Routledge
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Economic Research-Ekonomska Istraživanja

ISSN: 1331-677X (Print) 1848-9664 (Online) Journal homepage: https://www.tandfonline.com/loi/rero20

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To cite this article: Joanna Baran & Aleksandra K. Górecka (2019) Economic and environmental aspects of inland transport in EU countries, Economic Research-Ekonomska Istraživanja, 32:1, 1037-1059, DOI: 10.1080/1331677X.2019.1578680

To link to this article: https://doi.org/10.1080/1331677X.2019.1578680

Published online: 14 Jun 2019.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2019, VOL. 32, NO. 1, 1037–1058
https://doi.org/10.1080/1331677X.2019.1578680

Economic and environmental aspects of inland transport in EU countries

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ABSTRACT
Transport is one of the most essential sectors of the EU member state economies. 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. The largest proportion of freight transport in the European Union is done by road. 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) method. 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 empirical part is divided into a presentation of DEA results and correlation between the transport efficiency, gross domestic product (GDP), and CO_2 emissions results. Moreover, spatial analysis was used to characterize road and rail transport efficiency in EU member states. The last section gives a summary of the study, and the obtained results are compared with data from the literature review.

ARTICLE HISTORY
Received 1 January 2018
Accepted 24 September 2018

KEYWORDS
efficiency; DEA method; rail transport; road transport; environmental effects

SUBJECT CLASSIFICATION CODES
R11; R15; R40; O52

1. Introduction

Transportation is one of the most significant drivers of European trade and economic growth. 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 2015, total goods transport activities in the EU-28 were estimated at 3,517 billion tonne-kilometers (tkm, see Figure 1). The figure includes air and sea transport activity inside the EU (but between the EU and the rest of the world). Road transport accounts for 49% of the total, railroads for 11.9%, inland waterways for 4.2%, and oil pipelines for 3.3%. Intra-EU maritime transport is the second most important mode accounting for 31.6%, while air transport contributes only 0.1% of the total. This shows that road

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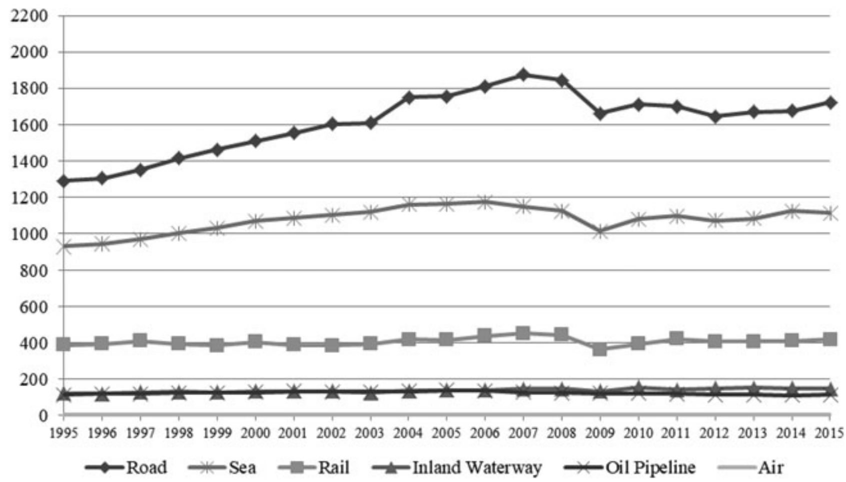

Figure 1. EU-28 performance by mode of freight transport in 1995–2015 (billion tonne-kilometers). Source: authors' calculation based on *Statistical Pocketbook 2016, EU Transport in Figures, Mobility and Transport*, Publications Office of the European Union, Belgium 2016; *Statistical Pocketbook 2017, EU Transport in Figures, Mobility and Transport*, Publications Office of the European Union, Belgium 2017 (https://ec.europa.eu/transport/facts-fundings/statistics_en)

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.

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, gross domestic product (GDP), and CO_2 emissions. The authors adopted two hypotheses:

H1: The level 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 paper is composed of five sections. In section 1 we present the introduction to the problem, research aims and hypotheses. In the second section there 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 measurement of transport efficiency by DEA method is described. In section 3 the methodology of data envelopment analysis is presented and the Spearman's rank correlation and the variables are described. The fourth part is divided into DEA results and correlation results. Spatial analysis data are presented to characterize the road and rail transport efficiency in EU countries. The last section includes concluding remarks. The paper is completed by a list of references and appendix.

2. Literature review

2.1. 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 30 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, Banister, Roberts, Prentice, & Edwards, 2007; Banister et al., 2000; UK Royal Commission on Environmental Pollution, 1994). Therefore researchers claim that the transport sector is responsible for various types of air pollution and 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.

DEA applications in environmental benchmarking and transportation have been a common research theme. Barnum et al. (2007) applied DEA to measure the efficiency of public transport in Chicago, and also examined the effects of external environmental factors on the efficiency of decision making units (DMUs). Lan & Lin (2003) propose 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 environmental externalities, data noise, and slack adjustment were taken into consideration. Su and Rogers (2012) examined multi-year transportation efficiency of OECD countries using DEA to determine efficiency scores. The model includes economic variables, freight hauled, value added, and economic contribution, ecological variables, fuel consumption, and CO_2 emissions. In this case the results indicate a strong trade-off between economic and emissions efficiency, both of them being difficult to develop and maintain over time. Tahzib and Zvijáková (2012) compared the impact of greenhouse gases of road, rail, and maritime transport. They 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 (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 and 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, Aslan, Yucel and Turgut (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, Sohag, Abdullah and Jaafar (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, Yang and Hwang (2015), the relationship between these factors and CO_2 emissions is changing dynamically.

Inversely, 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, 77.07% of carbon monoxide (CO) is emitted by non-transport sectors as compared to 20.06% by road transport and 2.06% by international and domestic shipping. Among the various types of pollutants, the transport sector produces the highest proportion of nitrogen oxides, or NOx (56.60%).

2.2. The measurement of transport efficiency by the data envelope analysis method

Transport is one of the key factors in the development of any modern society. In 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

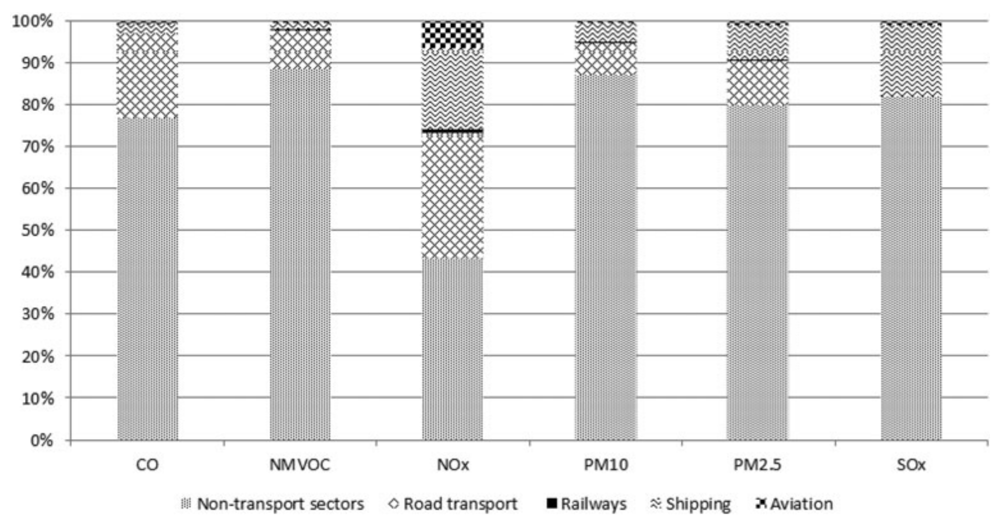

Figure 2. Contribution of the transport sector to total emissions of the main air pollutants.
Source: authors' elaboration based on European Environment Agency data, December 2017.

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 often fuel discussions on improving transport sector efficiency (Král & Roháčová 2013).

Lowell Knox (1993) defines the efficiency of a production unit in terms of a comparison between observed and optimal values of its output and input. The comparison can take the form of the ratio of observed to maximum potential output obtainable from the given input, or the ratio of minimum potential to observed input required to produce the given output. In these two comparisons the optimum is defined in reference to production possibilities, and therefore the efficiency is defined as a technical one.

Koopmans (1951) provides a definition of what we refer to as technical efficiency: an input-output vector is technically efficient if, and only if, increasing any output or decreasing any input is possible only by decreasing some other output or increasing some other input.

Farrell (1957) and much later Charnes and Cooper (1985) go back over the empirical necessity of treating Koopmans' definition of technical efficiency as a relative notion, which is relative to best observed practice in the reference set or comparison group. This provides a way of differentiating efficient from inefficient production units, but it offers no guidance concerning either the degree of inefficiency of an inefficient vector or the identification of an efficient vector or combination of efficient vectors against which to compar an inefficient vector.

Economic efficiency is the result of the activities of an enterprise which is given by the ratio of the output obtained to the inputs used. In its broader meaning, effectiveness means obtaining the best possible results in production at the lowest possible cost (Penc, 1997). In other words, a transportation enterprise exhibits economic effectiveness by optimising the process of selecting inputs and acting in such a way as to achieve optimal results given the market prices of both products/services and inputs.

Thus, effectiveness measures describe individual organisations (the microeconomic effectiveness of an institution) or certain processes within an organisation e.g. logistics (the effectiveness of a process), or even a defined group of firms (mezzo- and macroeconomic effectiveness). This phenomenon has its reflection in various thoughts of transport operations. The one which has been developed since the 18th century and influenced transport effectiveness is intermodal transport (McKenzie et al., 1993). Currently, the interest of synchromodal transport makes headway. Based on a mode-free concept and modal booking the whole transport system is supposed to be more sustainable than classic intermodallity (Agbo et al., 2017; Agbo & Zhang, Y. 2017).

Road or rail transport sectors are efficient if they minimise inputs at a given level of outputs, or maximise outputs at a given level of inputs. Efficient transport sectors are those that produce a certain amount or more outputs while spending a given amount of inputs, or using the same amount or fewer inputs to produce a given amount of outputs, as compared with other sectors in the test group.

Transport sector efficiency may be estimated by means of parametric and non-parametric frontier approaches. The former, including stochastic frontier analysis (SFA), thick frontier analysis (TFA), and the 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).

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, Odeck and Hjalmarsson (1996), Karlaftis (2004), Sampaio, Neto and Sampaio (2008), Yu (2008), Jain, Cullinane and Cullinane (2018), Klieštik (2009), Ozbek, Garza and Triantis (2009), Han and Hayashi (2008), Lan-Bing and Jin-Li (2010), Cruijssen, Dullaert and Joro (2010), Zhao, Triantis, Murray-Tuite and Edara (2011), Odeck and Bråthen (2012), Chiou, Lan and Yen (2012), Lau (2013), Merkert and Mangia (2014), Azadi et al. (2014) and Roháčová (2015).

Odeck and Hjalmarsson (1996) demonstrated the usefulness of the DEA model as a tool for evaluating the efficiency of trucks. The data comprised of trucks involved in road construction and maintenance production processes in the Norwegian road sector. 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 and Jin Li (2010) analysed 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. Sampaio et al. (2008) analysed 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. Yu (2008) explored efficiency and effectiveness for a group of 40 global railways in the year 2002, using traditional data development analysis and network data development analysis. Jain et al. (2008) analysed the relationship between ownership structure and technical efficiency through the application of DEA. A comparative analysis of 15 URTS reveals that privatization has a direct and positive bearing upon enhancing efficiency. Ozbek et al. (2009) applied DEA to measure the efficiency of 6 different hypothetical state departments of transportation in highway maintenance. Han and 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 and 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. Zhao et al. (2011) and Chiou et al. (2012) applied DEA to measure the efficiency of transportation routing. Odeck & Bråthen (2012) presented a meta-analysis of variations in seaports' mean technical efficiency (MTE) scores based on 40 studies published in refereed academic journals. They linked the variation in estimated MTE scores to differences in the following factors: the frontier methodology used, which essentially are the DEA and the SFA; regions where seaports are situated; type of data used; number of observations; and the total number of variables used. Lau (2013) applied DEA to measure efficiency and rationalise a distribution network as an alternative approach to the conventional method of optimising delivery routes and schedules through linear programming. Merkert & Mangia (2014) analysed the cost efficiency of 35 Italian and 46 Norwegian airports over time. They showed that particularly for regional and small airports, it was the level of competition that impacts on the airport's efficiency. Military use/ownership and size of airports also have a positive impact on efficiency although diseconomies of scale matter when infrastructure is taken into account. They found that Italian airports that are managed through a concession have higher efficiency scores than those with partial and temporary partial concessions. Azadi et al. (2014) proposed two DEA approaches to find targets for two-stage network structures. The objective of proposed approaches was to plan in a feasible region. The feasible region specifies bounds to ensure targets are within current operational capacity of transportation service providers (TSPs). Applying the approaches to set targets for 24 TSPs led to different results. However, proposed models ensure that the TSPs would be efficient in their current capacity. 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 and Lin (2003) used DEA and SFA methods to estimate the productive efficiency of 74 railway systems in 1999, while Michaelides, Belegri-Roboli, Karlaftis and Marinos (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.

The relation between the effectiveness of individual firms or sectors and a society, is of particular interest. What is effective at the level of an individual firm or sector is not necessarily effective at the level of a society. The activities of a given firm may cause large external costs, e.g. via environmental pollution having negative effects on local inhabitants (Ramanathan, 2006). From this point of view, the economic and environmental efficiency of a transportation firms or sector should be measured.

3. Methods

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 2014 (the latest available data), and were taken from the Eurostat database published by European Union as *Statistical Pocketbook, Mobility and Transport*. 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.

3.1. Data envelopment analysis

Based on the sample efficiency of transport sectors was evaluated using data envelopment analysis. Data envelopment analysis (DEA) is a non-parametric mathematical programming approach to measuring relative efficiencies of comparable decision making units (DMUs) with respect to multiple inputs and outputs. DMUs are usually described by several inputs that are spent for the production of several outputs. Let us consider the set E of n decision making units such that E = {DMU1, DMU2, … , DMUn}. Each of the units produces r outputs and spends m inputs for their production. Let us use xj = {xij, i = 1,2, … ,m} to denote the vector of inputs and yj = {yij, i = 1,2, … ,r} to denote the vector of outputs of the DMUj. Then, X is the (m, n) matrix of inputs and Y the (r, n) matrix of outputs.

The basic principle of DEA evaluation of the efficiency of DMUq, $q \in \{1,2, \ldots ,n\}$ consists in seeking a virtual unit with inputs and outputs defined as a weighted sum of inputs and outputs of the other units in the decision set -$\mathbf{X}\lambda$ a $\mathbf{Y}\lambda$, where $\lambda = (\lambda 1, \lambda 2, \ldots , \lambda n)$, and $\lambda > 0$ is the vector of weights of the DMUs. The virtual unit should be better (or at least not worse) than the analysed unit DMUq. The problem of identifying a virtual unit can generally be formulated as a standard linear programming problem (Cooper, Seiford, & Tone, 2007):

$$\begin{gathered} \text{minimize } \theta \\ \text{subject to } Y\ \lambda \geq \mathbf{y}^q \\ \mathrm{X}\lambda \leq \theta \mathrm{x}^{\mathrm{q}} \\ \lambda \geq 0 \end{gathered} \tag{1}$$

Equation 1 shows the basic philosophy of DEA models. The first model of this kind was developed by Charnes, Cooper, and Rhodes in 1978. DMUq is considered efficient if the virtual unit is identical to the evaluated unit (a virtual unit with better inputs and outputs does not exist). In this case, $\mathbf{Y}\lambda = \mathbf{y^q}$, $\mathbf{X}\lambda = \mathbf{x^q}$, and the minimum value of $z = \theta = 1$. Otherwise, the DMUq is not efficient and a minimum value of $\theta < 1$ can be interpreted as the need to proportionally reduce inputs in order to reach the efficient frontier. The presented model is input-oriented because its objective is to find a reduction rate of inputs in order to reach efficiency. An output oriented model can be formulated analogously.

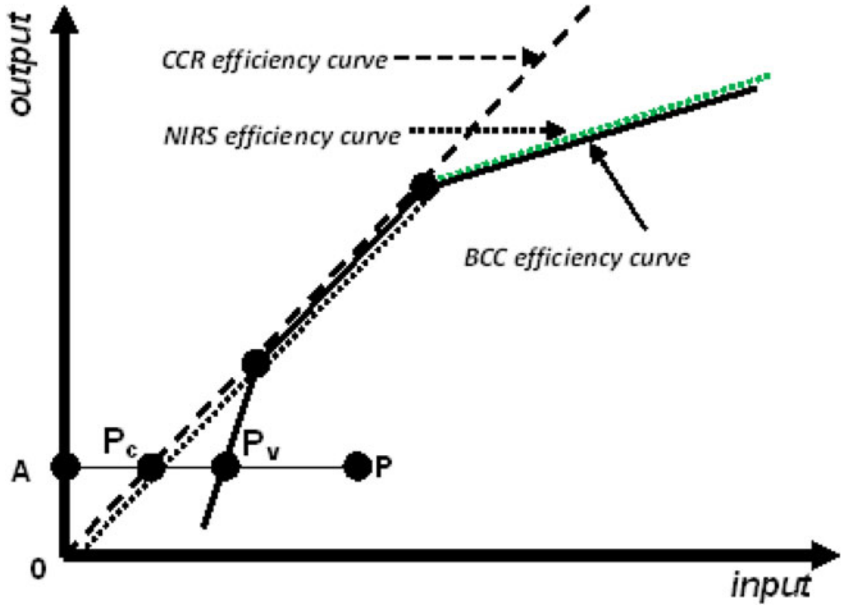

Figure 3. Scale efficiency according to the DEA method (model: 1 output and 1 input).
Source: based on Coelli et al. 2005.

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 (see Figure 3). The CCR model is used to calculate overall technical efficiency (TE), where TE for object P = APC/AP. The BCC model is used to calculate pure technical efficiency (PTE), where PTE for object P = APV/AP (Coelli, Prasada Rao, O'Donnell, & Battese, 2005).

DEA can be a powerful tool when used wisely. A few of the characteristics that make it useful are (Cooper, Seiford, & Zhu, 2004):

- DEA can handle multiple input and output models.
- It does not require an assumption that inputs to outputs are related by a function.
- DMUs are directly compared against a peer or combination of peers.
- Inputs and outputs can have very different units.
- DEA allows efficiency evaluation over time.

However, DEA also has some limitations:

- It is a deterministic rather than statistical technique and produces results that are particularly sensitive to measurement error (input and output specification and sample size).

- It only measures efficiency relative to best practices within a particular sample, and so comparisons of scores between different studies is not meaningful.
- It can be successfully used to estimate the relative efficiency of a DMU, but it converges very slowly to absolute efficiency (it reveals DMU performance against its peers but not a theoretical maximum).
- Being nonparametric, it is difficult to apply it to test statistical hypotheses, which is the focus of ongoing research.
- Its standard formulation creates a separate linear program for each DMU and can be computationally intensive.
- All efficient units are assigned the same score (1.00) and further ranking is not possible.

The selection of an 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 a significant effect on economic growth and development, so the first output measure is turnover to the economy from the transport sector. The second output measure is an absolute measure of tonnage hauled over distance.

Based on literature review CCR models aimed at maximizing outputs (output-oriented) were used to determine the relative efficiency of road and rail transport across Europe (Zhou, Ang, & Poh, 2008).

The following variables were used for DEA models of road transport (see Table I):

- output y_1 – turnover (billion euro)
- output y_2 – payload-distance (billion tonne-kilometers)
- input x_1 – employment
- input x_2 – length of road network (km)
- input x_3 – energy consumption (Mtoe)
- input x_4 – stock of registered goods vehicles.

In the next step, the efficiency of the rail transport sector in 2014 was evaluated. The following variables were used in DEA models of rail transport (see Table II):

- output y_1 – turnover (billion euros)

- output y_2 –payload-distance (billion tonne-kilometers)
- input x_1 – employment
- input x_2 – length of railways lines in use (km)
- input x_3 – energy consumption (Mtoe)
- input x_4 – stock of registered goods freight carriages.

DEA efficiency ratios were calculated in DEA Solver Pro 14.

3.2. Spearman's rank correlation coefficient

Spearman rank correlation (ρ) test was used to discover the strength of a link between the data to determine if the efficiency of a transport mode is correlated with the level of economic development and environmental pollution (2) (Parlińska et al., 2010).

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

where: $di = R_{xi}$ - R_{yi} – difference between the *i-th* rank for variable x and the *i-th* rank for variable yn – volume of a pair of observation

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

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

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

Spearman's correlation assesses monotonic relationships. It returns a value from -1 to 1, where:

- $+1$ = a perfect positive correlation between ranks,
- -1 = a perfect negative correlation between ranks,
- 0 = no correlation between ranks.

If there are no repeated data values, a perfect Spearman correlation of $+1$ or -1 occurs when each of the variables is a perfect monotone function of the other (Rees, 2000). The indexes were estimated in *Statistica 12.0* software.

The following variables were used in the calculation of Spearman rank correlation based on the equation above:

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.

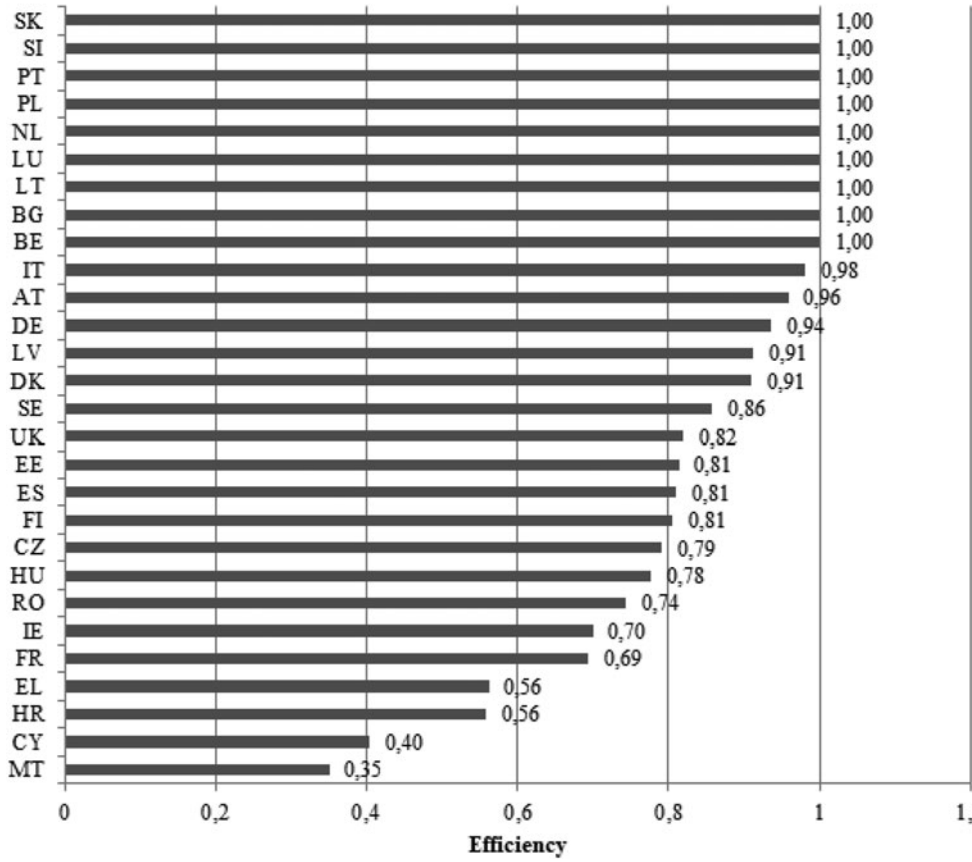

Figure 4. Efficiency DEA models of road transport for the 28 members of the European Union in 2014.

Source: authors' calculation based on *Statistical Pocketbook 2016, EU Transport in Figures, Mobility and Transport*, Publications Office of the European Union, Belgium 2016; *Statistical Pocketbook 2017, EU Transport in Figures, Mobility and Transport*, Publications Office of the European Union, Belgium 2017 (https://ec.europa.eu/transport/facts-fundings/statistics_en).

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.

First, a ranking of countries was created according to the efficiency index for the road transport sector (see Figure 4). The average technical efficiency of that sector in Europe in 2014 was fairly high with the DEA indicator in the CCR model being 0.87. The road transport sector that was effective in 9 out of 28 studied countries (with an efficiency ratio of 1); these included Slovakia, Belgium, Bulgaria, Slovenia, Portugal, Poland, the Netherlands, Luxembourg, and Lithuania.

This means that those countries made the best use of their inputs (workers, roads, means of transport, etc.) to achieve results such as turnover, freight payload-distance, etc.

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 efficiency DEA models, it can be seen that both groups contain the same number of countries recognised as effective and the same mean efficiency index equals 0.9 (see Table 1).

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 2014 was high (0.76). Full technical efficiency (with an efficiency index equal to 1) was achieved by nine counties: Slovakia, Belgium, Slovenia, Latvia, France, Italy, Austria, Ireland and Lithuania (see 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.

4.2. Spatial analysis of transport sector efficiency

As can been seen below (see Figure 6), no countries share the same efficiency of road and rail transport sectors. It is also very difficult to find any spatial regional

Table 1. Efficiency DEA model of road transport for new and old members of the European Union in 2014.

Road transportation in old EU members	Efficiency based on DEA model	Road transportation in new EU members	Efficiency based on DEA model
BE	1.00	BG	1.00
DE	1.00	EE	1.00
ES	1.00	LT	1.00
LU	1.00	PL	1.00
NL	1.00	SI	1.00
PT	1.00	SK	1.00
IT	0.98	RO	0.99
AT	0.97	CZ	0.94
DK	0.91	LV	0.91
SE	0.87	HU	0.87
FI	0.84	CY	0.71
UK	0.82	HR	0.68
IE	0.70	MT	0.61
FR	0.69		
EL	0.65		
Mean	*0.90*	*Mean*	*0.90*
Max	1.00	*Max*	*1.00*
Min	*0.65*	*Min*	*0.61*

Source: authors' calculation based on *Statistical Pocketbook 2016, EU Transport in Figures, Mobility and Transport*, Publications Office of the European Union, Belgium 2016; *Statistical Pocketbook 2017, EU Transport in Figures, Mobility and Transport*, Publications office of the European Union, Belgium 2017 (https://ec.europa.eu/transport/facts-fundings/statistics_en).

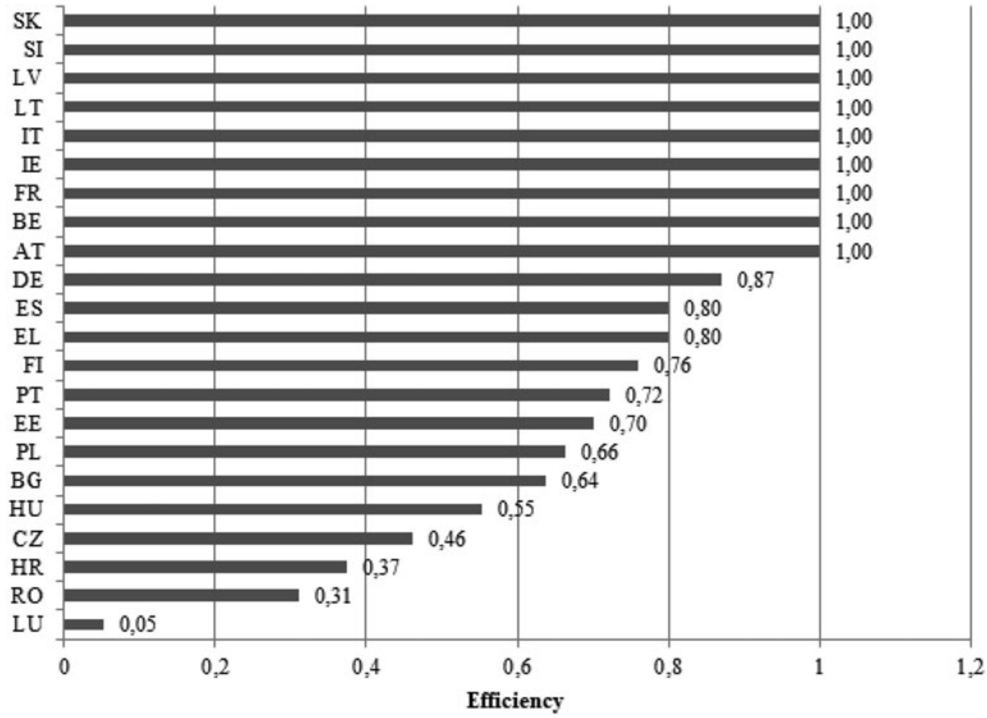

Figure 5. Efficiency DEA model of rail transport for 23 members of the European Union in 2014.
Source: authors' calculation based on *Statistical Pocketbook 2016, EU Transport in Figures, Mobility and Transport*, Publications Office of the European Union, Belgium 2016; *Statistical Pocketbook 2017, EU Transport in Figures, Mobility and Transport*, Publications Office of the European Union, Belgium 2017 (https://ec.europa.eu/transport/facts-fundings/statistics_en).

Table 2. Efficiency DEA model of rail transport for new and old members of European Union in 2014.

Rail transportation in old EU members	Efficiency based on DEA model	Rail transportation in new EU members	Efficiency based on DEA model
BE	1.00	LV	1,00
DE	1.00	LT	1.00
IE	1.00	SI	1.00
FR	1.00	SK	1.00
IT	1.00	HU	0.81
AT	1.00	BG	0.75
PT	1.00	EE	0.73
FI	1.00	CZ	0.72
EL	0.97	PL	0.67
ES	0.80	HR	0.54
LU	0.13	RO	0.33
Mean	*0.90*	*Mean*	*0.78*
Max	*1.00*	*Max*	*1.00*
Min	*0.13*	*Min*	*0.33*

Source: authors' calculation based on *Statistical Pocketbook 2016, EU Transport in Figures, Mobility and Transport*, Publications Office of the European Union, Belgium 2016; *Statistical Pocketbook 2017, EU Transport in Figures, Mobility and Transport*, Publications Office of the European Union, Belgium 2017 (https://ec.europa.eu/transport/facts-fundings/statistics_en).

convergence of transport effectiveness in European countries. This may suggest that despite EU regulations concerning the general investment policy, each EU member acts independently with different degrees of implementation of the EU transport

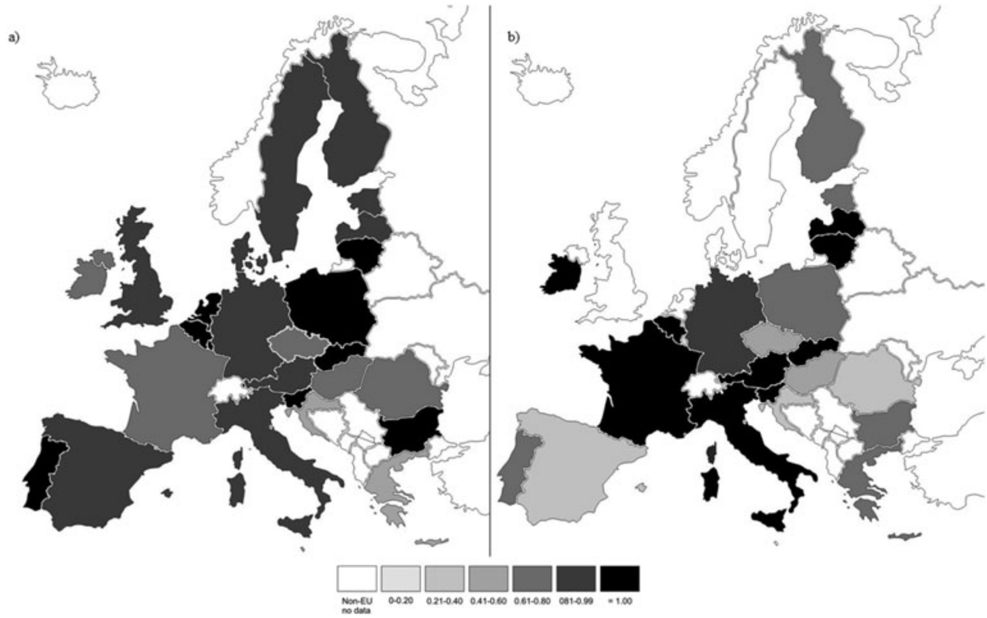

Figure 6. Spatial analysis of road (a) and rail (b) efficiency in EU countries.
Source: authors' elaboration based on DEA calculation.

strategy with no deep cooperation between each other. This also results in diverse levels of transport efficiency.

In the next step of the study, the technical efficiency of road transport sectors was compared with GDP per capita in individual countries (see Figure 7 and Table 3), giving rise to four groups.

4.3. 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 levels of CO_2 emissions from these modes of transport. Spearman correlation rank results, however, do not corroborate this.

The results show (Table 4) that correlations between the three variables are not statistically significant, with only a correlation found between GDP per capita and CO_2 emissions generated by the road transport sector ($\rho = 0.78267$). This result suggests that countries with higher GDP per capita are more likely to have higher CO_2 emissions from this sector.

Slightly different results are found for the rail transport sector, where there is no correlation between GDP per capita and CO_2 emission level (ρ=-0.065518) (see Table 5). In this case, no correlation coefficient is statistically significant. However, the results for EU countries divided into old and new member states are quite different (see Tables 6 and 7).

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

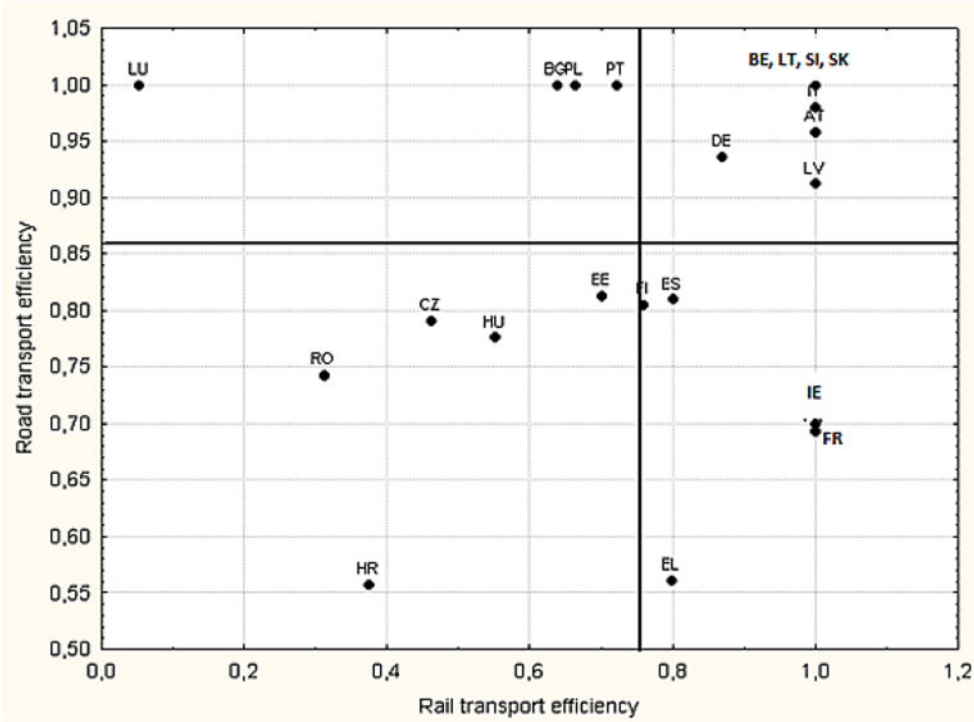

Figure 7. Groups of countries by levels of rail and road transport efficiency.
Source: own elaboration.

Table 3. Characteristics of groups of countries with different efficiency levels in terms of road and rail transport.

Group	Characteristic	Countries
I	The group of leaders in which both road and rail transport technical efficiency are above average of EU	Belgium, Lithuania, Slovenia, Slovakia, Italy, Austria, Germany, Latvia
II a	The group in which road transport sector efficiency is higher than EU average, however rail transport sector is not effective	Luxemburg, Bulgaria, Poland, Portugal
II b	The group in which rail transport sector effectiveness is higher than European average, and road transport sector effectiveness is low	Finland, Spain, Ireland, France, Greece
III	The group with low road and rail sector effectiveness – below average technical efficiency for EU	Croatia, Hungary, Czech Republic, Romania, Estonia

Source: authors' elaboration.

capita, the emissions of CO_2 generated by the road transport sector are lower by approximately 0.38. This trend also exists in old EU countries, however in this case the correlation is low (ρ= -0.2785671). Additionally, transport efficiency is weakly negative correlated with GDP per capita in the new EU members ($\rho = 0.140343$), while in the EU-15 the positive but weak correlation can be noticed ($\rho = 0.213936$).

Considering the rail transport sector (see Tables 8 and 9), there is a difference in trends between the old and new EU member states. In the EU-15, the variables are

Table 4. Spearman rank correlations (ρ) for road transport in EU countries.

Variable	Spearman rank correlations Correlation marked as * is significant important at $p<.05$		
	DEA	GDP per capita	CO_2
DEA	1.000000	0.121347	0.146932
GDP per capita	0.121347	1.000000	0.378267*
CO2	0.146932	0.378267*	1.000000

Source: authors' calculation in the *Statistica 12.0* software.

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

Variable	Spearman rank correlations Correlation marked as * is significant important at $p<.05$		
	DEA	GDP per capita	CO_2
DEA	1.000000	0.367951	0.082459
GDP per capita	0.367951	1.000000	−0.065518
CO2	0.082459	−0.065518	1.000000

Source: authors' calculation in the *Statistica 12.0* software.

Table 6. Spearman rank correlations (ρ) for road transport in new EU countries.

Variable	Spearman rank correlations Correlation marked as * is significant important at $p<.05$		
	DEA	GDP per capita	CO_2
DEA	1.000000	−0.140343	0.317866
GDP per capita	−0.140343	1.000000	−0.376892
CO_2	0.317866	−0.376892	1.000000

Source: authors' calculation in the *Statistica 12.0* software.

Table 7. Spearman rank correlation (ρ) for road transport in old EU countries.

Variable	Spearman rank correlations Correlation marked as * is significant important at $p<.05$		
	DEA	GDP per capita	CO_2
DEA	1.000000	0.213936	0.090370
GDP per capita	0.213936	1.000000	−0.278571
CO_2	0.090370	−0.278571	1.000000

Source: authors' calculation in the *Statistica 12.0* software.

correlated very weakly and without statistical significance. On the other hand, in the case the new EU countries, there is a quite moderate correlation ($\rho = 0.391695$) between GDP per capita and DEA efficiency, and a moderate negative correlation between CO_2 emissions and transport efficiency level ($\rho= - 0.362889$).

5. Conclusions

The paper presents the application of the DEA methodology to the evaluation of transportation (road and rail) sectors of the EU. 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 and important perspective on the problem of identifying efficiency-based correlations in national transport sectors. EU member states differ in terms of vehicle fleets,

Table 8. Spearman rank correlations (ρ) for rail transport in old EU countries.

Variable	Spearman rank correlations Correlation marked as * is significant important at $p<.05$		
	DEA	GDP per capita	CO_2
DEA	1.000000	0.075156	0.080937
GDP per capita	0.075156	1.000000	−0.127273
CO_2	0.080937	−0.127273	1.000000

Source: authors' calculation in the *Statistica 12.0* software.

Table 9: Spearman rank correlation (ρ) for rail transport in new EU countries.

Variable	Spearman rank correlations Correlation marked as * is significant important at $p<.05$		
	DEA	GDP per capita	CO_2
DEA	1.000000	0.391695*	−0.362889
GDP per capita	0.391695*	1.000000	−0.036447
CO_2	−0.362889	−0.036447	1.000000

Source: authors' calculation in the *Statistica 12.0* software.

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.

From the practical point of view the results of this analysis can be summarized as follows:

- Latvia, Slovenia, Slovakia and Belgium were the leaders in technical efficiency of both road and rail transport. They have the highest position in the ranking. Parameters of transportation activity in these transportation sectors may constitute a benchmark for other evaluated entities.
- Ineffective road and rail transportation sectors are in Croatia, Hungary, Czech Republic, Romania, and Estonia. Those countries are located at the bottom of the ranking list. The result of the low position of this variant in the ranking is technical efficiency below the average efficiency for EU.
- No statistical correlation was found between a country's economic condition (operationalized as GDP per capita) and road transport efficiency (operationalised as DEA) either in old or new EU member states, whilst in case of rail transport for EU members, and new countries in EU there are low positive correlation. This exception alone however is not sufficient to substantiate hypothesis H1, which cannot be fully accepted. It is not possible to give an unambiguous indication whether higher GDP per capita leads to higher technical efficiency of transport sectors.
- Likewise, no strong correlation was identified between the technical efficiency of the transport sector and CO_2 emissions. Nevertheless, here the two exemptions can be also mentioned. In new EU countries the results clearly present that more effective road transport leads to increasing CO_2 emission from this transport mode while higher efficiency of rail transport sector affects its decrease. Thus, CO_2 emission in some countries is inversely proportional to the degree of technical transport efficiency. Hypothesis H2 is partly confirmed. This result corresponds with the conclusions of the group of researchers claiming that level of air pollution from transport sector depends on transport mode. Consequently, it is than reasonable to create and

promote the integration of transport modes for transport sustainability growth. 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 which also should be investigated in the further studies.

From the methodological point of view the proposed approach for ranking and benchmarking of transportation sectors has a universal character and can be applied in a variety of industries. It is composed of the following stages:

- recognition of the DMU;
- definition of the variables based on the literature review;
- definition of DEA model (model orientation and type of returns to scale);
- computational experiments leading to the final ranking;
- correlation between the DEA efficiency and another variables.

The results encourage detailed and wide studies, which should encompass all transport modes comprising national transport sectors in order to investigate whether the transport sector is or is not the main air pollutant. 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 both the problem and the inputs and outputs of DEA models are open to discussion. From a methodological point of view it is interesting to verify whether different methods generate similar efficiency rankings of transport sectors. Moreover detailed analysis of the leaders in transportation efficiency is indicated as a benchmark for other evaluated transportation sectors.

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Appendix

Table I Data of road transport.

Country	(y_1) Turnover (billion duro)	(y_2) National and International Haulage (billion tkm)	(x_1) Employment (in 1 000)	(x_2) Length of road network (km)	(x_3) Energy Consumption (Mtoe)	(x_4) Stock of registered goods vehicles thousand
BE	11 315	31.8	59.1	155210	8.3	813.8
BG	3 140	27.9	58.8	19 678	2.7	411.8
CZ	7 630	54.1	116.6	130 680	5.6	615.3
DK	5 567	16.2	33.8	74 130	3.7	439.6
DE	36418	310.1	369.7	230377	52.7	2 889.8
EE	1 182	6.3	16.1	58 787	0.7	96.6
IE	2 508	9.8	19.4	96017	3.7	317.4
EL	2 605	19.2	35.5	117321	5.0	1 322.6
ES	30 988	195.8	302.6	666 415	25.7	5 025.5
FR	42 568	165.2	347.6	1071823	41.4	6 519.0
HR	1 266	9.4	22.2	26 820	1.8	143.7
IT	43 694	117.8	303.2	256 039	34.3	4 080.9
CY	143	0.5	1.9	9 765	0.6	104.4
LV	1 408	13.7	25.1	70 443	0.9	83.2
LT	3 350	28.1	55.8	72 591	1.6	99.7
LU	1 211	9.6	7.4	2 880	2.1	38.4
HU	4 702	37.5	66.7	203 310	3.6	478.4
MT	74	0.3	1.2	2 361	0.2	44.1
NL	19 457	70.9	111.7	138641	9.8	948.8
AT	9356	24.3	59.3	124 115	7.5	434.9
PL	21 716	250.9	303.0	415 122	15.0	3 340.6
PT	5 009	34.9	60.8	14310	5.2	1 237.0
RO	6 854	35.1	121.7	85 531	5.0	806.5
SI	2 235	16.3	212	38 874	1.8	87.3
SK	2 612	31.4	35.0	54 806	2.0	293.9
FI	6 111	23.4	45.7	78 093	3.8	542.9
SE	10 652	42.0	76.3	216976	7.4	581.2
UK	32 175	143.2	219.2	421 127	37.6	4 066.4

Source: own elaboration based on (Statistical Pocketbook, 2016, Statistical Pocketbook, 2017).

Table II Data of rail transport.

Country	(y_1) Turnover (billion euro)	(y_2) payload-distance (billion tkm)	(x_1) Employment (in 1 000)	(x_2) Length of railways lines in use (km)	(x_3) Energy Consumption (Mtoe)	(x_4) Stock of registered Goods Transport Wagons
BE	4422.20	7.28	36.64	3631	0.18	11612
BG	310.50	3.44	11.39	4023	0.03	5325
CZ	1581.10	14.57	27.47	9456	0.22	25965
DE	1088020	112.63	47.46	38836	1.34	91787
EE	113.80	3.26	1.30	1510	0.02	2931
IE	255.76	0.10	4.03	1894	0.05	450
EL	277.70	0.31	1.07	2238	0.06	3158
ES	2444.00	10.39	14.85	15901	0.26	13702
FR	6259.60	32.60	25.59	29386	0.87	15017
HR	247.30	2.12	5.10	2604	0.04	5518
IT	6237.20	20.16	39.47	17037	0.45	20515
LV	449.00	19.44	3.79	1853	0.07	12009
LT	469.40	14.31	10.80	1767	0.06	8784
LU	2.00	0.21	1.00	275	0.02	3895
HU	802.10	10.16	18.92	7892	0.15	11700
AT	2855.80	20.49	10.67	5058	0.22	18544
PL	2530.10	50.07	54.04	18942	0.32	61373
PT	198.20	2.43	0,74	2544	0.04	3170
RO	875.30	12.26	28.38	10770	0.19	35899
SI	265.10	4.11	0.70	1208	0.02	3148
SK	1187.60	8.83	13.49	3627	0.04	17006
FI	698.50	9.60	4.06	5944	0.09	9078

Source: own elaboration based on (Statistical Pocketbook 2016, Statistical Pocketbook 2017).