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Spatiality in freight transport efficiency

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ABSTRACT

The relationship between economic growth and transport sector is an important and popular topic for researchers, but it also has several untapped areas. To ensure continuous economic growth, it is necessary to answer how and to what extent economic sectors contribute to sustainability; what factors or sets of factors can determine freight performance in a country or region; and how it affects the global economy. This study aims to test the presence of spatial dependence. In this research, the authors looked for the spatial relationships between economic activity (GDP) and freight transport performance using spatial econometric models. The results showed that the spatial impact of freight transport performance and GDP significantly influence each other. The intensity calculation shows that the Baltic States have a high intensity in road freight transport, followed by the Central European region. Eastern Europe, including Russia and the Baltics, are prominent players in rail freight. Furthermore, the spatial econometric models have highlighted that a country with high GDP has some sort of "suction" effect on neighbouring countries with lower GDP along with the freight performance. This is especially true for rail freight. In the long run, the outlined results may even support strategic decision-makers in managing the economic impacts of both road and rail freight transport at the regional level.

KEYWORDS

Europe, freight transport, freight, intensity, GDP, spatial econometrics

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R11, R12

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1. INTRODUCTION – SPATIAL MODELLING IN TRANSPORT

Nowadays, there is an intense debate whether the transport sector has impacts on economic activity, or whether the spatial and geographical effects (e.g., distance) modify the direction of the impacts. It is difficult to determine whether economic activity affects freight transport or vice versa (Roson – Small 2013). Negative externalities – such as air pollution, congestion, accidents, or even noise effects – of freight transport on society and economy receive increasing attentions (Bektaş et al. 2019).

A study in 2016 by the International Transport Forum (ITF) provides evidence on the evolution of the volume of goods in terms of changes in the international trade trends, estimating their extent until 2050. Current shipments are expected to quadruple over the next 30 years, drastically increasing CO_2 and other greenhouse gas (GHG) emissions, driven by the increase in fuel consumption (Mattila – Antikainen 2011). The most significant mode of freight transport is road freight transport. In 2015, the road sector accounted for 75.8% of domestic and international freight transport performance in the European Union (EU). In many countries, only road freight transport exists on the market (Nowakowska – Grunt 2019).

Contrary to the ITF's vision, the goals pursued by the EU include, for example, 30% of the road freight over 300 km should be shifted to other modes of transport by 2030. Furthermore, another goal is to shift 50% of the road freight by 2050 to some alternative mode of transport, e.g., rail. The goal is also to create a European high-speed rail network by 2050, to build and complete the Transeuropean Transport Network (TEN-T), and to connect all airports to the core network (White Paper 2011). Rail transport plays a crucial role in sharing the burden of freight transport (mainly from the road). Thus, the elements identified in the TEN-T network are an essential part of integrating freight routes, as the same features will be applied to freight. A dedicated TEN-T rail freight network could also support this goal.

In line with this, in December 2020, the European Commission presented its sustainable and smart mobility strategy. As a result, as set out in the European Green Agreement, a 90% reduction in emissions can be achieved by 2050, thanks to an intelligent, competitive, safe, accessible and affordable transport system. In the spirit of sustainable transport, which affects not only passengers but also freight, the strategy has set targets for 2030, 2035 and 2050 such that almost all cars, vans, buses and new heavy goods vehicles will be zero-emission vehicles, rail freight will double, and the use of zero-emission marine vehicles and large aircraft in transport will increase.

In the light of the performance gains outlined, two questions arise:

1. In the last 10 years, has there been a spatial grouping of goods in Europe between countries or not, taking into account transport policy aspirations?
2. What economic conclusions can be drawn for the future?

Identification of the possible spatiality – as an added value – may even help economic experts to refute or support regional transport policy decisions. Many researchers deal with spatial modelling, thanks to the increasingly advanced, complex systems, task management software, and information technology tools that provide adequate computing and storage capacity. The location of economic operators and goods can also be identified, so the models could also have a spatial dimension.

In this article, we aim to model the spatial development of freight transport over time. Wiegmans et al. (2018) went into a great detail about analysing and comparing the efficiency of road and rail freight networks in terms of different geographical contexts. From the results, policy and regulatory conclusions were drawn across several continents and countries. In the case of Europe, the rail performance evaluation results show that the efficiency of rail freight companies needs to be increased, while the efficiency of the rail freight system needs to be addressed at a uniform European level (Witte et al. 2014).

Spatial modelling in transport can be done based on several methodologies. In the present case, three significant areas have been identified: (i) spatial equilibrium models; (ii) spatial statistical models (e.g., gravity models); and (iii) a particular version of statistical models, spatial econometric models, which are mainly used to explore the spatial relationships of economic processes (Table 1).

Table 1 clearly shows that the Computable-General Equilibrium (CGE) models in transport are widespread nowadays. Models that also examine the economic impacts of transport are called, depending on the area being modelled, Spatial, Multiregional or Interregional CGE models. In recent years, the leading Spatial General Equilibrium Models (SCGE) have come to the fore, characterised by continuous development (Boldizsár et al. 2020). Although these models are used in several approaches, they are mainly applied to study environmental impacts and energy use in transport (Abrell 2010; Hansen – Johansen 2017). Another modelling option for spatiality is Spatial Econometrics, a part of econometrics that addresses the problems generated by spatial autocorrelation and spatial heterogeneity in regression models based on cross-sectional panel data (Varga 2002).

The outlined spatial models and studies also exemplify that the analysis of the spatial effects of transport is a trendy and exciting field of research. Nevertheless, scientific literature lacks freight transport (mainly in terms of performance) and its economic effects related outcomes on the current situation in Europe. This paper aims to fill this gap with a severe examination of the context for spatiality and regional transport policy aspirations and their effects on each other. The results reflect the importance of freight transport policy, and the freight sector's unquestionable impacts on the economies of individual countries.

The fundamental question in this research is whether there is any spatial relationship between the economic performance of each European country – not just the EU countries – and the freight performance of the countries. What influence do they have on each other, and how do regions and areas influence each other? In order to answer these questions, a spatial econometric model is set up using international statistical data for countries in Europe.

In the second section, the applied mathematical-statistical tools are presented. In the third one, the results of the modelling are described and analysed. In the fourth section, the trends shown by the results are evaluated. The last section summarises the findings and identifies new research directions.

2. METHODOLOGY

As a first step in building a spatial econometric model, statistical data were collected on freight performance in each country over the past 10 years. Primary data were collected from public databases, the Eurostat, the OECD and the IMF websites. After the statistical preparation, the spatial econometric model was set up (Figure 1).

Table 1. Summary of relevant studies for spatial analysis

Author(s)	Modelling aspects	Area	Modelling methods	Parameters considered
Limão és Venables (2001)	Analysis of geographical effects	Global	Linear regression models (Gravity model)	Shipping cost, Geographical relationship, Infrastructure
Hummels (1999)	International trade modelling	Regional (USA, Canada)	Gravity model	Characteristics of neighbouring countries (e.g., everyday language use)
Moneta (1959)	Examining the relationship between developed-developing country couples	Different regions of the world	Examination of transport cost ratios	Transport emissions (weight, etc.), Unit cost
Kincses et al. (2013)	To explore the spatial structure of Europe's socio-economic structure	EU-27, Croatia, Switzerland, Norway, Macedonia	Area moving average; Potential model; Gravity model	GDP
Betarelli et al. (2020)	Investigation of the environmental impact of the Brazilian rail freight sector	Brazil	Dynamic CGE model	Commodity market supply and demand side for each commodity type (quantity)
Boonpanya – Masui (2021)	Assessment of the impact on the socio-economic situation and greenhouse gas emissions in Thailand	Thailand	CGE model	180 sectors
Shen et al. (2020)	Modelling of motorway networks from the perspective of freight transport	USA	Multi-level spatial-temporal freight optimisation model	Freight, Network and demographic-economic databases
Cardenete – López-Cabaco (2021)	Investigating the long-term environmental and economic impacts of new rail infrastructure known as the	Andalusia	CGE model	Freight performance, Greenhouse gases

(continued)

Table 1. Continued

Author(s)	Modelling aspects	Area	Modelling methods	Parameters considered
	Mediterranean Corridor			
Lindsey et al. (2014)	Scoring and ranking metropolitan markets according to the potential of industrial space consumption	USA – 20 big cities	The econometric model used in the analysis is a linear model of longitudinal data	Data on real estate, Demographic, macroeconomic and transport characteristics
Sahu et al. (2019)	Space-time interactions of freight transport between major Indian ports	India	Space-time dependent model (STARMA model)	Freight data
Lv – Li (2021)	Financial development is the link between CO_2 emissions	Global (97 countries)	Spatial econometric model	CO_2 emission, GDP, GDP/capita, Population density, GDP/energy used, Industry, Proportion of the urban population, Trade data
Sánchez-Díaz et al. (2016)	The attractiveness of freight transport and its relationship in urban environments	New York	Spatial econometric model	Facility data
Gao et al. (2016)	Relationship between freight index and Chinese GDP	China	Examination of correlation coefficients	GDP, Volume of freight transport
Kocziszky et al. (2015)	Examining the spatial structure of Europe	Europe	Gravity model	Population number, GDP
Wang et al. (2020)	Examining the spatial structure of Europe	China	Empirical analysis	GDP, Freight demand

Source: Own editing.

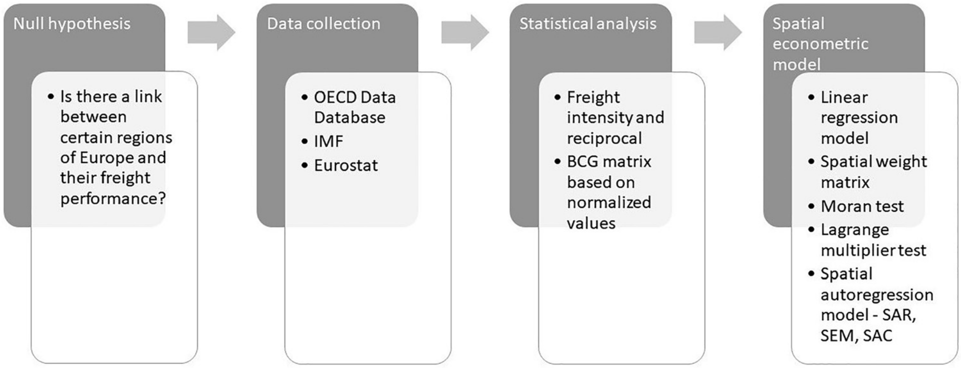

Fig. 1. Research framework

Our research aims to present the current situation (based on data from 2018) and also an earlier situation (2010) to analyse and compare not only the spatial, but also the temporal changes as well. With this spatial and temporal analysis, the question could be answered how freight transport in Europe has developed over the past 10 years.

For our hypothesis test, we first examined the relative value of the primary data, which showed the intensity of freight transport in the European countries. After this preliminary step, it was determined whether a spatial econometric analysis is feasible, and whether there can be any cluster on the continent from the perspective of freight transport and GDP. The values were also displayed as a matrix. This was followed by the spatial econometric analysis of the data, and then, the Akaike information criterion (AIC) and Likelihood-ratio test were used to verify the models.

The essential condition for an adequate econometric analysis of spatial data is the appropriate mapping of the spatial relations between the observation units. Both spatial statisticians and geographers claim that one of the defining features of spatial data is their tendency to heterogeneity and correlation. The econometric discussion of spatial autocorrelation requires a spatial representation that can capture the relative position of the units (Varga 2002).

The non-compliance of linear regression models with the Gaussian – Markov theorem can also be caused by spatial autocorrelation between the data (Anselin 1988; Varga 2002). The essence of this is that, like time series, the spatial units also influence each other according to the first law of geography (Tobler 1970). It can be assumed that the demands are spatially concentrated, so they are higher around each centre, while lower away from them. For the measurement of these values, spatial autocorrelation is available. To decide whether spatial autocorrelation exists, Moran's I-test can be applied (1) (Moran 1948).

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

where:

- N: number of observations,
- x_i, x_j: values measured at two points,
- μ: expected value of x,
- w_{ij}: one element of a spatial weight matrix,
- S_0: normalising factor – $S_0 = \sum_{i,j} w_{ij}$.

The values of test statistics are in the range of [−1; 1], the positive values of I indicate a positive, while its negative values indicate a negative spatial autocorrelation (Varga 2002). If Moran's test shows the possibility of autocorrelation, three types of spatial econometric models are considered: (i) spatial delay models; (ii) spatial error models; and (iii) a combined model. Lagrange multiplier tests are available to decide which spatial econometric model could be used (Anselin et al. 1996). These tests examine whether a parameter deviates significantly from zero (Maddala 1977).

The first model applied is the spatial delay model, in which the delay is interpreted as sliding in space (Varga 2002). The model can be described by the following formula:

$$\boldsymbol{y}_{(N\times1)} = \rho * \boldsymbol{W}_{(N\times N)} * \boldsymbol{y}_{(N\times1)} + \boldsymbol{X}_{(N\times K)} * \boldsymbol{\beta}_{(K\times1)} + \boldsymbol{\varepsilon}_{(N\times1)} \tag{2}$$

where:

- $\boldsymbol{y}$: the vector of the values of the result variable,
- ρ: spatial autoregression parameter,
- $\boldsymbol{W}$: row standardised (N × N) weight matrix,
- $\boldsymbol{Wy}$: the vector of the spatially delayed values of the result variable,
- $\boldsymbol{X}$: matrix of exogenous variables,
- $\boldsymbol{\beta}$: parameter vector of exogenous variables,
- $\boldsymbol{\varepsilon}$: vector of error terms $(\varepsilon \sim \mathcal{N}(0, \sigma^2))$.

The second is the spatial error model, in which spatial autocorrelation is a disturbing factor (Varga 2002). The model is given by the following formula:

$$\boldsymbol{y}_{(N\times1)} = \boldsymbol{X}_{(N\times K)} * \boldsymbol{\beta}_{(K\times1)} + \boldsymbol{\varepsilon}_{(N\times1)} \tag{3}$$

$$\boldsymbol{\varepsilon}_{(N\times1)} = \lambda * \boldsymbol{W\varepsilon} + \boldsymbol{\zeta}_{(\boldsymbol{Nx1})} \tag{4}$$

where:

- λ: spatial error parameter,
- $\boldsymbol{\varepsilon}$: the spatially autocorrelated vector of the error terms,
- $\boldsymbol{\zeta}$: error term filtered from spatial autocorrelation $(\zeta \sim \mathcal{N}(0, \sigma^2))$.

The third option is to use the two approaches together. There are several models for this (Zhukov 2010), of which the Spatial Autocorrelation Model (SAC) was significant. Its formula is as follows:

$$\boldsymbol{y}_{(N\times1)} = \rho * \boldsymbol{W}_{\boldsymbol{1}_{(N\times N)}} * \boldsymbol{y}_{(N\times1)} + \boldsymbol{X}_{(N\times K)} * \boldsymbol{\beta}_{(K\times1)} + \lambda * \boldsymbol{W}_{\boldsymbol{2}_{(N\times N)}} * \boldsymbol{\varepsilon}_{(N\times1)} + \boldsymbol{\zeta}_{(\boldsymbol{Nx1})} \tag{5}$$

Information criteria derived from likelihood values were used to compare the models.

During the modelling, all the neighbourhood matrices were prepared. First, the correlation between variables were approximated using the least-squares method (OLS) as a base case. Then the models described above (SAR, SEM and SAC) were constructed. After building the OLS, SAR, SEM and SAC models, the results were compared with the AIC, which estimates the relative amount of information lost by a given model: the less information lost, the better the quality of that model is (Cameron – Trivedi 2005).

$$AIC = 2k - 2\ln(L) \quad (6)$$

where:

- k: the number of estimated parameters of the model,
- L: the Maximum Likelihood value of the model probability function.

If the AIC test differs by less than two when the two models are compared; the two models do not differ significantly. In addition to AIC, the Likelihood-ratio test (LRT) was also used (Gary 1989). According to this approach, two models can be compared with each other based on their probability ratios. The examined models, in this case, represent exceptional cases of each other. The test formula is given in equation (7):

$$LRT = 2ln\frac{L_2}{L_1} = 2(lnL_2 - \ln L_1) \sim \chi^2_{df} \quad (7)$$

where:

- L_1: the probability value of one of the models,
- L_2: the probability value of the other model,
- df: the degree of freedom of the chi-square distribution, which is equal to the number of variables estimated in the surplus.

The steps of the presented spatial econometric modelling were carried out in the following.[1]

3. ANALYSIS

3.1. Freight intensity in the European countries

As a first step, we used an indicator from an international study, the "Guidelines on Sustainable Land Transport Indicators on Energy Efficiency and Greenhouse (GHG) Emissions in ASEAN", to look at how countries perform in freight-kilometre-based transport performance relative to GDP, which gives the intensity of freight. The indicator can be expressed as the quotient of freight transport performance and the level of the economy's GDP (ASEAN Secretariat 2019). Freight intensity is practically the number of goods transported per unit of GDP, expressed in tonne-kilometres. Intensity calculation was performed for both 2010 and 2018 (Figure 2). If a

[1]A more detailed explanation of the models is given in Sarmiento – Barbieri (2016) and Szabó – Török (2019). Spatial econometric analyses were performed in the R 3.4.0 environment (R Core Team 2017). Map tools (Bivand – Lewin – Koh 2017), *sp* (Bivand et al. 2013b; Pebesma – Bivand 2005), *spdep* (Bivand et al. 2013b; Bivand – Wong 2018), and the *spatialreg* (Bivand et al. 2013b, 2013a; Bivand – Piras 2015) libraries.

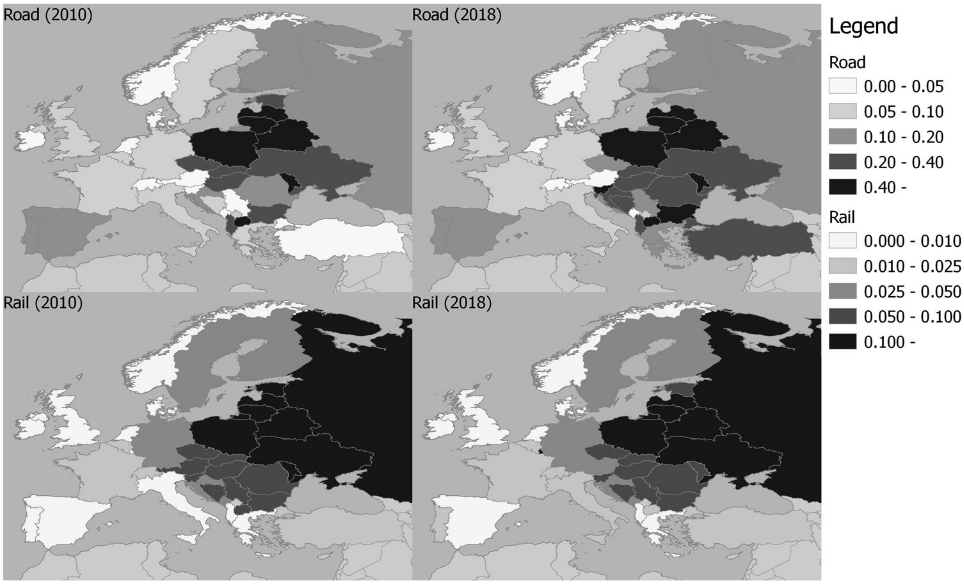

Fig. 2. Conceptual representation of the created spatial econometric model
Source: Own editing.

country has a high freight intensity, it can be concluded that it has a high freight performance with a lower GDP value. Conversely, a lower value is obtained for low freight performance and higher economic value.

In Figure 3, based on the intensity values, smaller groupings can already be observed, such as the railway values between the countries of the Baltic region and the outstanding railway performance of Russia and Ukraine. It is important to note that the historical past of the countries can largely explain these peculiarities and low proportions of GDP. In terms of road data, there is an increase for Turkey, Romania and Bulgaria. In our view, this may even have been due to the impact of the EU accession and, in this context, to the geographical proximity to Turkey. The intensity of Turkey may be affected because it is not subject to any regulations that could

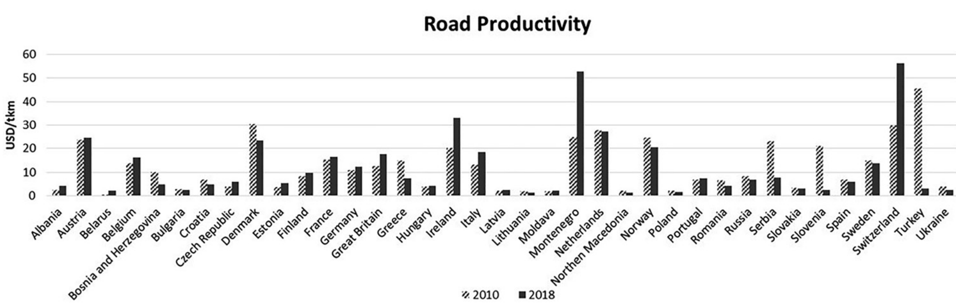

Fig. 3. Representation of road and rail freight intensities (tkm/USD)
Source: Own editing.

restrict it in any way, such as road haulage, and that, for example, the intention to join could include economic development. It is important to note that all of these assumptions in the present analysis do not answer such questions.

In the case of railway figures, a significant change is observed in the case of Luxembourg and a minor increase is found in Austria and Italy. These may indicate that the rail performance in these countries has increased significantly, for example, due to the EU's transport policy ambitions.

It is also important to note that the global economic crisis of 2008 had a significant impact. All of these can cause, for example, lower intensity values in the western world. However, the analysis also shows that there is no significant change in the western region by 2018, with almost no country showing a shift from the 2010 levels, which may also suggest that the freight sector has not been hit hard. For example, in the Central and Eastern European region, a positive change can be attributed to this, as the weaker economic structure in the region during the crisis may have had a more significant impact on the freight transport, and the recovery in 2018 is already apparent.

We also examined the reciprocal of the indicator, that is, the amount of GDP produced per unit of goods transported. In contrast to freight intensity, we found that rail values dominate road data in the reciprocal calculations (Figures 3 and 4). Albania, Greece and Ireland were left out of the reciprocal study, as these countries achieved outstanding results due to the low freight volumes and relative high GDP that they would greatly skew the results, if included. Figure 4 shows an outstanding productivity growth in the cases of Montenegro and Switzerland in terms of road freight transport. Interestingly, for other countries, values tend to stagnate. In the case of rail freight, a more significant increase is seen in one case, Great Britain. The values are either stagnant or show a declining trend in all other countries.

This suggests that GDP in the investigated countries has not changed too significantly and that the transport policy measures (even independently of the EU) have not impacted the freight modes and volumes considerably.

3.2. The Boston Consulting Group (BCG) matrix

The BCG matrix is a marketing tool that analyses and evaluates companies' strategic position in two dimensions in terms of relative market share and market growth rate (Harsáczki – Nagy 2014). Based on this, the data in two dimensions on the normalised economic performance, and the normalised value of goods transported were examined, and then displayed in the form of a diagram (Figure 5).

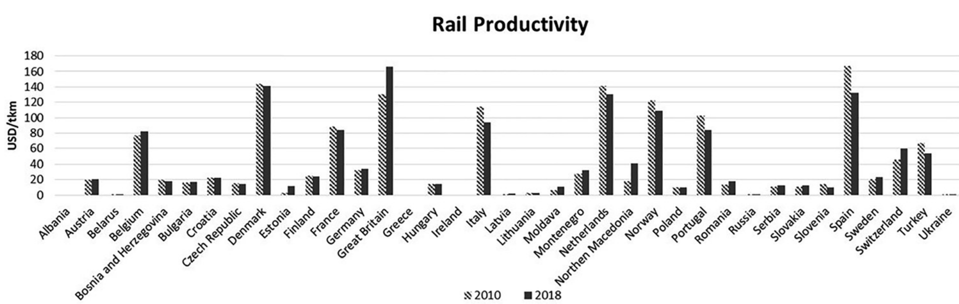

Fig. 4. Reciprocal values of freight intensity (productivity) for the road data set
Source: Own editing.

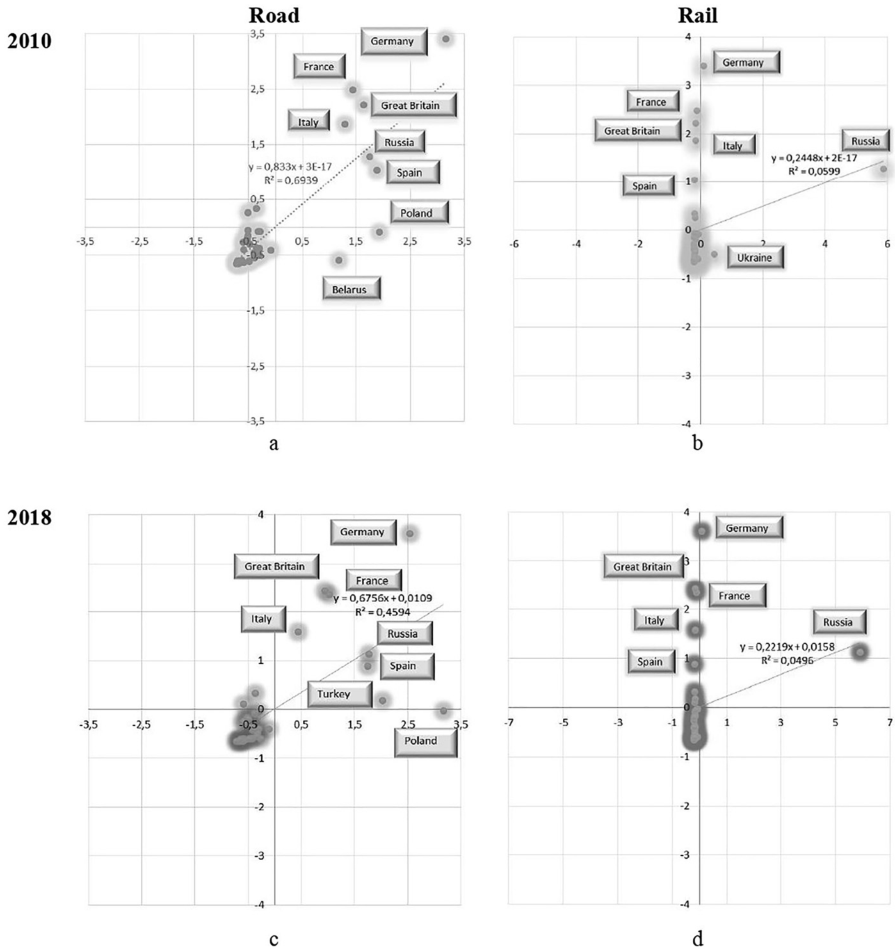

Fig. 5. **Reciprocal values of freight intensity (productivity) for the rail data set**
***Source*: Own editing.**

Figure 5 shows the country's situation on the BCG matrices created for both 2010 and 2018. Approximately three-quarters appear to converge to roughly one point, close to 0 for both the vertical and horizontal axes, suggesting that the vast majority of the surveyed countries are at nearly the same level in terms of economy and freight performance. This is true for both road and rail transport. At the same time, in the case of rail transport the normalized values differ the most along with GDP, while in the case of road transport, both GDP and performance results show a significant difference. Therefore, this means that the countries in the upper left quarters are essential sectors for road freight transport, and it is worth addressing these countries even at a strategic level (e.g., within the EU).

After examining the data series of 2010 and 2018, we investigated the dynamics of the data. It is also displayed in a matrix, what picture the country shows, and what changes have taken place. Figure 6 shows that there has been no significant change in the rail values over the last 10 years. The data series also includes the EU countries, where, as already highlighted in the literature review, the transport policy efforts explicitly address the shift to rail, most notably from roads. The examination of the road reveals that there have been many more changes and rearrangements in the last 10 years. An outstanding element, which was already reflected in the productivity calculation, was the situation in Turkey, which showed a significant increase. Italy, Britain, Germany and France went in the opposite direction, both economically and in the road freight performance.

3.3. Spatial econometric model

The data used in the spatial econometric model are as follows. GDP was considered as the outcome variable in the spatial econometric model (GDP_{2010}; GDP_{2018}; [million USD]), and freight performance was the explanatory variable on both road and rail ($ROAD_{2010}$; $RAIL_{2010}$; $ROAD_{2018}$; $RAIL_{2018}$; [tonne-kilometres]). The outcome variable indicates the economic impact of freight transport in a given country, while the explanatory variable, in this case, measures the freight performance required for economic growth. After setting up the empirical model, the structure of the space studied was determined. The neighbourhood matrix describing the spatial connection between countries was determined by a spatial weight matrix W. The following solutions have been chosen:

- Queen criterion: two countries are adjacent if they have a common border or edge.
- Inverse distance-based criterion: the *j*-th element of the *i*-th row is one if the *j*-th country is closer to the *i*-th region relative to a predetermined distance. We applied this method in two

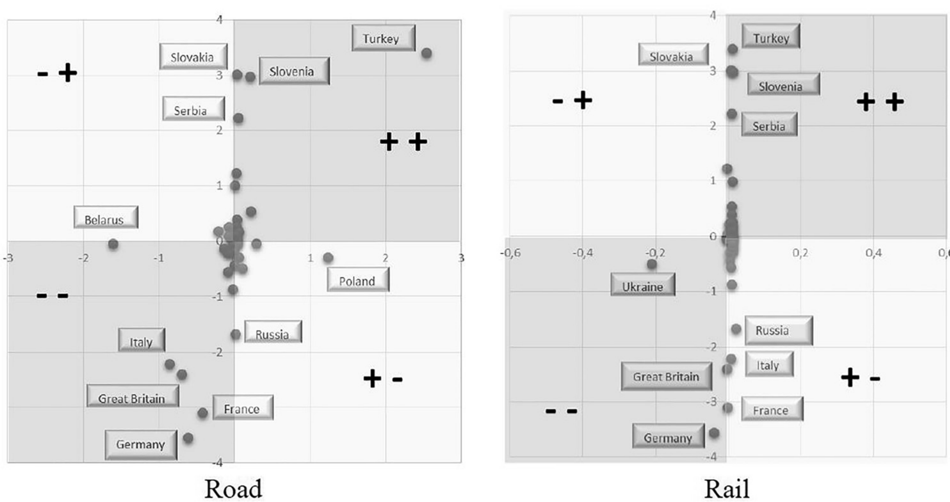

Fig. 6. BCG matrix of countries
Notes: a – 2010 road; b – Railway 2010; c – road 2018; d – 2018 railway (x axis– normalized performance, y axis – normalized GDP)
Source: Own editing.

ways. On the one hand, we examined how the centre of the countries are located to each other; on the other hand, we chose the position of the capitals. In both cases, the threshold was 750 km, as several models with different distances (600 km, 750 km, 1,000 km and 1,200 km) were created in the research, and the experience was that the countries of Europe could be best represented with this threshold. The large countries are also neighbouring and smaller regions do not converge.

- Binary / bastion (rook) criterion: two countries are adjacent if they have a common border, that is the j-th element of the i-th row is 1 if the i-th and j-th countries have a side. In our case, we did not use this method. Moran's I statistic was applied to all three weight matrices we generated (based on distance, capital and queen). With the help of this, we examined whether autocorrelation can be detected in the countries' GDP.

Based on Table 2, further studies were performed using the weight matrix generated by the Queen criterion. In this case, we found a stronger spatial econometric correlation in Moran's test with both road and rail data. A test with the inverse distance-based weight matrix was also performed, but the results did not change significantly; the queen neighbourhood matrix gave better results throughout.

The test result suggests a weaker but existence of positive autocorrelation for GDP for both 2010 and 2018 data series. This means that it is possible that the contribution of the freight transport performance to GDP matters to the neighbouring countries. Table 3 shows the OLS and Lagrange multiplier (L.M.) test results for the spatial models. The values of the t-test testing the significance of the coefficients are shown in parentheses. It is used to examine whether a given parameter is significantly different from zero. If so, it has an effect on our model. For the test, the values of the test statistics are shown in the table, where *** means $0 < P < 0.001$; ** indicates $0.001 < P < 0.01$; and * means $0.01 < P < 0.05$.

The establishment of the spatial econometric models followed this, the results of which are shown in Table 4.

During the modelling, three econometric models in three applications were also estimated. Based on the AIC, in each case the SEM model proved to be the best one for the 2010 road dataset. In all other cases, the SAC model proved to be the best. In addition to the AIC values, the results of the Likelihood-Ratio Test are available directly from the authors.

Table 2. Results of global Moran's I-statistics

Spatial weight matrix	The value of Moran's I-statistics	Expectation	Variance
W_dist_2010	0.0030	−0.0286	0.0104
W_dist_2018	0.0286	−0.0286	0.0104
W_CAP_2010	0.0381	−0.0278	0.0093
W_CAP_2018	0.0626	−0.0278	0.0093
W_queen_2010	**0.2233**	**−0.0278**	**0.0160**
W_queen_2018	**0.2299**	**−0.0278**	**0.0160**

Source: Own editing.

Table 3. Result of the OLS estimate and the Lagrange multiplier

	2010		2018	
	Road	Rail	Road	Rail
OLS – Intercept	46518.751	4.097e+05	1.556e+05	3.996e+05
	(0.492)	(2.770)**	(1.131)	(2.445)*
Road	8.817		6.498e+00	
	(8.670)***		(5.273)***	
Rail		5.511e+00		8.580e+00
		(1.594)		(2.110)*
Sample number	37	37	37	37
R^2	0.6823	0.06769	0.4427	0.1128
Corrected R^2	0.6733	0.04105	0.4268	0.08747
LM_{lag} – TEST	2.494	4.1414*	4.4686.	4.7377*
LM_{error} – TEST	5.1326*	5.3366*	3.6706*	6.6051*
Robust LM_{lag}- TEST	0.24883	0.76968	1.0217	0.58949
Robust LM_{error}- TEST	2.8875	1.9648	0.22375	2.4569
SARMA	5.3814	4.6923	6.1063	7.1946

Source: Own editing.

4. DISCUSSION

The volume of road freight transport resulted in higher GDP from the 2010 data series. However, there was a change in the road data series between 2010 and 2018. At the same time, the intensity calculation shows that there has been an increase in the number of road freight volumes, which may also have an effect on the change in spatiality. Furthermore, the road model suggests that, due to the international relations, road freight transport has a smaller impact on GDP (“neighbouring countries pull-down”).

Let us look at an example. Suppose we want to estimate GDP along the rail freight transport. In that case, the influence of nearby countries on a given observation unit (GDP) has a negative effect (lambda is positive, while rho is negative). The same can be said for the 2018 road data series. Overall, for the 2010 dataset the SEM model provides the best results, whereas from the 2018 road, and the 2010 and 2018 rail data, the SAC model gave the best results.

As previously indicated in the presentation of the spatial econometric models’ results, there was a change from the 2010 to the 2018 data series. One of the reasons for this may be that the new member states of the EU, which joined in 2004, were able to pick up the pace by 2018, with an increasing share in the road freight transport, thus modifying our model and making their impact visible, as well as activating the spatial delay. The EU transport policy efforts over the last

Table 4. Results of spatial econometric models

	2010		2018	
	Road	Rail	Road	Rail
SAR				
Intercept	−32502.8054	2.5071e+05	2.5452e+04	2.2125e+05
	(−0.3122)	(1.4352)	(0.1801)	(1.1647)
Road	8.6794		6.4407e+00	
	(8.9923)		(5.6503)	
Rail		6.0986e+00		9.2155e+00
		(1.8666)*		(2.4080)*
Sample number	37	37	37	37
Rho	0.11579	0.19866	0.1614	0.20023
	(1.382)	(1.4953)	(1.5871)	(1.5766)
SEM				
Intercept	4.1497e+04	3.2697e+05	1.3135e+05	3.0051e+05
	(0.3750)	(1.9048)	(0.8693)	(1.5814)
Road	8.7954e+00		6.3735e+00	
	(9.5813)*		(5.5787)	
Rail		6.9466e+00		1.0519e+01
		(2.2063).		(2.8649)*
SAMPLE NUMBER	37	37	37	37
Lambda	**0.32124**	0.25191	0.22196	0.27742
	(2.0679)	(1.7871)	(1.5252)	(1.9936)
SAC				
Intercept	2.0955e+05	6.8024e+05	5.8799e+05	7.1322e+05
	(0.4267)	(1.7388)	(1.2694)	(1.6545)
Road	8.1442e+00		4.5677e+00	
	(3.5058)*		(5.1357)***	
Rail		5.2813e+00		7.8390e+00
		(2.1678)***		(2.6825)***
Sample number	37	37	37	37

(continued)

Table 4. Continued

	2010		2018	
	Road	Rail	Road	Rail
Rho	−0.18197	**−0.7037**	**−0.68602**	**−0.67857**
	(−0.37476)	**(−3.5404)**	**(−4.4874)**	**(−3.6128)**
Lambda	0.55383	**0.73255**	**0.81628**	**0.74485**
	(0.99406)	**(6.5343)**	**(9.0109)**	**(6.9414)**

Source: Own editing.

10 years have not proved totally successful yet. They certainly had an impact (somewhat moderated) on the road freight transport and also supported rail freight transport, fundamentally changing the outcome of the rail equations.

In line with the AIC indicator, we obtained the same result with the calculation of the Likelihood Ratio Test, proving that our spatial modelling worked adequately and established a spatial correlation concerning GDP if we want to estimate the freight volumes. This is also true for both road and rail data.

5. CONCLUSIONS

In our article, on the one hand, we sought to answer whether there is a spatial econometric relationship between road and rail freight performance and the economic activity of a given country represented by GDP. Considering the 2010 and 2018 data, it was examined whether the EU's transport policy aspirations over the last 10 years show any level of change in terms of spatiality. In terms of timeliness, we found a change on the roadside between the 2010 and 2018 data series, so it can be concluded that the European freight policy has significantly impacted road freight transport.

The main limitation of the research is the coherent database on economic activity and transport performance. The temporal change of spatial analysis is based on two samples from 2010 to 2018; however, more frequent sampling could slightly change the results and could be a solid basis for forecasting. The findings are limited to analysis; based on them no forecast can be done. The model is based on discrete values, although it could even be examined for a continuous dataset, which could already support future forecasting. Another limitation is the quasi-static economic and legal environment that has been considered in the analysis. However, according to the railway models, no significant changes have occurred in the subsector in the last 10 years. Railway models have very similar values both quantitatively and relative to the GDP indicators.

In terms of spatiality, it can be said that there is a spatial correlation between the examined data if we estimate the GDP and its development along with the quantities of transported goods. In the 2010 road model, the SEM model gave the best solution, while in the other three cases, the SAC model proved to be the most effective one. It also shows that rail freight has not undergone any significant changes in the last 10 years, while road freight transport has shown a remarkable change. Spatial econometric models have highlighted that nowadays, a high-GDP country has some sort of "suction" effect on neighbouring countries with lower GDP along with the freight performance, especially for the rail freight. The road model suggests that, due to international relations, road freight transport has less impact on GDP than rail. In the Baltic region, as well as in Russia and Ukraine, there is a very strong intensity of rail freight transport. In the light of all these, it may be worth examining in more detail, possibly at the regional level, in terms of freight volumes and economic opportunities. It may raise further questions about how the individual transport policy and transport strategy decisions worked for the smaller regions, as can be seen from the complete analysis, the hopes placed on them have not been met. An answer can also be found from this analysis in terms of what the appropriate measures might be. In addition to freight transport, it may be an exciting new area of research to examine whether a similar relationship exists in terms of spatiality. This provides a reasonable basis for further research opportunities.

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