (4)$$

Where $\mathrm{CO_2}PC_{it}$, $\mathrm{CO_2}PC_{i,t-1}$ stands for current and past levels of per capita CO_2 emissions for the country *i* at the time *t* respectively. X_{it} is a vector of independent variables such as income per capita, squared of income per capita, trade openness and population density.

The disturbance term consists of an unobservable country-specific fixed effect which is constant over time λ_i, an unobserved time effect controlling for common shocks originated from political or technological source γ_t and a component that varies across both countries

[1] In a maximization utility framework, the second-order conditions imply negative denominators in equation (3).

and periods which we assume to be uncorrelated over time e_{it}. ψ and β are parameters to be estimated.

Estimating equation (4) presents a number of challenges. Firstly, there is endogeneity between CO_2 emissions and income per capita, CO_2 emissions and trade openness. Secondly, there is a lagged value of CO_2 emissions at the right-hand side (RHS). To overcome these difficulties, equation (4) could be estimated by the generalized GMM of Arellano and Bond difference (Arellano and Bond, 1991) or the system GMM estimator (Blundell and Bond, 1998). These estimators usually take the first difference to eliminate the fixed effects term and then use the lagged value of the RHS as instruments to estimate the coefficients. However, the difference GMM estimator may suffer from small sample bias due to weak instruments. Thus, the estimation of equation (4) is done by a system GMM that estimates equation (4) as a system of two equations, one in first differences and the other one in levels.

The second model allows for spatial interdependence in the study. The estimated model is a time-space simultaneous model (Anselin, et al., 2008):

$$\mathrm{CO}_2PC_{it} = \varphi \mathrm{CO}_2PC_{i,t-1} + \rho W\mathrm{CO}_2PC_{it} + X_{it}\beta + \lambda_i + \gamma_t + e_{it} \qquad (5)$$

W is the spatial weight matrix, defined as the five-nearest neighbors of every country in the sample[2] and implemented in Stata software by the user-written command « spwmatrix » (Jeanty, 2010). ρ is the spatial interdependence parameter and we hypothesize that this parameter will be positive and significant at conventional levels. φ and β are parameters to be estimated.

[2] The spatial weight matrix is row-standardized.

Equation (5) is estimated using the spatial dynamic panel estimator. This consists of extending the moment restrictions of Blundell and Bond (1998)'s estimator to the time-space simultaneous model. One main issue to address is the endogeneity of the spatial lag of CO_2 (WCO_2PC_{it}) in the RHS of equation (5). This variable is endogenous to CO_2PC_{it} as the levels of CO_2 emissions in each country depend on the weighted average of that in neighboring countries. We deal with this and the lagged by using the Blundell and Bond (1998)'s system GMM estimator with the Windmeijer (2005)'s finite-sample correction. In addition to using lagged values of the endogenous variables as instruments, we further use spatially lagged (exogenous) explanatory variables, i.e exogenous variables that are correlated with the endogenous variable but are themselves exogenous, making them valid instruments (Davies and Vadlammanti, 2013). We also address the endogeneity of the covariates such as the income per capita and trade openness by instrumenting them by their lagged values. There is also an issue of too many instruments that may overfit the instrumented variables and cause finite sample bias in particular weak specification tests such as Hansen J-test of overidentifying restrictions (Hansen, 1982). We follow Roodman (2009) by collapsing the instruments in order to reduce the instrument count which tends to mitigate finite sample bias. Our estimation strategy is similar to the works of Davies and Vadlammanti (2013), Bouayad-agha and Vedrine (2010). Lastly, we report the results of the two tests which are commonly used in the literature to test the consistency of the system GMM estimator namely the Hansen J-test and Arellano–Bond test of first-and second-order autocorrelation. The Hansen J-test explore whether the lagged values of covariates are valid instruments. The Arellano–Bond test of first-and second-order autocorrelation checks whether the first and second-serial order of the differenced error term are correlated. By default, the first-serial order correlation of the disturbance term is expected whereas the null hypothesis of the absence of the second-serial order correlation of the disturbance term must not be rejected.

The list of countries used in the study (see appendix) and the variables were obtained from the World Bank Development Indicator (WDI). Table 1 presents the different variables used in the study.

[Insert Table 1 about here]

4. Results and discussion

4.1. *Preliminary results*

We plot the per capita CO_2 emissions with the weighted per capita CO_2 emissions in the contiguous countries (Moran I plot). As shown by Figure 2, it is interesting to note that there is a positive relationship between the levels of per capita CO_2 emissions and those in the neighboring countries. Furthermore, we gauge if this positive correlation is significant. The p-value (0.00) of the coefficient of the partial correlation (0.63) between the levels of per capita CO_2 emissions and those in the contiguous countries suggests that this positive association is significant at 1% level. Thus, it seems relevant that the levels of per capita CO_2 emissions at the country level are positively related to the levels of per capita CO_2 emissions in adjacent countries. However, we will investigate this using rigorous econometric modeling.

[Insert Figure 2 about here]

4.2. *Baseline results*

Table 2 presents estimates for the dynamic panel and spatial dynamic panel. The coefficients on the lagged values of per capita CO_2 emissions are positive (0.90, 0.78 for the dynamic panel and spatial dynamic panel respectively) and significant at 1% level, signaling a significant degree of persistence in per capita CO_2 emissions in European countries. This justifies the use of a dynamic panel model. This finding suggests *hysteresis* in CO_2 emissions in European countries. Furthermore, we find an inverted U-curve between per capita CO_2 emissions and per capita income for the dynamic panel and spatial dynamic panel as well, implying that as income per capita increases, per capita CO_2 emissions in European countries increase at a decreasing rate. More importantly is the significance of the spatial interdependence coefficient $(\rho = 0.08)$ in the spatial dynamic panel. The results suggest that there is a positive and significant (5% level) cross-border spillover effect of per capita CO_2 emissions. Thus, a higher level of per capita CO_2 emissions in a nearby country leads to a domestic increase in per capita CO_2 emissions.

The Arellano-Bond AR(1) test for autocorrelation of the residuals rejects the null hypothesis that the residuals are not autocorrelated for both models. However, the test of AR(2) fails to reject the absence of the second-serial order correlation of the residuals. The Hansen test for overidentification restrictions on the instruments is significantly higher than zero, suggesting that the instruments are uncorrelated with the residuals.

[Insert Table 2 about here]

4.3. *Sensitivity analysis*

A number of sensitivity tests were carried out. Firstly, we refine the results reported above by using different definitions of the concept of neighborhood. We therefore use three spatial weight matrices to explore spatial interdependence in CO_2 emissions among European countries: 10-nearest neighbors, social network spatial weight matrix based on the fact that countries are neighbors if they speak the same official language[3], inverse distance squared spatial weights matrix using the projected latitudes and longitudes[4]. As can be seen in Table 3, past levels of per capita CO_2 emissions affect current levels of per capita CO_2 emissions irrespective of the definition of neighborhood. Furthermore, the levels of per capita CO_2 emissions at the country level are positively and statistically related to the levels of per capita CO_2 emissions in adjacent countries except for the inverse distance squared spatial weights matrix. We still find evidence of an inverted U-curve between CO_2 emissions and per capita income for the spatial dynamic panel regardless of the definitions of the concept of neighborhood. The results provided at the bottom of Table 3 also reveal that the three models are satisfactory. The Hansen-J overidentification test is satisfactory as is the Arellano-Bond test and the test for autocorrelation in residuals AR(2). We usually expect to reject the test for AR(1).

[Insert Table 3 about here]

Secondly, we examine the effect of being among the 15 member countries of the European Union (EU) on CO_2 emissions. The 15 member countries are: France, Belgium, Germany, Italy, Luxembourg, Netherlands, Denmark, Ireland, United Kingdom, Greece, Portugal, Spain, Austria, Sweden and Finland. These member countries took more binding Kyoto emissions targets than others. An EU dummy is therefore included in the models (EU-15 takes 1 for the member countries of European Union that took more binding Kyoto emissions targets and 0 for others). The results provided in Table 4 substantiate a significant degree of persistence in per capita CO_2 emissions in European countries for all the models, an

[3] The official languages of European countries were obtained from "Centre d'Études Prospectives d'Information Internationales (CEPII)" available at http://www.cepii.fr/anglaisgraph/bdd/distances.htm

[4] We use a distance cut-off of 73 miles. This cut-off was chosen based on the greatest Euclidean distance.

EKC for all the models except for the five-nearest neighbors and that the levels of CO_2 emissions of a country in Europe vary on average in the same direction as its neighbors only for the 10-nearest neighbors ($\rho = 0.09$) and social network spatial weights matrix ($\rho = 0.12$). Furthermore, though the coefficients of EU-15 are negative for all the spatial dynamic models, the results however do not support statistical evidence of the effect of being among the 15 member countries of the EU on CO_2 emissions.

[Insert Table 4 about here]

5. Conclusions

This study addresses the issue of spatial interdependence in the environmental Kuznets curve which has been ignored in previous studies. Emissions within a particular country could be affected by emissions from neighboring countries. Using panel data on European countries over the period 1961-2009, we provide first evidence of cross-border spillover effect of per capita CO_2 emissions in Europe. The results derived from the spatial dynamic panel substantiate a significant degree of persistence in per capita CO_2 emissions in European countries over time. More interestingly, it is found that per capita CO_2 emissions in a nearby country lead to a domestic increase in per capita CO_2 emissions and overall, the results are robust irrespective of the definitions of the concept of neighborhood. We still find statistical evidence of an inverted U-curve between CO_2 emissions and per capita income after controlling for spatial interdependence.

The findings are relevant for policymaking. Since the results confirm that transboundary pollution associated with CO_2 emissions is a major issue in European countries, one possible solution to reduce CO_2 emissions is to adopt more binding rules, reductions plans, invest in green technologies, renewable energies and due to spatial interdependence effects, this will lead to the reductions of CO_2 emissions in other nearby countries.

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Figure 1: Nash equilibrium

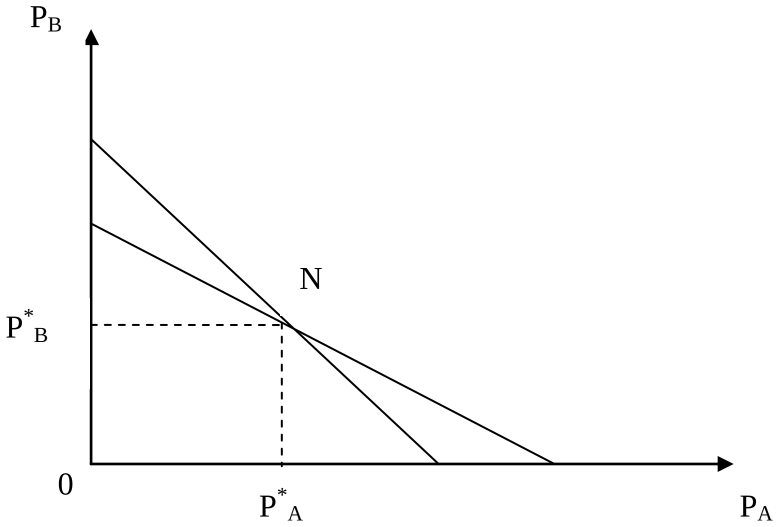

Figure 2: CO_2 emissions and weighted CO_2 emissions of adjacent countries

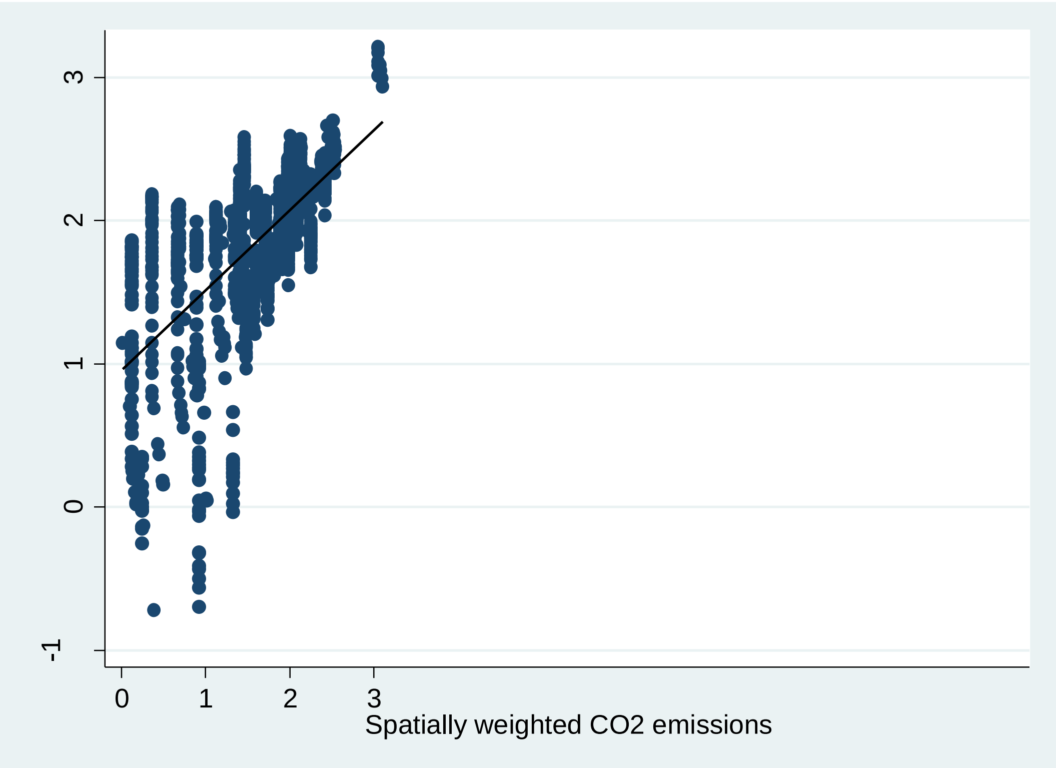

Table 1: Description of the variables

Variables	Description	Mean	SD	Min	Max
Lnco2pc	Per capita CO_2 emissions (metric tons).	1.84	0.57	-0.72	3.21
Lngdppc	Gross domestic product per capita.	9	1.1	5.85	10.94
Ltrade	Trade openness (the sum of exports and imports of goods and services measured as a share of gross domestic product).	4.30	0.47	2.81	5.81
Popden	Population density. People per square kilometer of land. It is the midyear population divided by the land area in square kilometers.	140.3	199.56	1.79	1293.72

Notes: SD means standard deviation. All the variables are reported in logarithm except the Popden which is thousands.

Table 2: Econometrics results of dynamic panel versus spatial dynamic panel

Variables	Dynamic panel	Spatial dynamic panel
Lnco2pc(-1)	0.90***	0.78***
	(0.07)	(0.08)
Lngdppc	0.15***	0.61**
	(0.04)	(0.22)
$(Lngdppc)^2$	-0.01***	-0.03**
	(0.002)	(0.01)
Ltrade	-0.08	0.01
	(0.05)	(0.04)
Popden	1.08	-0.02
	(1.99)	(0.04)
ρ		0.08**
		(0.03)
AR(1)	-3.53	-3.44
P-value of AR(1)	0.00	0.00
AR(2)	0.93	1.17
P-value of AR(2)	0.35	0.24
Hansen-J statistic	37.59	38.43
P-value of Hansen-J statistic	0.35	0.84

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Lnco2pc (-1) is the lagged value of the Lnco2pc. AR(1) and AR(2) are Arellano-Bond autoregressive of order 1 and 2 respectively. The number of instruments is kept at 10.

Table 3: Econometrics results of the spatial dynamic panel based on the definition of the spatial weight matrix

Variables	W1	W2	W3
Lnco2pc(-1)	0.76***	0.77***	0.78***
	(0.08)	(0.06)	(0.09)
Lngdppc	0.61***	0.28**	0.63**
	(0.22)	(0.10)	(0.31)
$(\text{Lngdppc})^2$	-0.03***	-0.02**	-0.03*
	(0.01)	(0.01)	(0.02)
Ltrade	0.01	-0.0001	-0.06
	(0.03)	(0.03)	(0.05)
Popden	-0.003	0.003	0.24
	(0.04)	(0.07)	(0.26)
ρ	0.13**	0.20**	0.001
	(0.06)	(0.06)	(0.001)
AR(1)	-3.43	-3.35	-3.43
P-value of AR(1)	0.00	0.00	0.00
AR(2)	1.16	1.07	1.11
P-value of AR(2)	0.25	0.29	0.27
Hansen-J statistic	38.22	38.66	38.49
P-value of Hansen-J statistic	0.84	0.83	0.81

Notes: Standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Lnco2pc (-1) is the lagged value of the Lnco2pc. AR(1) and AR(2) are Arellano-Bond autoregressive of order 1 and 2 respectively. The number of instruments is kept at 10. W1, W2, W3 are the spatial weight matrices defined as the 10-nearest neighbors, social network spatial weights matrix based on the fact that countries are neighbors if they speak the same official language, inverse distance squared spatial weights matrix respectively. All these matrices are row-standardized.

Table 4: Econometrics results with the dummy variable of member countries of European Union (EU-15)

Variables	Dynamic panel	five-nearest neighbors	W1	W2	W3
Lnco2pc(-1)	0.90***	0.79***	0.77***	0.79***	0.78***
	(0.07)	(0.07)	(0.09)	(0.06)	(0.08)
Lngdppc	0.16***	0.48	0.53**	0.32**	0.62*
	(0.06)	(0.30)	(0.25)	(0.16)	(0.31)
$(\text{Lngdppc})^2$	-0.01**	-0.02	-0.03*	-0.02**	-0.03*
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Ltrade	-0.09	-0.03	-0.02	-0.02	-0.06
	(0.06)	(0.04)	(0.04)	(0.04)	(0.05)
Popden	1.09	0.02	0.02	0.17	0.24
	(2.03)	(0.09)	(0.07)	(0.21)	(0.33)
EU-15	0.02	-0.14	-0.11	-0.12	-0.001
	(0.11)	(0.09)	(0.09)	(0.07)	(0.15)
ρ		0.04	0.09*	0.12**	0.001
		(0.03)	(0.04)	(0.05)	(0.001)
AR(1)	-3.52	-3.43	-3.41	-3.47	-3.44
P-value of AR(1)	0.00	0.00	0.00	0.00	0.00
AR(2)	0.92	1.14	1.15	1.07	1.13
P-value of AR(2)	0.35	0.25	0.25	0.29	0.26
Hansen-J statistic	36.40	36.50	36.33	35.74	38.49
P-value of Hansen-J statistic	0.36	0.86	0.87	0.88	0.78

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Lnco2pc (-1) is the lagged value of the Lnco2pc. AR(1) and AR(2) are Arellano-Bond autoregressive of order 1 and 2 respectively. The number of instruments is kept at 10. EU-15 takes 1 for the member countries of European Union that took more binding Kyoto emissions targets and 0 for others. W1, W2, W3 are the spatial weight matrices defined as the 10-nearest neighbors, social network spatial weights matrix based on the fact that countries are neighbors if they speak the same official language, inverse distance squared spatial weights matrix respectively. All these matrices are row-standardized.

Appendix: List of countries

Albania, Austria, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Macedonia. FYR, Malta, Moldova, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russian Federation, Serbia, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom.