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Spatial Econometric Analysis of Carbon Dioxide Emission – European Case Study

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ABSTRACT

The level of greenhouse gas emissions is one of the most important issues today, both professionally and politically, because a lower level of greenhouse gas emission is mandatory for a sustainable economy. Besides industry and households, the transport sector is also responsible for these emissions. For this reason, it may be essential to set up a model with which the amount of CO_2 emissions could be estimated or predicted. This article presents a model that examines the extent of economic development and CO_2 emissions in European countries. The result is establishing a pattern requiring a longer time series. If the pattern is proven, a clear reassessment of the current relationship between economic development and environmental protection should be made.

KEYWORDS

spatial econometrics; spatial statistics; CO_2 emission; transportation geography.

1. INTRODUCTION

An increasingly important issue today is the extent of carbon dioxide emissions. The compound also occurs naturally in the air and has played a key role in developing terrestrial life as a greenhouse gas (GHG). However, the development of our economy built on burning carbon-based resources resulted in increased carbon emissions, which gradually increased the Earth's temperature [1, 2]. The expected GDP growth of countries results in increasing energy consumption, which results in higher GHG emissions [3]. The severity of the problem is characterised by the fact that reducing emissions is a priority for many international as well as political organisations.

One of the most important sources of carbon dioxide emissions (in addition to industry and households) is transport [4, 5], which is why it is definitely advisable to prioritise the issue. The European Union's most important transport policy document, the White Paper – Roadmap to a Single European Transport Area – Towards a competitive and resource efficient transport system [6], contains numerous directives on reducing transport emissions for a sustainable future. In the case of GHGs, the stated goal is to reduce emissions to 60 percent of that of 1990 by 2050.

The role of transport in GHG emissions has been one of the most important issues in recent years [7]. Zefreh, Ádám Török and Árpád Török [8] demonstrate how the type of the internal combustion engine in vehicles affects GHG emissions and thus the externalities generated by transport. There are several possibilities to mitigate this and to study this field is also of great importance [9–11]. However, numerous parameters are available that have an effect on GHG emissions, such as the slope of the road infrastructure [12], the pattern of commuting [13] or the availability of seaports and dry ports [14]. Another approach to the externalities is how the emission levels affect people's health [15].

Carbon emissions at different levels are very often estimated using regression models. Xu and Lin, in their model [16, 17], examined different provinces of China, taking into account, among other things, GDP and the number of passenger cars. Using a linear regression model, Kamruzzaman, Hine, and Yigitcanlar examined the CO_2 emissions from transport in Northern Ireland [18]. A multilevel regression analysis was built for Brazilian states to investigate CO_2 emissions [19].

In this article, three factors in modelling carbon-dioxide emissions are considered, namely population, economy and transportation. The aim is to build a simple model that can be used to predict the evolution of emissions in European countries [20–22]. Another goal is to include spatial specialties in the model.

2. METHODOLOGY

We aimed to set up a spatial econometric model for the transportation sector's carbon dioxide emissions. Thus, in this section, a short overview is given about this method before the models used are introduced.

2.1 Spatial econometric models

The essence of spatial econometric models is to handle the possible spatial autocorrelation in the error vector of regression models [23, 24]. The Gauss–Markov Theorem states [25] that if the Gauss–Markov conditions are satisfied, the given estimate is BLUE (Best Linear Unbiased Estimation). One Gauss–Markov condition is that the error terms must be independent of each other; that is, u_i and u_j are independent for $\forall i \neq j$, where u_i and u_j are the two elements of the error vector of the linear regression model. This is not the case for autocorrelation because then, like time series, spatial units also influence each other according to the first law of geography [26]. It can be assumed that the demands are spatially concentrated, higher around each centre and lower when moving away from them. To determine whether spatial autocorrelation exists, Moran's I test can be applied; see *Equation 1* [27].

$$I = \frac{N}{S_0} \frac{\sum_{i,j} (w_{ij}(x_i - \mu)(x_j - \mu))}{\sum_i (x_i - \mu)^2} \tag{1}$$

where:

N – number of observations,

x_i, x_j – measured units in two points (elements of $\boldsymbol{x}$),

μ – the expected value of $\boldsymbol{x}$,

w_{ij} – an element of the spatial weight matrix,

$S_0 = \sum_{i,j} w_{ij}$.

In accordance with the methodology proposed in the literature, two types of binary weight matrices have been applied in our research: (i) the spatial units have an effect on each other, depending on whether they share a common point (1) or not (0); (ii) whether the spatial units are closer to each other than a given distance. A detailed description of this method can be found in [23, 24, 28–30].

If the existence of spatial autocorrelation is proven, three types of models can be set up: (i) the spatial lag model (SAR – spatial autoregressive), (ii) the spatial error model (SEM), (iii) the spatial autocorrelation model (SAC). In order to decide which model should be used, the Lagrange Multiplier Test is available [29, 31]. If it can be assumed that the spatial lagged dependent variable also affects the dependent variable, the SAR model should be chosen. In this case, the following regression formula (*Equation 2*) can be applied [24]:

$$\boldsymbol{y}_{(N\times 1)} = \rho \boldsymbol{W}_{(N\times N)} \boldsymbol{y}_{(N\times 1)} + \boldsymbol{X}_{(N\times K)} \boldsymbol{\beta}_{(K\times 1)} + \boldsymbol{\varepsilon}_{(N\times 1)} \tag{2}$$

where:

$\boldsymbol{y}$ – vector of the dependent variables,

ρ – spatial autoregressive parameter,

$\boldsymbol{W}$ – weight matrix,
$\boldsymbol{X}$ – matrix of the independent variables,
$\boldsymbol{\beta}$ – coefficient vector,
$\boldsymbol{\varepsilon}$ – vector of errors ($\varepsilon \sim \mathcal{N}(0,\sigma^2)$).

If spatial dependence can be eliminated from the model, and the spatial effects can be transferred to the error term, the SEM model should be used. In this case, the formulas presented below (*Equations 3 and 4*) can be used [24]:

$$\boldsymbol{y}_{(N\times 1)} = \boldsymbol{X}_{(N\times K)}\boldsymbol{\beta}_{(K\times 1)} + \boldsymbol{\varepsilon}_{(N\times 1)} \tag{3}$$

$$\boldsymbol{\varepsilon}_{(N\times 1)} = \lambda \boldsymbol{W}\boldsymbol{\varepsilon} + \boldsymbol{\zeta} \tag{4}$$

where:
λ – autoregressive error parameter,
$\boldsymbol{\varepsilon}$ – vector of spatially dependent errors,
$\boldsymbol{\zeta}$ – vector of spatially independent errors ($\zeta \sim \mathcal{N}(0,\sigma^2)$).

The third option is to use the two approaches together. There are several models for this [32], of which the Spatial Autocorrelation Model (SAC) was used because this is the one that can handle two different weight matrices simultaneously. Its formula is *Equation 5*.

$$\boldsymbol{y}_{(N\times 1)} = \rho \boldsymbol{W}_{1(N\times N)}\boldsymbol{y}_{(N\times 1)} + \boldsymbol{X}_{(N\times K)}\boldsymbol{\beta}_{(K\times 1)} + \lambda \boldsymbol{W}_{2(N\times N)}\boldsymbol{\varepsilon}_{(N\times 1)} + \boldsymbol{\zeta} \tag{5}$$

For the steps of calculation and a more detailed explanation behind the models, see [29, 30]. Spatial econometric analyses were performed in the *R 3.4.0* environment [33]. The *maptools* [34], *sp* [35, 36], *spdep* [35, 37] and *spatialreg* [35, 38, 39] libraries were used during the analysis.

2.2 Data and models

The basic concept of our models is to explain CO_2 emissions by population, GDP and motorisation index in 31 European countries. Similar analyses are also available for China [16, 17] and Nigeria [40]. Similarly, spatial econometric approach is widely used for this kind of analysis [41, 42]. The countries were selected based on the Eurostat database; only those countries where all data were available were considered. The countries involved are shown in the following map (*Figure 1*).

In our model, the increase in emissions between 2016 and 2017 is explained by the change in population, the 2017 stock of passenger cars and the magnitude of the annual change in GDP between 2009 and 2017. We identified two suitable models. The difference between the two models is that we took into account the number of passenger cars in 2017 (extended model – EM) – *Equation 7*, and in the other model we did not

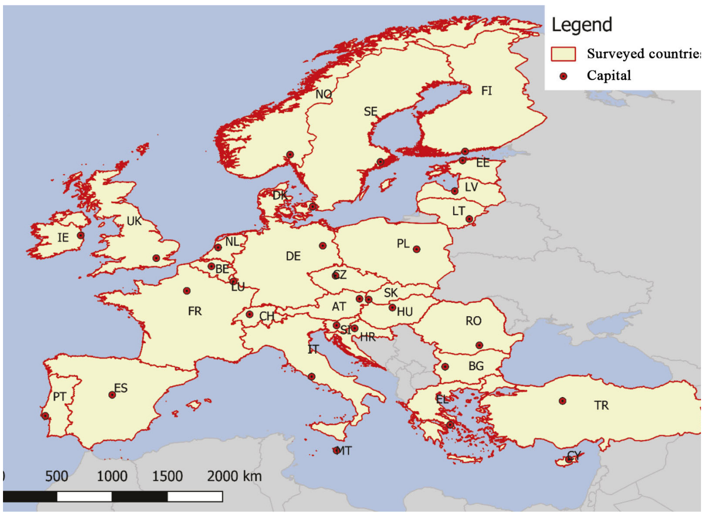

Figure 1 – Map of the surveyed countries

(base model – BM) – *Equation 6*. The data come from the Eurostat website; where the number of passenger cars was incomplete, so national statistics were also considered.

$$y = \alpha + \beta_1 d_{lak}^{2016/2017} + \beta_2 d_{GDP}^{2016/2017} + \beta_3 d_{GDP}^{2015/2016} + \beta_4 d_{GDP}^{2014/2015} + \beta_5 d_{GDP}^{2013/2014} + \beta_6 d_{GDP}^{2012/2013} + \beta_7 d_{GDP}^{2011/2012} + \beta_8 d_{GDP}^{2010/2011} + \beta_9 d_{GDP}^{2009/2010} \quad (6)$$

$$y = \alpha + \beta_1 d_{lak}^{2016/2017} + \beta_2 m + \beta_3 d_{GDP}^{2016/2017} + \beta_4 d_{GDP}^{2015/2016} + \beta_5 d_{GDP}^{2014/2015} + \beta_6 d_{GDP}^{2013/2014} + \beta_7 d_{GDP}^{2012/2013} + \beta_8 d_{GDP}^{2011/2012} + \beta_9 d_{GDP}^{2010/2011} + \beta_{10} d_{GDP}^{2009/2010} \quad (7)$$

where:

y – dependent variable (change in the carbon-dioxide emission between 2016 and 2017),

d_{lak}^{j} – yearly change of the country's population in the j^{th} time period,

d_{GDP}^{j} – yearly change in the GDP in the j^{th} time period,

m – number of passenger cars in 2017.

The calculations showed that the data is spatially autocorrelated, so we also built a spatial econometric model. Since the Lagrange Multiplier Test did not provide an adequate result to decide which models could be used, we used all three types for both models to compare a total of six spatial econometric models.

Thus, in general, six models can be compared to each other. The difference between them is that we can use the SAR, SEM or SAC spatial econometric models on BM or EM set of independent variables. In other words, we can use each model determined by *Equations 2–5*, with two different ***X*** matrices containing the independent variables of *Equations 6 and 7*.

In sum, the steps of the analysis were the following:

1) Setting up classic linear regression models for BM and EM (*Equations 6 and 7*),
2) Choosing the proper weight matrix based upon the Moran's I test for BM and EM (*Equation 1*),
3) Comparing the spatial econometric models (*Equations 2–5*).

The results are interpreted in the same order.

3. RESULTS

Table 1 contains the parameters of the BM and EM classic linear models. In general, significant parameter values show an increasing trend, so it is likely that over the years, the same rate of GDP growth will be accompanied by faster-increasing CO_2 emissions. Of course, due to the shortness of the time series, it is not possible to verify this from the data; further studies are needed. The significance level of the t-values is denoted as: if $p<0.1$;* if $p<0.05$; ** if $p<0.01$; and *** if $p<0.001$.

Figure 2 – Spatial relations of the surveyed counties according to the WD weight matrix [34]

For the classic linear regression models, it was proven that the error terms are autocorrelated, so we examined whether autocorrelation existed. To do this, three weight matrices were examined; (i) a neighbourhood-based (WB), where two countries interact when they are contiguous; (ii) two countries are adjacent if their centres of gravity (centroids) are closer than 750 km to each other (WD); (iii) whether their capitals are closer than 1000 km to each other (WD_cap). These matrices were examined for both models to see if autocorrelation could be detected. The results of the Moran's test are illustrated in *Table 2*.

Table 1 – The results of the classic linear regression models [35, 38, 39]

	BM		EM	
Intercept	3.1700		3.6640	
	[3.3510]	**	[3.1410]	**
$d_{lak}^{2016/2017}$	-4.9121		-5.4860	
	[-4.7160]	***	[-4.1940]	***
m			7.792E-05	
			[0.7400]	
$d_{GDP}^{2016/2017}$	0.0708		0.0305	
	[0.2940]		[0.1220]	
$d_{GDP}^{2015/2016}$	1.0893		1.1080	
	[3.4150]	**	[3.4260]	**
$d_{GDP}^{2014/2015}$	0.1657		0.2332	
	[1.3990]		[1.5490]	
$d_{GDP}^{2013/2014}$	0.6396		0.4789	
	[1.9260]	.	[1.1970]	
$d_{GDP}^{2012/2013}$	-0.1674		-0.0255	
	[-0.4790]		[-0.0630]	
$d_{GDP}^{2011/2012}$	0.4661		0.5599	
	[1.9360]	.	[2.0400]	.
$d_{GDP}^{2010/2011}$	-0.0513		-0.1305	
	[-0.2880]		[-0.6230]	
$d_{GDP}^{2009/2010}$	0.4671		0.4706	
	[2.8070]	*	[2.7960]	*

Table 2 – The results of the Moran's 1 test [35, 38, 39]

	BM		EM	
WB	0.1206		0.0523	
	[1.2889]		[0.8879]	
WD	0.1986		0.1511	
	[2.1112]	*	[1.7894]	.
WD_cap	0.0183		-0.0074	
	[0.6064]		[0.3488]	

As can be seen, in the case of the matrix calculated based on the centroid distances, a spatial autocorrelation can be detected; thus, we will apply this matrix in the following. The relationships are illustrated in the following map (*Figure 2*). The red line between the two centroids denotes that the countries are spatially related to each other.

Although the presence of spatial autocorrelation was confirmed by the Moran's test, we could not identify the applicable spatial econometric type models using the Lagrange Multiplier Test [29]. Thus, we built three types of spatial econometric models for BM and EM; the first one is a spatial delay-based model (SAR), the second one is a spatial error-based model (SEM) and the third one is a spatial autocorrelation (SAC) model.

Table 3 – The results of the spatial econometric models [35, 38, 39]

	SEM				SAR				SAC			
	BM		EM		BM		EM		BM		EM	
Intercept	3.217		3.339		3.149		3.632		3.529		3.596	
	[4.292]	***	[3.874]	***	[3.328]	***	[3.418]	***	[3.907]	***	[3.661]	***
$d_{lak}^{2016/2017}$	-4.785		-4.937		-4.901		-5.469		-4.934		-5.032	
	[-5.806]	***	[-5.128]	***	[-5.426]	***	[-5.069]	***	[-5.764]	***	[-5.155]	***
m			2.52E-05				7.81E-05				1.81E-05	
			[0.307]				[0.921]				[0.222]	
$d_{GDP}^{2016/2017}$	0.082		0.070		0.073		0.034		0.059		0.051	
	[0.468]		[0.389]		[0.355]		[0.164]		[0.332]		[0.283]	
$d_{GDP}^{2015/2016}$	0.961		0.967		1.092		1.113		0.886		0.895	
	[3.677]	***	[3.707]	***	[3.950]	***	[4.058]	***	[3.162]	**	[3.194]	**
$d_{GDP}^{2014/2015}$	0.158		0.179		0.165		0.232		0.168		0.183	
	[1.734]	.	[1.561]		[1.635]		[1.887]	.	[1.827]	.	[1.593]	
$d_{GDP}^{2013/2014}$	0.656		0.599		0.644		0.486		0.587		0.549	
	[2.806]	**	[2.025]	*	[2.152]	*	[1.429]		[2.258]	*	[1.749]	.
$d_{GDP}^{2012/2013}$	-0.147		-0.104		-0.169		-0.028		-0.098		-0.070	
	[-0.584]		[-0.354]		[-0.581]		[-0.087]		[-0.378]		[-0.236]	
$d_{GDP}^{2011/2012}$	0.381		0.420		0.468		0.563		0.326		0.358	
	[1.872]	.	[1.825]	.	[2.295]	*	[2.485]	*	[1.502]		[1.466]	
$d_{GDP}^{2010/2011}$	0.011		-0.012		-0.053		-0.134		0.054		0.036	
	[0.076]		[-0.076]		[-0.340]		[-0.749]		[0.339]		[0.206]	
$d_{GDP}^{2009/2010}$	0.408		0.409		0.468		0.472		0.389		0.391	
	[3.356]	***	[3.353]	***	[3.357]	***	[3.428]	***	[3.183]	**	[3.182]	**
ρ					0.002		0.002		-0.022		-0.021	
					[0.038]		[0.062]		[-0.578]		[-0.545]	
λ	0.428		0.406						0.470		0.453	
	[2.511]	*	[2.322]	*					[2.863]	**	[2.700]	**

4. DISCUSSION

Our assumptions are more emphasised in the case of spatial econometric models than in the case of classic linear regression models. GDP growth has taken place in a more sustainable framework since the 2008/09 crisis, but as time goes on, GDP growth will increasingly accelerate CO_2 emissions. Based on *Table 3*, it can be seen to what extent the annual GDP change affected CO_2 emissions. The recovery from the crisis was achieved by strengthening the emission rate – depending on the model, the parameter varied between 0.389 and 0.472, so it differed significantly from zero in all cases. Besides, only the change in GDP in 2015/16 significantly affected CO_2 emissions – depending on the model, it varied between 0.886 and 1.113 – and in some cases, the period of the years 2011/12, 2013/14, and 2015/16 has had an impact. The significant parameters indicate by what percentage the change in GDP modified the CO_2 emissions; in the case of the non-significant parameters, such a correlation cannot be statistically demonstrated because we cannot reject the null hypothesis that the parameter takes a value of 0.

In all cases, the population change had a negative impact on our model, which can be considered somewhat contrary to the previous expectations. There are many reasons for this; for example, where the population is growing, the CO_2 emissions are lower, or it can also be seen as an indicator that the European population is becoming more environmentally conscious. Of course, to reveal the exact reasons, further investigations are required, which are not part of this study.

What still seems to be outlined is that the increase in emissions is not affected by the size of the car fleet, according to these calculations. This result also contradicts the expected results; however, it is essential to highlight that this may be an indicator that the increasingly strict EURO standards are working, i.e. even though the number of passenger vehicles is increasing, the development of technology makes it possible for this not to be reflected in the CO_2 emissions. Naturally, the clarification of this also depends on further research.

5. CONCLUSION

To sum up, a spatial econometric model for carbon emissions data was presented that considers changes in population, GDP and the number of passenger cars in the surveyed European countries. The calculations indicate that the output depends on the population size as well as the change in GDP; however, the number of passenger cars alone does not affect the model. Changes in GDP increasingly influence our model over the years, which paints a very negative outlook due to the mainstream policy of constantly growing national economies, which is in coherence with e.g. [43].

The key aspect of the choice of methodology was the presentation of the applicability of the spatial econometric tool system, and we set up our model accordingly, which, however, does not lack empirical provability. The progress of the years and the increase in output caused by GDP growth is an important hypothesis of this article. However, no clear proof was obtained due to the short time series caused by the data. An important improvement would be if more countries could be included in the analysis, but the Eurostat database currently does not allow this.

The main limitation of this analysis is the lack of proper data. The time series are short and the number of available countries is low. However, the characteristics of the results are clear, which clears the way to further analysis. According to this model, the number of passenger cars does not affect the change in carbon dioxide emission, but the GDP does. This can be due to the fact that the GDP contains the yearly emitted mileage of passenger cars (and HGVs), so the analysis of this kind of data is the main direction of further studies. In the future, the analysis should be repeated with the increasing penetration of the different electric vehicles because it can be assumed that the carbon dioxide emission could be moderated with higher penetration.

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A szén-dioxid kibocsátás térökonometriai elemzése – európai elemzés

Absztrakt

Az üvegház hatású gázok kibocsátásának mértéke napjaink egyik legfontosabb kérdésköre, mind szakmai, mind pedig politikai szinten. Ezen gázok kibocsátásáért az ipar, és a háztartások mellett a közlekedési szektor is felelős. Emiatt kiemelt jelentőségű lehet egy olyan modell felállítása, amellyel a CO_2 kibocsátás mértékét becsülni, illetve előre jelezni tudjuk. Jelen cikkben egy olyan modellt állítottunk fel, amely a gazdasági fejlődés és a CO_2 kibocsátás mértékét vizsgálja az európai országok esetében. Az eredmény egy olyan mintázat megállapítása, amelynek igazolásához hosszabb idősorok szükségesek, azonban beigazolódása esetén egyértelműen át kell értékelni a gazdaságfejlesztés és a környezetvédelem jelenlegi kapcsolatát.

Kulcsszavak

térökonometria; térstatisztika; szén-dioxid kibocsátás; közlekedésföldrajz.