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DEA Assessment of Socio-economic Development of European Countries

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Abstract:

Research Question: The study is aimed to explore the achieved level of socio-economic development of European countries, providing their efficiency analysis. **Motivation:** Current trends in the social wellbeing quantification indicate the neediness to change the perception of growth that relies solely on economic performance and the requisite to develop new approaches in measuring societal progress that, in addition to economic, includes the social performance of the national economy. Modern concepts are designed to encompass both the economic aspect and social goals. Therefore, the purpose of this paper is to contribute to the development of a methodological approach that can be applied to assess the level of socio-economic development. **Idea:** The study has been developed with the main idea to empirically assess and quantify the socio-economic development of European countries in order to improve traditional performance measures, which are primarily focused on economic aspects, omitting other aspects of sustainability. **Data:** A sample of 32 European countries was empirically analysed based on the data on socio-economic development indicators in 2018 (employment rates, mean equivalised net income, GDP per capita PPS, and percentage of people at risk of poverty and social exclusion) obtained from EU Statistics on Income and Living Conditions (EU-SILC) and Eurostat database. **Tools:** The assessment of the achieved level of socio-economic development was carried out using a Data Envelopment Analysis (DEA) based on the BCC output-oriented model with four output variables. **Findings:** Most of the EU28 countries (26 out of 28) do not achieve satisfactory levels of socio-economic efficiency. Additionally, countries of Northern and Western Europe achieve greater socio-economic efficiency, compared to the countries of Southern Europe. Four countries have a satisfactory level of socio-economic efficiency (the Czech Republic, Luxembourg, Switzerland and Norway). **Contribution:** This paper contributes to the existing literature in the field of socio-economic sustainability assessment through testing of the model with empirical data on European countries.

Keywords: socio-economic development, data envelopment analysis, sustainable development, undesirable outputs, people at risk of poverty or social exclusion.

JEL Classification: O11, O52, O57, I30, C44, C67

1. Introduction

Socio-economic development implies the existence of adequate policies focused on sustainable social prospects and economic progress. The ultimate goal of social development is to improve a sustainability in the wellbeing of a society as a whole and it can be achieved only by continuously increasing the economic standard of the population in the country. Sustainable development plays an important role in a modern society that seeks to "meet the needs of current generations without compromising the ability of future generations to meet their own needs" (World Commission on Environment and Development, 1987). Promoting sustainable development requires the implementation of concrete actions, programmes and policies, which include a simultaneous struggle and achievement of environmental, economic, and social goals. Setting adequate sustainability goals requires some knowledge and understanding of the current level of sustainability. The traditional approach to assessing the level of development of a particular national economy involves analysing the level of realized gross domestic product (hereafter abbreviated as GDP). However, it is evident that the established practice of relying solely on GDP as a measure of national growth, to propose appropriate development strategies is not adequate (Decancq & Schokkaert, 2016; Kubiszewski

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et al., 2013; Jones & Klenow, 2016). A number of authors point out that focusing on GDP leads to conflict with the achievement of sustainable development goals, especially those related to the social equality and environmental welfare (Nahman et al., 2016). Nevertheless, the fact that GDP, even so, prevails in wellbeing contexts is generally regarded as compelled by the absence of a more suitable index, rather than the result of social consensus (Fleurbaey, 2009). Unlike the present emphasis on maximizing consumption and production of goods and services, it is crucial to create measures that will give equivalent importance to every aspect of human, social and environmental welfare (Nahman et al., 2016). Various indices of social progress have been developed as an attempt to include both social and environmental indicators to measure people's quality of life. However, the majority of human wellfare indices (for instance the Human Development Index), in addition to evaluating certain aspects of social development, fail to explain the complex relationships between social progress and economic development or do not succeed to quantify social progress (Charles & D'Alessio, 2019). Sen (2000) suggested that when creating a measure of socio-economic development, it is important to assess all the elements that affect living standards and to overcome income-based estimates. Porter, Stern and Green (2016) consider that monitoring social performance is an important task because it leads to the establishment of better policies and better decisions by governments and corporations, thereby ultimately contributing to the advancement of economic growth. Decancq and Schokkaert (2016) believe that it is necessary to create a development assessment model that goes beyond traditional measures of economic growth and progress since traditional indicators of economic growth do not fully reflect the progress of the country and do not accurately reflect the factors important for progress.

The main problem in sustainability assessment are the numerous interpretations and aspects of this concept, making it difficult to define the measures of sustainability level achieved. Although the theoretical definition of sustainability is clear, it is less clear how to make it operational in the empirical analysis (Oskam & Feng, 2008). To answer the question of whether a particular system is sustainable, it is often necessary to define a benchmark, indicators and benchmarking methods (Pascucci, Polman & Slangen, 2012). Numerous researchers have tried to evaluate different aspects of sustainable development. Strezov, Evans and Evans (2017) examined nine different indices for quantifying sustainable development and determined that most of the indices considered either the socio environmental, socio economic, or just environmental and economic dimensions, while only two of them measured all three dimensions of sustainable development. Spaiser et al. (2017) proposed a data-driven approach for quantifying and monitoring sustainable development. Several studies attempted to offer a tailor-made composite index that will measure sustainability (Salvati & Carlucci, 2014; Ivaldi, Bonatti & Soliani, 2016; Panda, Chakraborty & Misra, 2016; Rodrigues & Franco, 2019; Khalid, Sharma & Dubey, 2019; Alaimo & Maggino, 2020). However, despite a large number of proposed methodologies for measuring distinctive features of sustainability, most of them face the problem of aligning the multidimensional nature of the sustainability concept with the need to create a single, synthetic measure of sustainability that would be useful for policymakers (Gerdessen & Pascucci, 2013).

Therefore, the paper aims to contribute to the development of a methodology that can simplify the procedure for assessing socio-economic development taking into account the multidimensional nature of the concept. Applying Data Envelopment Analysis (DEA), based on indicators showing a measure of poverty, social exclusion and material deprivation, as well as other socio-economic indicators, the objective is to quantify and compare the levels of socio-economic development of the European countries (Stanković et al., 2019).

The rest of the paper is structured so that in addition to the introduction and conclusion, it also contains the following two sections: 1) Research methodology 2) Data and model formulation; 3) Research results and discussions.

2. Research Methodology

Data Envelopment Analysis (DEA) is a non-parametric approach applied to evaluate the effectiveness of decision-making units (DMUs) using linear programming techniques in situations where multiple inputs and outputs make comparison difficult (Boussofiane, Dyson & Thanassoulis, 1991; Eskelinen, 2017). It was developed in 1978 by Charnes, Cooper, and Rhodes (Charnes, Cooper, & Rhodes, 1978) as a technique for evaluating and comparing the performance of a set of DMUs with multiple inputs and outputs. The advantage of the method is that it does not require a priori determined weight coefficients, thus reducing the subjectivity and influence of the decision-maker. Efficiency is quantified as the ratio of the weighted sum of the outputs to the weighted sum of the inputs (Thanassoulis & Silva, 2018; Omrani, Adabi & Adabi, 2017). Using the DEA method, a subset of the most efficient DMUs from the total set is identified, whose realized efficiency is quantified by 1. The DEA also calculates the efficiency levels of the remaining DMUs, with measures of estimated efficiency ranging between 0 and 1. DEA models can be input oriented when the goal is to minimize inputs for a given output level, or output-oriented models when the goal is to maximize outputs for a given input level (Al-Refaie, Hammad & Li, 2016). Besides, depending on the treatment of the returns on scale, the CCR model (Charnes, Cooper, & Rhodes, 1978) with the constant returns on scale and the BCC model (Banker, Charnes, & Cooper, 1984) with the variable returns on scale can be identified.

When formulating the model, the existence of n decision-making units $j=1,\dots n$ is assumed, with each decision-making unit producing s different outputs from m different inputs. The mathematical model of the output-oriented BCC model can be represented via relations (Seiford & Zhu, 2002):

$$\max \eta \tag{1}$$

Subject to:

$$\sum_{j=1}^{n} z_j x_j + s^- = x_0 \tag{2}$$
$$\sum_{j=1}^{n} z_j y_j - s^+ = \eta y_0 \tag{3}$$
$$\sum_{j=1}^{n} z_j = 1 \tag{4}$$
$$z_j \geq 0, j = 1,2 \dots n \tag{5}$$

Where x_j is a vector of inputs whose j^{th} element x_{ij} represents the amount of i input and used by the j^{th} decision-making unit, y_j is an output vector whose r^{th} element y^{rj} represents the amount of output r produced by the j^{th} decision-making unit, while x_o and y_o denote the input and output vectors of DMU_o under evaluation.

The use of the DEA methods in the field of sustainable development has expanded in recent years, especially given the fact that the efficiency assessed by the DEA method can be interpreted as an index of sustainability of each observation unit (Cherchye et al., 2007). The main advantage is that, in addition to identifying inefficient DMUs, the DEA enables the identification of best practices to strive for. A large number of papers apply the DEA methodology to assess differences in the achieved levels of social sustainability, both between countries and regions of a given country (Murias, Martinez & De Miguel, 2006; Adler, Yazhemsky & Tarverdyan, 2010; Charles & D'Alessio, 2019; Iribarren et al., 2016).

On the other hand, the question arose on how to explain unwanted variables in a particular process, that is, how to treat undesirable inputs and undesirable outputs. Traditional DEA models rely on the assumption that inputs must be minimized and that outputs must be maximized. However, Koopmans (1951) notes that processes can also create unwanted results. Färe et al. (1989) created a nonlinear DEA model to evaluate the performance of systems in which there are desired results to be maximized and undesirable results to be minimized. Also, there are situations where it is necessary to increase the inputs and reduce some of the outputs to improve the efficiency of the decision unit (Jahanshahloo et al., 2005). Seiford and Zhu (2002) have refined the traditional DEA model and created an output-oriented BCC model that incorporates undesirable outputs. The problem of undesirable outputs is particularly present in the assessment of the effectiveness of sustainable development, especially if environmental variables (such as the amount of waste produced) are included in the analysis. Thus, the total results of the system (Y) can be categorized as good or desirable outputs (Y^g), and as poor or undesirable outputs (Y^b), with the tendency to increase good and decrease poor outputs (Seiford & Zhu, 2002). However, the traditional DEA models tend to increase the output without making the distinction among desirable and undesirable outputs. Therefore, Färe et al. (1989) modified the standard BCC model in order to improve desirable and reduce undesirable outputs (Seiford & Zhu, 2002):

$$\max \Gamma \tag{6}$$

Subject to:

$$\sum_{j=1}^{n} z_j x_j + s^- = x_0 \tag{7}$$
$$\sum_{j=1}^{n} z_j y_j^g - s^+ = \Gamma y_0^g \tag{8}$$
$$\sum_{j=1}^{n} z_j y_j^b - s^+ = \frac{1}{\Gamma} y_0^b \tag{9}$$
$$\sum_{j=1}^{n} z_j = 1 \tag{10}$$
$$z_j \geq 0, j = 1,2 \dots n \tag{11}$$

The abovementioned model is not adequate in situations when the transformation of undesirable outputs is performed, and in order to preserve convexity and linearity in DEA, Seiford and Zhu (2002) have formulated the following linear program:

$$\max h \quad (12)$$

Subject to:

$$\sum_{j=1}^{n} z_j x_j \leq x_0 \quad (13)$$
$$\sum_{j=1}^{n} z_j y_j^g \geq h y_0^g \quad (14)$$
$$\sum_{j=1}^{n} z_j \bar{y}_j^b \geq h \bar{y}_0^b \quad (15)$$
$$\sum_{j=1}^{n} z_j = 1 \quad (16)$$
$$z_j \geq 0, j = 1,2 \ldots n \quad (17)$$

Where $\bar{y}_j^b = -y_j^b + w > 0.$

Various research works have applied DEA in the environmental studies for the assessment of performance of DMUs that produce both desirable and undesirable outputs (Liu, Lu & Lu, 2016; Chen & Jia, 2017; Sueyoshi & Yuan, 2017; Halkos & Petrou, 2018b; Wu et al., 2016; Song et al., 2018; Zhou, Poh & Ang, 2016; Beltrán-Esteve & Picazo-Tadeo, 2017; Kao & Hwang, 2019; Halkos & Petrou, 2019b).

Dealing with undesired outputs certainly ultimately affects the effectiveness of DMUs. To address the problem of undesirable outputs several approaches have been developed. The four most common approaches for treating undesirable outputs in the DEA model are identified in the literature (Halkos & Petrou, 2018a; Halkos & Petrou, 2019a):

- Ignoring undesirable outputs - involves a mere neglecting of the undesirable outputs, thus eliminating their effect on the final score. However, Yang and Pollitt (2009) state that this approach can lead to inaccurate results that do not give a true picture of the effectiveness of decision-making units.
- Treating undesirable outputs as inputs - in many efficiency studies this approach has been applied and assumes handling of unwanted outputs as usual inputs.
- Application of nonlinear models - involves treating undesirable outputs as usual outputs, with the assumption that undesirable output values cannot be increased without affecting the values of other desirable outputs (Färe et al., 1989).
- Application of the needed transformations - there are several ways to perform transformations of undesirable outputs:
    - o The first option is the ADD approach proposed by Koopmans (1951) according to which the transformation is performed by applying the relation (U) = −U. The application of this transformation may lead to the appearance of negative values which require the use of additive models (Seiford & Zhu, 2005).
    - o The second option is to apply the transformation (U) = −U + β, which eliminates the occurrence of negative values. However, this kind of transformation may affect the results, and it is thus recommended for the value of β to be equal to the maximum value of the undesirable output (Zanella, Camanho & Dias, 2015).
    - o The third option is to apply an inverse function based on the relation f (U) = 1 / U.

It should be noted that the variable returns on scale are assumed in all cases with data transformation (Wojcik, Dyckhoff & Gutgesell, 2017).

3. Data and Model Formulation

Social risk represents the possibility of one or more persons being exposed to negative social conditions that threaten social sustainability. One of the five main goals of the Europe 2020 strategy is to reduce poverty by taking out at least 20 million people from the at-risk-of-poverty or social exclusion group by the end of 2020 (Poverty in Europe, 2020). The problem of measuring poverty and social exclusion is a contemporary task among academic researchers and, at the same time, an operationally relevant topic at all levels of policymaking. In 2018, 109.2 million people in the European Union (EU) lived in households at risk of poverty or social exclusion, accounting for 21.7% of the total population (Eurostat, 2020). Data on population at risk of poverty or social exclusion are obtained from the EU Statistics on Income and Living Conditions (EU-SILC) surveys aimed at gathering an appropriate and comparable multidimensional microdata on social exclusion, poverty, income, and living conditions. To analyse the achieved level of socio-economic sustainability, in addition to data on people at risk of poverty or social exclusion, it is necessary to include other indicators of socio-economic development and sustainability presented in Table 1 (Stankovic et al., 2019). To obtain a composite indicator of socio-economic development, based on the available data, the model with four output variables was created, where one output variable represents an undesirable output, and for this analysis the transformation (U) = −U + β is conducted.

Table 1: Description of the variables of the DEA-BCC model

	Variable name	Description
Desirable output variables	The employment rate	The employment rate is defined as the extent to which available labour resources are used. It is calculated as the ratio of employees to the working-age population and is considered a key social indicator when analysing labour market trends.
	Median Equivalised Net Income	Median Equivalised Net Income is the median total income of all households, after tax and other deductions, available for consumption or savings divided by the number of household members converted to equivalent adults (using the so-called OECD Equivalence Scale).
	GDP per capita PPS	GDP per capita (based on PPS) is a Gross Domestic Product converted to comparable values using the purchasing power standard and divided by the total population.
Undesirable output variable	People at risk of poverty or social exclusion	Percentage of people who are either at risk of poverty or severely materially deprived or living in a very low work intensity household.

The creation of a composite index using the DEA method has been proposed by Cherchye et al. (2007) suggesting the approach named „Benefit-of-the-Doubt". The composite indicator is obtained based on the model that is identical to the input-oriented model with constant returns-to-scale and unit input for all DMUs. However, Zanella et al. (2015) suggest that the composite indicator can be also obtained using the output-oriented model. Additionally, Lovell and Pastor (1999, p. 48) state that "an output-oriented CCR model with a single constant input and an input-oriented CCR model with a single constant output coincide with the corresponding BCC models". Therefore, the BCC output-oriented model will be assessed.

4. Research Results and Discussions

An analysis of the effectiveness of the achieved level of socio-economic development was performed using the Benchmarking package for R software. According to the obtained efficiency index, mean socio-economic efficiency is 110.90%, with nineteen countries attaining efficiency score which is better than the average. Based on the estimated measure of the socio-economic development of European countries (Figure 1), it is observed that the countries of Northern and Western Europe achieve greater socio-economic efficiency, while the countries of Southern Europe record lower levels of socio-economic efficiency. Four countries have a satisfactory level of socio-economic efficiency (the Czech Republic, Luxembourg, Switzerland and Norway). Most of the EU28 countries (26 out of 28) do not achieve satisfactory levels of socio-economic efficiency.

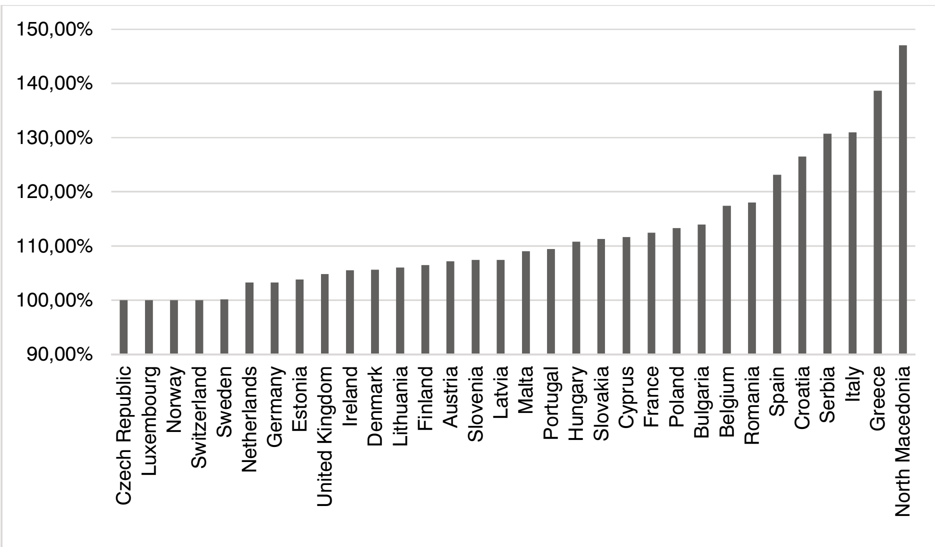

Figure 1: Results of the efficiency analysis

The low level of socio-economic efficiency of the EU countries can be justified by the fact that there is an obvious inequality in the EU countries. In the EU in 2017, the top 20% of the population (with the highest income) received 5.1 times more income than the bottom 20%, with this ratio varying significantly across the Member States, from 3.5 in the Czech Republic to 8.2 in Bulgaria (Income inequality in the EU, 2020). Additionally, it can be observed that the group of new EU members (EU13) globally has a higher average efficiency than the group of old members (EU15), which is in accordance with the findings of the group of authors Melecky, Stanickova and Hanclova (2019) who examined the level of social and economic development of the European Union (EU28) countries. The EU enlargement was supposed to provide the new EU member states (EU13) to converge towards the living standards achieved by the old EU member states (EU15), which is supported by the results of the analysis. Consequently, EU accession can be a chance to improve the living standards of candidate countries (Serbia and Northern Macedonia), which, according to the results of the analysis, are at the very bottom in terms of the achieved level of socio-economic efficiency.

To determine the robustness of the obtained results, a sensitivity analysis was performed. The sensitivity analysis of the results encompasses two types of analysis. The first one is a sensitivity analysis of model changes, and the second one is a sensitivity analysis of data variations. Regarding the sensitivity analysis of model changes, in addition to the assessed model, four complementary models were created (Table 2). Each of the models uses a different combination of output variables and assumes a uniform input, to examine the impact of output variable choice on the results as suggested by Nissi and Sarra (2018). The purpose of this sensitivity analysis is to examine the consistency of the obtained results (Cylus, Papanicolas & Smith, 2017), and to determine whether the efficiency of different countries depends on the selection of socio-economic indicators. The results of the correlation analysis indicate that regardless of the changes of variables in complementary models, there is a significant positive correlation between the results of the original model and each of the complementary models. Regarding the countries that were efficient in the original model, Switzerland remained efficient in all complementary models, Norway and the Czech Republic are efficient in all complementary models except Model 4, while Luxembourg is efficient in all complementary models except Model 3. Countries that were inefficient in the original model remained inefficient in the complementary models. Based on these results, it can be concluded that the results of the conducted efficiency analysis are consistent concerning changes in output variables as similar groups of countries form the efficiency frontiers in all model specifications.

Table 2: Complementary models and correlation coefficients

	Model 1	**Model 2**	**Model 3**	**Model 4**
Output variables	Median Equivalised Net Income	The employment rate	Median Equivalised Net Income	Median Equivalised Net Income
	GDP per capita PPS	GDP per capita PPS	The employment rate	GDP per capita PPS
	People at risk of poverty or social exclusion	People at risk of poverty or social exclusion	People at risk of poverty or social exclusion	The employment rate
Spearman's rho correlation coefficient	.779**	1.000**	.964**	.985**
Sig. (2-tailed)	.000	.000	.000	.000
N	32	32	32	32

To examine the effects of sampling variations on the DEA estimates bootstrapping was employed. The application of bootstrapping in the DEA may improve the reliability of the results since it offers the possibility to rectify the deviation of efficiency estimates and to provide the confidence intervals of efficiency measure (Simar & Wilson, 1998). The essence of bootstrapping is resampling by simulating the process of generating data to repeatedly evaluate parameters (Munim, 2020). Figure 2 discloses the sensitivity of efficiency scores concerning sampling variations. The results indicate that efficiency scores of European countries change when corrected for bias. The efficiency of all countries declined during the bootstrapping process which indicates that the obtained assessments of socio-economic efficiency might be overestimated since the original efficiency estimates almost overlap with the lower-bound.

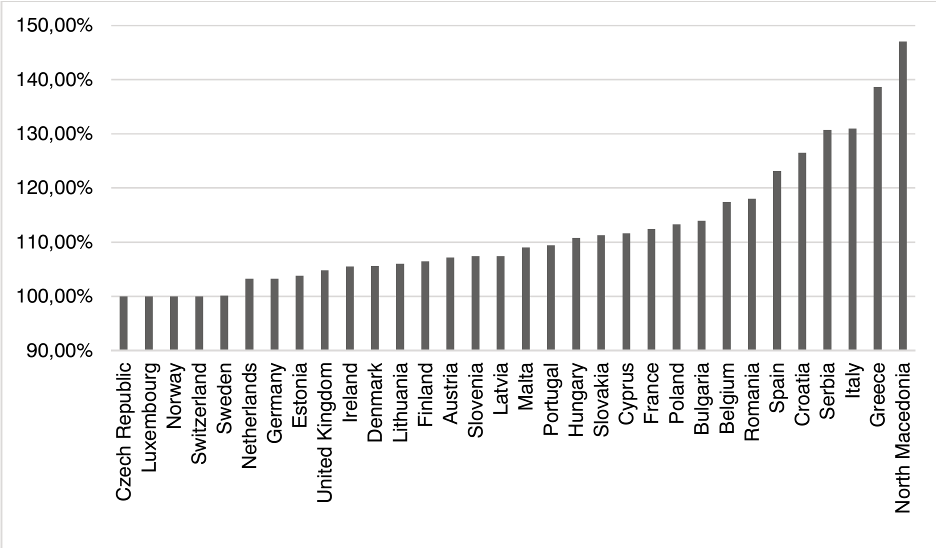

Figure 2: Confidence intervals and bootstrap efficiency

Conslusion

The need to measure the overall development of a national economy requires new approaches that take into account both economic and social indicators. The paper aimed to demonstrate the benefits of a non-parametric, DEA approach in the assessment of socio-economic efficiency, especially in conditions where undesirable outputs occur, which is a fairly common situation in sustainability studies. The implementation of the DEA method enables the integration of various aspects of development and enables decision-makers to adequately increase efficiency. The unique assessment provided by the DEA approach enables comparison of European countries. The benefit of this comparison is that policymakers are presented with a set of best countries that can be used as best practice for lagging countries. In other words, the most successful countries can provide guidance on establishing best practices to be adopted in the lagging countries, thus contributing to the implementation of sounder and more effective policies in the upcoming period.

Future research can be developed in different directions. One possible direction is to capture the pre-2018 period to track the evolution of country efficiency. It is also possible to carry out further analysis of effective countries in terms of their ranking using super-efficiency DEA. Incorporating environmental indicators to obtain a comprehensive measure of sustainability can also be worth exploring in future research.

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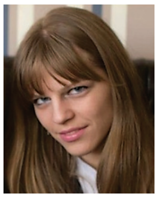

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