Environmental performance in OECD countries: A non-radial DEA approach

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Data Envelopment Analysis (DEA) has become popular in performance measurement in the environmental area because it can provide a synthetic standardised performance index when pollutants are appropriately incorporated into the traditional DEA framework. Existing studies on the application of DEA to measure the environmental performance often follow the concept of a radial efficiency. In this paper, we use the non-radial and non-oriented DEA approach (SBM model) with undesirable output under the condition of constant rerun to scale. Since the slacks-based model (SBM model) integrates all the slacks in inputs and desirable outputs into a whole, the result can provide some standardised composite index with a higher discriminating power for modelling environmental performance. We apply the SBM model to measure environmental performance in OECD countries during the 1995-2014 period. We can see that the environmental performance of OECD countries as a whole has improved from 1995 to 2014. As the most efficient countries, we considered France, Italy and Switzerland, which were efficient during the wholly analysed period. On the other hand, the lowest efficiency was in countries like the Czech Republic, Hungary, Poland, and Slovakia. The highest progress obtained the Lithuania, where the efficiency score increased from 10.17 % in 1995 to 26.22 % in 2014. The biggest fall is evident in the case of Portugal, where the efficiency score fell from 40.8 % in 1995 to 29.55 % in 2014.

Key words: *Data Envelopment Analysis (DEA), Environmental performance, Undesirable outputs, Non-radial model, OECD countries*

Introduction

Numerous studies across all different industries explore the measurement of efficiency in many fields of activity. The choice of the analysis applied in these studies depends on their focus. While the focus of some studies is on the product or the production process, other studies focus on plant, companies or industrial sector (Kalb, 2010; Rajnoha, Lesníková, 2016). The regional analysis of the environmental effects as many benchmark studies introduce is still beneficial. According to the study by Wang, Lu, Wei (2013) for most Chinese regions, they did not recommend to increase or maintain their current scales of production. Alternatively, they should pay more attention to technology innovation of energy efficiency improvement. China has enormous energy conservation and emission reduction potentials. Study of Li, Fang, Yang, Wang, Hong (2013) proves that fiscal decentralisation and technology progress can increase environmental efficiency overall while economic scale and the regional difference can also influence the efficiency.

First attempts to measure the efficiency of economic units were based on the application of the efficiency indexes with a weighted average of inputs compared to a weighted average of outputs. The most known superlative index numbers are the Tornquiest-Theil-translog index and Fischer Ideal index (Tornquist, 1936). As the problems with the circularity and characteristic appearance, it is not recommended to do the multilateral comparative analysis of the time series data. Even though, the study of Caves, Christensen, Diewert (1982) shows that indexes are adequate for multilateral comparison using cross-section data and panel data. These indexes are not widely used in developing empirical comparative methods (Knight, Rosa, 2011). The disadvantage of the superlative multilateral indexes is that they rely on the fact, the price of the products is always positive (Pittman, 1983). In a study by Diewert (1979) the index number theory is divided into three approaches: statistical, the test approach and the functional approach. The functional approach helps to understand better and decide whether the usage of indexes is implemented appropriately or not. The study of Samuelson Swamy (1974) appertain to the functional approach, deals with the relationship between index techniques and the functions of production and utility.

Author (Farrell, 1957) in his study of farmers technical and price efficiency emphasises that measuring the productive efficiency should have some practical background. According to his study, it is more reasonable to compare the firm with the comparable firms than to compare firm with the theoretically efficient ideal that is

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hard to reach. The emphasis of his study is on the importance of using more than one input. The problems of characteristic and circularity are avoided.

Environmental issues have become an inseparable part of everyday life and are an indispensable tax on the comfort that most of the world today can afford. These problems affect all the environmental compartments, i.e. water, air, soil, and biota, and is not even a person exempt. The environmental efficiency index may be used to decide whether the economic agent is environmentally efficient (Rajnoha et al., 2017). Färe, Grosskopf, Lovell, Pasurka (1989) propose the development of a hyperbolic graph efficiency approach, which seeks the maximum simultaneous uniform expansion for the desired outputs and contraction for the inputs and undesirable outputs. This study is the modification of Farrell approach. It takes into account the study of Pittman (1983) that informs about the necessity of dividing the outputs into desirable and undesirable outputs. When analysing the environmental effects of firms, different environmental performance indicators may serve to analyse and identify the lagers and the leaders. As the conclusion of the study Färe, Grosskopf, Tyteca (1996) affirms, the adoption of tradeable permits would imply considerable differences among companies. The indicators that provide information about environmental performance would be a useful tool to gather the information for public decision-makers about the new policy that should be implemented to be more eco-efficient. The other approach towards environmental performance indicators is mathematical programming. The study of Seiford, Zhu (2002) evaluates the relative efficiencies and inefficiencies of similar organisational units (DMUs) by using Data Envelopment Analysis (DEA). Identification of efficient frontier allows bettering deciding whether the increasing level of output or decreasing the level of inputs is needed to improve the performance of DMU. As the term envelope says, the data are enveloped by the piecewise linear frontier in such a way that the radial distances to the frontier are minimised (Kulshreshtha. Parikh, 2002). As the methodology of measuring the efficiency differs, the results obtained from analysis differs too. In Färe et al. (1996) the comparison of Jaggi and Friedman model to environmental performance indicator on the same dataset was made. Models show significant divergence, caused by different ways of dealing with undesirable outputs. Two main non-parametric methods for the environmental performance analysis is data envelopment analysis (DEA) and free disposal hull (Yagi, Fujii, Hoang, Managi, 2015). DEA enables to do the simulation of the effect of any regulatory standard on production and provides the information about all lower and upper limits beyond which production is impossible (Charnes, Cooper, Rhodes, 1978). Two competing approaches to efficiency are a stochastic frontier estimation and DEA (Zaim, Taskin, 2000; Reinhard, Lovell, Thijssen, 2000). Data envelopment analysis is widely used to study the efficiency of energy industries, particularly in the mining industry (Kulshreshtha, Parikh, 2002; Tsolas, 2011; Vaninsky, 2006; Wossink, Denaux, 2006; Halkos, Tzeremes, 2009; Sueyoshi, Yuan, Goto, 2017; Murty, Kumar, Paul, 2006; Zaim, Taskin, 2000; Reinhard et al., 2000; Welch, Barnum, 2009; Zofío, Prieto, 2001; Zhou, Poh, Ang, 2016). Seiford, Thrall (1990) compare the mathematical programming to the regression approach of modelling DEA. The regression approach is criticized because of its „only“ residuals side and the absence of the judgement on efficiency – it is not possible to identify the sources of inefficiency and the influence of the outliers is noticeable. The only requirement for the DEA is a single observation (for each input and output) per DMU. It may cause sensitivity to variable selection, model specification, and data errors. One of the methodologies to analyse the environmental efficiency is a non-radial and non-oriented Data Envelopment Analysis (DEA), namely the SBM model. According to (Mardani, Zavadskas, Streimikiene, Jusoh, Khoshnoudi, 2017) DEA is used mostly to explore the energy efficiency. Papers that do analysis while using DEA are based on areas: environmental efficiency, economic and eco-efficiency, energy efficiency issues, renewable and sustainable energy, water efficiency, energy performance, energy saving, integrated energy efficiency etc.

In the context of environmental performance measurement, the assumption used by traditional DEA models that all the outputs should be maximised is not appropriate when undesirable outputs are also generated as the by-products of the desired outputs in the production process. By the global environment conservation awareness, undesirable outputs of productions and social activities, for example, air pollutants and hazardous wastes, are being increasingly recognised as dangerous and undesirable. Thus, the development of technologies with less undesirable outputs is an important subject of concern in every area of production. Färe et al., (1989) presented one of the methods how the undesirable outputs could be involved in the evaluation. This method, based on the concept of weak disposable reference technology, also called the environmental DEA technology, has been adopted in environmental performance measurement for example in study of Reinhard et al., (2000); Zaim, Taskin, (2000); Zaim (2004); Zofío, Prieto, (2001); Zhou, Ang, Poh, (2006, 2008); Zhou, Poh, Ang, (2007).

This paper aims to apply the non-radial and non-oriented DEA model (SBM model) with undesirable outputs to measure environmental performance in OECD countries during the period from 1995 to 2014. We organised the remainder of the paper as follows. The next section deals with methodology issue and present data used in the analytical part of the paper. Then we present the results of the analysis. The last section concludes the study.

Methodology and data

DEA was first applied to the public sector, specifically to estimate the efficiency of schools, without information on prices. This formulation is known as the CCR (Charnes et al., 1978) The CCR model should not be used in many situations. In 1984 the BCC model was introduced as the extension of the CCR model and included even the situation when the returns to scale at different points on the production frontier are increasing/constant or decreasing (Ray, 2004). Difference between CCR and BCC model is that in the BCC model the assumption of a variable return to scale is used. Classification of DEA models is as follows: radial and oriented, radial and non-oriented, non-radial and oriented, non-radial and non-oriented. Oriented means that the model is input or output oriented, while radial means that the primary concern of model is proportional reduction/enlargement of inputs and output. We can use the bootstrap DEA with repeat sampling of correlation estimation to analyse the small data sample (Song, Zhang, Liu, Fisher, 2013). Most studies about the application of DEA to environmental performance evaluation follow the concept of the radial efficiency measures. According to (Zhou et al., 2007) using radial efficiency measures often leads to the case where a lot of evaluated production units (countries or individual companies) have the same efficiency score of 1 and hence the difficulty in ranking the environmental performance of these production units only based on their efficiency scores. Since non-radial efficiency measures have a higher discriminating power when evaluating the efficiency of production units, the non-radial DEA models seem to be more effective in measuring environmental performance. In the case of environmental performance evaluation, it is also necessary to extend the traditional non-radial DEA models into the case where undesirable outputs exist.

Consider a production process in which desirable and undesirable outputs are jointly produced. Assume that $\mathbf{x} = (x_1, \dots, x_n)$, $\mathbf{y^g} = (y_1^g, \dots, y_n^g)$ and $\mathbf{y^b} = (y_1^b, \dots, y_n^b)$ denote the vectors of inputs, desirable outputs and undesirable outputs respectively. The production teghnology can then be conceptually described as $P = \{(\mathbf{x}, \mathbf{y^g}, \mathbf{y^b}) : \mathbf{x} \text{ can produce } (\mathbf{y^g}, \mathbf{y^b})\}$. In order to reasonably model a production process that produce both desirable and undesirable outputs, the following two assumptions are imposed on *P* by Färe et al. (1989):

1. Outputs are weakly disposable, i.e. if $(\mathbf{x}, \mathbf{y^g}, \mathbf{y^b}) \in P$ and $0 \le \theta \le 1$, then $(\mathbf{x}, \theta\mathbf{y^g}, \theta\mathbf{y^b}) \in P$. This assumption states that the proportional reduction in desirable outputs and undesirable outputs is possible.
2. Desirable outputs and undesirable outputs are null-joint, i.e. $(\mathbf{x}, \mathbf{y^g}, \mathbf{y^b}) \in P$ and $\mathbf{y^b} = 0$ imply that $\mathbf{y^g} = 0$. This assumption indicates that the only way to eliminate all undesirable outputs is to end production process.

Although the production technology *P* has been well-defined conceptually, it can not be directly used in the application. In the DEA scope, as described in Färe et al. (2004), *P* can be characterised by the piecewise linear combination of the observed data.

Suppose that there are *n* DMUs (decision-making units) each having three factors: inputs, desirable outputs and bad (undesirable) outputs, as represented by three vectors $x \in R^m, y^g \in R^{s_1}$, and $y^b \in R^{s_2}$. We define the matrices X, Y^g, and Y^b as follows. $X = [x_1, \dots, x_n] \in R^{m \times n}$, $Y^g = [y_1^g, \dots, y_n^g] \in R^{s_1 \times n}$, and $Y^b = [y_1^b, \dots, y_n^b] \in R^{s_2 \times n}$. We assume $X > 0, Y^g > 0$, and $Y^b > 0$ (Cooper et al., 2007).

We can define the production possibility set

(*P*) by $P = \{(x, y^g, y^b) \mid x \ge X\Upsilon, y^g \le Y^g\Upsilon, y^b \ge Y^b\Upsilon, \Upsilon \ge 0\}$, where $\Upsilon \in R^n$ is the intensity vector (Cooper et al., 2007). Since *P* is formulated in the DEA framework, as argued by Färe et al. (2004), it could be termed as the environmental DEA technology. Notice that the above definition corresponds to the constant return to scale technology when undesirable outputs are considered.

A DMU_o (x_o, y_o^g, y_o^b) is efficient in the presence of undesirable outputs if there is no vector $(x, y^g, y^b) \in P$ such that $x_o \ge x$, $y_o^g \le y^g$ and $y_o^b \ge y^b$ with at least one strict inequality. By this definition, we can modify the non-radial and non-oriented SBM model as follows:

SBM-Undesirable

$$\rho^* = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{ro}^g} + \sum_{r=1}^{s_2}\frac{s_r^b}{y_{ro}^b}\right)} \tag{1}$$

Subject to

$$x_o = X\Upsilon + s^- \tag{2}$$

$$y_o^g = Y^g\Upsilon - s^g \tag{3}$$

$$y_o^b = Y^b\Upsilon + s^b \tag{4}$$

$$s^- \ge 0, s^g \ge 0, s^b \ge 0, \Upsilon \ge 0$$

The vector $s^- \in R^m$ and $s^b \in R^{s_2}$ correspond to excess in inputs and bad outputs, respectively, while $s^g \in R^{s_1}$ expresses shortage in good outputs. The objective function (1) is strictly decreasing with respect to $s_i^-(\forall i)$, $s_r^g(\forall r)$ and $s_r^b(\forall r)$ and the objective value satisfies $0 < \rho^* \leq 1$. Let an optimal solution of the above program be $(\Upsilon^*, s^{-*}, s^{g*}, s^{b*})$. Then the DMU_o is efficient in the presence of undesirable outputs in and if $\rho^* = 1$, i.e., $s^{-*} = 0$, $s^{g*} = 0$, and $s^{b*} = 0$ (Cooper et al., 2007).

Note that the set of constraints on undesirable outputs (4) in the model (1) can guarantee that DMU has now been a competent practitioner in pure environmental performance. Therefore, model (1) can be used to evaluate the economic inefficiency of DMU by a slacks-based efficiency measure ρ^* after its pollutants are adjusted to their minimal levels. The slack variables could be used to identify and estimate the causes of economic inefficiency.

If the DMU_o is inefficient, i.e. $\rho^* < 1$, it can be imporved and become efficient by deleting the excesses in inputs and bad outputs, and augmenting the shortfalls in good outputs by the following projection (Cooper et al., 2007):

$$\widehat{x_o} \leftarrow x_o - s^{-*} \quad (5)$$

$$\widehat{y_o^g} \leftarrow y_o^g + s^{g*} \quad (6)$$

$$\widehat{y_o^b} \leftarrow y_o^b - s^{b*} \quad (7)$$

If a DMU has a larger ρ^* than another DMU, then it has a better environmental performance than the other. Obviously, the index derived from the model (1) can provide an objective way for decision makers and environmental analysts to quantify and compare the environmental performance of different firms or entities (Zhou et al., 2007).

We decide to apply the non-radial and non-oriented DEA model (SBM model) with undesirable outputs. Through the model, we can calculate the environmental performance of selected countries in the OECD from 1995 to 2014. In this study, we employed the primary energy consumption (PEC) as input. The only desirable output is a gross domestic product (GDP). As the undesirable outputs (also called pollutants) are considered carbon dioxide (CO2), sulphur oxides (SOx) and nitrogen oxides (NOx) emissions. The number of input (*m*) and output (*s*) variables was set up according to the essential condition of DEA model that the number of variables should be lower than one-third of the analysed production units (*n*), i.e. $(m+s)<n/3$. In our sample of analysed countries (22) it means, that the number of variables should be lower than 7. The reason why we decide to use only five variables is that with the increasing number of input and output variables the efficiency score of analysed production units increase and much more production units are considered efficient.

Tab. 1. Summary statistics for 22 OECD countries in 1995-2014.

	PEC (ton per one labour person)	**GDP (USD per one labour person)**	**NOx (ton per one labour person)**	**SOx (ton per one labour person)**	**CO_2 (ton per one labour person)**
Minimum	2.8528	11013.01	0.01418	0.0004	0.0001
Maximum	19.2262	171012.04	0.11416	0.2113	0.0062
Average	8.0217	71886.57	0.05235	0.0360	0.0016
Standard deviation	3.1759	36221.82	0.01985	0.0364	0.0014

Source: Prepared by authors

As the countries involved in the analysis have different size, we decided to standardise them. As the tool for standardisation, we used the value of labour force in individual countries. We divided all variables involved in the analysis by the value of labour force which eliminates the size differences between the countries. We collected the data on environmental variables from OECD Environmental Data (OECD Statistics, 2017), Statistical Review of World Energy (World Energy, 2017), and the data about the labour force from the World Bank database (World Bank, 2018) Table 1 gives the descriptive statistics of the data involved in the analysis expressed on one labour person in the specified countries.

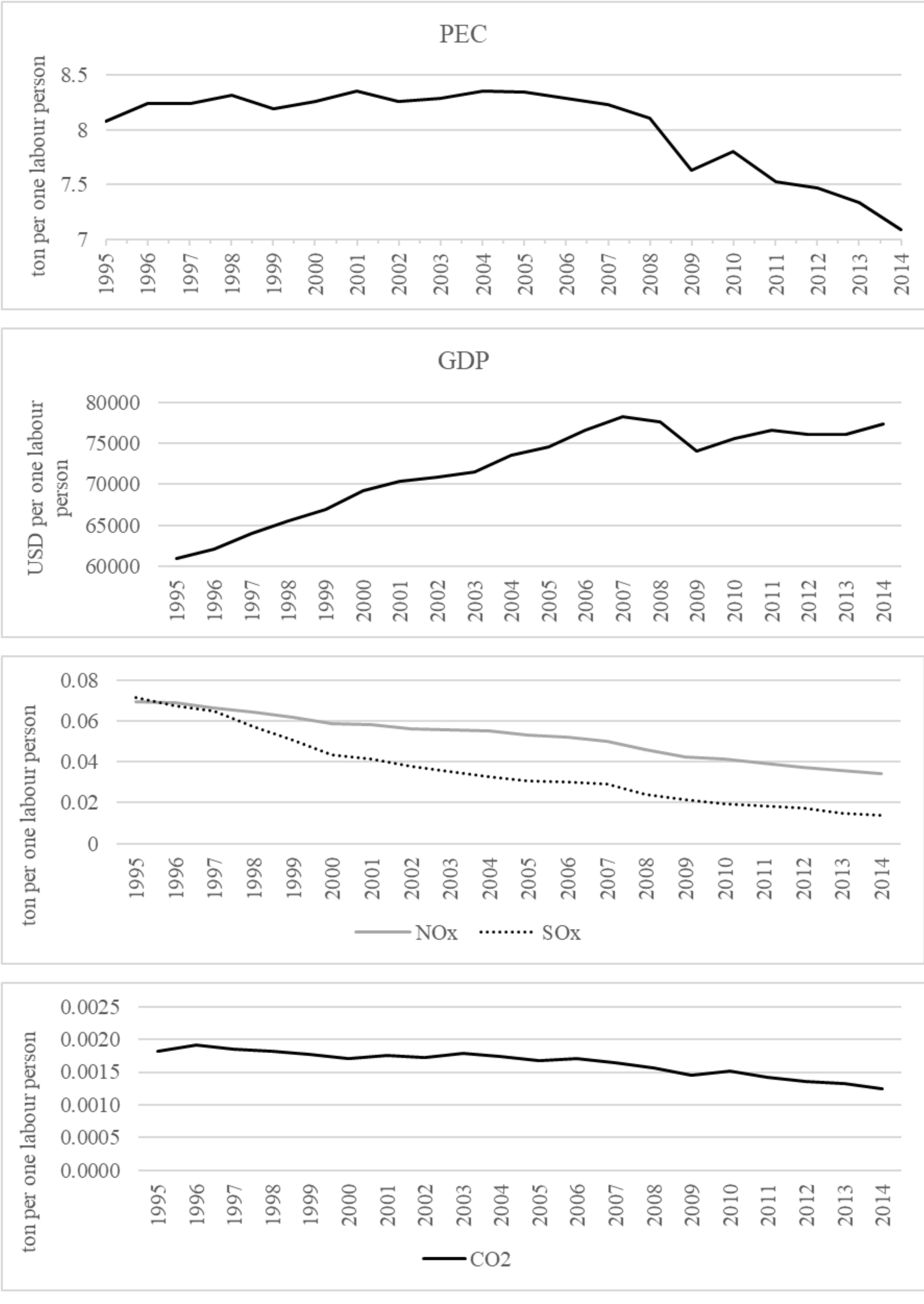

Fig. 1. The development of input and output variables, OECD average. Source: Prepared by authors

Figure 1 displays the development of variables, average values for all countries during the wholly analysed period. As can be seen according to the average values the primary energy consumption significantly decreased since 2005. The decrease can also be seen in the case of the production of undesirable outputs: carbon dioxide (CO_2), sulphur oxides (SOx) and nitrogen oxides (NOx). On the other hand, the gradual increase can be monitored in case of GDP expressed in constant prices of 2010. The gradual increase was shortly interrupted by the financial crisis, which hit all countries around the world after 2007.

Results

The correlation matrix of inputs and outputs was calculated to see if there was a significant relationship between the input and output variables. Table 2 shows the results of the analysis. All the correlation coefficients in the table are below 0.71, which indicate that a significantly high correlation does not exist between input and the output variables. It indicates that DEA analysis could be used as one of the conditions of the DEA model is that the input and output variables should not be highly correlated.

Tab. 2. Correlation matrix of input and output variables.

	PEC (ton per one labour person)	GDP (USD per one labour person)	NOx (ton per one labour person)	SOx (ton per one labour person)	CO_2 (ton per one labour person)
PEC	1				
GDP	0.704279	1			
NOx	0.456997	0.201574	1		
SOx	-0.31383	-0.53904	0.371496	1	
CO2	0.362085	0.265264	0.479356	-0.01957	1

Source: Prepared by authors

On the other hand, the value of correlation coefficient between input and output variables should not be equal or close to zero. The value close to zero indicates that the input has no impact on the output variable, which signalises that the model is not adequately specified. In our sample, the value of correlation coefficient between input (PEC) and output variables (GDP, NOx, SOx, and CO_2) is always higher than 0.31, which indicate that our input variable can influence the development of output variables. This way the underlying conditions have been met, and therefore the DEA model may be used.

Tab. 3. Environmental efficiency for 22 OECD countries in 1995-2014.

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Austria	0.4679	0.4564	0.4794	0.4787	0.4920	0.4888	0.4888	0.4570	0.4464	0.4364
Belgium	0.2932	0.2685	0.2873	0.2796	0.2993	0.3075	0.3075	0.2914	0.2794	0.2783
Czech Republic	0.1497	0.1451	0.1497	0.1515	0.1679	0.1635	0.1635	0.1546	0.1508	0.1502
Denmark	0.5677	0.4656	0.5632	0.5901	0.6415	0.7107	0.7107	0.6662	0.6073	0.6439
Finland	0.2648	0.2504	0.2782	0.2803	0.2998	0.3138	0.3138	0.2922	0.2740	0.2777
France	1	1	1	1	1	1	1	1	1	1
Germany	1	1	1	1	1	1	1	1	1	1
Greece	0.3694	0.3582	0.3776	0.3576	0.3774	0.3770	0.3770	0.3648	0.3646	0.3667
Hungary	0.1655	0.1547	0.1718	0.1748	0.1852	0.2009	0.2009	0.1978	0.2014	0.2042
Ireland	0.4151	0.4077	0.4496	0.4439	0.4735	0.4948	0.4948	0.4962	0.5239	0.5318
Italy	1	1	1	1	1	1	1	1	1	1
Lithuania	0.1017	0.0945	0.1160	0.1135	0.1372	0.1462	0.1462	0.1366	0.1430	0.1449
Netherlands	0.3534	0.3405	0.3797	0.3893	0.4218	0.4258	0.4258	0.3957	0.3901	0.3703
Norway	0.3839	0.4220	0.4385	0.4225	0.4207	0.4525	0.4525	0.4095	0.4538	0.4447
Poland	0.1185	0.1152	0.1300	0.1395	0.1522	0.1724	0.1724	0.1658	0.1647	0.1666
Portugal	0.4080	0.3999	0.4267	0.3974	0.4064	0.4092	0.4092	0.3825	0.3697	0.3671
Slovakia	0.1148	0.1169	0.1317	0.1323	0.1342	0.1314	0.1314	0.1272	0.1372	0.1425
Spain	0.6228	0.6156	0.5925	0.5915	0.5963	0.5742	0.5742	0.5587	0.5683	0.5564
Sweden	0.3154	0.3129	0.3316	0.3256	0.3549	0.3767	0.3767	0.3752	0.3965	0.3693
Switzerland	1	1	1	1	1	1	1	1	1	1
Turkey	0.4786	0.4552	0.4699	0.4733	0.4667	0.4599	0.4599	0.4399	0.4538	0.4710
United Kingdom	0.6111	0.5910	0.6492	0.6644	0.7210	0.7077	0.7077	0.7453	0.7892	0.8161
Average	0.4637	0.4532	0.4737	0.4730	0.4885	0.4960	0.4960	0.4844	0.4870	0.4881

Source: Prepared by authors

The non-radial and non-oriented DEA model (SBM model) with undesirable outputs under the assumption of a constant return to scale is applied to calculate the environmental efficiency of 22 OECD countries from 1995 to 2014. We specified the weight of each undesirable outputs (CO2, SOx, and NOx) as 0.33, which implies that the reduction of these undesirable outputs has the same degree of importance. Table 3 and Table 4 shows the obtained SBM efficiency scores of evaluated countries. It is evident that the environmental performance of OECD countries as a whole has been improved from 1995 to 2014. It should be stated that the higher the value of efficiency, the more efficient the country is. A country is efficient if its efficiency value is 1. If the value is lesser than 1, the country is not efficient and can improve its outputs to be efficient by learning from the efficient countries. The efficient countries that inefficient country references can be determined from a linear programming model.

Tab. 4. Environmental efficiency for 22 OECD countries in 1995-2014.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Austria	0.4070	0.4240	0.4264	0.4352	0.4452	0.4110	0.4148	0.4219	0.4281	0.4161
Belgium	0.2680	0.2747	0.2672	0.2700	0.2931	0.2677	0.2738	0.3010	0.2983	0.3023
Czech Republic	0.1507	0.1584	0.1598	0.1718	0.1769	0.1635	0.1577	0.1662	0.1681	0.1676
Denmark	0.6419	0.5957	0.6020	0.6374	0.6652	0.6118	0.6068	0.7046	0.6844	0.6672
Finland	0.2958	0.2848	0.2849	0.3031	0.3048	0.2713	0.2817	0.3029	0.3075	0.2964
France	1	1	1	1	1	1	1	1	1	1
Germany	1	1	1	1	0.9350	0.9154	0.9131	0.9028	0.8453	0.8405
Greece	0.3431	0.3506	0.3390	0.3550	0.3555	0.3306	0.2849	0.2903	0.2985	0.2982
Hungary	0.1882	0.1988	0.1921	0.1990	0.2072	0.1925	0.1885	0.2094	0.2275	0.2216
Ireland	0.5043	0.5259	0.5099	0.4999	0.5372	0.5221	0.5385	0.5708	0.5990	0.6111
Italy	1	1	1	1	1	1	1	1	1	1
Lithuania	0.1594	0.1791	0.1730	0.1811	0.1708	0.2226	0.2116	0.2296	0.2608	0.2622
Netherlands	0.3471	0.3630	0.3556	0.3783	0.3788	0.3480	0.3414	0.3696	0.3837	0.3835
Norway	0.3706	0.4130	0.3682	0.3684	0.3979	0.3882	0.3516	0.3448	0.3753	0.3434
Poland	0.1574	0.1614	0.1648	0.1717	0.1881	0.1726	0.1674	0.1846	0.1888	0.1889
Portugal	0.3417	0.3537	0.3430	0.3647	0.3584	0.3319	0.3151	0.3472	0.3171	0.2955
Slovakia	0.1343	0.1514	0.1701	0.1759	0.1868	0.1741	0.1726	0.1920	0.1889	0.1966
Spain	0.5561	0.5704	0.5426	0.6037	0.6279	0.6331	0.5940	0.5729	0.6044	0.5695
Sweden	0.3521	0.3957	0.3799	0.3885	0.4095	0.3788	0.3650	0.3828	0.4383	0.3813
Switzerland	1	1	1	1	1	1	1	1	1	1
Turkey	0.4935	0.4549	0.4107	0.4160	0.3815	0.4018	0.4064	0.4120	0.4609	0.4197
United Kingdom	0.8286	0.8357	0.8577	0.8725	0.8809	0.8744	1	0.8923	0.8960	1
Average	0.4791	0.4860	0.4794	0.4906	0.4955	0.4823	0.4811	0.4908	0.4987	0.4937

Source: Prepared by authors

We can see that only three countries were marked as efficient during the wholly analysed period. In the case of France, Italy and Switzerland the relation of inputs, outputs and undesirable outputs within the evaluation set able them to be marked as efficient with environmental efficiency score equal to one. The efficiency score equal to one can also be seen in the case of Germany from 1995 to 2008, but then the environmental efficiency started to decrease. Also, the United Kingdom can be considered environmental effects, but only in 2011 and 2014.

The progress between the first and last analysed year can be seen in case of Belgium (3.09 %), Czech Republic (11.97 %), Denmark (17.52 %), Finland (11.92 %), Hungary (33.89 %), Ireland (47.42 %), Netherland (8.51 %), Poland (59.46 %), Slovakia (71.23 %), Sweden (20.88 %), and United Kingdom (63.64 %), while the highest progress is evident in the case of Lithuania, where the efficiency score increased from 10.17 % in 1995 to 26.22% in 2014 (increase by 157.84 %). The fall is evident in the case of seven countries: Austria (-11.07 %), Germany (-15.95 %), Greece (-19.28 %), Norway (-10.55 %), Spain (-8.55 %), Turkey (-12.30 %), and the biggest fall is evident in case of Portugal, where the efficiency score falls from 40.8 % in 1995 to 29.55 % in 2014 (decrease by 27.57 %).

Besides determining the efficiencies of the countries, our approach can also provide the benchmarks for the inefficiency countries to be efficient. As our model is non-oriented, if the evaluate country intents to achieve efficiency, the country can reduce its inputs and reduce its undesirable outputs while increasing its desirable outputs simultaneously. For ease of illustration, we take only the year 2014 as an example. The countries expected inputs and outputs and corresponding incensement or decrements (in percentage form) of the current inputs and outputs are shown in Table 5.

These benchmarks provide the targets for OECD countries´ local governments to balance the development of economic growth and environmental protection. For example, in Slovakia intends to be efficient within the analysed group of countries, it should reduce its the primary energy consumption to the value 1.62996 ton per one labour person (reduction by 71.44 %) and reduce its considered carbon dioxide (CO_2) emissions by 86.72 %, sulphur oxides (SOx) emission by 97.33 % and nitrogen oxides (NOx) emissions by 87.62 %.

We must take in interpreting the results of this paper some limitations of DEA models. Thus far we have employed a technique in capturing environmental performance in selected OECD countries using the SBM methodology. We should be aware that the results of DEA techniques show relative efficiency depending on the collected sample. This fact results from the fact that all efficiency estimations of decision-making units are affected by how we sample the DMUs since the efficient frontier line is drawn from the given sample. Therefore, including other countries into the sample would have brought different results. The panel data over the years for multiple countries can also show intertemporal changes in efficiency and technology development separately using Malmquist index, which should be part of our future research.

Tab. 5. Benchmark of the 22 OECD countries to be efficient in 2014.

	PEC (ton per one labour person)		**GDP (USD per one labour person)**		**NOx (ton per one labour person)**		**SOx (ton per one labour person)**		**CO_2 (ton per one labour person)**	
	Projection	**Change [%]**	**Projection**	**Change [%]**	**Projection**	**Change [%]**	**Projection**	**Change [%]**	**Projection**	**Change [%]**
Austria	4.22604	-44.94%	92880.81	0.00%	0.00998	-70.92%	0.00115	-65.37%	0.00068	-57.59%
Belgium	4.57400	-59.17%	100528.31	0.00%	0.01080	-72.40%	0.00125	-85.20%	0.00074	-52.77%
Czech Republic	1.83038	-75.77%	40228.46	0.00%	0.00432	-86.40%	0.00050	-97.90%	0.00030	-83.07%
Denmark	5.25016	-12.06%	115389.07	0.00%	0.01240	-68.47%	0.00143	-62.87%	0.00085	-59.57%
Finland	4.18117	-57.90%	91894.60	0.00%	0.00988	-81.13%	0.00114	-92.91%	0.00068	-78.12%
France	7.86094	0.00%	90938.58	0.00%	0.02866	0.00%	0.00531	0.00%	0.00014	0.00%
Germany	6.59842	-10.23%	85875.14	0.00%	0.02872	0.00%	0.00497	-40.81%	0.00021	0.00%
Greece	2.27006	-57.43%	49891.70	0.00%	0.00536	-89.14%	0.00062	-97.52%	0.00037	-69.88%
Hungary	1.40055	-68.38%	30781.48	0.00%	0.00331	-87.52%	0.00038	-93.63%	0.00023	-75.02%
Ireland	5.25060	-16.19%	115398.73	0.00%	0.01240	-64.32%	0.00143	-83.82%	0.00085	-74.65%
Italy	5.77855	0.00%	80398.91	0.00%	0.03111	0.00%	0.00516	0.00%	0.00021	0.00%
Lithuania	1.34516	-61.59%	29564.14	0.00%	0.00318	-91.16%	0.00037	-96.77%	0.00022	-91.06%
Netherlands	4.32043	-52.09%	94955.30	0.00%	0.01020	-57.29%	0.00118	-63.43%	0.00070	-28.85%
Norway	7.66107	-55.03%	168376.34	0.00%	0.01810	-69.00%	0.00209	-65.58%	0.00124	-51.13%
Poland	1.32502	-73.64%	29121.59	0.00%	0.00313	-92.04%	0.00036	-99.17%	0.00021	-46.07%
Portugal	1.94407	-58.63%	42727.23	0.00%	0.00459	-85.81%	0.00053	-94.22%	0.00031	-59.84%
Slovakia	1.62996	-71.44%	35823.65	0.00%	0.00385	-87.62%	0.00044	-97.33%	0.00026	-86.72%
Spain	3.91178	-31.50%	59237.88	0.00%	0.01926	-49.66%	0.00312	-71.96%	0.00022	0.00%
Sweden	4.61601	-53.87%	101023.42	0.00%	0.01106	-57.82%	0.00129	-68.07%	0.00074	0.00%
Switzerland	6.00229	0.00%	131919.41	0.00%	0.01418	0.00%	0.00164	0.00%	0.00097	0.00%
Turkey	2.27265	-46.91%	35815.46	0.00%	0.01014	-62.94%	0.00300	-96.00%	0.00014	0.00%
United Kingdom	5.69015	0.00%	79750.98	0.00%	0.02873	0.00%	0.00920	0.00%	0.00019	0.00%

Source: Prepared by authors

Conclusion

The literature on production frontiers is further extended and modified to measure environmental performance in addition to capturing efficiency at the decision-making unit level. The primary methodology to analyse environmental efficiency is a non-radial Data Envelopment Analysis (DEA) that fulfils the fundamental role of modelling undesirable outputs in environmental performance measurement. DEA can easily handle different situations depending on the user targets. Discussion of some proposed methods indicates that they have certain shortcomings when the materials balance condition is applicable. The existence of particular regulatory constraints established by the authority poses new questions on the reasonable limits between which the constraint must be set. Since there are no globally agreed-upon targets for CO_2 reductions, institutional aspects of the industry should be integrated into any attempts to apply our findings in an actual policy setting. Climate change is among the direct environmental challenges. Still, too little progress has been made to mitigate its effects. However, dramatic progress is possible when measurement and management practices align. When dealing with undesirable output production, it is important to note whether all type of gas generation should be compared to efficient production processes or compared to environmentally inefficient processes. A surveillance system is required which would increase the cost of regulation at the aggregate level. Another requirement is the management of environmental and economic performance through the development and implementation of appropriate environment-related accounting systems and practices. The question that remains open is how it is possible to quantify efficiency scores that reflect the ability of firms to produce desired output with the lowest undesirable production and how standards definitions can be explicitly introduced into this analytical framework. The results of the analysis provided in previous sections show that the correlation does not exist between input and the output variables. As the correlation coefficient between input (PEC) and output variables (GDP, NOx, SOx, and CO_2) was always higher than 0.31, an input variable can influence the development of output variables and so, it indicates that DEA analysis could be used. In general, there are substantial economic gaps between the European countries. While wealthy highly developed countries as France, Switzerland or Germany produce the highest levels of climate emissions but still invest in the green innovation, the Eastern part of Europe seems to be behind them. The analysis provided in this research admits that there also exist the differences between the European countries even in the environmental field. Countries of varying economic development have divergent climate emissions trajectories.

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