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Assessing sustainable economic development efficiency: a DEA approach

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Abstract

Background: Widely used in efficiency analysis, data envelopment analysis (DEA) found its use in country efficiency measurement concerning the achievement of desired values of macroeconomic indicators, most often the goals from the category of economic growth.

Purpose: The objective of the paper is to examine the possibility of DEA application in sustainable development research.

Methodology: The analysis was conducted using a non-oriented DEA model with variable return-to-scale in a group of 26 EU countries and Serbia, as a membership candidate. Four variables were used as input variables: inflation rate, unemployment rate, poverty rate and ecological footprint per capita. Three variables were used on the outputs side: inequality-adjusted human development index, GDP per capita and ecological deficit or reserve per capita. The annual data was collected for the time period of eight years, form 2010 until 2017.

Findings: Results show that Finland is the only country efficient throughout the entire period. Average efficiency close to maximum was achieved by the Netherlands. Significant efficiency was achieved by Luxembourg, Germany and Sweden among countries that were EU members before 1995. Among other EU countries, Slovenia and Hungary achieved efficiency on a nearly maximum level. Also, efficient in more than half of the observed years were Cyprus and Romania. The most inefficient countries were the three Baltic countries: Lithuania, Latvia, and Estonia. Among the EU member countries before 1995, Italy and Portugal were the most inefficient. Concerning EU candidate Serbia, the efficiency achieved was generally close to average.

Limitations: The performed analysis can answer the question of which country is the most efficient on the way to sustainability. However, the DEA method cannot show whether a country is developing absolutely sustainably or unsustainably, because DEA is a relative method and can only measure efficiency compared to the other units.

Keywords: data envelopment analysis; efficiency; sustainable development; European Union

Introduction

Technical efficiency was first defined by Koopmans (1951), as a state in which producers can produce more of a certain output if and only if they lower the production of another output or uses more of certain input. The decades-long search for adequate measurements of technical efficiency resulted in the conception of *data envelopment analysis (DEA)* in the second half of the 20th century, with foundations in the work of Michael James Farrell (1957). Development of this method made efficiency measurement on the 0-1 scale possible by putting into ratio summed weights of multiple outputs and inputs, even if presented in different and non-comparable units of measurement. The creators of the first CCR DEA model (Charnes, Cooper & Rhodes, 1978) presupposed diverse applications in efficiency testing, regarding both profit and non-profit institutions.

Parallel with the ongoing pursuit of adequate technical efficiency measurements, *sustainable development* caught more attention from theoreticians and policymakers. Significant attention to this universal goal for humanity was drawn by members of the Club of Rome by the publication of *'Limits to Growth'* (Meadows et al., 1972). At the dawn of the new millennium, the United Nations (UN) published *Millennium Declaration* (2000) with set *Millennium Development Goals*, while later in the 21st century the knowledge on the subject was systematized and *Millennium Development Goals* transformed into 17 *Sustainable Development Goals*. Although there are no generally accepted definitions and indicators concerning sustainable development, most often it is perceived from (1) economic, (2) social, and (3) environmental aspects (Bojović, 2011).

The objective of this paper is to test the possibility of DEA application in sustainable development assessment, aiming to create a single efficiency indicator that includes all three aspects of sustainable development at the same time. For the purpose of the paper, an adequate DEA model and input and output variables had to be selected. First and second sections present theoretical analysis of both DEA method and sustainable development phenomenon in comparison to economic growth and development respectively, based on existing literature. The third section is dedicated to model and variables to be included selection, and also to the selection of *decision-making units (DMU)* to be observed. For purposes of model simplicity, the impact of excluded variables is abstracted. The fourth section is dedicated to the presentation and quantitative and qualitative interpretation of analysis results.

Hypotheses *H1: Data envelopment analysis is applicable in sustainable development assessment* and *H2: Data envelopment analysis relativity limits application in sustainable development assessment* present a starting standpoint for this paper. Both hypotheses are a result of an examination of literature from relevant fields. Methods of theoretical analysis and quantitative and qualitative analysis of DEA results calculated from panel data (2010-2017) involving 27 countries were used in the paper. The data was collected from relevant and credible sources (UN, The World Bank, and Global Footprint Network) and additionally adjusted due to certain specificities of mathematical method.

1. Literature review

While testing the efficiency of states of the United States in agriculture in his work *The Measurement of Productive Efficiency* Farrell (1957) was the first to develop methods of productive efficiency measurement as a ratio between different inputs and a certain output or different outputs and a certain input. Such approach presented a step further from using average labour productivity as referent value in efficiency measurement because it included diverse inputs while focusing on technical competency and objective output instead of minimal production costs. Further development of methods for efficiency assessment was needed. The most significant contribution was made by Charnes, Cooper, and Rhodes (1978) through the development of data envelopment analysis (DEA), specifically the CCR model. What DEA enabled was the inclusion of multiple different input and output variables at the same time.

1.1. Data envelopment analysis

Data envelopment analysis can be defined as a non-parametric decision making method with a set objective of maximum efficiency (Charnes, Cooper & Rhodes, 1978). DEA was derived from the classical microeconomic theory of production. The focus of analysis is on decision making units (DMU), subjects that use multiple inputs to generate multiple outputs (Škare & Rabar, 2016). DEA has been accepted as a useful tool for performance assessment and ranking of DMUs

(Rahmani et al. 2020). An important step to successful DEA application is choosing organisations or subjects of the same kind as DMUs. Also, it is necessary to use the same variables as inputs and outputs for every particular DMU, and make sure that quantitative data on variables used as inputs and outputs is already existent. Like Farrell's (1957) method, DEA remains sensitive to input and output variable selection.

It has already been stated that DEA was derived from the classical theory of production. The aforementioned theory uses Pareto-optimality as an ultimate indicator of efficiency (Charnes, Cooper, Golany, Seiford & Stutz, 1985). Conditions (1) and (2) from the previous paragraph that have to be met to achieve efficiency substantiate the essence of Pareto-optimum – the inability of any position improvement without any other position worsening. DEA-calculated efficiency presents an extension of the Pareto-Koopmans efficiency concept (Krivonozhko, Utkin, Volodin, Sablin & Patrin, 2004).

DEA calculates efficiency as a ratio between a weighted sum of outputs and the weighted sum of inputs. Diverse inputs and outputs have to be aggregated to form one virtual output and one virtual input (weighted sums), that would thereafter be put into ratio. Due to such approach, it is necessary to ponder inputs and outputs, to multiply them by technical coefficients according to their respective relative relevance (Cook & Seiford, 2009). Technical coefficients are treated as variables in DEA linear programming model formulation and are not mutually comparable. Solving a specific linear programming problem results in calculating technical coefficients, which is a solution recommended by the creators of the first DEA model (Charnes et al., 1978), lacking clearly defined multiplicators.

Such formulation allows the inclusion of inputs and outputs expressed in diverse and mutually incomparable units of measure, which is one of DEA's biggest advantages (Škare & Rabar, 2016). Some other advantages have already been mentioned, first and foremost the possibility of multiple inputs and outputs inclusion at the same time. Formulating a production function explicitly is unnecessary to conduct a DEA calculation. Additionally, after determining efficiency lower than maximum, DEA can point out sources of inefficiency through dual prices, calculated by solving a linear programming problem.

The main disadvantages of DEA are sensitivity to the choice of input and output variables and the inability to predict. DEA presents an ex-post analysis based on already known data (Škare & Rabar, 2016). 'Rule of thumb' states that, to apply DEA successfully, the number of selected DMUs has to be at least two to three times higher than the number of variables used as inputs and outputs combined, so that efficiency results would be adequately dispersed (Sarkis, 2007).

1.2. Economic growth, development and sustainability

The problem of *economic growth* presents one of the most important problems that concern economists and politicians. Economic growth is an increase in the production of goods and services in a national economy and is measured as the growth of a macroeconomic aggregate gross domestic product (GDP) over an observed period, most often annually. On the other hand, additionally to quantitative growth, *economic development* presupposes structural changes in production and distribution, and as such has a qualitative aspect as well. Economic growth is a necessary condition of economic development (Acemoglu, 2012).

The standpoint of abandonment of exclusive usage of GDP in welfare measurement is increasingly gaining its foothold. Many authors, including van den Bergh (2009; 2022) and Kubiszewski et al. (2013), point out the problems of extensive GDP usage and signify the necessity of developing and using alternative indicators (Beyond GDP). Still, GDP remains the most used macroeconomic indicator due to its simplicity and clarity, while economic policy founded upon neoclassical economics places its focus on high economic growth as its only goal (Bojović, 2011).

In their book *Limits to Growth*, a group of authors (Meadows et al., 1972) comprehensively examined the problem of sustaining the trends of growth of population, production, and pollution at the time, in circumstances of resource scarcity, most importantly in the production of food and energy. The research objective was to point out that the unsustainability problem was a global one and to formulate the world model that shows the co-dependency of variables connected to studied phenomena. In the following decades, growing attention was dedicated to the problem of *sustainable development*. According to Wang et al. (2022), economic development and energy consumption have increased ecological issues of sustainable economics. Nevertheless, with labour and capital, energy is an essential input for the economic growth (Mardani et al. 2017). Therefore, its careful inclusion in the model as an input is of great importance. In support of this, Halkos et al. (2015) reported that high production efficiency level of a country does not ensure a high eco-efficiency performance.

The lack of consensus on the definition of sustainable development presents a big obstacle in the research of sustainable development. Dominantly, sustainability is observed from three aspects: (1) aspect of economic progress, (2) aspect of environment preservation, and (3) aspect of social development. Simultaneous achievement of goals related to all three aspects is a necessity, while goals achievement must be maintained in the long run also. The cohesion of policies aimed at achieving such goals is not simple and presents another problem of sustainable development (Petrov, Trivić & Ćelić, 2018). In terms of applying all three aspects, Matsumoto et al. (2020) examines labour, capital and energy as common inputs with gross domestic product, carbon dioxide and particulate matter emissions and waste as outputs.

Made by the United Nations (UN), the *'Millennium Declaration'* (2000) obliged signing sovereign countries to cooperate in achieving *Millennium Development Goals* by 2015 (Sachs & McArthur, 2005). In 2012, *Millennium Development Goals* were redefined into 17 *Sustainable Development Goals* in the process during which the knowledge concerning the field of sustainable development was systematized (Sachs, 2012).

Considering the lack of a universally accepted definition of sustainable development, many contexts in which sustainable development is mentioned, and terminology, data, and measurement methods not being systematized, formulation of a universally accepted set of indicators of sustainable development was not achieved. Different initiatives through time defined different indicators, but none of those succeeded in gaining a stable foothold as theoretically supported and politically relevant (Petrov et al., 2018). According to Labaj et al. (2014), it is of urgent need to develop new approaches for assessing the economic performance while taking into account economic as well as social and environmental goals.

2. Research methodology

DEA tends to present DMU efficiency in outputs maximisation while using minimum inputs or inputs minimization while attaining maximum outputs. Additionally, DEA is conducted based on existent and known data on inputs and outputs. Taking specified DEA characteristics and general availability of macroeconomic data into consideration, hypothesis *H1: Data envelopment analysis is applicable in sustainable development assessment* can be defined.

After the analysis has been conducted, the production possibility frontier, as an analysis result of the most efficient observed DMU, is reached empirically. Thereby, DMU can be either below or on the production possibility frontier. It is deducted that the production possibility frontier is determined by the efficiency of the most efficient observed DMU, which in return can be regarded as maximally efficient.

The DMUs on the production possibility frontier are marked as having the efficiency of 1, while those DMUs that are below the frontier are marked as having the efficiency somewhere in the range from 0 to 1, depending on the distance to the frontier (Škare & Rabar, 2016). The analysis results are therefore dependent on the selection of DMUs to be included as well. It can further be said that DEA presumes maximum efficiency achievable as efficiency manifested by the most efficient included DMU.

Every particular DMU can be characterised as either relatively efficient or relatively inefficient. To characterise certain DMU as efficient, the following conditions must be met: (1) it is impossible to increase any output without decreasing other output or increasing any input and (2) it is impossible to decrease any input without increasing other input or decreasing any output (Charnes, Cooper & Rhodes, 1981).

The fact that DEA is a relative method allows comparing DMUs and benchmarking, but does not state enough on whether the most efficient DMU, despite being characterised as efficient, achieves satisfactory absolute levels of input and output values (whether absolute levels of inputs and outputs are in cohesion with targeted referent values, if there are such). Therefrom stems the hypothesis *H2: Data envelopment analysis relativity limits application in sustainable development assessment*.

CCR and BCC models are two basic DEA models. CCR model was first developed by the creators of the method itself (Charnes et al., 1978) and it is named after their initials. The objective function of the non-linear CCR model contains maximum efficiency h_0 of the observed DMU as a weighted sum of its outputs y_{r0} multiplied by technical coefficients u_r, where

(1.1.) $r = 1, \dots, s$

with s being the number of different outputs; divided by the weighted sum of its inputs x_{i0} multiplied by technical coefficients v_i, where

(1.2.) $i = 1, \dots, m$

with m being the number of different inputs. Constraints contain efficiencies of all the other DMUs as ratios between weighted sums of outputs y_{rj} and inputs x_{ij}, where

(1.3.) $j = 1, \dots, n$

with n being the number of DMUs observed, and the condition of technical coefficients being higher than a small positive value ε (Cook & Seiford, 2009). The efficiency of other DMUs can be lower than or equal to 1, and inserted values of inputs and outputs always have to be equal to or higher than 0. In the further development of the model (Charnes et al., 1981), condition of non-negativity was replaced with the condition of positivity, to avoid neglection of the impact of certain input or output by multiplying them with a technical coefficient of 0. Objective function and constraints are formulated as ratios, which makes the model non-linear and non-convex. It is possible to rearrange the model to become a linear programming problem.

The primal DEA linear programming model is called the weight problem, while the dual model is called the envelopment problem. Reduced to linear programming, with regards to usage of above-designated marks, the weighted problem is formulated (Martić, Novaković & Baggia, 2009):

o.f.

$$(1.4.)\ \mathrm{Max} h_0 = \sum_{r=1}^{s} u_r y_{r0}$$

s.t.

$$(1.5.)\ \sum_{i=1}^{m} v_i x_{i0} = 1$$

$$(1.6.)\ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$$

$$(1.7.)\ u_r \geq \varepsilon,\ \ r = 1, \dots, s$$

$$(1.8.)\ v_i \geq \varepsilon, i = 1, \dots, m.$$

Formulating dual problem results in dual variable λ_j, a weighted sum of j-th DMU, and s_i^+ and s_i^-, which represent output increasements or input decreasements respectively, necessary for DMU to become efficient.

With regards to orientation, the DEA model can be input-oriented if the ratio shown is output/input, output-oriented if the ratio shown is input/output, and non-oriented (Cook & Seiford, 2009). In every stage of the development of the CCR model, constant return-to-scale was presumed. The first extension of the CCR model was made by Banker, Charnes, and Cooper (1984) and it was named BCC model after their initials. Efficiency measurement calculated using the BCC model represents efficiency measurement when differences in the scale of production are ignored. Another constraint was added to the model for variable return-to-scale to be tolerated (Škare & Rabar, 2017). Every DMU in the BCC model is compared only to DMUs that have a similar scale of production. Therefore, presuming multiple DMU groups with different scales, the BCC model shows more efficient single DMUs in the same sample than the CCR model, with the efficiency of every single DMU being higher than the one calculated by the CCR model (Martić, Novaković & Baggia, 2009).

2.1. Applying DEA in sustainable development assessment

There are four main phases in conducting an efficiency study using the DEA method:

1. Defining and selecting decision-making units whose relative efficiency should be determined
2. Determining input and output variables that are relevant and suitable for assessing the relative efficiency of selected decision-making units
3. Selection of an adequate DEA model
4. Solving DEA models, analysis and interpretation of results.

In the first phase, it is actually decided what will be the subject of the analysis. Furthermore, it is important to determine the primary goal of decision-making units and, based on it, determine whether they strive to minimize input or maximize output variables. The previous phases create preconditions for solving the model and analysis of the solution, which should lead to certain conclusions regarding the level of efficiency and ways of improvement. It is also necessary to choose which input and output variables will be used in the analysis. Nowadays, various variants of DEA model are developed in different areas of application. Therefore, selection of the adequate DEA model is also an important step in the analysis.

Numerous authors (Golany & Thore, 1997; Afonso & St. Aubyn, 2013; Škare & Rabar, 2017; Koisova, Grmanova, Skrovankova & Kostrova, 2019; Marcikić Horvat et al., 2021) examined the phenomena of economic growth and development, while applying various DEA models and selecting different combinations of input and output variables. Taking a high level of GDP per capita or high GDP growth rate as an objective desired to be achieved by policy, without a maximum limit, those variables are qualified to be selected for the model as output variables, while factors decreasing the level of GDP or slowing its growth could be included as input variables, just like factors that present the additional effort in achieving growth.

Can DEA be further applied to analyse sustainable development, its characteristics taken into consideration? There is a possibility of achieving high GDP or high GDP growth rate, but in such a manner that is devastating for the environment. That is why Mardani et al. (2018) introduced possible applications of inputs and outputs of DEA in the fields of environmental and energy economics. Simultaneously, it is necessary to consider social development, dimensions such as equity and the quality of an individual's life. While examining sustainable development, it is not only necessary to have economic growth analysed from the quantitative aspects, but from the qualitative aspect too.

To examine the applicability of DEA in sustainable development research, the model to be applied to inspect the data has to be defined. Such a model should include countries as DMUs and a certain number of variables as inputs and outputs. The final version of the analysis includes countries of the European Union excluding Malta, and Serbia as a candidate for membership. This sample was taken from a variety of possible combinations based on data availability for countries in a time period and the geopolitical importance of the European Union.

The analysis time frame is a period from the year 2010 to the year 2017. Selection of time period in the 21st century was needed to present the state after the adoption of *The Millennium Declaration* (United Nations, 2000), the first instance of global policy direction toward sustainable development. For the start year, 2010 was taken in order to eliminate the effects of the global economic crisis of 2008 as much as possible, while 2017 was taken for the end year because it is the last year for which the data on all the variables included has been published. With sustainable development being a long-run category, every country is observed every year as an independent DMU. That way, a country is not only compared with other countries in a given year but also with the results of previous or following years.

The variables had to be selected so that they illustrate all three aspects of sustainable development. The input variables are:

1. inflation rate (GDP deflator) – the indicator of price (in)stability and monetary stability
2. unemployment rate – indicator in which percentage labour force does not participate in the production process
3. poverty rate, measured as a percentage of the population of a country living below a poverty threshold of 3.2 United States dollars per capita daily, purchase-power-parity adjusted
4. ecological footprint per capita – the measure of the negative influence of human activity on the environment. It indicates whether nature is capable of renewing itself at the rate at which the society exploits it, where natural capacity is characterised as biocapacity and the negative effects of human activity on the environment as the ecological footprint (Sarkodie, 2021).

Variables used as outputs are:

(1) inequality-adjusted human development index (IHDI) – Human development index (HDI) is a composite indicator that measures life quality by taking into consideration life expectancy, education, and purchasing power of a resident. Adjusted for inequality, it shows such quality in an environment where a certain degree of inequality is present, taking HDI as a potential that can be achieved, while IHDI represents the actual situation (Alkire & Foster, 2010).

(2) GDP per capita – national output relative to the population size

(3) ecological deficit or reserve per capita – the difference between biocapacity and ecological footprint relative to the size of the population. It indicates whether or not the effects of economic activity on the environment overcome the effects that the environment could withstand while maintaining the current resource renewal rate, and how big is the positive (reserve) or negative (deficit) gap (Lin et al., 2015).

Inflation rate and ecological deficit or reserve per capita are such indicators that they can be negative. As DEA was not perceived to include negative variable values, those values have to be adjusted (Portela, Thanassoulis & Simpson, 2004). The absolute of the most negative value concerning every of the stated variables was added to the value of those variables for every DMU. That way the inflation of the DMU with the most intensive deflation was considered 0 for the purposes of the analysis, while every DMU maintained the same difference. The identical procedure was undertaken for the ecological deficit or reserve per capita.

The data regarding IHDI and poverty rate was retrieved from United Nations Development Programme, Human Development Data Centre. Regarding GDP per capita, unemployment rate and inflation rate the source used was World Bank Open Data, while the data regarding biocapacity and ecological footprint, based on which ecological deficit or reserve was calculated, was retrieved from Global Footprint Network, Open Data Platform. Table 3.1 contains correlation coefficients between variables.

The analysis included 27 countries across 8 years, which makes for 216 DMUs, compared by efficiency computed based on data for 7 variables, with biocapacity also being included as it is used to calculate ecological deficit or reserve. DEA model selected to be used is a non-oriented model presuming variable return-to-scale. Constant return-to-scale would require that every DMU operates at an optimum scale, which is not always the case (Marcikić Horvat et al., 2021).

Table 1 Variable correlation coefficients

	IHDI	Poverty rate	GDP per capita	Inflation rate	Unemployment rate	Ecological footprint per capita	Biocapacity per capita	Ecological deficit
IHDI	1.00							
Poverty rate	-0.62	1.00						
GDP per capita	0.73	-0.44	1.00					
Inflation rate	-0.20	0.23	-0.07	1.00				
Unemployment rate	-0.57	0.36	-0.51	-0.08	1.00			
Ecological footprint per capita	0.36	-0.27	0.50	0.11	-0.23	1.00		
Biocapacity per capita	0.33	-0.12	0.15	0.10	-0.22	0.28	1.00	
Ecological deficit or reserve per capita	0.13	0.03	-0.12	0.04	-0.09	-0.28	0.85	1.00

Source: the authors' calculation

Descriptive statistics concerning variables is shown in Table 2 Taking into consideration characteristics of DEA, usage of variables measured in mutually incomparable units should present no problem for the analysis (Škare & Rabar, 2016).

Table 2 Descriptive statistics for variables

	n	Min	Max	Mean	Std. Deviation
IHDI	216	0.676	0.882	0.797	0.053
Poverty rate	216	0	12.63	1.30	2.03
GDP per capita	216	5589	123514	32003	23011
Inflation rate	216	-2.98	8.91	1.55	1.62
Unemployment rate	216	2.89	27.47	10.44	5.14
Ecological footprint per capita	216	2.70	15.82	5.21	2.04
Biocapacity per capita	216	0.21	13.03	3.52	3.11
Ecological deficit or reserve per capita	216	-14.31	7.10	-1.69	3.51

Source: the authors' calculation

3. Results and Discussion

The results of the conducted analysis are shown in Tables 3 and 4. Finland is the only country efficient throughout the entire period. Average efficiency close to maximum was achieved by the Netherlands, inefficient in 2012, 2013, and 2015, but being close to maximum efficiency. Significant efficiency was achieved by Luxembourg, which was only inefficient in 2015 and 2017, Germany, inefficient only in 2010 and 2016, and Sweden, inefficient in the time period 2010-2012, among countries that were EU members before 1995. Among other EU countries, Slovenia achieved efficiency on a nearly maximum level, being inefficient in the time period 2011-2013, while Hungary was on average close to efficiency, being inefficient in 2011, 2013, and 2014. Also, Cyprus and Romania were efficient in more than half of the observed years.

The most inefficient countries were the three Baltic countries: Lithuania, Latvia, and Estonia, in that order. Throughout the entire period, either Lithuania or Latvia was the most inefficient country. The most significant drop in efficiency occurred in Latvia, which went from the maximum efficiency in the first observed year to the efficiency of 0.77 in the last observed year. Estonia was slightly more efficient in 2015 and 2017 than in the rest of the observed period. Among the EU member countries before 1995, the most inefficient were Italy and Portugal.

The most significant improvement was that achieved by Cyprus, going from efficiency of 0.81 in the first year to being efficient during the period 2013-2017. Other improving countries include France, achieving an efficiency of 0.86 in the first year and being efficient in 2014 and 2017, Poland, going from 0.80 in the first year to 0.99 in the last year, while being efficient in 2016, Slovakia, and Serbia. Greece improved during the first half of the observed period but deteriorated during the second half.

EU member countries before 1995 were on average more efficient than other EU countries. Concerning EU candidate Serbia, the efficiency achieved was generally close to average, falling behind only slightly. Serbia was efficient in 2015 and more efficient than an average country in 2017. The countries were most efficient on average in 2014 and 2015 with an efficiency score of 0.95 and least efficient in 2011 with a score of 0.91 and in 2010 with a score of 0.92, with the difference being small.

Also, similar to the findings of Matsumoto et al. (2020), the EU countries experienced the sustainable efficiency improvement during the observed period, although fluctuations were observed in most cases.

Table 3 DEA efficiency scores by country and year (part 1)

Country	Efficiency				
	2010	2011	2012	2013	2014
EU members in 1995*					
Austria	0.93	0.94	0.95	0.93	0.94
Belgium	0.89	0.92	0.91	0.91	0.92
Denmark	0.96	1.00	1.00	0.99	0.99
Finland	1.00	1.00	1.00	1.00	1.00
France	0.86	0.93	0.90	0.92	1.00
Germany	0.96	1.00	1.00	1.00	1.00
Greece	0.86	0.82	0.89	1.00	0.96
Ireland	1.00	0.96	0.96	0.97	1.00
Italy	0.82	0.83	0.86	0.88	0.89
Luxembourg	1.00	1.00	1.00	1.00	1.00
Netherlands	1.00	1.00	0.99	0.99	1.00
Portugal	0.82	0.90	0.92	0.90	0.93
Spain	0.91	0.95	0.98	0.95	0.98
Sweden	0.94	0.99	0.97	1.00	1.00
Other EU countries**					
Bulgaria	0.93	0.85	0.92	1.00	0.96
Croatia	1.00	0.80	0.82	0.90	0.98
Cyprus	0.81	0.92	1.00	1.00	1.00
Czech Republic	1.00	0.94	0.90	0.91	0.92
Estonia	0.79	0.82	0.78	0.82	0.82
Hungary	1.00	0.97	1.00	0.99	0.98
Latvia	1.00	0.81	0.82	0.80	0.77
Lithuania	0.77	0.79	0.78	0.81	0.80
Poland	0.80	0.82	0.84	0.90	0.91
Romania	0.96	0.91	1.00	1.00	1.00
Slovakia	0.87	0.87	0.93	0.92	0.94
Slovenia	1.00	0.96	0.98	0.99	1.00
EU candidate country					
Serbia	0.88	0.84	0.91	0.90	0.93
Yearly average	0.92	0.91	0.93	0.94	0.95

Notes:*Although a member country in 1995, United Kingdom is excluded from the analysis as it is no longer a member of the EU, **Due to unavailability of data for every variable, Malta is excluded from the analysis

Source: the authors' calculation

Table 4 DEA efficiency scores by country and year (part 2)

Country	Year			
	2015	2016	2017	Average
EU members in 1995				
Austria	0.91	0.94	0.94	0.94
Belgium	0.92	0.92	0.93	0.92
Denmark	0.99	0.99	1.00	0.99
Finland	1.00	1.00	1.00	1.00
France	0.92	0.94	1.00	0.93
Germany	1.00	0.99	1.00	0.99
Greece	0.90	0.90	0.89	0.90
Ireland	0.99	0.99	1.00	0.98
Italy	0.89	0.87	0.88	0.87
Luxembourg	0.98	1.00	0.98	0.99
Netherlands	0.99	1.00	1.00	1.00
Portugal	0.89	0.84	0.82	0.88
Spain	0.97	0.89	0.89	0.94
Sweden	1.00	1.00	1.00	0.99
Other EU countries				
Bulgaria	0.89	0.88	0.90	0.92
Croatia	0.96	0.95	0.94	0.92
Cyprus	1.00	1.00	1.00	0.97
Czech Republic	1.00	0.98	1.00	0.96
Estonia	0.94	0.83	0.92	0.84
Hungary	1.00	1.00	1.00	0.99
Latvia	0.82	0.77	0.77	0.82
Lithuania	0.82	0.80	0.77	0.79
Poland	0.97	1.00	0.99	0.90
Romania	0.97	1.00	1.00	0.98
Slovakia	0.96	1.00	0.92	0.93
Slovenia	1.00	1.00	1.00	0.99
EU candidate country				
Serbia	1.00	0.91	0.97	0.92
Yearly average	0.95	0.94	0.94	0.93

Source: the authors' calculation

Comparative analysis of countries regarding measured relative efficiency is enabled by performed calculation using retrieved data. The best results were calculated for countries having high values of output variables and having low values of input variables, all while maintaining an adequate cohesion of values concerning economic development, social development, and environment preservation. The efficiency of every country aiming to achieve various diverse sustainable development goals at the same time was examined through a calculation using the DEA model, which allows confirmation of the hypothesis *H1: Data envelopment analysis is applicable in sustainable development research.*

By such an approach the comparison of countries based on efficiency was enabled, taking into consideration that the maximum efficiency is the efficiency exhibited by the most efficient country in its most efficient year. Still, it is very important to conclude whether the country is sustainable or not when examining sustainable development. Although it shows how efficient a country is in achieving and coordinating activities towards the achievement of goals, while being compared with other countries, this analysis cannot answer the question of whether a country is sustainable or not. Being the most efficient of the group does not necessarily mean it is absolutely sustainable, just that it is relatively more or less efficient than the other.

Taking into consideration that in addition to comparison and ranking of the countries one against the other, the sustainable development analysis needs to include a mark on whether a country can be considered sustainable or not, the DEA method could be used in sustainable development analysis while being complemented by another method or indicator that overcomes this disadvantage. Therefore, hypothesis *H2: Data envelopment analysis relativity limits application in sustainable development research* is confirmed. Additionally, DEA cannot be used to predict future values and changes of the indicators, but only to analyse already acquired data, and conduct *ex-post* analysis, where other additional problems exist concerning the scope of the analysis if the data is largely unavailable.

One of the possible solutions to overcome these disadvantages is to measure precisely the potentials and sustainability limits for countries and to measure (in)efficiency through the gaps to the potential values. Generally, DEA can be used to comparatively measure and analyse the efficiency of countries on their way to sustainability, but it is impossible to give the final verdict on whether some countries can be considered sustainable or not. Also, the results of the relative DEA method depend largely on both variable and DMU selection, so it is necessary to try out different input-output combinations of the variables and different scopes of analysis regarding the time frame and countries observed.

Conclusion

Widely used in efficiency analysis, the DEA method found its use in country efficiency measurement concerning the achievement of desired values of macroeconomic indicators, most often the goals from the category of economic growth. Based on the objective of the paper, it contains the examination of DEA applicability in sustainable development measurement. The ultimate sustainable development goal is reaching economic sustainability in the frame dictated by the environment while achieving both intragenerational and intergenerational justice and equality (Bojović, 2011).

Using acquired data, the analysis was conducted using a non-oriented DEA model with variable return-to-scale in a group of 27 countries: 26 current EU countries and 1 membership candidate. The inflation rate, unemployment rate, poverty rate, and ecological footprint per capita were used as input variables, while output variables used were GDP per capita, IHDI, and ecological deficit or reserve per capita. Successful conduct of the analysis resulted in confirmation of the hypothesis *H1: Data envelopment analysis is applicable in sustainable development research*. In other words, both economic and environmental variables significantly affect overall efficiency of observed countries (Matsumoto et al., 2020). Therefore, He at al. (2016) recommended improving the level of agricultural modernization, increasing the proportion non-fossil energy, developing renewable energy and reducing pollutant emission in order to promote sustainable economic growth.

Bearing in mind the problem examined in this paper, DEA should be used carefully by linking technology innovation in science with political and managerial efforts and so reducing the problem related to climate change and environmental pollution (Sueyoshi et al., 2017). Mostly, technical progress is the most powerful contributor to economic growth, while political and management efficiency are the two main obstacles preventing further improvement (Wang & Feng, 2015). For this reason, measuring the efficiency of economic growth plays an important role in the decision-making process and reducing managerial inefficiency.

Analysis can answer the question of which country is the most efficient on the way to sustainability, or what are all the countries that are efficient in achieving high output variable and low input variable values, or in coordinating the achieving of different goals related to sustainable development at the same time. However, the DEA method cannot show whether a country is developing absolutely sustainably or unsustainably, because DEA is a relative method and can only measure efficiency compared to other units, without stating whether that efficiency is enough to achieve the ultimate goal. These statements are a confirmation of the hypothesis *H2: Data envelopment analysis relativity limits application in sustainable development research*.

Limitations of this study are mainly linked with the applied methodology, since the results of DEA models highly depend on the selection of sample and variables. DEA is a relative method and can only measure efficiency compared to other units. Therefore, modification of the selection of countries in the analysis or choice of different input or output variables would definitely change the results of DEA analysis which is the interesting topic for further research. Further steps that could be taken to improve the possibility to apply the DEA method in sustainable development analysis could be finding better ways to measure country potentials regarding variables and gaps of actual to potential values, and improving the databases in order to provide for further measurements through changing variable combinations and inclusion of different DMUs.

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