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So close, no matter how far: A spatial analysis of CO_2 emissions considering geographic and economic distances

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Abstract
In recent years, the effects of climate change have become a topic of growing interest in the literature. Many works claimed the importance of spillover effects while studying CO_2 emissions. Most part of them considers these indirect effects from a geographical perspective. The reduction of transportation costs makes other factors more important. Thus, the main aim of this paper is to analyse the existence of spatial dependence, considering geographical and economic proximity and comparing both measures. Empirically, we make use of the World Input–Output database with a worldwide focus from 2000 to 2014. Based on an environmentally extended multiregional input–output model, we estimate the CO_2 emissions embodied in the domestic production and international trade between countries. To analyse the dependence from both perspectives, we carry out a spatial econometric analysis and make use of two different spatial weight matrices. The results offer a new approach on this field, highlighting the importance of the spillover effects to explain the CO_2 emissions of the local country, showing that economic proximity is even more important than geographical one.

KEYWORDS
climate change, CO_2 emissions, MRIO analysis, spatial econometric model, spillover

1 | INTRODUCTION

Increasing concerns about climate change and its consequences, such as floods, extreme temperatures, and natural disasters, have brought to the fore the urgency of global cooperation agreements to effectively reduce the level of emissions in the atmosphere (Bohm, 1993; Edmonds et al., 2008; Pizer, 2006). The IPCC of 2014 indicates an objective of 40%–70% GHG emissions reduction by 2050.

Various international agreements such as the Kyoto Protocol of 1997 and, more recently, the Paris Agreement of December 2015 are examples of efforts to organise a global response to the threat of climate change and to support the decarbonization of the global economy (see FCCC/CP/2015/L.9/Rev.1 [UN, 2016]). Therefore, the United Nations have included climate change and its consequences among its 17 Sustainable Development Goals (see IPCC, 2018).

Thus, the necessity of environmental policies to achieve these objectives is clear. To make them more effective, we have to focus not only on a country's own behaviour but also on the links with other countries. Since the beginning of globalisation, countries have been more connected each time. That is, interactions among countries/regions also became important while explaining the environmental phenomenon.

In this context, previous literature has addressed the existence of spillover effects in a globalised context, finding that indeed there is spatial autocorrelation, and that being surrounded by globalised countries reduces the level of emissions (Meng et al., 2017; You & Lv, 2018). In other words, my 'neighbours' behaviour affects my emissions and so on. However, how can we define 'neighbours'? Previous literature usually used the geographical distance as main variable (see, for instance, Shahnazi & Dehghan Shabani, 2021; Yang et al., 2019, 2021). Others take into consideration not the spillover among countries, but the spillover of different factors such as technology (Huang et al., 2020; Wen et al., 2020).

With the reduction of tariffs and transportation costs, the geographical distance loses importance in favour of other economic factors. In this sense, economic distance has been used for the analysis of other aspects, such as employment or economic growth (Conley & Ligon, 2002; Conley & Topa, 2002). Economic distance can be defined as the productive structure proximity between countries. That is, the more similar is the productive structure of two countries, the higher is their economic interaction, especially in terms of trade. In our specific framework of multisectoral analyses, this implies that two or more countries present economic proximity if their productive specialisation, in terms of sectoral weights over total value added, are similar. Some papers already included the economic dependence through technological improvements and their spillovers (Rios & Gianmoena, 2018).

In this context, the main aim of this paper is to analyse the spatial dependence of CO_2 emissions including these two kinds of distances, geographic and economic. This will allow us to compare results and distinguish the main differences and similarities of both perspectives. To the best of our knowledge, this is the first work that includes the economic distance concept for the analysis of CO_2 emissions, being the main contribution of this work.

In order to drive our aim, we use some spatial econometric techniques. In current literature, it is possible to find several studies that analyse the impact of climate change with a spatial econometric analysis as well as studies that focus on the evolution of CO_2 emissions to evaluate whether there are spatial correlations between specific sector and global areas (see Kim et al., 2015). We will use two kinds of weight matrices: *K* nearest neighbours for geographical distance, and the correlation of specialisation indices for economic distance.

According to previous literature, and acknowledging the multisectoral and multiregional character of global production flows and the associated emissions, our paper makes use of the multiregional input–output model (MRIO) for the world economy to obtain the calculations of CO_2 emissions that will take a production-side perspective. Multiregional and multisectoral input–output (MRIO) models have been used as an important tool to examine the impacts in the domestic and foreign interdependences among countries (see, for instance, Duarte, Pinilla, et al., 2018; Duarte, Sánchez-Chóliz, et al., 2018). Besides, these models allow the study of the main drivers of the variable embodied in the MRIO models (see Xu & Dietzenbacher, 2014). Therefore, this type of models covers the study of complexity of the trade-emissions nexus. We will also use this MRIO framework to calculate our weigh matrix of economic distance. In short, it should be remarked that we contribute to this specific stream of literature, which combines spatial econometrics with input–output analyses, by adding the 'economic' dimension to the mere geographical distance in the study of CO_2 emissions embodied in trade.

This work is structured as follows. Section 2 presents the literature review. Section 3 presents the methodology used in this paper. First, we show how we calculate the emissions embodied in global production of each country (domestically consumed and traded with other countries); we continue explaining our regressions as well as the spatial model. Section 4 introduces the main results. Finally, Section 5 provides some concluding remarks and policy implications.

2 | LITERATURE REVIEW

Environmental research on embodied carbon emissions in trade has recently experimented an impressive expansion. Sato (2014) conducted a survey on publications regarding this topic, highlighting the coherence of qualitative results among articles, despite the existence of quantitative disparities due to the use of different methods and databases for estimating emissions. Furthermore, concerning methodological aspects, she found that MRIO models have a big representation in this field, revealing themselves as a valid and extended tool for conducting this research.

According to Xu and Dietzenbacher (2014), embodied emissions in trade grew at a higher rate than global emissions during the period 1995–2007. Undoubtedly, there exists an evident nexus between emissions, growth and development (Kang et al., 2016; Lv & Li, 2021; Steinberger et al., 2012). Thus, the study of the evolution, causes and consequences of embodied emissions in trade has been an important topic in recent years (Sakai & Barrett, 2016; Zhong et al., 2018).

From a geographical perspective, carbon emissions in trade are undoubtedly a global concern. However, these studies have usually focused on the United States, and mostly China (Dai et al., 2021; Su et al., 2013; Su & Ang, 2013; Weber & Matthews, 2007). Obviously, the development of China in the past decades, as well as other characteristics as its size, make this country an attractive and relevant contender for emissions analyses. Nonetheless, in an ever-changing world in which the position of China as a developed country seems to be consolidating, moving to a global focus might be necessary, even more as we seem to be entering into what has been named the 'post-China era' (Arce et al., 2016).

Moving on to the big topical block we are studying, that is, spatial spillovers of embodied emissions, we can also establish some principal traits as to the existing literature. As happened in the general case of embodied emissions in trade, the main focus has been put in the case of China, either as a regional or local level (Meng et al., 2017; Wang et al., 2019). More specifically, some studies focused on spillovers at industry-level (Ren et al., 2014). For example, Yang et al. (2019) studied the spatial spillovers on the transportation sector, while Wen et al. (2020) focused on the construction industry. Moreover, research on global spillovers have also been conducted (You & Lv, 2018).

In addition, it seems reasonable that, when talking about spillover effects, the way these are distributed is also taken into account. Another extended line of research has then been that of analysing disparities that have arisen as a result of these effects (Liu & Liu, 2019; Su et al., 2018; Wei et al., 2020). Moreover, returning to the topic of policy, the spillover effects that regulation on emissions can generate and their resulting inequalities are also object of study (Jiang & Ma, 2021).

Furthermore, it seems evident that technological change, innovation and energetic transition can reduce embodied emissions in trade (Chen & Lee, 2020). A plethora of studies focuses on the spatial spillover effects as a result of this phenomena. Jiao et al. (2018) analysed the technology spillover effects on carbon emissions in China at a regional level. In turn, Costantini et al. (2013) conducted a similar study for Italian regions, while Ren et al. (2021) extended it to the whole European Union.

However, as prolific as the literature on spatial spillovers of CO_2 emissions from a geographical perspective appears to be (Li & Lin, 2017; Wang & Zhu, 2020), little attention has been paid to the fact that embodied emissions in traded goods and services can be imported from any corner of the world. We are then positing that economic distance (in terms of structural similarities between countries, which can drive to proximity in trade) can be a non-negligible factor in the determination of these spatial spillovers, besides pure geographical distance (Conley & Ligon, 2002). To the best of our knowledge, no studies have been conducted at a global level in this direction. Nonetheless, there are precedents of analyses using both geographic and economic weight matrices, mostly for the Chinese case, at a national level, (Wang et al., 2018; Wang & He, 2019; Wen & Liao, 2019), and at urban and industrial levels (Han et al., 2018; Lou et al., 2021); but also for the Middle East and North Africa (Aghasafari et al., 2021).

3 | METHODOLOGY

3.1 | CO_2 emissions in a MRIO context

Using the multiregional input–output tables from WIOD, the World Input–Output Database, developed by Timmer et al. (2015) and data on CO_2 emissions from the recent database published by the Joint Research Centre of the European Commission,[1] we calculate the CO_2 emissions embodied in global production and trade at the sectoral level.[2] Several previous works (e.g. Bolea

[1]It is fully consistent with the 2016 release of WIOD. See https://ec.europa.eu/jrc/en/research-topic/economic-environmental-and-social-effects-of-globalisation.

[2]Other databases that we consider are EUROSTAT, OECD, CAIT and the World Bank.

et al., 2020) use these tables to carry out environmental analysis because of its capacity to describe the economic relations across 28 European countries and 15 non-European countries, hence covering almost 80% of total international trade from 2000 to 2014. We use CO_2 instead of another gas because it is the main contributor (62%) of accumulated GHG emissions, and it has displayed the highest growth rates over the last decades.

In what follows, we present the main features of the methodological approach adopted. We can estimate an environmental MRIO model (Isard, 1951; Miller & Blair, 2009) on the basis of the input–output methodology as follow:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{y} \tag{1}$$

Equation (1) represents the equilibrium equation in a global multiregional context, where $\mathbf{x}$ denotes the total output; $\mathbf{A}$ is the matrix of technical coefficients where each of its elements (a_{ij}^{rs}) reflects the intermediate input i of a country r necessary to produce a unit of output j in country s; and $\mathbf{y}$ is the vector of final demand, where each representative element f_i^{rs} is the final demand of good i produced in country r and consumed in country s. This equation can also be expressed in terms of the well-known Leontief inverse matrix $\mathbf{L}$ as follows:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y} = \mathbf{L}\mathbf{y}. \tag{2}$$

In addition, we can consider the vector of emissions directly generated by countries and sector $\mathbf{c}$. We can define the vector of direct emissions coefficients $\mathbf{e} = \mathbf{c}\left(\hat{\mathbf{x}}\right)^{-1}$, showing the direct emissions per unit of output (emission intensity). If we pre-multiply Equation (2) by the diagonalized vector of direct emission coefficients for each country and sector, we obtain the amount of emissions $\boldsymbol{\Omega}$ generated across countries and sectors as follows:

$$\boldsymbol{\Omega} = \hat{\mathbf{e}}\mathbf{L}\hat{\mathbf{y}}, \tag{3}$$

where each element Ω_{ij}^{rs} represents the CO_2 emissions generated in sector i of country r to meet the final demand of sector j in country s.

We make the sum of the elements by rows, but eliminating the domestic emissions beforehand. In consequence, our variable of interest measures how the direct emissions of a country and sector are incorporated in its sales to other countries and through the global production process. In other words, we consider the CO_2 emissions embodied in trade, exported by each country.

Therefore, the decomposition degree of these flows and the use of this multiregional and multisectoral methods, allows us a more complete view of the complex global process of generation of emissions, and the analysis of the cross-country relationships. In consequence, the disaggregation of emissions by country, sector and year, can be very representative of the behaviour and movements of this variable around the world.

Once the variable of interest has been defined in this MRIO framework, in the next section we explore its potential determinants and the empirical strategy to capture the main relationship between economic and environmental perspectives.

3.2 | Data analysis and econometric regressions

As is commonly shown in the literature (Duarte et al., 2017; Duarte, Sánchez-Chóliz, et al., 2018; Fan et al., 2006), the total demand that explains the consumption of final goods and services is a key determinant in the evolution of emissions. So, the demand effect is normally explained by changes in the countries' GDP, which is our first independent variable measured at constant prices of year 2000 and obtained from the World Bank. Besides, the generation of emissions is mostly affected by the evolution of international trade among countries. Therefore, we consider the share of net exports (exports minus imports) over output (Netexpoutput) as an important explicative variable[3] (see, for instance, Hu et al., 2020).

In addition, the specialisation degree of countries can be driving a large part of emissions evolution, especially the share of the energy sector in total output as well as the share of high technology industrial sectors and transport sector in total output (ES, HT, TS, respectively) calculated from WIOD too and being the most representative sectors of the behaviour of economies. As is well known in literature (Duarte et al., 2017; Fan et al., 2006), the technology is another key factor to explain the evolution of emissions. A proxy to the technological stage of each country is the backward linkages which, in a MRIO context, represents the share of non-domestic value added from foreign input providers (Arriola et al., 2020; Duarte, Pinilla, et al., 2018). In that way, we include in our model total backward linkages, obtained as the sum of each column of matrix A (including the main diagonal). Finally, it is important to consider the environment-energy-growth nexus (see, for instance, Dogan & Seker, 2016). For that, we consider the energy production from non-renewable sources (NRE) calculated as the difference between total energy production and energy production from renewable sources from ENERDATA; energy use per capita, which represent the energy of the country using as unit kg of oil equivalent per capita (obtained from the World Bank); and finally, a dummy variable with value 1 if a country signed the Kyoto protocol by the beginning of the sample period (see Kohl, 2014; Kohl & Trojanowska, 2015). In comparison to previous literature, we take advantage of the MRIO framework to calculate independent variables. Thus, the use of sectoral emissions allows us to capture the source of emissions, while backward linkages show technology from other perspective.

Therefore, in Table 1, we show the description measurement of the independent variables.

We have to note that there can be an endogeneity problem between the variables CO_2 emissions and NRE. There is an extremely wide-ranging literature on the relationship between renewable or non- renewable energy and carbon emissions (see Apergis et al., 2018; Dogan & Seker, 2016). Many of these works adopt the two-stage least square (2SLS) approach, the dynamic generalised method of moment (GMM) estimators or the Granger causality test, to check the possible endogeneity problems. In this paper, we use the Granger causality test for the whole sample that can be seen in Table 2.

After checking the results of Table 2, we can conclude that the direction of the causality relationship for the sample countries is from NRE to CO_2 emissions. Therefore, we can assume that the NRE variable is not endogenous, and there is no problem because the possible endogeneity is suppressed.

Following standard practice, the first regression that we model is a non-spatial pooled OLS regression model, which is used as a baseline, and we show it in Equation (4):

[3]It is calculated from the 2016 release of WIOD.

TABLE 1 Description and measurements of variables in the model on CO_2 emissions.

Variables	Description	Measurement
GDPp00	GDP at constant prices of year 2000	Billions of dollars
Netexpoutput	Share of net exports (exports minus imports) over output	Index
ES	Energy sector	CO_2 emissions embodied in energy sector
HT/OUT	Share of High technology industrial sectors in total output	CO_2 emissions embodied in HT per unit of total output
TS	Transport sector	CO_2 emissions embodied in TS
Backward linkage	Proxy to the technological stage	Ratio
NRE	The energy production from non-renewable sources	TwH = terawatt per hour
Energy use	Energy use refers to use of primary energy before transformation to other end-use fuels	Energy of the country using as unit kg of oil equivalent
Kyoto	Kyoto protocol	Dummy: 1 = if a country signed the Kyoto protocol; 0 = otherwise

Source: Own elaboration.

TABLE 2 Results from Granger causality test.

Null hypothesis	*F* statistics (*p*-value)	Direction
CO_2 does not Granger-cause NRE	4.72 (.1128)	NRE → CO_2
NRE does not Granger-cause CO_2	8.55 (.0001)	NRE → CO_2

Source: Own elaboration.

$$lnCO_2pc_{i,t} = \alpha_{i,t} + \beta_i\left(X_{i,t}\right) + \varepsilon, \tag{4}$$

where $\alpha_{i,t}$ is a constant, $lnCO_2pc_{i,t}$ is our dependent variable that represents the CO_2 emissions embodied in supply chains in country *i* and time period *t*; $X_{i,t}$ is the matrix of independent variables.

We include the WIOD's rest of the world block in the calculation of CO_2 embodied emissions in trade flows to have a completely closed economy. However, in the following analysis, we only consider the 43 countries (excluding the rest of the world block). Therefore, all the variables appear for 43 countries of the sample, being the individual unit of our study, and for the full time period, 2000–2014. Hence, from now, the following models contain observations for country *i* (being $i = 1, \ldots, 43$) and for year *t* (being $t = 2000, \ldots, 2014$). Following this line, we run the panel data models. After applying Hausman test, in Equation (5) we show the panel data model with fixed effects as follow[4]:

[4]The results of Hausman test indicate that the most appropriate model is the FE panel model (*p*-value = .00185) as can be seen in Appendix 1.

$$lnCO_2pc_{i,t} = \alpha_{i,t} + \beta_i(X_{i,t}) + f_i + \varepsilon, \tag{5}$$

where $\alpha_{i,t}$ is a constant and f_i is the usual individual fixed effects.

However, the panel data model with fixed effects presents a high correlation among fixed effects and the dummy variables, in our case the Kyoto variable. Hence, to avoid this issue, we introduce it in a multiplicative way (see Aichele & Felbermayr, 2015; Grunewald & Martinez-Zarzoso, 2016), as it can be seen in Equation (5).

$$lnCO_2pc_{i,t} = \alpha_{i,t} + \beta_j(X_{j,t}) + \beta_k Kyoto(X_{k,t}) + f_i + \varepsilon, \tag{6}$$

where $\alpha_{i,t}$ is a constant and f_i is the usual individual fixed effect. Unlike the Equation (5), $X_{j,t}$ is the matrix of independent variables with the exception of "Kyoto" variable which is included in a multiplicative way.[5]

Once the model is established, we have to check the presence of structural instability of Kyoto vs no Kyoto groups. To do this, the Chow test is used to confirm the presence of these differences. After running this test, we obtain a p-value of .011, indicating that there is some kind of spatial heterogeneity, that is, our observations behave differently according to whether they have ratified the Kyoto protocol or not. Thus, it seems that model of Equation (6) is the one that works better for our purposes.

3.3 | Spatial analysis

As previously stated, we aim to identify the behaviour of CO_2 emissions, taking into account, not only the spatial geographical effects, but also the economic ones. To conduct a spatial econometric analysis, the first step is to test for spatial autocorrelation in the dependent variable for CO_2 emissions within the countries. Following this, we apply some tests to determine the appropriate econometric method. This section describes these tests, the econometric model as well as the descriptive features of the data.

To test for spatial autocorrelation within the dependent variable, we use the classical global Moran's I test because it is the most robust test for this issue.[6] As previously established, to conduct this test, we need to calculate an appropriate spatial weight matrix (W) for our data. To consider the spatial geographical effects, we make use of the k-nearest neighbours (being in our case $k=5$) matrix that characterises the degree of spatial dependence of the spatial units within the geographical country of interest.[7] On the other hand, to measure the economic spatial effects (economic distance or proximity) we use a spatial weight matrix based in the productive structure of the countries. Through the specialisation indices of the different sectors (Balassa, 1965), we calculate the correlation coefficients to assess the greater or lesser economic distance between the countries. Those with a correlation coefficient greater than 0.5 are considered "economically close" neighbours and are assigned 1 in the weight matrix, the rest take a value of 0. The weights

[5]The results for Equations (4–6) appear in Appendix 1 (Tables A1 and A2).

[6]Test results fall between −1 and 1 and tends to 0 when no spatial autocorrelation is found.

[7]We create other weight matrix for $k=2$ nearest neighbours to check our results, obtaining similar results. The results of this weight matrix are available upon request.

TABLE 3 Tests for spatial econometric method selection.

K nearest neighbours	$k=5$ (*p*-value)	Economic weight matrix (*p*-value)
Global Moran's *I*	.0412	2.21e−16
LM-test: no spatial error	.03503	2.20e−16
LM-test: no spatial lag	3.41e−09	2.57e−13
RLM-test: no spatial error	2.38e−09	2.20e−16
RLM-test: no spatial lag	6.66e−16	1.06e−11

Source: Own elaboration.

in the matrixes are row standardised, which ensures that relative, not absolute, distance matters.

Using the spatial weight matrix (W), we run the Lagrange Multiplier (LM) (see Anselin, 2010) and the robust-LM (RLM) (see Anselin et al., 1996) tests on the residuals of the OLS estimation. These tests indicate if we can reject the OLS specification in favour of the spatial models. These results are detailed in Section 4.

Following this scheme, we test for the possibility to extend the baseline models (4–6), to include spatial interaction effects. Based on previous literature, there may exist spatial dependence not only in the dependent variable (CO_2 emissions pc) but in the explanatory variables too. We expand the baseline models using a general specification for static spatial panel models to include these effects as is shown in Equation (7):

$$lnCO_2pc_{i,t} = \tau_n\alpha_{i,t} + \lambda W_{ij}lnCO_2pc_{i,t} + \beta_j\left(\boldsymbol{X}_{j,t}\right) + \theta W_{ij}\boldsymbol{X}_{j,t} + \varepsilon_i + \omega_t + \mu_{it}, \tag{7}$$

$$\mu_{it} = \rho W_{ij}\mu_{it} + \varepsilon_{it}; \varepsilon_{it} \sim N\left(0, \sigma^2\right),$$

where $lnCO_2pc_{i,t}$ is the dependent variable for each unit of the sample and time period; τ_n is the $n \times j$ vector of ones for the constant term α and β; and θ are the $j \times 1$ vector of parameters associated with the $n \times j$ matrix of explanatory variables and the spatially explicit explanatory variables, respectively.

Given the above equations and the explanations of possible spatial dependency and autocorrelation issues, in Section 4, we explain in detail the process of model selection for our data.

4 | RESULTS

In this section, we first present the test for spatial dependence in the endogenous variable (CO_2 emissions pc). Second, the results of the panel OLS model, and then, the estimations and analysis of results obtained using the correct specification of a spatial model.

4.1 | Tests for spatial dependence and spatial model selection

We start applying Global Moran's *I* test on the residuals. From the results in Table 3, we can see that it is significant at the 5% level with both weight matrixes, indicating the presence of spatial spillovers in our data. However, it can be observed that the spatial dependence present in our observations is much stronger and more significant when the economic distance weight matrix is considered (0.0412 vs. 2.21e−16). With this first result, we begin to answer one of our key questions raised at the beginning. Moran's *I* test is showing a clear economic spatial dependence and a slight geographical spatial dependence.[8]

The LM tests for the spatial error and spatial lag models also show statistical significance as well as the robust LM (RLM) tests in both cases. These tests reveal statistical significance at the 1% level for all of them. Therefore, from these results, we may deduce that from the presence of significant spatial dependence in the data, it would be inappropriate to use the OLS model because it presents biased and inconsistent estimations, and it may be best to estimate a spatial model.

Given the results previously obtained with the Hausman test and the Chow structural rupture test, and considering the results of Table 3, we can conclude that the best spatial model for panel data that suits our sample would be the SARAR panel fixed effects model in both cases. This spatial panel model contains spatial lag in the dependent variable and spatial error autocorrelation.

4.2 | Spatial regressions

After calculating all needed checks, in Table 4, we show the results of the SARAR panel fixed effects model, taking into account the differentiation among Kyoto and non-Kyoto countries, using geographical and economic distance.

It is noteworthy that both the spatial autocorrelation parameter and the coefficient for spatial lag of the dependent variable are statistically significant, suggesting that there are spatial dependence and spatial autocorrelation in the data controlled with these parameters from both perspectives. While considering geographical distance, results suggest that an increase in the GDP, in the participation of the transport sector, and in the NRE, increases the level of CO_2 emissions. The latter effect is in line with findings in previous literature, in the sense that changes in the energy mix with a higher role of renewable energies can curtail the impact of trade emissions (Zhong et al., 2018). On the other hand, for the Kyoto countries, an increase in the participation of the energy and transport sectors, and in the technology component, cause an increase in the level of emissions generated. We can see that there are significant differences between the countries that signed the Kyoto protocol and those that did not (expected results after what was obtained with the Chow test).

Considering economic distance, the first and most relevant result is the significance of the variables, not only that of the spatial coefficients but also that of the rest of the explanatory ones. In line with the results obtained with Moran's *I* test (see Table 3), Table 4 shows the importance of economic distance in explaining the evolution of carbon dioxide emissions generated by trade. In this case, the results suggest that, for the total countries, an increase in the GDP, in the participation of the energy and transport sectors, in the level of energy production from non-renewable sources (NRE), and in the use of primary energy before transformation (energy use), cause an increase in the level of CO_2 emissions generated. Therefore, the results suggest that, if we consider the economic distance, most of the conditioning factors of the generation of emissions have a significant impact on it, and not only the local factors (within the country itself), but also the factors of the 'economically closest' countries.

[8]The scatter plots for both indices can be seen in Appendix 2 (Figure A1 and A2).

TABLE 4 SARAR panel fixed effects model for geographical and economic distance.

SARAR model with fixed effects	Total countries	Kyoto countries
ρ (coefficient for spatial error autocorrelation)	0.24338* (0.05636)	
λ (the coefficient for WY)	0.40084* (0.02836)	
d. (lnGDPp00)	0.04875* (0.046367)	0.0458 (0.8299)
netexpoutput	0.019946 (0.46367)	−0.0869* (0.05995)
Ln(ES)	−0.3263* (0.04846)	0.2765** (0.01295)
HT/OUT	−0.4174 (0.7487)	0.4914 (0.7086)
Ln(TS)	0.2986** (0.00175)	0.3175** (0.0164)
d.backward	−0.2513 (0.1173)	0.3551* (0.03870)
Ln(NRE)	0.1598* (0.0289)	−0.1181 (0.4379)
Ln(energyuse)	0.0961 (0.6605)	−0.2368 (0.2988)
R^2	.52854	
AdjR^2	.5062	
Spatial Hausman test	p-value = .04789 n = 588	

SARAR panel fixed effects model	Geographical distance		Economic distance	
	(1)	(2)	(3)	(4)
k = 5 nearest neighbours' weight matrix	Total countries	Kyoto countries	Total countries	Kyoto countries
ρ (coefficient for spatial error autocorrelation)	0.2434 (0.056)		0.6020 (2.2e16)	
λ (coefficient for WY)	0.4008 (0.028)		−0.6655 (0.002)	
d. (lnGDPp00)	0.0488 (0.046)	0.0458 (0.829)	0.6181 (0.046)	0.0011 (0.088)
netexpoutput	0.0199 (0.464)	−0.0869 (0.059)	−0.0002 (0.096)	−0.0749 (0.183)

TABLE 4 (Continued)

SARAR panel fixed effects model	Geographical distance		Economic distance	
	(1)	(2)	(3)	(4)
$k=5$ nearest neighbours' weight matrix	Total countries	Kyoto countries	Total countries	Kyoto countries
Ln(ES)	−0.3263 (0.048)	0.2765 (0.013)	0.0619 (0.008)	0.1728 (0.085)
HT/OUT	−0.4174 (0.749)	0.4914 (0.709)	1.0771 (0.543)	−0.8544 (0.632)
Ln(TS)	0.2986 (0.002)	0.3175 (0.016)	0.5095 (0.047)	0.5623 (0.074)
d.backward	−0.2513 (0.117)	0.3551 (0.039)	−0.1143 (0.536)	0.2535 (0.203)
Ln(NRE)	0.1598 (0.029)	−0.1181 (0.438)	0.0537 (0.049)	0.1187 (0.056)
Ln(energyuse)	0.0961 (0.661)	−0.2368 (0.298)	0.4349 (0.097)	0.7305 (0.013)
R^2	.5285		.5226	
AdjR^2	.5062		.5035	
Spatial Hausman test	p-value = .0479		p-value = .0369	
	n = 602		n = 602	

Source: Own elaboration.

*: the variable is significant at 10% level.

**: the variable is significant at 5% level.

***: the variable is significant at 1% level.

However, it is well-known that the coefficients of the SARAR panel model do not directly reflect the marginal effects of the corresponding explanatory variables on the dependent variable. So, in Table 5, we report the direct, indirect and total effects of the independent variables in the following tables, making use of both spatial weight matrices.

We can observe that the direct effects of the independent variables are a little bit different from their coefficient estimates. These results are due to the spillover or indirect effects with the closest neighbours. Let us start focusing on geographical distance. In this case, the direct effect of GDP_{p00} for the total countries of our sample is 0.0479 and its coefficient estimate in Table 4 is 0.0488 (not always exactly matches the 'total effect' coefficient), while its spillover effect is equal to 0.0013. Another example is TS (transport sector), whose direct effect is 0.311, while its total coefficient was 0.2986, being its spillover effect 0.1878. If we focus on the indirect effects, interesting results emerge. If we focus on all the countries, for GDP_{p00} and ES (energy sector), the spillover effect is significant. In the first case, it is 0.0013, that is, an increase in economic development in all neighbouring countries increases CO_2 emissions in the local country. These results are in line with previous literature that states that economic growth goes by the hand of more intensive production processes (Kasperowicz, 2015; Mardani et al., 2019). However, for ES variable, it is −0.2052, that is, an increase in the share of energy sector in the closest neighbours decrease the level of CO_2 emissions in the focus country. This could be associated with the

TABLE 5 Direct, indirect, and total effects with geographical and economic distance.

	Geographical distance			Economic distance		
Total countries	**Direct effects**	**Indirect effects (spillovers)**	**Total effects**	**Direct effects**	**Indirect effects (spillovers)**	**Total effects**
d.(lnGDPp00)	0.0479 (0.036)	0.0013 (0.046)	0.0491 (0.032)	0.6035 (0.035)	0.0015 (0.027)	0.6184 (0.046)
netexpoutput	0.0207 (0.936)	0.0125 (0.943)	0.0332 (0.944)	−0.0001 (0.094)	0.0000 (0.1379)	−0.0001 (0.094)
Ln(ES)	−0.3395 (0.014)	−0.2052 (0.026)	−0.5447 (0.021)	0.0506 (0.005)	−0.0135 (0.055)	0.0371 (0.001)
HT/OUT	−0.4341 (0.049)	−0.2625 (0.157)	0.6966 (0.124)	0.8822 (0.577)	−0.2354 (0.641)	0.6467 (0.5336)
Ln(TS)	0.3106 (0.041)	0.1878 (0.299)	0.4984 (0.049)	0.4173 (0.149)	−0.1140 (0.044)	0.3059 (0.043)
d.backward	−0.2615 (0.699)	−0.1581 (0.548)	−0.4196 (0.357)	−0.0936 (0.946)	0.0250 (0.925)	−0.0686 (0.932)
Ln(NRE)	0.1662 (0.047)	0.1005 (0.326)	0.2667 (0.315)	0.0440 (0.044)	0.0117 (0.326)	0.0557 (0.061)
Ln(energyuse)	0.0999 (0.369)	0.0604 (0.471)	0.1603 (0.524)	0.3562 (0.049)	−0.0951 (0.055)	0.2611 (0.032)
	Geographical distance			**Economic distance**		
Kyoto	**Direct effects**	**Indirect effects (spillovers)**	**Total effects**	**Direct effects**	**Indirect effects (spillovers)**	**Total effects**
K_d.(lnGDPp00)	0.0476 (0.369)	0.0288 (0.562)	0.0764 (0.426)	0.0008 (0.051)	0.000 (0.056)	0.0011 (0.057)
K_netexpoutput	−0.0904 (0.369)	−0.0546 (0.440)	−0.1451 (0.435)	−0.0614 (0.167)	0.0163 (0.126)	−0.0450 (0.176)
K_ln(ES)	0.2876 (0.041)	0.1739 (0.045)	0.4615 (0.039)	−0.1415 (0.089)	0.0038 (0.052)	−0.1037 (0.062)

TABLE 5 (Continued)

	Geographical distance			Economic distance		
Kyoto	**Direct effects**	**Indirect effects (spillovers)**	**Total effects**	**Direct effects**	**Indirect effects (spillovers)**	**Total effects**
K_HT/OUT	0.5111	0.3090	0.8201	−0.6998	0.1868	−0.5130
	(0.204)	(0.214)	(0.227)	(0.254)	(0.365)	(0.211)
K_ln(TS)	0.3303	0.1997	0.5301	0.4605	0.1229	0.5889
	(0.016)	(0.043)	(0.020)	(0.036)	(0.061)	(0.049)
K_d.backward	0.3693	0.2233	0.5927	0.2076	−0.055	0.1521
	(0.134)	(0.039)	(0.098)	(0.955)	(0.946)	(0.963)
K_ln(NRE)	−0.1229	−0.0743	−0.1972	0.0972	−0.0259	0.0713
	(0.085)	(0.098)	(0.096)	(0.096)	(0.026)	(0.021)
K_ln(energyuse)	−0.2463	−0.1489	−0.3952	0.5982	0.1597	0.7579
	(0.156)	(0.125)	(0.113)	(0.041)	(0.055)	(0.063)

Source: Own elaboration.

emissions involved in energy imports. In the case of Kyoto countries, the indirect effect for ES, TS, and backward are significant. For example, in the case of TS (transport sector) is 0.1997, that is, an increase in the participation of transport sector in the neighbouring economies, increases the level of CO_2 emissions in the local country. Note that these variables are novel in our paper (as stated before), so these are the firsts findings in this line.

We focus now on economic distance results. If we observe the results for total countries, it is worth noting that most of the spillover effects are significant, except for the variables "netexports", "HT/OUT", and "backward", which suggests that economic proximity has a great weight in the generation of CO_2 emissions from the local country. For example, we can see that the spillover effects of the GDP and the NRE variables generate a positive impulse in the CO_2 emissions of the local country. Thus, an increase in these variables in the economically close countries causes an increase in the emissions generated in the local country (going in the same direction as direct effects). However, other variables such as the energy and transport sectors generate a negative spillover effect on local emissions. Namely, an increase in the participation of these sectors in countries that are economically close to the local country, causes a decrease in the generation of local CO_2 emissions. In other words, countries can benefit from the production structure of the 'economic neighbours'. On the other hand, if we look at the results corresponding to the countries that have ratified the Kyoto protocol, we find some relevant differences. The same sectors (ES and TS) that previously had a negative spillover are now positive. In other words, for these 'Kyoto countries', an increase in the participation of these sectors in the countries that are close in economic terms generates an increase in CO_2 emissions. The explanation behind could be the stronger interaction between countries due to the intensive similarities of Kyoto countries. However, the spillover effect associated with the economic variable, the GDP, continues to generate a positive boost in the CO_2 emissions of the local country, as well as the "energy use" variable. This effect of increasing GDP in local emissions can be related to previous literature, in the sense that carbon emissions outflows generally go from developing to developed countries, which would reinforce these trends (Zhong et al., 2018).

Therefore, these results highlight the importance of considering the spatial dependence to choose the determinants of CO_2 emissions, which was already identified in previous literature as a driver of carbon emissions embodied in trade (see Duarte, Pinilla, et al., 2018; Zhong et al., 2022). Indeed, the generation of CO_2 emissions in a country is not only affected by the effects of internal or local policies, but also by the effects of external characteristics and economic policies implemented by its closest neighbours. Our results suggest that contrary to what is usually analysed in this field, economic distance matters, much more so than geographic distance. In terms of the generation of emissions associated with trade, it seems that the behaviour of countries that have a certain economic proximity to the local country greatly affects the level of CO_2 emissions generated. Therefore, not only does it matter who the closest neighbours are geographically, but the similarity of productive structures also plays an important role in this area.

5 | CONCLUSIONS AND POLICY IMPLICATIONS

The spatial dependence of CO_2 emissions has been widely studied in literature. However, most part of it considers a geographical perspective, although other factors could be as important. In this context, the aim of this paper is to analyse the spatial dependence issue considering both geographic and economic distance, which is define as production structure proximity (or structural productive similarities between countries).

From our results, we can conclude that, in the last two decades, spillovers are stronger when considering economic distance. Geographical distance is still significant, but it becomes less important as tariffs and transportation costs reduce, and trade between far countries increases. These results imply that the intensity of trade is based on their economic proximity, which entails stronger spillover effects of trade, having consequences on the levels of CO_2 emissions embodied in it and the way it should be measure.

More in detail, we observe that spillovers of energy use and production of non-renewable energy are significant while considering economic distance. That is, trade with non-clean countries reinforces CO_2 emissions. However, this is not happening from the geographical distance perspective, where technology (measured through backward linkages) is significant. We get a positive sign and, thus, those countries with a stronger backward linkage affect other countries more, increasing their interactions and, in consequence, their level of CO_2 emissions. Finally, GDP per capita is not significant in geographical terms for Kyoto countries, but it is when considering the economic distance. The higher is the GDP per capita of my neighbours, the higher the level of local CO_2 emissions is. As it is well known, most developed countries pollute more as their production processes are more intense. It is significant from both perspectives while considering the whole sample, which can be explained by the role of China in international pollution in the last years. Therefore, once again it seems to be demonstrated that economic distance is important to explain the level of contamination of the countries. It not only matters who you are geographically surrounded by, but who your main trade partners are, those with whom you share greater economic proximity. Besides, depending of the distance considered some variables behave differently. This highlights the importance of an adequate approximation to spillovers in other to better define environmental policies.

As policy recommendations, we can say that we should take different policies for those that ratify global agreements and those that do not. More important, official reports should consider spatial dependence, not only considering geographical proximity, but also economic factors. Globalisation has increased the linkages between countries, affecting the environmental phenomena as well. Besides, as previously said, economic proximity in more significant while explaining dependences among countries and these dependences tend to increase CO_2 emissions. This is due to the higher participation of developed countries (more similar among them) in the global supply chains. Global policies should encourage trade with other kind of countries less similar to them. In this sense, world trade organisations should foster the commercial relations between developed and transition and developing countries. Besides the usual advantages in terms of development that would arise from these policies, we have seen that global reductions in CO_2 emissions would also be obtained. Then again, for developed countries to achieve these reductions in emissions, they should engage in commercial relationship with developing countries that are not intensively pollutant. Perhaps, this situation is hard to imagine in any kind of trade that does not involve staples or other non-pollutant commodities, thus, the difficulty of implementing a policy involving, namely, industrial inputs. Finally, all this connects to the 'China shock', as it is a highly pollutant developing country and a global commercial leader. Its behaviour might affect other economically close developing countries, which would increase their level of local emissions, generating a vicious circle that could muddle up our recommended policies. The spatial spillovers on 'economic neighbours' is then a not so trivial issue, and so should be properly addressed by policy designers.

All in all, this paper shows the importance of economic dependence in explaining CO_2 emissions and the relevance of taking it into account for the implementation of global policies. In future research, it would be convenient to consider a wider sample including more developing countries. However, this paper opens a promising line of research in relation to the different ways countries or regions can be connected and how this is related to the environmental problems.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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APPENDIX 1

Results pooled OLS model and panel fixed/random effects models (with structural breakdown or not)

TABLE A1 Results for Equations (4) and (5).

	Pooled OLS	Panel FE	Panel RE
ΔLn(GDPp00)	0.0465	0.4351	0.4404
	(0.914)	(0.001)	(0.001)
Netexports/Output	−0.0265	0.049	0.0375
	(0.004)	(0.005)	(0.017)
Ln(ES)	−0.0132	−0.0157	−0.02485
	(0.683)	(0.574)	(0.361)
HT/OUT	0.0993	−0.0433	0.0321
	(0.069)	(0.796)	(0.792)
Ln(TS)	−02802	0.1141	0.0827
	(3.77e−10)	(0.015)	(0.066)
Δbackward	0.0688	−0.1073	−0.1070
	(0.761)	(0.046)	(0.053)
Ln(NRE)	0.0399	−0.0722	−0.0540
	(0.000)	(4.08e−05)	(0.000)
Ln(energyuse)	0.9055	1.0917	1.0424
	(2e−16)	(2e−16)	(2e−16)
kyoto	−0.899	Omitted	−0.3420
	(2.08e−09)		(0.079)
R^2	0.6930	0.5594	0.5623
Adj R^2	0.6882	0.5193	0.5555
$n = 602$			
Hausman test		p-value = .002	

Source: Own elaboration.

APPENDIX 2

Scatter plots of Moran's *I* test. Geographical vs. Economic distance

TABLE A2 Results for Equation (6).

Model 2 (FE)	Total countries	Kyoto countries
Δ(lnGDPp00)	0.3971	0.3601
	(0.193)	(0.029)
netexpoutput	0.0002	0.1515
	(0.992)	(2.33e−13)
Ln(ES)	0.3145	−0.2846
	(0.038)	(0.054)
HT/OUT	−0.2397	0.2915
	(0.865)	(0.837)
Ln(TS)	−0.1453	0.3515
	(0.433)	(0.006)
Δbackward	−0.1514	0.1325
	(0.228)	(0.338)
Ln(NRE)	−0.1962	0.1013
	(0.098)	(0.003)
Ln(energyuse)	1.5227	−0.4826
	(2.33e13)	(0.022)
R^2	.6116	
Adj R^2	.5682	
Hausman test	p-value = 2.743e−05	
Chow test	p-value = .011	
Breuch-Godfrey/Wooldridge test	p-value = 2.2e−16	
	$n = 602$	

Source: Own elaboration.

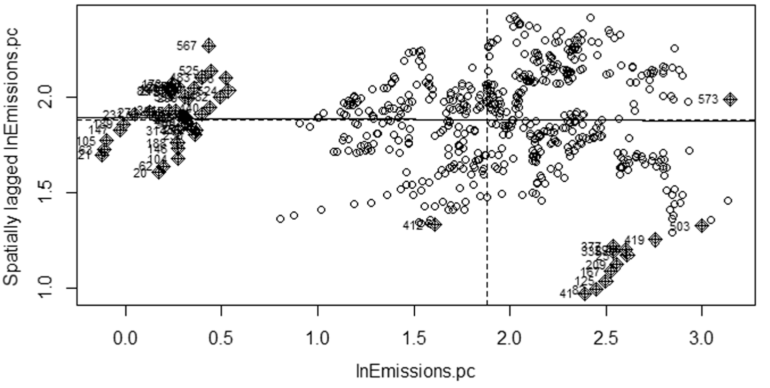

FIGURE A1 Scatter plot of Moran's I ($k = 5$ closest neighbours' weight matrix).

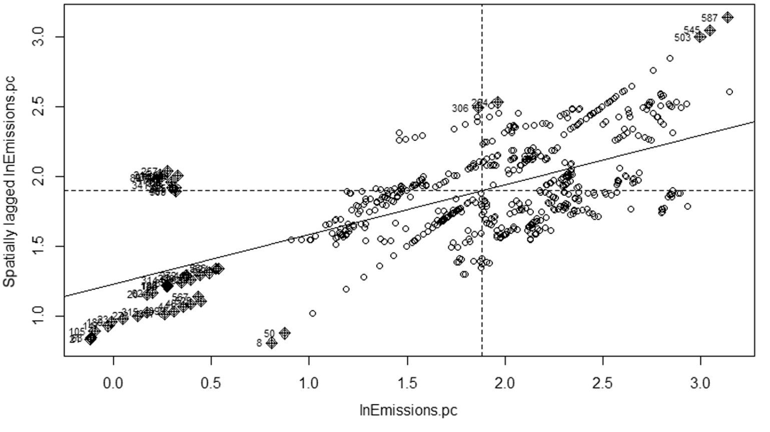

FIGURE A2 Scatter plot of Moran's I (Economic weight matrix).