APPLICATION OF DATA ENVELOPMENT ANALYSIS FOR CALCULATION OF TECHNICAL, ECO AND SOCIAL WELFARE EFFICIENCY IN NATIONAL EUROPEAN ECONOMIES

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Abstract

In recent history there have been develop new approaches for measuring the economic performance of the firms and national economies. The new concepts take into account simultaneously economic as well as social and environmental goals. One of the concept is using extended Data Envelopment Analysis models. They measure the so-called eco-efficiency and social indicators to take into account social performance. So far, these models used just basic variables (overall emissions). To get analysis that is more detailed we extended the number of variables. As the older analysis have been done for European countries, we also perform the analysis of 31 European countries in the year 2015 to be able more compare the results.

Keywords

Data Envelopment Analysis, Technical Efficiency, Eco-Efficiency, Social Welfare Efficiency

I. Introduction

Nowadays, the economic activity of countries is not measured solely on the basis of GDP. Current trends look a lot at the environmental aspects of the product. The new concept of ecological efficiency (eco-efficiency) is currently a big issue. This concept was introduced by Schaltegger and Sturm (1989) and defined as ratio between environmental impact added and value added. It is used as a common denominator incorporating different outcomes of economic activities (production of undesirable goods jointly with desirable goods) aims at achieving more goods and services with fewer resources as well as less waste and emissions. The fact that even the European Union and the OECD see the eco-efficiency as one of the major strategic elements in its work on sustainability and competitiveness shows that it is important to pay attention of this issue.

There are many ways how to measure efficiency. The problem of eco-efficiency is that variables, which are needed for the analysis, are very specific. More precisely, some of the variables are so called undesirable or they are not in monetary units. Therefore there is need to use models, which are taking this into account. For example, waste or emissions are often used and they are define as undesirable outputs in un-monetary units and therefore do not allow to be aggregated by one monetary value. These difficulties can be overcome by using Data envelopment analysis (DEA). DEA model are using a non-parametric production-frontier methodology with multiple input and output variables. There is many types of DEA models. Models made by Korhonen and Luptáčik (2004) and Labáj et al. (2013) were specially made for eco-efficiency. These models are also used in this analysis. The aim of this article is the extension of their models with the use of new special output undesirable outputs – different types of emission. This should help to get closer analysis of "eco-situation" in European countries.

The paper is organized as follows. Approaches of productivity analysis and specific DEA models are presented in Chapter 2. Chapter 3 describes a structure of the problem and corresponding data

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sets. The results and the close analysis are in the Chapter 4. The final conclusion summarizes the main contributions of this paper and some proposals for a further research are provided in the last Chapter 5.

II. Methodology

Approaches of productivity analysis

There are two main approaches to productivity analysis in the literature. The first one is a neoclassical approach. This approach is connected to Solow´s seminal paper (1957) and work by Griliches (1995) for example. The neoclassical approach is based on standard neoclassical production function. Through growth accounting methodology decomposes the output growth into the contribution of growth in inputs and the contribution of residual that is referred as productivity growth. The assumption of this approach is needed specific production function. The disadvantage of the approache is that neoclassical growth accounting does not distinguish between efficiency change and technical change. In addition, it is not able to model multiple input/output production processes.

The second approach is a frontier approach. The frontier approach may be further divided into Stochastic Frontier Approach (SFA) and Data Envelopment Analysis (DEA). SFA is econometric technique and it is restricted to single output production. It attempts to distinguish the effects of noise from those of inefficiency, thereby providing the basis for statistical inference. DEA is non-parametric technique based on mathematical programming. Advantage of the mathematical programming is a suitability for a multiple input/output production system analysis. DEA also does not need price information and equilibrium assumption to equate price and marginal product. The weights required for aggregation of inputs and outputs are obtained as an integral part of the optimization process.

Both approaches are wildly used. They track changes in the output-input ratio; the analytical implications are quite distinct. The neoclassical approach imputes productivity growth to factors of production, but cannot distinguish a movement towards the production possibilities frontier and a movement of the frontier. The frontier approach allows decomposing productivity growth into a movement of the economy towards the efficiency frontier and a shift of the frontier. Productivity change is equal to efficiency change plus technical change. The frontier approach, however, is not capable of imputing value to factor inputs.

Another advantage of DEA is that efficiency may be measured by inputs and outputs in different units (no need to have all the variables expressed in monetary units). So environmental and social aspects may extend the analysis. For example, this is seen in work by Lábaj et al. (2013). Their work was used as inspiration – the new concept and measurement of welfare beyond GDP and evaluate different development scenarios. Based on this new concept and measurement other variables are edited and closer analysis is done.

DEA models for eco-efficiency (undesirable outputs)

As it was mentioned, this article deals with the new concept of eco-efficiency considers inputs, desirable outputs and undesirable outputs in one model and takes economic as well as ecological aspects simultaneously into account. The main problem in developing of the eco-efficiency indicators is the lack of monetary evaluations like market prices for the undesirable outputs (the waste and emissions). As already mentioned DEA is able to use the data in different units and therefore can provide an appropriate methodology for measuring of the eco-efficiency. There is a lot of literature on the topic of DEA models when some outputs are undesirable (for example – Färe et al (1989)). There are also many approaches – for example translation transformation based on work by Koopmans (1952), transformation of multiplicative inverse used by Lovell et al. (1995) and basic method – change the meaning of the variable used by Liu and Sharp (1999).

Korhonen and Luptáčik (2004) proposed different variants of DEA models for the evaluation of eco-efficiency in a single period. More precisely, they made three models – first model has used negative weights for unwanted outputs, the second model has taken the unwanted outputs as inputs and in the last model, the negative weights are used for the inputs. They show that the set of (strong) efficient decision-making units (DMUs) is the same for all models. However, the different variants provide a deeper insight into the underlying sources of eco-efficiency differential across DMUs and therefore show different ways of increasing eco-efficiency. Later, in the work by Lábaj et al. (2013) the work is extended for social aspects as well.

In this article, we follow the models in Korhonen and Luptáčik (2004), Lábaj et al. (2013) and extend with new variables.

The relative technical efficiency of the DMU unit is define as the ratio of its total weighted output to its total weighted input. Mathematically, it can be define as:

$$e_h = \frac{\sum_{j=1}^{S} v_j y_{jh}}{\sum_{i=1}^{R} u_i x_{ih}}, h = 1, \dots, T, \tag{1}$$

where we suppose, a set of T DMUs ($\mathrm{DMU_h}$ for $h = 1, \dots, T$), let input and output variables data be $X = \{x_{ih}, i = 1, \dots, R; h = 1, \dots, T\}$ and $Y = \{y_{jh}, j = 1, \dots, S; h = 1, \dots, T\}$, respectively. Also, u_i for $i = 1, \dots, R$ and v_j for $j = 1, \dots, S$ be the weights of the i-th input variable and the j-th output variable, respectively.

Charnes et al. (1978) have proposed the first CCR model to measure the efficiency score of the under evaluation unit, $\mathrm{DMU_Q}$ where $Q \in \{1, \dots, T\}$. The mathematical model is following:

$$\begin{aligned} \max e_Q &= \frac{\sum_{j=1}^{S} v_j y_{jQ}}{\sum_{i=1}^{R} u_i x_{iQ}} \\ s.t. \quad & \frac{\sum_{j=1}^{S} v_j y_{jh}}{\sum_{i=1}^{R} u_i x_{ih}} \leq 1, \quad h = 1, \dots, T \\ & u_i, v_j \geq \varepsilon, i = 1, \dots, R; \; j = 1, \dots, S \\ & \varepsilon > 0 \end{aligned} \tag{2}$$

However, it is non-linear model; more precisely, it is the model of linear-fractional programming. On the other hand, the model can be transferred by Charnes-Cooper transformation to the standard linear programming problem:

$$\begin{aligned} \max \quad & e_Q = \sum_{j=1}^{S} v_j y_{jQ} \\ s.t. \quad & \sum_{i=1}^{R} u_i x_{iQ} = 1 \\ & \sum_{j=1}^{S} v_j y_{jh} - \sum_{i=1}^{R} u_i x_{ih} \leq 0, h = 1, \dots, T \\ & u_i, v_j \geq \varepsilon, i = 1, \dots, R; \; j = 1, \dots, S \\ & \varepsilon > 0 \end{aligned} \tag{3}$$

where $Q \in \{1, \dots, T\}$. $\mathrm{DMU_Q}$ is CCR-efficient if and only if $e^* = 1$ and if there exists at least one optimal solution (u^*, v^*) with $u^* > 0$ and $v^* > 0$ for the set $Q \in \{1, \dots, T\}$. The inefficient units have a degree of relative efficiency that belongs to interval $[0,1)$. Note: The model must be solved for each DMU separately.

The model (2) is called a multiplier form of input-orient CCR model. However, for computing and data interpretation, it is preferable to work with model that is dual associated to model (2). The model is referred as envelopment form of input-oriented CCR model; see Charnes et al. (1978).

There also exists the multiplier form of output-oriented CCR model. The output-oriented CCR model gives the same results as the input-oriented CCR model. It can also be seen in Charnes et al. (1978).

The models introduced so far are classic DEA models. It means that input and output variables are considered as desirable. As we are going to work with some undesirable outputs, we should define them for DMUs. Let desirable outputs are $Y^g = \{y_{jh}, j = 1, \dots, S; h = 1, \dots, T\}$ with the weights of the j-th output variable v_j for $j = 1, \dots, S$. Then lets undesirable outputs are $Y^b = \{y_{lh}, l = S + 1, \dots, M; h = 1, \dots, T\}$ with the weights of the l-th output variable v_l for $l = S + 1, \dots, M$.

Korhonen and Luptáčik (2004) in their work proposed that, the evaluation of eco-efficiency could be addressed by decomposing the problem in two parts – **Model A** (2) and **Model B** (4). First model have to measure technical efficiency in a standard way described by the fractional program (2). Second model have to measure ecological efficiency. This model is taking into account the ratio of a weighted sum of desirable outputs to a weighted sum of undesirable outputs. The mathematical model is following:

$$\begin{aligned} \max e_Q &= \frac{\sum_{j=1}^{S} v_j y_{jQ}}{\sum_{l=S+1}^{M} v_l y_{lQ}} \\ s.t.\ & \frac{\sum_{j=1}^{S} v_j y_{jh}}{\sum_{l=S+1}^{M} v_l y_{lh}} \leq 1, \quad h = 1, \dots, T \\ & v_j, v_l \geq \varepsilon, j = 1, \dots, S;\ l = S + 1, \dots, M \\ & \varepsilon > 0 \end{aligned} \tag{4}$$

The model (4) can also be linearized subsequently:

$$\begin{aligned} \max \quad & e_Q = \sum_{j=1}^{S} v_j y_{jQ} \\ s.t.\ & \sum_{l=S+1}^{M} v_l y_{lQ} = 1 \\ & \sum_{j=1}^{S} v_j y_{jh} - \sum_{l=S+1}^{M} v_l y_{lh} \leq 0, h = 1, \dots, T \\ & v_j, v_l \geq \varepsilon, j = 1, \dots, S;\ l = S + 1, \dots, M \\ & \varepsilon > 0 \end{aligned} \tag{5}$$

Indicators from both models are then used in the DEA output-oriented model as the outputs with inputs equaling 1. In this way, the indicator for eco-efficiency is provided.

As it was mentioned, there are different models, which can be used to treat the undesirable and desirable output variables simultaneously. According to work by Lábaj et al. (2013), the following two alternatives are represented.

The first model is denoted as **Model C** (6). It is model with negative sign for undesirable output variable. In this model, the DMUs control the inputs. In order to increase the eco-efficiency, the DMUs will reduce proportionally the inputs. The mathematical model is following (note: we do present just the linearized model):

$$\begin{aligned} \max \quad & e_Q = \sum_{j=1}^{S} v_j y_{jQ} - \sum_{l=S+1}^{M} v_l y_{lQ} \\ s.t.\ & \sum_{i=1}^{R} u_i x_{iQ} = 1 \\ & \sum_{j=1}^{S} v_j y_{jh} - \sum_{l=S+1}^{M} v_l y_{lh} - \sum_{i=1}^{R} u_i x_{ih} = 1 \leq 0, h = 1, \dots, T \\ & u_i, v_j, v_l \geq \varepsilon, i = 1, \dots., R, j = 1, \dots, S;\ l = S + 1, \dots, M \end{aligned} \tag{6}$$

$$\varepsilon > 0$$

The second model is denoted as **Model D** (7). In this model are undesirable output variables treated as input variables. The mathematical model is following (note: we do present just the linearized model):

$$\begin{aligned} \max \quad & e_Q = \textstyle\sum_{j=1}^{S} v_j y_{jQ} \\ s.t. \quad & \textstyle\sum_{l=S+1}^{M} v_l y_{lQ} + \sum_{i=1}^{R} u_i x_{iQ} = 1 \\ & \textstyle\sum_{j=1}^{S} v_j y_{jh} - \sum_{l=S+1}^{M} v_l y_{lh} - \sum_{i=1}^{R} u_i x_{ih} = 1 \leq 0, h = 1, \dots, T \\ & u_i, v_j, v_l \geq \varepsilon, i = 1, \dots., R, j = 1, \dots, S;\ l = S+1, \dots, M \\ & \varepsilon > 0 \end{aligned} \tag{7}$$

In this model, attempt to increase eco-efficiency requires simultaneous reduction of both input variables and undesirable output variables. Note: The eco-efficiency indicator obtained by Model C cannot be greater than efficiency score from Model D. For more detail, see Korhonen and Luptáčik (2004).

So far, models for input orientation had been introduced. On closer examination, and previews to work by Korhonen and Luptáčik (2004) and Lábaj et al. (2013) it is seen that output oriented models are better. This can be justified, for example, by the fact that to reach efficiency frontier we must control output variables (as the goals of economic policy). Input variables like capital stock cannot be easily changed within a short time period, so the output orientation seems to be reasonable. The question about the assumption of constant returns to scale is also important. Analyzed DMUs seems to have large variability. The variable returns to scale (VRS) seems to be more reasonable as well. In work by Banker et al. (1984) was introduced this type of model for measuring pure technical efficiency with VRS-BCC model. Overall, in our analysis, we apply BCC output oriented model while adopting the approach to treating undesirable outputs of models C and D as well. This is same as previous work by Korhonen and Luptáčik (2004) and Lábaj et al. (2013). To be more clear, we introduce Model C and Model D with VRS assumption and we denote them **Model C-O** (8) and **Model D-O** (9), respectively. The mathematical model of Model C-O is following (note: we do present just the linearized model):

$$\begin{aligned} \min \quad & e_Q = \textstyle\sum_{i=1}^{R} u_i x_{iQ} + \mu \\ s.t. \quad & \textstyle\sum_{j=1}^{S} v_j y_{jQ} - \sum_{l=S+1}^{M} v_l y_{lQ} = 1 \\ & \textstyle\sum_{i=1}^{R} u_i x_{ih} - \sum_{j=1}^{S} v_j y_{jh} + \sum_{l=S+1}^{M} v_l y_{lh} + \mu \geq 0, h = 1, \dots, T \\ & u_i, v_j, v_l \geq \varepsilon, i = 1, \dots., R, j = 1, \dots, S;\ l = S+1, \dots, M \\ & \varepsilon > 0 \\ & \mu \in (-\infty, \infty) \end{aligned} \tag{8}$$

The mathematical model of Model D-O is following (note: we do present just the linearized model):

$$\begin{aligned} \min \quad & e_Q = \\ & \textstyle\sum_{l=S+1}^{M} v_l y_{lQ} + \sum_{i=1}^{R} u_i x_{iQ} + \mu \\ s.t. \quad & \textstyle\sum_{j=1}^{S} v_j y_{jQ} = 1 \\ & \textstyle\sum_{l=S+1}^{M} v_l y_{lh} + \sum_{i=1}^{R} u_i x_{ih} - \sum_{j=1}^{S} v_j y_{jh} + \mu \geq 0, h = 1, \dots, T \\ & u_i, v_j, v_l \geq \varepsilon, i = 1, \dots., R, j = 1, \dots, S;\ l = S+1, \dots, M \\ & \varepsilon > 0 \end{aligned} \tag{9}$$

$$\mu \in (-\infty, \infty)$$

As in Lábaj et al. (2013), we are creating several models to provide new indicators to measure the economic performance of national economies in terms of welfare beyond GDP. We are expanding the DEA models to introduce new variables, specifically focusing on variable denoted as emissions – different types of emissions. An overview of all models and variables is given in Table 1.

Table 1 Overview of employed models

Model	Specification	Description	Inputs	Outputs
1.	Model A(O)	Technical efficiency	capital, labor	GDP
2.	Model A(O)	Eco-efficiency	capital, labor	GDP, emissions
2.1.		Eco-efficiency – agricultural	capital, labor	GDP, emissions in agricultural (-)
2.2.		Eco-efficiency – livestock	capital, labor	GDP, emissions in livestock (-)
2.3.		Eco-efficiency – enteric fermentation	capital, labor	GDP, emissions in fermentation (-)
2.4.		Eco-efficiency – manure management	capital, labor	GDP, emissions in management (-)
2.5.		Eco-efficiency – managed agricultural soils – direct N2O emissions	capital, labor	GDP, emissions N2O(-)
3.	Model C(O)	Income inequality-adjusted efficiency	capital, labor	GDP, 1-Gini
4.	Model D(O)	Social welfare efficiency	capital, labor, emissions	GDP, 1-Gini
4.1.		Social welfare efficiency – agricultural	capital, labor, emissions in agricultural	GDP, 1-Gini
4.2.		Social welfare efficiency – livestock	capital, labor, emissions in livestock	GDP, 1-Gini
4.3.		Social welfare efficiency – enteric fermentation	capital, labor, emissions in fermentation	GDP, 1-Gini
4.4.		Social welfare efficiency – manure management	capital, labor, emissions in management	GDP, 1-Gini
4.5.		Social welfare efficiency – managed agricultural soils – direct N20 emissions	capital, labor, emissions N2O	GDP, 1-Gini
5.	Model B(O)	Ecological efficiency	emissions	GDP
5.1.		Ecological efficiency – agricultural	emissions in agricultural	GDP
5.2.		Ecological efficiency – livestock	emissions in livestock	GDP
5.3.		Ecological efficiency – enteric fermentation	emissions in fermentation	GDP
5.4.		Ecological efficiency – manure management	emissions in management	GDP
5.5.		Ecological efficiency – managed agricultural soils – direct N20 emissions	emissions N2O	GDP

Source: authors (2017)

Model 1 is standard output oriented DEA model measuring the pure technical efficiency by taking capital and labour as input variables and GDP as output variable. Model 2 is extended Model 1. There are two output variables, besides GDP there is also output variable – emissions. We treated emissions in this model as additional output taking with negative sign (see Model C). This is same for the rest of the models with different types of emissions. Model 3 is also an extension of Model 1 by adding of the Gini index as the income inequality indicator. Using the Gini index as an output variable we transformed (as Lábaj et al. (2013)) it by subtracting from one (denoted further as Gini1). The higher value of Gini1 (in other words lower Gini index) means better performance with respect to social welfare. Model 4 is an extension of Model 3. We included in this model again emissions. In this case, emissions are treated as input. Model 3 and Model 4 are based on Model D. The other approach was carried out by computing ecological scores using Model A and Model B. In Model 5, we computed ecological efficiency as described by (4). These all models have been done based on work by Lábaj et al. (2013). The improvement of these models is use of different types of emissions.

III. Data

Lábaj et al. (2013) analysed economic growth and social welfare in and in their work, they measured the performance of 30 European countries (EU-27 countries plus Iceland, Norway and Switzerland) for year 2010. We have used 31 European countries (EU-28 countries plus Iceland, Norway and Switzerland) for the year 2015. We extended the matrix of variables – different types of emissions.

The most important question for all DEA models is to choose the proper input and output variables. As it was mentioned, we are inspired by work Lábaj et al. (2013) so the basic used variables are same. The input variables are capital stock in PPS and labor in thousands of persons employed. It is because these variables are employed by national economies (DMUs) to produce GDP. We took GDP data at current prices (million purchasing power standards). GDP is used as desirable output variables for all DMUs as well as Gini index. Gini index represents income inequality (negative impact for the social welfare). Emissions are greenhouse gases (CO2, N2O in CO2 equivalent, CH4 in CO2 equivalent, HFC in CO2 equivalent, PFC in CO2 equivalent, SF6 in CO2 equivalent, NF3 in CO2 equivalent) from all sectors and indirect CO2 (excluding LULUCF and memo items, including international aviation). They are used as undesirable output variable. Emissions are in thousands of tones. We also detect more types of emissions – emissions produced by agriculture, livestock, enteric fermentation, manure management and managed agricultural soils – direct N2O emissions.

All data are taken from EUROSTAT. Table 2 gives general information about input and output variables.

Table 2 Descriptive statistics of input and output variables

	max	min	average	St.dev.
Labor	42979,0	183,7	7638,0	10555,5
Emissions	926479,0	2578,9	147276,2	208830,4
Emissions in agriculture	78372,9	65,9	14451,2	19163,7
Emissions in livestock	42658,0	45,6	8567,8	10938,7
Emissions in enteric fermentation	34580,2	30,9	6393,0	8390,3
Emissions in manure management	10243,3	14,7	2174,7	2856,4
Emissions in managed agricultural soils - direct N2O emissions	27318,5	15,1	4385,4	6139,0
GDP	2927262,9	11556,0	496007,2	721249,4
Gini index	37,9	23,6	29,9	4,3
Capital	7989,2	15,8	1348,8	2081,5

Source: authors (2017)

IV. Empirical analysis

Table 3 gives results for technical, eco- and social efficiency of all 31 European countries for the year 2015. Eleven countries are technical efficient (Model 1 – M 1) in year 2015 (France, Germany, Iceland, Ireland, Latvia, Luxembourg, Malta, Poland, Romania, Slovakia and United Kingdom).

Among these efficient countries are many countries with a very strong economy (for example – Italy, Lithuania, Hungary, Switzerland, Netherlands and Belgium). The lowest efficiency scores are achieved in Cyprus, Finland and Greece. Technical efficiency score means that if the score is equal 0,811 (Austria) then under the given labor and capital inputs, Austria should increase GDP by 19 % if this country would like to become efficient. Average efficiency for Model 1 is 0,881 and twelve countries are below this average (for example Slovenia, Norway, Czech Republic and so on).

General eco-efficiency is seen in Model 2 (M 2) and specific eco-efficiencies are in Model 2.1-2.5 (M 2.1-2.5). Models 2 are including the emissions, as output variable and the rest of variables are same as in Model 1. This mean that the efficiency score of Model 2 (M 2) has to be same or higher than for Model 1 (M 1). There are seven countries than improved their score – Denmark, Hungary, Norway, Portugal, Spain, Sweden and Switzerland. It is due to their strength in environmental performance. For example, Switzerland had technical efficiency equal to 0,921 by Model 1. By Model 2, Switzerland become eco-efficient. The rest of the countries that did not change the efficiency score indicate relative weakness in the environmental performance. If we compare our result with results of work by work Lábaj et al. (2013) for year 2010. We can see some similarities, for example, that Switzerland is eco-efficient but it is not technically efficient country. Average efficiency for Model 2 is 0,891 and again twelve countries are below this average (same as in case of Model 1).

If we compare results of all Models 2 we can see that generally models with specific type of emissions are more eco-efficient then generally. This means that the rest of emissions, which we did not cover, are costing problems with eco-efficiency. For example, if eco-efficiency score of Austria is 0,811 and eco-efficiency score for emissions from agricultural is 0,895 then we can see that agricultural does not does not cause such a weakness in eco-efficiency and the problem is in another department. Just Denmark, Hungary and Spain seem to show that special types of emissions cause the low eco-efficiency.

Model 3 (M 3) includes also social aspects of economic development. Again, it means that Model 3 is extension of Model 1 so the efficiency score of Model 3 should by same or higher. If we look at the results, we can see that ten countries has higher efficiency score for Model 3, the rest of countries has the same efficiency score. There are thirteen countries efficient. Average efficiency for Model 3 is 0,908 and twelve are below this average, but in this case, Norway (it become efficient) and the Czech Republic are not below the average as before and new “problematic” countries are Bulgaria and Spain.

Table 3 Efficiency scores (technical, eco-efficiency and social efficiency) of European countries for the year 2015

		Technical efficiency	Eco-efficiency						Income inequality-adjusted efficiency
		M 1	M 2	M 2.1	M 2.2	M 2.3	M 2.4	M 2.5	M 3
1	Austria	0,811	0,811	0,895	0,893	0,885	0,915	0,893	0,859
2	Belgium	0,917	0,917	1,000	1,000	1,000	0,935	1,000	1,000
3	Bulgaria	0,897	0,897	0,900	0,983	0,996	0,913	0,897	0,897
4	Croatia	0,769	0,769	0,771	0,770	0,771	0,769	0,772	0,769
5	Cyprus	0,666	0,666	0,667	0,666	0,668	0,666	1,000	0,666
6	Czech Republic	0,813	0,813	0,907	0,910	0,934	0,813	0,916	0,925
7	Denmark	0,718	0,758	0,785	0,799	0,839	0,718	0,761	0,796
8	Estonia	0,719	0,719	0,720	0,719	0,719	0,719	0,759	0,719
9	Finland	0,639	0,639	0,754	0,796	0,794	0,752	0,674	0,808

10	France	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
11	Germany	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
12	Greece	0,588	0,588	0,639	0,650	0,645	0,627	0,637	0,588
13	Hungary	0,926	1,000	0,926	0,934	1,000	0,926	0,926	0,926
14	Iceland	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
15	Ireland	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
16	Italy	0,971	0,971	1,000	1,000	1,000	1,000	1,000	0,971
17	Latvia	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
18	Lithuania	0,964	0,964	0,964	0,964	0,964	0,964	0,964	0,964
19	Luxembourg	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
20	Malta	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
21	Netherlands	0,918	0,918	0,946	0,937	0,955	0,918	0,950	0,959
22	Norway	0,827	0,844	0,998	1,000	1,000	1,000	0,969	1,000
23	Poland	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
24	Portugal	0,702	0,742	0,818	0,807	0,799	0,810	0,844	0,702
25	Romania	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
26	Slovakia	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
27	Slovenia	0,842	0,842	0,847	0,845	0,846	0,842	1,000	0,892
28	Spain	0,887	0,898	0,895	0,887	0,901	0,887	0,902	0,887
29	Sweden	0,806	0,861	0,867	1,000	0,885	1,000	0,850	0,885
30	Switzerland	0,921	1,000	1,000	1,000	1,000	1,000	1,000	0,923
31	United Kingdom	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000

Source: authors (2017)

Table 4 shows results for Models 4 – Model 4 with general emissions and Models 4.1-4.5 with specific emissions. Models 4 are the most complex ones. They takes into account economic, environmental and social indicators simultaneously. There are efficient from 15 to 17 countries. If we compare general Model 4 with Model 1, there are five more countries efficient. This is caused by more useful variables in the analysis. Austria is very nice example of increasing efficient score if we look at this country from more point of views. Technical efficiency is equal to 0,811, eco-efficiency is same, but if look at economic and social indicators simultaneously the score is getting higher (0,859) and highest is if we look at economic, environmental and social indicators simultaneously – efficiency score is 0,871.

Average efficiency for Model 4 is 0,930 and just eleven countries are below the average. Again the Czech Republic is below the average, together with Bulgaria and Spain. Slovenia in this case is under the average same as Norway and Sweden which actually become efficient.

If we compare all Models 4 together, we can see that the number of efficient countries is similar (from 15 to 17). There are always same countries efficient just Hungary is efficient in case of Models 4 and 4.3. Also Sweden is not efficient in all models, more precisely in case of Model 4.2 and 4.5. This means that these two countries are dealing with emissions very well, but in some special cases they should improve. For example, Sweden should look at emissions in case of agricultural.

Table 4 Efficiency scores (social eco-efficiency) of European countries for the year 2015

		M 4	M 4.1	M 4.2	M 4.3	M 4.4	M 4.5
1	Austria	0,871	0,905	0,902	0,897	0,923	0,903

2	Belgium	1,000	1,000	1,000	1,000	1,000	1,000
3	Bulgaria	0,897	0,922	0,985	0,996	0,930	0,897
4	Croatia	0,867	0,772	0,771	0,772	0,769	0,815
5	Cyprus	0,666	0,672	0,668	0,673	0,666	1,000
6	Czech Republic	0,925	0,926	0,925	0,941	0,925	0,931
7	Denmark	0,882	0,822	0,831	0,854	0,796	0,806
8	Estonia	0,719	0,727	0,725	0,725	0,724	0,787
9	Finland	0,808	0,816	0,844	0,846	0,808	0,808
10	France	1,000	1,000	1,000	1,000	1,000	1,000
11	Germany	1,000	1,000	1,000	1,000	1,000	1,000
12	Greece	0,589	0,676	0,684	0,673	0,682	0,671
13	Hungary	1,000	0,933	0,947	1,000	0,926	0,926
14	Iceland	1,000	1,000	1,000	1,000	1,000	1,000
15	Ireland	1,000	1,000	1,000	1,000	1,000	1,000
16	Italy	0,973	1,000	1,000	1,000	1,000	1,000
17	Latvia	1,000	1,000	1,000	1,000	1,000	1,000
18	Lithuania	0,980	0,964	0,964	0,964	0,964	0,964
19	Luxembourg	1,000	1,000	1,000	1,000	1,000	1,000
20	Malta	1,000	1,000	1,000	1,000	1,000	1,000
21	Netherlands	0,959	0,959	0,959	0,959	0,959	0,967
22	Norway	1,000	1,000	1,000	1,000	1,000	1,000
23	Poland	1,000	1,000	1,000	1,000	1,000	1,000
24	Portugal	0,852	0,839	0,826	0,816	0,832	0,903
25	Romania	1,000	1,000	1,000	1,000	1,000	1,000
26	Slovakia	1,000	1,000	1,000	1,000	1,000	1,000
27	Slovenia	0,951	0,892	0,825	0,892	0,892	1,000
28	Spain	0,890	0,900	0,825	0,906	0,887	0,904
29	Sweden	1,000	0,921	1,000	1,000	1,000	0,900
30	Switzerland	1,000	1,000	1,000	1,000	1,000	1,000
31	United Kingdom	1,000	1,000	1,000	1,000	1,000	1,000

Source: authors (2017)

In Table 5 are presented results for Model 5. This model measures ecological efficiency. The difference between Model 1 and Model 5 is that in Model 5 emissions are treated as input variable. There are efficient just four countries (France, Germany, Malta and Switzerland). Generally, the ecological efficiency is much lower than eco-efficiency. The average of eco-efficiency (Model 2) is equal to 0,891 and the average ecological efficiency (Model 5) is 0,582.

Table 5 Efficiency scores (ecological) of European countries for the year 2015

		M 5	M 5.1	M 5.2	M 5.3	M 5.4	M 5.5
1	Austria	0,641	0,714	0,673	0,622	0,698	0,599
2	Belgium	0,584	0,639	0,629	0,677	0,435	0,529
3	Bulgaria	0,232	0,259	0,467	0,503	0,280	0,124
4	Croatia	0,418	0,425	0,468	0,534	0,246	0,265
5	Cyprus	0,329	0,471	0,418	0,567	0,166	1,000

6	Czech Republic	0,391	0,518	0,604	0,742	0,334	0,369
7	Denmark	0,561	0,337	0,357	0,456	0,187	0,232
8	Estonia	0,224	0,313	0,395	0,385	0,338	0,149
9	Finland	0,428	0,423	0,618	0,649	0,423	0,208
10	France	1,000	0,700	0,700	0,700	0,794	0,700
11	Germany	1,000	1,000	1,000	1,000	1,000	1,000
12	Greece	0,376	0,419	0,460	0,438	0,432	0,313
13	Hungary	0,462	0,463	0,629	0,758	0,350	0,231
14	Iceland	0,379	0,257	0,258	0,265	0,188	0,187
15	Ireland	0,561	0,215	0,206	0,177	0,294	0,168
16	Italy	0,879	1,000	1,000	1,000	0,824	1,000
17	Latvia	0,466	0,206	0,342	0,327	0,313	0,077
18	Lithuania	0,437	0,213	0,302	0,302	0,229	0,104
19	Luxembourg	0,560	0,887	0,770	0,736	0,732	1,000
20	Malta	1,000	1,000	1,000	1,000	1,000	0,004
21	Netherlands	0,638	0,574	0,513	0,605	0,307	0,509
22	Norway	0,608	0,826	0,893	0,829	0,923	0,508
23	Poland	0,446	0,455	0,525	0,500	0,494	0,385
24	Portugal	0,498	0,551	0,563	0,531	0,546	0,436
25	Romania	0,508	0,305	0,279	0,249	0,330	0,330
26	Slovakia	0,404	0,619	0,917	0,945	0,630	0,284
27	Slovenia	0,418	0,424	0,382	0,405	0,242	0,393
28	Spain	0,772	0,637	0,562	0,682	0,411	0,643
29	Sweden	0,880	0,812	1,000	0,934	1,000	0,441
30	Switzerland	1,000	1,000	0,899	0,929	0,681	1,000
31	United Kingdom	0,936	0,932	0,819	0,713	1,000	0,973

Source: authors (2017)

V. Conclusion

The aim of the article was to measure the performance in terms of welfare beyond GDP. The special DEA models have been used for 31 European countries. These nonparametric special models took into account simultaneously economic as well as social and environmental indicators. The extension of previous research was that in this article we have used different types of emissions to see in which type of environment the countries need to improve. Various model specifications allow us to capture different characteristics of economic development. As the different types of emissions are used there should be shown different possibilities for economic policy to increase the efficiency. The results show the strengths and weaknesses of different countries in different indicators. The most problematic seems to be livestock. Overall, same countries are efficient by all models and with improving the variables the efficiency scores is improving.

In future work, we would like to improve input and output variables and make closer analysis of all European countries in time.

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