CORRELATION BETWEEN INLAND TRANSPORT EFFICIENCY, GDP AND ENVIRONMENTAL ASPECTS IN EU COUNTRIES

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Abstract

Transport is said to be one of the essential sectors of the EU member state economies. Therefore, measurement of the efficiency of transport operations seems to be interesting from the perspective of both the economy as a whole and individual companies operating in the transport sector. Currently however, it is also crucial to pay attention for environmental aspects of transport sector, which describe its sustainability. This idea is supported particularly by developed countries.

The purpose of this paper is to determine the efficiency of road and rail freight transport in old and new European Union countries based on the Data Envelopment Analysis (DEA) and to specify its correlation to CO_2 emission and GDP indicators.

To that end, the authors present a literature review reflecting the current state of research on the importance of transport and its development in relation to the economy and environmental problems. Additionally, the methods of data analysis and variables are described. The last section gives a summary of the study, and the obtained results are compared with data from the literature review.

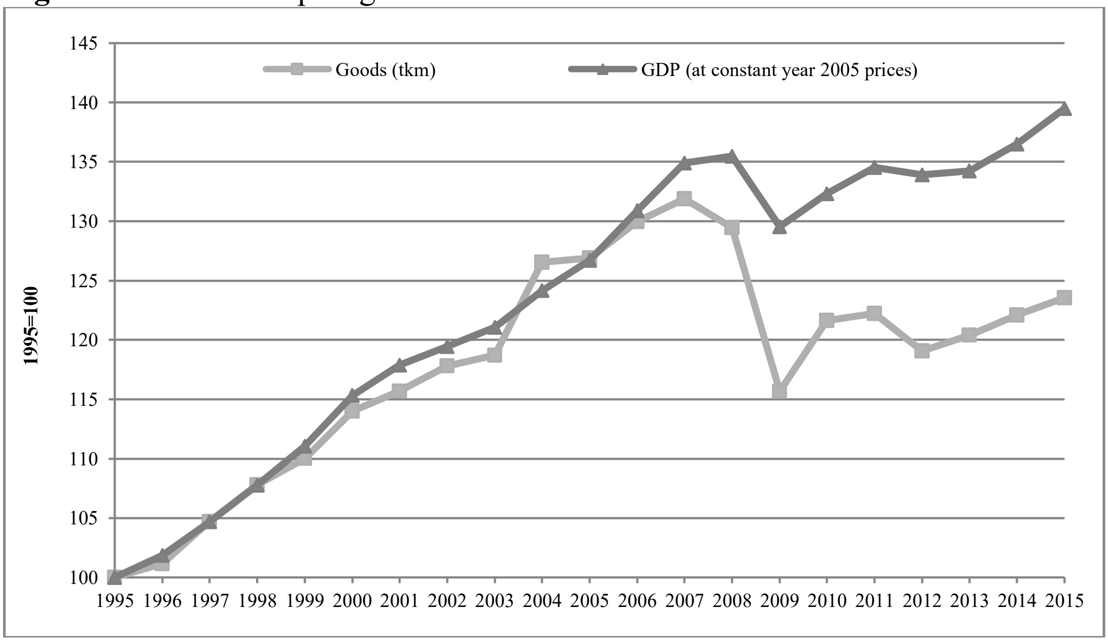
Key words: efficiency, DEA method, inland transport, environmental effects, GDP

1. INTRODUCTION

Transportation is one of the most significant drivers of European trade and economic growth (Figure 1). The freight transport network is thought to be the backbone of the supply chain as it enables efficient goods distribution and enhances accessibility to distant markets. Therefore, EU projects and reports reveal a strong focus on freight transport as a factor contributing to European prosperity and employment.

In 2014, total goods transport activities in the EU-28 were estimated at 3,524 billion tonne-kilometres. Road transport accounts for 48.3% of the total, railroads for 11.8%, inland waterways for 4.3%, and oil pipelines for 3.2%. Intra-EU maritime transport is the second most important mode accounting for 32.3%, while air transport contributes only 0.1% of the total. This shows that the road and rail are the predominant inland transport modes in Europe. The economic importance of transport, however, should be considered in connection with its externalities and indeed there is a lively discussion among researchers concerning the extent to which the transport sector influences the environment of the region. Since the largest share of freight transport is done by road and rail, the present authors focus on these two modes.

Figure 1. EU-28 transport growth in 1995–2015



Source: authors calculation based on Eurostat

2. AIMS AND METHODS

The primary aim of this paper is to assess the technical efficiency of road and rail transport in European countries and create a ranking of those countries in this regard based on research results. It is important to perform cross-country efficiency evaluations to advise the policy-makers where their countries stand relative to each other and which are the best performing ones.

The second goal is to examine correlations between the transport efficiency index, GDP, and CO_2 emissions. The authors adopted two hypotheses:

H1: The degree of transport efficiency corresponds to the economic situation of the country.

H2: CO_2 emissions from inland transport modes are inversely proportional to the degree of technical transport efficiency.

The present study involves secondary data. The literature review was based on papers published in scientific journals and reports on transport economics and the environment.

All variables are from 2013 (the latest available data), and were taken from the Eurostat database. The dataset contains a sample of statistics on road transport efficiency in the EU-28 and rail transport performance in 22 EU countries (without CY, DK, MT, NL, SE, and UK). To the best of our knowledge, the present study is the first attempt to calculate the efficiency of road and rail transport performance in old and new EU countries and shows its correlation with CO_2 emission indexes for both transport modes.

The study consists of three steps. First, it measures the efficiency of road and rail transport by Data Envelopment Analysis for old and new EU countries separately. Subsequently, the correlation between the economic standing of countries and the efficiency of road and rail transport sector is presented using spatial analysis. Finally, the influence of rail and road transport efficiency on selected indicators of environmental pollution is investigated.

The paper is organised as follows: the first section is a literature review reflecting the current state of research on the importance of transportation and its development in relation to the economy and environmental problems. Subsequently, the methods of data analysis and the variables are described. The empirical section is divided into DEA results and correlation results. The last section gives a summary of the study, with the results being compared with data from the literature review.

2.1. Data Envelopment Analysis

Two DEA models (CCR and super-efficiency DEA) were deployed for efficiency calculations. The DEA model may be presented mathematically in the following manner (Cooper et al., 2007):

$$\max \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \tag{1}$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \qquad u_r, v_i \ge 0 \tag{2}$$

where s is quantity of outputs, m is quantity of inputs, u_r is weights denoting the significance of respective outputs, v_i is weights denoting the significance of respective outputs, y_{rj} is amount of output of r - th type ($r = 1,\ldots,$ R) in j - th object, x_{ij} is amount of input of i - th type ($n = 1,\ldots,$ N) in j - th object, ($j = 1,\ldots,$J).

In the DEA model m of inputs and s of diverse outputs come down to single figures of "synthetic" input and "synthetic" output, which are subsequently used for calculating the object efficiency index. The quotient of synthetic output and synthetic input is an objective function, which is solved in linear programming. Optimized variables include u_r and v_i coefficients which represent weights of input and output amounts, and the output and input amounts are empirical data (Cooper et al., 2007).

By solving the objective function using linear programming it is possible to determine the efficiency curve called also the production frontier, which covers all most efficient units of the focus group. Objects are believed to be technically efficient if they are located on the efficiency curve (their efficiency index equals 1, which means that in the model focused on input minimization there isn't any other more favourable combination of inputs allowing a company or sector to achieve the same outputs). However, if they are beyond the efficiency curve, they are technically inefficient (their efficiency index is below 1). The efficiency of the object is measured against other objects from the focus group and is assigned values from the range (0, 1). In the DEA method Decision Making Units (DMU) represent objects of analysis (Charnes et.al., 1978).

DEA models may be categorised based on two criteria: model orientation and type of returns to scale. Depending on model orientation, technical efficiency is calculated with a focus on input minimization or output (effect) maximization. Taking into account the type of returns to scale, the following models are distinguished: the Charnes–Cooper–Rhodes (CCR) model with constant returns to scale, the Banker–Charnes–Cooper (BCC) model with changing returns to scale, and the non-increasing returns-to-scale (NIRS) model (Coelli et al., 2005).

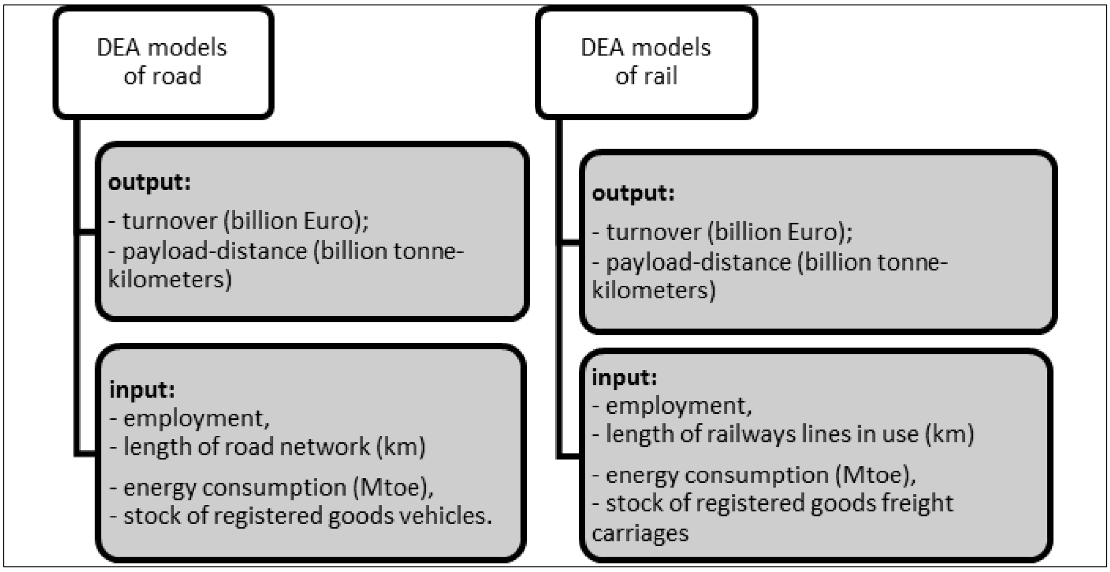
Equation 1 shows the basic philosophy of DEA models. The first model of this kind was developed by Charnes, Cooper, and Rhodes in 1978. In standard DEA models, the efficiency score is limited to unity (1). Nevertheless, the number of efficient units identified by DEA models and reaching the maximum efficiency score of 1 may be relatively high, especially as in problems with a small number of DMUs the efficient set may contain almost all the units. In such cases, it is very important to have a tool for diversification and classification of efficient units. Consequently, several DEA models have been developed for that purpose. In these models, the efficiency scores of inefficient units remain lower than 1, while those for efficient units can be higher than 1. Thus, the efficiency score may be taken as a basis for a complete ranking of efficient units. The DEA models that relax the condition for unit efficiency are known as super-efficiency models.

The selection of appropriate set of inputs and outputs (variables) is highly important when measuring the efficiency of transportation sectors. One of its aspects is to fulfil an initial condition regarding the number of inputs and outputs in relation to the number of DMUs. In this context, Ozbek et al. (2009) postulate the following rule for the minimal number (n) of DMUs $n \geq 2ms$, where m is the number of inputs and s is the number of outputs. The total number of inputs and outputs, which characterize transport sectors fulfils the condition.

An advantage of using DEA is that it does not require all inputs and outputs be measured in constant units. Thus, based on the literature review, as inputs we use variables related to labour, land and capital. Our choices are: a) the employee number as the labour measurement, b) the railways/ road network length, c) stock of vehicles and wagons as the capital measurement. Energy consumption was used as the equivalent of the earth. Transportation has the significant effect on economic growth and development, so first output measure, turnover to the economy from the transport sector. The second output measure is an absolute measure of tonnage hauled over distance.

CCR models aimed at maximizing outputs (output-oriented) were used to determine the relative efficiency of road and rail transport across Europe. The following variables were used for DEA models of road and rail transport (Figure 2).

Figure 2. The variables for DEA models



2.2. Spearman Rank Correlation

Spearman rank correlation (ρ) test was used to compare the data to determine if the efficiency of a transport mode is correlated with the level of economic development and environmental pollution (2).

$$\rho = \frac{\frac{1}{6}(n^3 - n) - (\sum_{i=1}^{n} d_i^2) - T_x - T_y}{\sqrt{\frac{1}{6}(n^3 - n) - 2T_x)(\frac{1}{6}(n^3 - n) - 2T_y)}} \tag{2}$$

where:

$di = Rx_i - Ry_i$ – difference between the *i-th* rank for variable x and the *i-th* rank for variable y

T_x T_y – factors for tied ranks described by (2):

$$T = \frac{1}{12} \sum_j (t_j^3 - t_j) \tag{3}$$

where:
t_j number of observations for the *j-th* rank in the 458nalysed data set.

The following variables were used in the calculation of Spearman rank correlation:
z_1 – CO_2 emissions separately for road and rail transport
z_2 – country's GDP per capita
z_3 – DEA index separately for road and rail transport

3. LITERATURE REVIEW

3.1. Strategic Objectives of Transport Sector

Economic development is closely associated with growth in the volume of freight transported and logistics services. Transport itself, it is not a goal but a means of economic development and a prerequisite for achieving social and regional cohesion (Kitnerová, 2008). The functioning of the transport market is influenced by national economic and social policies. In this sense, transport companies may be interpreted to constitute not only part of the economy, but also part of the infrastructure. The proportion between market forces and government interventions is one of the factors characterizing the transport market. These macroeconomic and microeconomic considerations provoke the discussion on improving transport sector efficiency (Kráľ & Roháčová, 2013). From the business perspective, companies take into account their economic results (microeconomic approach) however, whole transport sector needs to act according to national and international legislation (macroeconomic approach). Nowadays, European transport policy regulates the development of transport and integration of transport network from the technical point of view (infrastructure and transport corridors) with great emphasis on environmental aspect. There is the consensus that policies must be sustainable in the sense that they respect the living conditions of both present and future generations. Sustainable transport policy encompasses many related but distinct aspects, such as climate, air quality, security, traffic safety, and health (Connelly, 2007; Eliasson & Proost, 2015, Road map to a…, 2011). Therefore, it is significant to investigate transport issues as a whole and present how the transport sector efficiency created by companies, influence the economic growth of regions/countries and what kind of impact it has on environmental aspects.

Transport sector efficiency may be estimated by the traditional economic indicators, parametric and non-parametric methods. The issue of transport efficiency is usually considered in literature from a one-dimensional perspective, using conventional economic indicators, such as: density and utilization of infrastructure, percentage of land miles uncongested, tonne-kilometres, labour and asset productivity (Twaróg, 2004; Fechner & Szyszka, 2012; Hamamcioglu & Oğuztimur, 2015; Prońko 2016). Nevertheless, parametric and non-parametric methods for the assessment of the efficiency of transport are very popular tools for transportation research too. The parametric approach, including stochastic frontier analysis (SFA), thick frontier analysis (TFA), and distribution free approach (DFA), estimate the productivity of the frontier in a particular functional form with constant parameters. On the other hand, the non-parametric frontier approach does not assume any particular functional form for the frontier. The most commonly used non-parametric frontier methods are data envelopment analysis (DEA) and free disposal hull (FDH).

DEA applications in environmental benchmarking and transportation have been a common research theme. Recently, DEA has been used in areas such as individual truck performance (Odeck & Hjalmarsson, 1996), transportation routing (Chiou et al., 2012; Zhao et al., 2011), rail transport (Yu, 2008; Jain et al., 2008), maritime transport (Odeck & Bråthen, 2012), air transport (Merkert & Mangia, 2014), national-scale environmental performance (Zhou et al., 2008; Ramanathan, (2006), and logistics networks and green supply chains (Azadi et al., 2014; Lau, 2013).

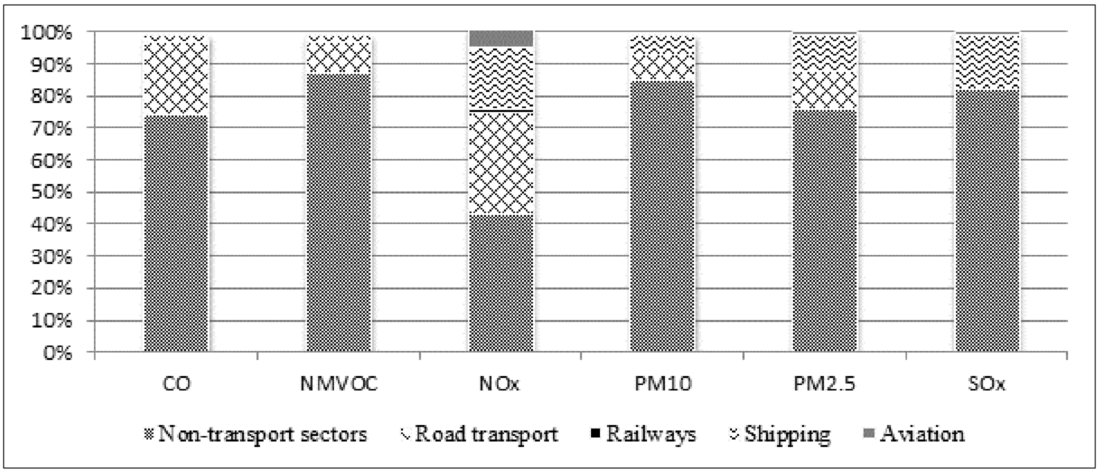
3.2 Transportation and its Environmental Effects

Increasing transportation activity, which is crucial to economic development, has resulted in motorization and congestion becoming the dominant factors of environmental pollution (Button, 2013; Tahzib & Zvijáková, 2012). For the last thirty years, the environmental implications of modern transport have attracted growing attention (Button, 2013). Numerous researchers have examined the direct and indirect effects of transportation on the environment, most of which are adverse (Woodcock et al., 2007; Banister et al., 2000; UK Royal Commission…, 1994). The transport sector is responsible for various types of air pollution, substantial amounts of waste, including scrapped vehicles and waste oil. Indeed, the transport infrastructure and operations can divide or destroy natural habitats of flora or fauna (Stead, 2008). In the EU, the freight transport sector contributes a significant proportion of total surface transport emissions (McKinnon, 2007). Research has focused on noise emissions, local air pollution, and water contamination. Pollutants such as NOx, CO_2, and chlorofluorocarbons are not only detrimental to plants and animals, but may also exert a global impact on climate change.

In their comparison of the impact of greenhouse gases of road, rail, and maritime transport, Tahzib & Zvijáková (2012) found that road transport is the greatest contributor of CO_2 emissions, which has direct implications for the EU policy on CO_2 reduction. This has been corroborated by Gioti Papadaki's (Gioti Papadaki, 2012) discussion of the Europe 2020 strategy including specific goals such as reducing greenhouse gas emissions by 20% against the 1990 baseline by the year 2020. The EU intends to additionally increase that reduction by an extra 30% provided that other developed countries also contribute proportionally to their capabilities and commit themselves in international agreements. This goal is particularly important because, as noted by Ben Jebli and Belloumi (Ben Jebli & Belloumi, 2017), a 1% increase in real GDP leads to decreasing CO_2 emissions by 0.57%. A country's development and regulations lead to lower air pollution. The question arises as to whether a similar relationship holds for the efficiency ratios of individual transport modes and pollution levels, which has serious ramifications for sustainability. Therefore, taking into account the importance of the transport sector to the European economy, it is crucial to incentivize radical changes to achieve substantial improvements in transportation environmental performance. Ucak et al. (2015) found a positive association between economic growth and CO_2 emissions, which varied significantly across low-income and high-income countries. Similar evidence was produced by Begum et al. (2015). They both reported that GDP growth, population growth, and high-polluting fossil fuels had a significant impact on carbon emissions. Furthermore, according to Wu et al. (2015), the relationship between these factors and CO_2 emissions is changing dynamically.

Interestingly, another group of studies suggests that the transport sector is not responsible for environmental pollution to a considerable degree. The European Environment Agency has released a report containing data on economic sectors which are the main air pollutants in Europe (see Figure 2), according to which the largest pollutants are the non-transport sectors. For instance, 74% of carbon monoxide (CO) is emitted by non-transport sectors as compared to 23% by road transport and 2% by international and domestic shipping. Among the various types of pollutants, the transport sector produces the highest proportion of nitrogen oxides, or NOx (58%).

Figure 2. Contribution of the transport sector to total emissions of the main air pollutants



Source: Based on European Environment Agency data.

At the problem is still on, it is than worth to investigate it, and try not only calculate the single indexes of transport and its external effects, but also the whole transport sector efficiency and its relation to environmental and economic variables.

2.3. DEA in transportation research

The application of the DEA technique to the transport sector is not new; in fact it is quite widespread, especially in evaluating airports, seaports, roads, railways, and urban transport companies. It has been used both for calculating the efficiency of transport companies and in cross-country comparisons. The measurement of transport efficiency by the DEA has been described in, for instance, Karlaftis (2004), Lan & Lin (2003), Barnum et al. (2007), Sampaio et al. (2008), Klieštik (2009), Ozbek et al. (2009), Han & Hayashi (2008), Lan-Bing & Jin-Li (2010), Cruijssen et al. (2010), Su & Rogers (2012), and Roháčová (2015).

Karlaftis (2004) employed DEA to evaluate the efficiency and effectiveness of 256 US transit systems over a 5-year period (1990–1994) and, in the next step, measured the economies of scale in transit systems based on performance assessment. Lan-Bing Li & Jin-Li Hu (2010) analyzed the railway system in all Chinese regions, first assessing railway efficiency by DEA and Malmquist Productivity Index from both static and dynamic viewpoints, and then identifying the key factors affecting railway efficiency by Tobit regression. Barnum et al. (2007) applied DEA to measure the efficiency of public transport in Chicago; they also examined the effects of external environmental factors on the efficiency of decision making units (DMUs). In turn, Sampaio et al. (2008) analyzed the technical efficiency of 19 transport systems in Europe and Brazil. Klieštik (2009) employed an input- and output-oriented CCR model to evaluate the efficiency of 15 transport companies in the Slovak Republic. Ozbek et al. (2009) applied DEA to measure the efficiency of 6 different hypothetical state departments of transportation in highway maintenance. Han & Hayashi (2008) investigated the efficiency of urban public transport systems in China using a DEA approach based on data from 652 Chinese cities in 2004 and 2006. Lan & Lin (2003) proposed a four-stage DEA procedure for estimating the technical efficiency and service effectiveness of railway transport, and a four-stage method for measuring productivity and sales capability growth, in both cases taking into consideration environmental externalities, data noise, and slack adjustment. Cruijssen et al. (2010) described a practical application of various DEA models in an analysis of the Flemish road transport sector to identify differences between subgroups of respondents. The results demonstrated that, in general, Flemish road transportation companies operated at unacceptably low efficiency levels. Su & Rogers (2012) examined multi-year transportation efficiency of OECD countries using DEA to determine efficiency scores. The model included economic variables, freight hauled, value added, and economic contribution, ecological variables, fuel consumption, and CO_2 emissions. The results indicated a strong trade-off between economic and emissions efficiency, both of them being difficult to develop and maintain over time. Roháčová (2015) applied DEA to demonstrate a relatively new perspective on the optimization of urban public transport (UPT) systems.

In addition, some authors have concurrently applied both non-parametric and parametric methods to the transport sector. For instance, Lan & Lin (2003) used DEA and SFA methods to estimate productive efficiency of 74 railway systems in 1999, while Michaelides et al. (2009) compared DEA and SFA results in measuring technical efficiency of international air transport using a panel of the world’s 24 largest network airlines for the period 1991–2000.

4. RESEARCH

4.1. Economic Efficiency of Road And Rail Transport

The choice of freight transportation mode has a profound effect on logistics companies, infrastructure providers and society as a whole. The efficiency of freight transport is important because it has a major effect on a number of economic and environmental factors. This section of the paper focuses on the difference in efficiency between rail and road freight transport.

While the DEA method assumes that a comparison involves homogeneous objects, road transport in individual EU countries varies in terms of development, political situation, access to EU funds, infrastructural expenditures, historical determinants, geographical location, etc. Therefore, the studied countries were divided into 2 groups: old and new members of the European Union. Comparing the results of super-efficiency DEA models, it can be seen that both groups contain the same number of countries recognised as effective. However, the group of new EU countries recorded a higher mean super-efficiency index than the old EU countries (see Table 1), which may indicate that they are intensively developing their road transport in a way that transforms inputs into results more efficiently.

Table 1. Super-efficiency DEA model of road transport for new and old members of the European Union

Road transport in old EU members	Super-efficiency DEA	Road transport in new EU members	Super-efficiency DEA
LU	2.32	BG	2.59
PT	1.40	SI	1.44
NL	1.38	LT	1.39
DE	1.07	SK	1.07
BE	1.04	EE	1.06
ES	1.02	PL	1.04
FI	0.84	LV	0.91
DK	0.83	CZ	0.88
SE	0.81	HU	0.80
IT	0.75	RO	0.69
UK	0.73	HR	0.69
AT	0.72	CY	0.52
FR	0.71	MT	0.46
IE	0.66		
EL	0.56		
Mean	*0.99*	*Mean*	*1.04*
Max	*2.32*	*Max*	*2.59*
Min	*0.56*	*Min*	*0.46*

Source: authors'calculation

In the next step, the efficiency of rail transport in the EU countries was calculated using the CCR DEA model. The average technical efficiency of rail transport sectors in the EU in 2013 was not very high (0.66). Full technical efficiency (with an efficiency index equal to 1) was achieved by five counties: Slovakia, Belgium, Slovenia, Latvia, and France (see Figure 5). In turn, the super efficiency DEA models for rail transport showed France, Belgium, and Slovakia to be the most efficient at 1.65, 1.65, and 1.40, respectively (Figure 5).

In the case of rail transport, the old EU countries were characterised by a higher efficiency than the new ones (see Table 2), which suggests that here improving efficiency may be more difficult than in the case of road transport. EU rail investment in new EU countries occurred only after 2004. In many new EU countries, railway modernization is continuing. Thus, a more efficient use of the available inputs (infrastructure, means of transport, etc.) is to be expected in the new EU members in the future.

Table 2. Super-efficiency DEA model of rail transport for new and old members of European Union

Rail transportation in old EU members	Super-efficiency DEA	Rail transportation in new EU members	Super-efficiency DEA
FR	2.86	SI	1.50
BE	1.76	SK	1.49
PT	1.13	LV	1.34
AT	1.12	EE	0.90
DE	1.09	LT	0.86
FI	1.08	PL	0.66
IT	0.82	BG	0.51
ES	0.57	HU	0.44
IE	0.23	CZ	0.39
EL	0.14	RO	0.30
LU	0.01	HR	0.28
Mean	*0.98*	*Mean*	*0.79*
Max	*2.86*	*Max*	*1.50*
Min	*0.01*	*Min*	*0.28*

Source: authors' calculation

Based on the results above it was possible to classify the countries into the groups which are characterised by the level DEA, GDP per capita and CO_2 emission.

As can be seen (see Table 3) all the countries with GDP per capita above EU average are the old EU countries, however only Luxemburg, The Netherlands, Belgium and Germany presents the road transport efficiency above EU average. Moreover, although Spain and Portugal GDP per capita is lower than EU average, the road transport is effective there.

Table 3. Groups of the countries characterised by road efficiency level, GDP per capita and CO_2 emission*

Efficiency	GDP per capita		CO_2 emission	
	above EU average	below EU average	above EU average	below EU average
effective	LU, NL, BE, DE	ES, PT, **EE, SI,SK,LT,PL,BG**	ES, DE, **PL**	BE, PT,LU, NL, **SK, EE, LT, SI,BG**

ineffective	DK, IE,AT,FI,SE, FR,IT,UK	EL,**CY,MT,CZ, LV, HR,HU,RO**	FR, UK, IT	EL,AT,SE,DK,IE, FI, **CZ, MT, RO, HU, HR, LV, CY**

* new EU members are marked as bold font
Source: authors' own elaboration

The interesting notice can be done about the new EU members as Estonia, Slovenia, Slovakia, Lithuania, Poland and Bulgaria. Despite from low GDP per capita index, the road transport efficiency is high. As for the environmental issue and DAE level, the situation is slightly different. In Spain, Germany, Poland CO_2 emission is above EU average in spite of the high road transport efficiency. High CO_2 emission together with ineffective road transport was in three old EU member countries: France, United Kingdom and Italy.

Table 4. Groups of the countries characterised by rail efficiency level, GDP per capita and CO_2 emission*

Efficiency	GDP per capita		CO_2 emission	
	above EU average	below EU average	above EU average	below EU average
effective	FR, AT, BE, FI, DE	PT, **SI, SK, LV**	DE, FR, **LV**	AT, BE, FI, PT, **SK, SI**
ineffective	LU, IE, IT	EL, ES, **CZ, EE, LT, PL, HU, HR, RO, BG**	ES, **PL, CZ, RO**	EL, IE, IT, LU, **HU, LT, EE, HR, BG**

* new EU members are marked as bold font
Source: authors' own elaboration

In the case of rail transport efficiency level, DGP per capita and CO2 emission it is also difficult to find some homogenous groups which can be characterised together (Table 4). Some ole EU member countries with high level of GDP per capita have ineffective rail transport (Luxemburg, Ireland and Italy). From the other hand, there are such as Slovenia, Slovakia, Latvia with lower GPD index but with effective technical rail transport. In order to make the results more precise, the statistical correlation of DEA level, GDP per capita and CO_2 emission is needed to be done.

4.2. The Statistical Correlation of DEA Efficiency Levels, CO2 Emissions, and GDP Per Capita

Varied levels of rail and road transport efficiency in old and new EU members may suggest that these factors may be linked to the GDP of those countries. Based on some reports included in the literature review, this can also be a significant factor influencing level of CO_2 emissions. The results for EU countries divided into old and new member states are quite different (see Tables 5 and 6).

Table 5. Spearman rank correlations (ρ) for road transport in new EU countries

Variable	Spearman rank correlations Correlations marked * are statistically significant at p<.05		
	DEA efficiency index	GDP per capita	CO_2 emissions
DEA efficiency index	1.000000	0.205234	0.106061
GDP per capita	0.205234	1.000000	-0.603306*
CO_2 emissions	0.106061	-0.603306*	1.000000

Source: authors' calculation

Table 6. Spearman rank correlation (ρ) for road transport in old EU countries

Variable	Spearman rank correlations Correlations marked * are statistically significant at p<.05		
	DEA efficiency index	GDP per capita	CO_2 emissions
DEA efficiency index	1.000000	0.182143	-0.121429
GDP per capita	0.182143	1.000000	-0.428571
CO_2 emissions	-0.121429	-0.428571	1.000000

Source: authors' calculation

In the case of road transport, there is a significant negative correlation between CO_2 emissions and GDP per capita. In the new EU members with higher GDP per capita, the emissions of CO_2 generated by the road transport sector are lower by approximately 0.6. This trend also exists in old EU countries, however in this case the correlation is moderate (ρ= -0.42857). In turn, transport efficiency is weakly correlated with GDP per capita in the new EU members (ρ=0.205234). The EU-15 countries reveal a similar, albeit not statistically significant, trend (ρ=0.182143).

Table 7. Spearman rank correlations (ρ) for rail transport in old EU countries

Variable	Spearman rank correlations Correlations marked * are statistically significant at p<.05		
	DEA efficiency index	GDP per capita	CO_2 emissions
DEA efficiency index	1.000000	-0.209091	0.227273
GDP per capita	-0.209091	1.000000	-0.200000
CO_2 emissions	0.227273	-0.200000	1.000000

Source: authors' calculation

Table 8. Spearman rank correlation (ρ) for rail transport in new EU countries

Variable	Spearman rank correlations Correlations marked * are statistically significant at p<.05		
	DEA efficiency index	GDP per capita	CO_2 emissions
DEA efficiency index	1.000000	0.590909	-0.336364
GDP per capita	0.590909	1.000000	-0.118182
CO_2 emissions	-0.336364	-0.118182	1.000000

Source: authors' calculation

Considering the rail transport sector (see Tables 7 and 8), there is a difference in trends between the old and new EU member states. In the EU-15, the variables are correlated very weakly and without statistical significance. On the other hand, in the case of the rail transport sector in the new EU countries, there is a quite strong correlation (ρ=0.590909) between GDP per capita and DEA efficiency, and a moderate negative correlation between CO_2 emissions and transport efficiency levels.

5. CONCLUSIONS

Although DEA has been used in many studies on the environmental impact of the transport industry, to the best of the authors' knowledge no reports exist on correlations between transport efficiency and economic development in conjunction with environmental externalities. This paper offers a new perspective on the problem of identifying efficiency-based correlations in national transport sectors. EU member states differ in terms of vehicle fleets, infrastructure intensity, volume of goods transported, and employment rate in the transport sector; all of these may influence transport sector efficiency and should be taken into account, which was the main objective of the paper.

Studies have indicated that Latvia, Slovenia, Slovakia and Belgium were the leaders in technical efficiency of both road and rail transport. No statistical correlation was found between a country's economic situation (operationalized as GDP per capita) and transport efficiency (operationalized as DEA) either in old or new EU member states, with the only exception being rail transport in new EU members. Nevertheless, this exception alone is not sufficient to substantiate hypothesis H1, which cannot be accepted. Similarly, no strong correlation was identified between the technical efficiency of the transport sector and CO_2 emissions, which is consistent with reports showing that the transport sector is not the main CO_2 pollutant. Thus, hypothesis H2 is not substantiated, either. Nevertheless, one must bear in mind that the transport sector produces other externalities, such as noise, space degradation, and local pollution with PM10 and NOx.

The presented results encourage further research, which should encompass all transport modes comprising national transport sectors. One should also consider including passenger transport, as in some countries it may have a stronger influence on the efficiency of the transport sector than freight movement. This means that the inputs and outputs of DEA models are open to discussion.

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