Use of indexes in evaluating environmental and health efficiency

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Abstract

Widespread in THE literature is the conclusion that air pollution is associated with various health problems. The present study discusses two discrete Data Envelopment Analysis (DEA) models and two related indexes. This approach has been adopted in previous research by Halkos & Argyropoulou (2021a, 2021b, 2022). Consequently, this paper uses inputs and insights published in the above-mentioned studies to evaluate the efficiency of managing pollutant levels in terms of health status at a country level. The main objective here is to offer useful tools to researchers, so that depending on their needs they can refer to the appropriate methodology, comparing the above evaluation models and presenting their capabilities, advantages and disadvantages.

Keywords Environmental Efficiency; Mortality; DEA; Energy; Air pollution; Health effects; Sustainable Development Goals; Bertelsmann Index; Distance Measure Index.

JEL Codes: C67; I10; I15; O13; O44; Q01; Q40; Q53; Q56.

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1. Introduction

Air pollution is the deterioration of air quality because of changes that occur (e.g., chemical or physical) caused by nature itself or due to human activities. Air pollution is divided into indoor and outdoor pollution. Indoor air pollution refers to the air we breathe at home and generally indoors. Both natural and man-made causes cause outdoor air pollution. The main sources in the case of pollution generated by nature outdoors are biological decay volcanoes, lightning, and forest fires with the sulfur and nitrous oxides emitted. Furthermore, grasses, plants, trees, and dust storms with the particles emitted contribute to increased pollution levels. Outdoor air pollution attributed to anthropogenic activities is widely caused by fossil fuel burning. Most specifically, this situation is based on the use of coal, oil, and natural gas in power plants—also, industrial units, refineries, households, and transportation (e.g., old vehicles) contribute to this type of pollution (Halkos 1993, 1994; Halkos et al., 2021).

The assumption that air pollution devastates the health status of organisms is not recent. This was acknowledged in the first years of the 20th century. Specifically in 1930 in the Meuse valley (Firket, 1931) and in 1948 in Donora, Pennsylvania (Ciocco & Thompson, 1961), with the most important being the great London smog of 1952. The latter proved to be disastrous, as the very high levels of particulate-based smog. Consequently, various health effects and, primarily, respiratory tract infections, such as bronchitis, hypoxia, and bronchopneumonia, led to the death of 4000-12000 people. Not surprisingly, the reality of those years confirmed that increased concentration of air pollutants creates negative (adverse) impacts on human health status.

Interestingly, the economic aspect of such a situation deserves our attention. Air pollution is linked with considerable expenses for medical reasons. Based on calculations of the OECD (2016), these expenses were estimated at 21 billion dollars worldwide in 2015, with loss of both labor productivity (due to increase in days lost from illness), as well as to loss of land productivity. The latter is caused by acid rain, which releases toxic chemicals into the air, water, and soil. Cohen et al. (2005) claim that air pollution increases morbidity. Moreover, 800.000 annual premature deaths worldwide can be a global burden of disease because of outdoor air pollution. Finally, air pollution and the resulting health problems in an area deter foreign business and tourism and deterring foreign businesses and tourists, reducing revenue derived from these sectors.

Simultaneously, there is a rising interest for analytical and comparative reasons regarding the health care systems and questionable environmental efficiency within the context of non-parametric and parametric applications. In a literature review processed by Varabyova and Müller (2016), the health systems' efficiency concerning countries in the OECD was discussed. Additionally, Halkos and Tzeremes (2011) reviewed the current literature on performance measurements and processed conditional non-parametric methodologies to estimate efficiency levels regarding public health care provision at a regional level. Finally, Song et al (2012) investigate the various methodologies that have been used in the evaluation of environmental efficiency.

2. Background and Relevant Literature

The categories in which atmospheric pollutants are classified are four. The first category includes *gaseous pollutants* - for instance, SO_2, NO_x, CO, ozone and volatile organic compounds. Variations in atmospheric composition are largely due to gaseous pollutants, mainly emitted by burning fossil fuels. More specifically, sulfur dioxide (SO_2) is an extremely reactive gas with a strongly irritating odor. Carbon monoxide (CO) is an odorless, colorless gas formed due to burning biomass and incomplete combustion of carbon in fuels caused by transportation (e.g., vehicles) and power generation from coal-fired and heating (Godish, 2003). Specifically, carbon monoxide reduces the body's oxygen and relevant needs of the body's organs (e.g., heart and brain) and tissues. Furthermore, at very high levels, it is responsible for poisoning, creating death conditions. Ozone (O_3) consists of 3 bonded oxygen atoms. Ozone is the core element of smog and it is created because of the interaction between sunlight and releases from vehicles and or industry. Problems in health conditions caused by ozone inhalation are varied. Such are chest pain, cough, throat irritation and congestion, worsening bronchitis and asthma, and limiting lung function.

Volatile organic compounds (VOCs) are mainly indoor pollutants. Concentrations of VOCs are greater in indoor air environments than outdoors. VOCs can cause many serious health issues. Starting from nose, eye, and throat irritating health issues, they can create shortness of breath, dizziness, headaches, fatigue, nausea, and skin quality issues. Problems in health status include lung irritation, liver damage, kidneys, or central nervous system due to increased concentrations of these pollutants. Intense and long-lasting exposure to these pollutants will create health issues for the liver, kidneys, and central nervous system. On the contrary, short-term exposure does not cause particular health problems. In many cases, some sort of VOCs is under investigation since they cause cancers, whereas some are proven carcinogens. Therefore, the health effects caused by volatile organic compounds depend on the degree of concentration, the duration of exposure to the chemicals and the degree of sensitivity of the organism, as people with asthma, for example, are more sensitive.

The second category includes *persistent organic pollutants*. These pollutants include as dioxins. Dioxins are considered in the environment for a long period of time. They also accumulate in the food chain, mainly in the fatty tissue of animals. Dioxins are recognized as very toxic, and great attention should be paid to experts in the field to protect our health status. A wide range of problems have their roots in the toxicity of dioxins. Reproductive issues, developmental and hormonal problems, and immune system damage are some issues that should be considered. Moreover, the World Health Organization (2016) argues that this toxicity can cause cancer.

The third category concerns *heavy metals*. Heavy metals include mercury, lead, arsenic, cadmium, and other toxic metals. These pollutants are investigated in the environment. These releases are the output of processes that humans put into practice. For instance, heavy metals are released due to coal and waste burning, metal mining and smelting, industrial processes, and volcanic emissions as well (Lee et al., 2002; Godish, 2003). Due to their toxicity, high concentrations might be responsible for delays in the development process, many cancers, endocrine disorders, immune, kidney damage, neurological, and other disorders (Moreira & Moreira, 2004).

The last category is a *mixture of particles of different sizes and chemical compositions of PM10 and PM2.5*. These pollutants originate from soil and road dust, diesel exhaust, combustion and industrial process releases, construction and demolition, powdered pesticides, bioaerosols, and volcanic ash (Dickey, 2000; Brook et al., 2004). The toxicity of particles largely depends on their size, as the smaller they are, the easier it is for them to penetrate into the alveoli of the lungs, making them extremely dangerous to human health. (Brunekreef, 2005). More specifically, these pollutants cause severe health issues: premature deaths, heart or lung diseases, irregular heart rhythms, worsening asthma, non-fatal heart attacks, problematic lung function and increased respiratory symptoms such as airway irritation, coughing, or difficulty breathing. (Atkinson et al., 2010; Meister et al., 2012; Correia et al., 2013; Fang et al., 2013; Cadelis et al., 2014).

The connection of the above discussed air pollutants with the body systems they impact are presented in the following table (Table 1).

Table 1 Effects of pollutants on body systems

	SO_2	NO	Heavy metals	PM	O_3	CO	Dioxins
Respiratory system	x	x	x	x	x		
Cardiovascular system			x	x		x	x
Nervous system			x				x
Urinary system			x				
Digestive system							x
Exposure during pregnancy			x				x

From the above analysis, there is an understandable matching between air pollutants to various health problems regarding many body systems.

Another source of health problems, which according to WHO (2008) affects one third of the world's population, is also water pollution, which is closely related to poor hygiene and shortage drinking water safely, causing 1.6 million deaths annually (WHO, 2009). According to WHO (2002), the most serious waterborne diseases are cholera, acute diarrhoea, legionellosis and typhoid fever. In fact, cholera has re-emerged in Africa. Cholera was absent for almost a century. This issue should be of high importance and needs further and serious consideration (Ashbolt, 2004). Other diseases also linked to lack of water and poor sanitation are hepatitis A and E viruses, the parasitic protozoan Giardia lambia and rotaviruses (Ashbolt, 2004).

As mentioned above, air's pollution impacts on health status also have various economic effects. OECD (2016), categorizes these impacts into decreased labor productivity, greater health spending, and lower crop yields. In addition, (OECD, 2016) estimates that in 2060, globally, lost working days will be approximately 3.75 billion days. Furthermore, the cost of health effects due to air pollution in OECD countries (including deaths and illnesses) was estimated based on the Willingness-to-Pay approach to be $1.7 trillion in 2010 (OECD, 2014). The cost of premature deaths caused by air pollution concerning European Region countries is estimated at around 1.4 trillion dollars. The total cost of health effects caused by air pollution is estimated annually at approximately 1.6 trillion dollars. (WHO, 2015)

3. Methodologies and Data used

This study presents two Data Environmental Analysis (DEA) models and two indicators adopted to evaluate the effectiveness of managing pollutants concerning health status:

i) the DEA model in its simple form

ii) the DEA model under the two-step approach

iii) Two SDG indexes:

- the simple mean Bertelsmann Index (BI)
- the OECD's Distance Measure Index (DMI)

The analysis helps researchers to select the appropriate, for each case, research method.

3.1 The simple DEA model

3.1.1 The method

DEA is a non-parametric methodology. It uses the linear programming approach. It is employed to evaluate the relative efficiency of a group of comparable decision-making units (DMUs), by processing several inputs to create several outputs (Charnes et al., 1978). Practically, the estimated relative performance of each DMU is compared with the most efficient DMU. The most efficient DMUs in the sample is treated as a benchmark No assumptions are required concerning the production function and the relevant mathematical form that supports it. Furthermore, relationships that are hidden to other methodologies are disclosed.

Cooper et al. (2011) argue that DEA concerns either constant returns to scale (e.g., CRS DEA models), or variable returns to scale (e.g., VRS DEA models). In the first case, a change in inputs or outputs results in a proportional change in outputs or inputs respectively. In the second case, changes in inputs or outputs do not result in a proportional change in outputs or inputs respectively.

Assuming free disposal, which implies possibility not to use or destroy inputs or outputs without cost and convexity. This methodologically indicates that when two observations are possible, then all linear combinations between them are possible as well. The output set DEA estimator to measure the efficiency for a given input-output combination (x, y) can be defined as:

$$\hat{\Psi}_{DEA} = \{(x, y) \in \mathbb{R}_{+}^{p+q} \,|\, y \leq \sum_{i=1}^{n} \gamma_i Y_i ; x \geq \sum_{i=1}^{n} \gamma_i X_i \,, for\ (\gamma_i, \ldots, \gamma_n)$$

$$s.t. \sum \gamma_i = 1; \gamma_i \geq 0, i = 1, \ldots, n\}$$

where $\hat{\Psi}_{DEA}$ under the constraint $\sum_{i=1}^{n} \gamma_i = 1$ allows for VRS and is often referred as $\hat{\Psi}_{DEA-VRS}$ (Banker et al., 1984), while if the equality constrained $\sum_{i=1}^{n} \gamma_i = 1$ is dropped, then $\hat{\Psi}_{DEA}$ allows for CRS (Daraio and Simar, 2007).

In particular, adopting output orientation, the output efficiency score estimator is defined by solving the following linear program:

$$\hat{\lambda}(x_0, y_0) = \sup\{\lambda \,|\, (x_0, \lambda y_0) \in \hat{\Psi}_{DEA}\},$$

$$\hat{\lambda}(x_0, y_0) = \{\max \lambda \,|\, \lambda y_0 \leq \sum_{i=1}^{n} \gamma_i Y_i ; x_0 \geq \sum_{i=1}^{n} \gamma_i X_i ; \lambda > 0, for\ (\gamma_i, \ldots, \gamma_n)$$

$$s.t. \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0; i = 1, \ldots, n\}$$

While, using an input-orientation, the estimator of the input efficiency score can be defined by solving the following linear program (Daraio and Simar, 2007):

$$\hat{\theta}(x_0, y_0) = \inf\{\theta \,|\, (\theta x_0, y_0) \in \hat{\Psi}_{DEA}\},$$

$$\hat{\theta}(x_0, y_0) = \{\min \theta \,|\, \sum_{i=1}^{n} \gamma_i Y_i ; \theta x_0 \geq \sum_{i=1}^{n} \gamma_i X_i ; \theta > 0, for(\gamma_i, \ldots, \gamma_n)$$

$$s.t. \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0; i = 1, \ldots, n\}$$

Nevertheless, the biased efficiency scores from the application of traditional DEA models can be obtained (Löthegren and Tambout, 1999). Correcting for this bias is achieved using the DEA bootstrapping method (Simar and Wilson, 1998), which is a statistical process which replaces the original data set. This concerns an iterative replacement process which in turn creates a simulated data set. (Efron, 1979)

The bootstrapping estimated bias of $\hat{\theta}(x, y)$ is attained by the next equations:

$$\widehat{bias}[\hat{\theta}(x,y)] = B^{-1}\sum_{b=1}^{B}\hat{\theta}_b^*(x,y) - \hat{\theta}(x,y)$$

Hence, the bias corrected estimator is determined by the following subtraction:

$$\tilde{\hat{\theta}}(x,y) = \hat{\theta}(x,y) - \widehat{bias}[\hat{\theta}(x,y)]$$

$$= \hat{\theta}(x,y) - \left[B^{-1}\sum_{b=1}^{B}\hat{\theta}_b^*(x,y) - \hat{\theta}(x,y)\right]$$

$$= \hat{\theta}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}_b^*(x,y) + \hat{\theta}(x,y)$$

$$= 2\hat{\theta}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}_b^*(x,y)$$

where $\tilde{\hat{\theta}}(x,y)$ is the bias corrected estimator,

$\hat{\theta}(x,y)$ is the estimator of $\theta(x,y)$,

$\hat{\theta}^*(x,y)$ is the estimator of $\hat{\theta}(x,y)$,

B is the number of the bootstrapping generated pseudo – samples $X_n^{*,b}$, and $\hat{\theta}_b^*(x,y)$ is the Monte Carlo approximation of the $\hat{\theta}^*(x,y)$ distribution ($b = 1, \ldots, B$).

Then, the bootstrap (Simar and Wilson, 1998) algorithm a Return To Scale (RTS) test is adopted. The null hypothesis is the following:

$$H_0: \Psi^{\theta} \text{ is globally CRS}$$

Consequently, the alternative hypothesis is defined as:

$$H_1: \Psi^{\theta} \text{ is VRS}$$

It is used as test statistics the mean of the ratios of the efficiency scores:

$$T(X_n) = \frac{1}{n}\sum_{i=1}^{n}\frac{\hat{\theta}_{CRS,n}(x_i,y_i)}{\hat{\theta}_{VRS,n}(x_i,y_i)}$$

By construction $\hat{\theta}_{CRS,n}(x_i,y_i) \leq \hat{\theta}_{VRS,n}(x_i,y_i)$ we reject the null hypothesis if the statistics T is too small. The p-value of the H_0 is received by the following mathematical type:

$$p - value = Prob[T(X_n) \le T_{obs} | H_0 is\ true]$$

where T_{obs} is the value of T computed on the original observed sample X_n.

Due to the difficulty of p-value's accurate calculation, this value is approximated by using the bootstrap (Simar and Wilson, 1998) algorithm as follows:

$$p - value \approx \sum_{b=1}^{B} \frac{I(T^{*,b} \le T_{obs})}{B}$$

where $T^{*,b} = T(X_n^{*,b})$.

3.1.2 The empirical Application

In this research Halkos & Argyropoulou (2021a) use two DEA model specifications. The Model 1 considers as two inputs Capital Stock and Labor Force in a production function setup, while uses as a desirable output Gross Domestic Production (GDP) and as an undesirable (bad) output Mortality. The Model 2 concerns as an additional input Environmentally Related Tax Revenue, while the rest remain the same as in Model 1. The undesirable output of mortality due to pollution was treated using a directional distance function.

The data to process the analyses consider the years 2000, 2005, 2010, 2014, 2015 and 2016 and concern the European countries.[1] Table 1 presents the received p-values regarding the RTS test (with B=999). These p values concern each reference year and each of the two models adopted in the present study. As it is observed, based on the p-values the H_0 of CRS is accepted, whereas in the case of model 2 the null hypotheses of CRS is rejected, while the p-value = 0.0000. The results of the two DEA applications have been published in Computational Economics by Springer (Halkos and Argyropoulou, 2021a).

[1] The countries used are Austria, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, the Netherlands, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom The sources of the data were the following:

- OECD (https://stats.oecd.org/index.aspx?queryid=72722)
- Annual macro-economic database of the European Commission (https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/macro-economic-databese-ameco/download-annual-data-set-macro-economic-database-ameco_en#capital-stock)
- Knoema World Data Atlas (https://knoema.com/pjeqzh/gdp-per-capita-by-country-statistics-from-imf-1980-2023?country=Portugal)

DataMarket (https://datamarket.com/data/set/1uty/labor-force#!ds=1uty!1w3z=2z.31.6r.56.q:1w40=2&display=line).

Table 1 Returns to scale test results

	2000	2005	2010	2014	2015	2016
Model 1 (inputs: net capital stock, labor outputs: GDP, mortality (bad output))						
p value	0.0781	0.0731	0.033	0.036	0.0631	0.0991
Model 2 (inputs: environmentally related tax revenue, net capital stock, labor outputs: GDP, mortality (bad output))						
p value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

3.2 The two-stage DEA model

DEA models processed in two-steps are considered systems consisting of more than one interconnected process (Kao, 2009) through first-stage outputs called intermediate variables which are transformed into second-stage inputs (Zha and Liang, 2010). This approach is extensively adopted to elaborate on efficiency issues, for instance, in healthcare, environmental and energy matters.

3.2.1 The method

Two core structures exist: the series and the parallel structure. In a series structure all internal processes are linked in a serial form. In this case the outputs of each stage serve as an input to the next stage as an intermediate set of data. Figure 1 shows a series structure. To characterize this structure efficient (efficiency of the DMU), all processes must be efficient (Shahroudi et al., 2011).

Figure 1: A simple two-stage DEA series structure

In contrast, in a parallel structure, all processes operate independently as shown in Fig. 2 (Keikha-Javan and Rostamy-Malkhalifeh, 2016).

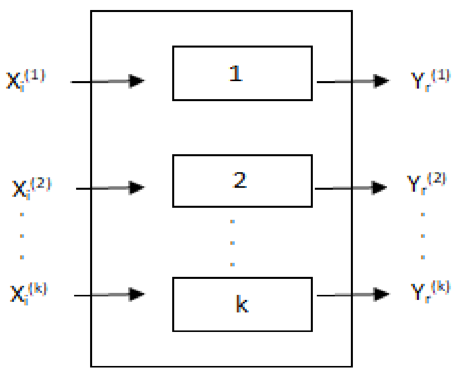

Figure 2: A parallel structure

A two-stage DEA system has four classifications (Halkos et al., 2014):

i) The independent two-stage DEA system. In this case no potential interaction between the two stages is present (Wang et al., 1997; Seiford and Zhu, 1999).

ii) The connected two-stage DEA approach. In this case the calculating process for the overall efficiency considers the interactions between the two stages (Chen and Zhu, 2004).

iii) The relational two-stage DEA model. In this case the overall and individual stage efficiencies are related with a mathematical relationship. This relationship can be additive (Chen et al., 2009) or multiplicative (Kao and Hwang, 2008).

iv) Finally, the game theory models (Liang et al., 2006, 2008). This approach explores the supply chain by considering a seller-buyer game under both non-cooperative and cooperative cases.

In the existing Literature, there is a considerable number of two-stage DEA studies. These studies include undesirable variables by adopting the additive model (Chen et al., 2009). Halkos & Argyropoulou (2021b) applied a modified multiplicative Kao and Hwang (2008) two-stage DEA model considering the existence of undesirable variables They used the R programming language. R programming language is a free and open-source (Ross Ihaka and Robert Gentleman in 1993 developed this language). This programming language can be used in statistical computing, for data analysis and robust scientific research. This approach by Halkos & Argyropoulou (2021b) is not observed in relevant studies. It widely enriches the existing literature and provides new opportunities in this research field.

The multiplicative two-stage model (Kao and Hwang, 2008) considers the conventional CCR (Charnes et al, 1978) DEA model. This model is used to measure the efficiency of DMUp. Interestingly, it assumes the constant returns-to-scale. According to this model if the i-th input of j-th DMU (j=1,…,n) is denoted by $X_{ij}, i = 1, \dots, m$ and the r-th output of j-th DMU (j=1,…,n) by $Y_{rj}, r = 1, \dots, s$, then the efficiency of DMUp is calculated by the following equations:

$$E_p = Max \frac{\sum_{r=1}^{s} w_r Y_{rp}}{\sum_{i=1}^{m} v_i X_{ip}} \tag{1}$$

$$\text{s.t. } \frac{\sum_{r=1}^{s} w_r Y_{rj}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1, \; j = 1, \dots, n$$

$$w_r, v_i \geq a, r = 1, \dots, s; i = 1, \dots, m$$

where α is a small non-Archimedean number (Charnes et al, 1979; Charnes and Cooper, 1984). Based on the model above, each DMU applies m inputs in order to produce s outputs. Ep stands for the relative efficiency score of DMUp. If E equals to1 then that DMUp is efficient. If Ep<1 then that DMUp is considered non efficient.

Model (1) represents a linear fractional program. This Model can be transformed into the following linear program:

$$E_p = Max \sum_{r=1}^{S} w_r Y_{rp} \tag{2}$$

$$\text{s.t. } \sum_{i=1}^{m} v_i X_{ip} = 1$$

$$\sum_{r=1}^{S} w_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0, j = 1, \dots, n$$

$$w_r, v_i \geq a, r = 1, \dots, s; i = 1, \dots, m$$

Taking into account the series two-stage DEA process (Figure 1), the efficiencies of DMUp in the first and the second stages are respectively determined as:

$$E_p^1 = \frac{\sum_{d=1}^{D} h_d^1 Z_{dp}}{\sum_{i=1}^{m} v_i X_{ip}} \text{ and } E_p^2 = \frac{\sum_{r=1}^{S} w_r Y_{rp}}{\sum_{d=1}^{D} h_d^2 Z_{dp}}$$

where v_i $(i = 1, \dots, m)$ and h_d^1 $(d = 1, \dots, D)$ are the input and output weights in the first stage and h_d^2 $(d = 1, \dots, D)$. The w_r $(r = 1, \dots, s)$ denote the input and output weights concerning the second stage.

Kao and Hwang (2008) document the efficiency DEA models of stage 1, , and stage 2, based on the following equations:

$$E_p^1 = Max \frac{\sum_{d=1}^{D} h_d Z_{dp}}{\sum_{i=1}^{m} v_i X_{ip}} \tag{2i}$$

$$\text{s.t. } \frac{\sum_{d=1}^{D} h_d Z_{dj}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1, \ j = 1, \dots, n$$

$$h_d, v_i \geq a, d = 1, \dots, D; i = 1, \dots, m$$

$$E_p^2 = Max \frac{\sum_{r=1}^{S} w_r Y_{rp}}{\sum_{d=1}^{D} h_d Z_{dp}} \tag{2ii}$$

$$\text{s.t. } \frac{\sum_{r=1}^{S} w_r Y_{rj}}{\sum_{d=1}^{D} h_d Z_{dj}} \leq 1, \ j = 1, \dots, n$$

$$w_r, h_d \geq a, r = 1, \dots, s; d = 1, \dots, D$$

Practically, these two models are the same as model (1). The overall efficiency model connects the two sub-processes developed by Kao and Hwang (2008) with regards to the following types:

$$E_p = Max \frac{\sum_{r=1}^{S} w_r Y_{rp}}{\sum_{i=1}^{m} v_i X_{ip}} \tag{3}$$

$$\text{s.t. } \frac{\sum_{r=1}^{S} w_r Y_{rj}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1,\ j = 1, \ldots, n$$

$$\frac{\sum_{d=1}^{D} h_d Z_{dj}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1, j = 1, \ldots, n$$

$$\frac{\sum_{r=1}^{S} w_r Y_{rj}}{\sum_{d=1}^{D} h_d Z_{dj}} \leq 1, j = 1, \ldots, n$$

$$w_r, v_i, h_d \geq a, r = 1, \ldots, s; i = 1, \ldots, m; d = 1, \ldots, D$$

Based on Charnes and Cooper (1962)'s transformation, models (2i), (2ii) and (3) can be converted into the linear programs (LP) for solution, as follows:

$$E_p^1 = Max \sum_{d=1}^{D} h_d Z_{dp} \tag{4i}$$

$$\text{s.t. } \sum_{i=1}^{m} v_i X_{ip} = 1$$

$$\sum_{d=1}^{D} h_d Z_{dj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0, j = 1, \ldots, n$$

$$h_d, v_i \geq a, d = 1, \ldots, D; i = 1, \ldots, m$$

$$E_p^2 = Max \sum_{r=1}^{S} w_r Y_{rp} \tag{4ii}$$

$$\text{s.t. } \sum_{d=1}^{D} h_d Z_{dp} = 1$$

$$\sum_{r=1}^{S} w_r Y_{rj} - \sum_{d=1}^{D} h_d Z_{dj} \leq 0, j = 1, \ldots, n$$

$$w_r, h_d \geq a, r = 1, \ldots, s; d = 1, \ldots, D$$

$$E_p = Max \sum_{r=1}^{S} w_r Y_{rp} \tag{5}$$

$$\text{s.t. } \sum_{i=1}^{m} v_i X_{ip} = 1$$

$$\sum_{r=1}^{S} w_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0, j = 1, \ldots, n$$

$$\sum_{d=1}^{D} h_d Z_{dj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0, j = 1, \ldots, n$$

$$\sum_{r=1}^{S} w_r Y_{rj} - \sum_{d=1}^{D} h_d Z_{dj} \leq 0, j = 1, \ldots, n$$

$$w_r, v_i, h_d \geq a, r = 1, \ldots, s; i = 1, \ldots, m; d = 1, \ldots, D$$

By solving model (5) optimal multipliers w_r^*, v_i^* and h_d^* can be obtained. As a result, the efficiencies are calculated as:

$$E_p = \frac{\sum_{r=1}^{S} w_r^* Y_{rp}}{\sum_{i=1}^{m} v_i^* X_{ip}}, \quad E_p^1 = \frac{\sum_{d=1}^{D} h_d^* Z_{dp}}{\sum_{i=1}^{m} v_i^* X_{ip}}, \quad E_p^2 = \frac{\sum_{r=1}^{S} w_r^* Y_{rp}}{\sum_{d=1}^{D} h_d^* Z_{dp}}$$

Multiplying the numerator and the denominator of E_p with the same quantity $\sum_{d=1}^{D} h_d^* Z_{dp}$, we receive:

$$E_p = \frac{\sum_{r=1}^{S} w_r^* Y_{rp} \cdot \sum_{d=1}^{D} h_d^* Z_{dp}}{\sum_{i=1}^{m} v_i^* X_{ip} \cdot \sum_{d=1}^{D} h_d^* Z_{dp}} \Rightarrow E_p = \frac{\sum_{d=1}^{D} h_d^* Z_{dp}}{\sum_{i=1}^{m} v_i^* X_{ip}} \cdot \frac{\sum_{r=1}^{S} w_r^* Y_{rp}}{\sum_{d=1}^{D} h_d^* Z_{dp}} \Rightarrow E_p = E_p^1 \cdot E_p^2$$

Yet, the optimal coefficients concerned by model (5) might not be unique. Consequently, the product may not be unique too. Therefore, comparing one or all DMUs has no common basis. To overcome this issue, the researcher can find that set of multipliers that creates the largest whereas maintaining the overall performance score by using (5). Consequently, model (6) is developed by Kao and Hwang (2008) based on the following types:

$$E_p^1 = Max \ \sum_{d=1}^{D} h_d Z_{dp} \tag{6}$$

$$\text{s.t. } \sum_{i=1}^{m} v_i X_{ip} = 1$$

$$\sum_{r=1}^{S} w_r Y_{rp} - E_p \sum_{i=1}^{m} v_i X_{ip} = 0$$

$$\sum_{r=1}^{S} w_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0, j = 1, \ldots, n$$

$$\sum_{d=1}^{D} h_d Z_{dj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0, j = 1, \ldots, n$$

$$\sum_{r=1}^{S} w_r Y_{rj} - \sum_{d=1}^{D} h_d Z_{dj} \leq 0, j = 1, \ldots, n$$

$$w_r, v_i, h_d \geq a, r = 1, \ldots, s; i = 1, \ldots, m; d = 1, \ldots, D$$

After estimating E_p^1 based on model (6), the efficiency regarding the second stage is given by $E_p = E_p^1 \cdot E_p^2$ as $E_p^2 = \frac{E_p}{E_p^1}$.

3.2.2 The empirical Application

In this research, Halkos & Argyropoulou (2021b) concern the performance of 23 countries[2] has been estimated from 1990 to 2017. Table 3 presents the 23 countries in research:

1	Australia	13	Japan
2	Austria	14	Luxembourg
3	Belgium	15	Netherlands
4	Canada	16	New Zealand
5	Denmark	17	Norway
6	Finland	18	Portugal
7	France	19	Spain
8	Germany	20	Sweden
9	Greece	21	Switzerland
10	Iceland	22	United Kingdom
11	Ireland	23	United States
12	Italy		

Table 3 The list of the 23 countries used in the analysis

Figure 3 shows the model's structure:

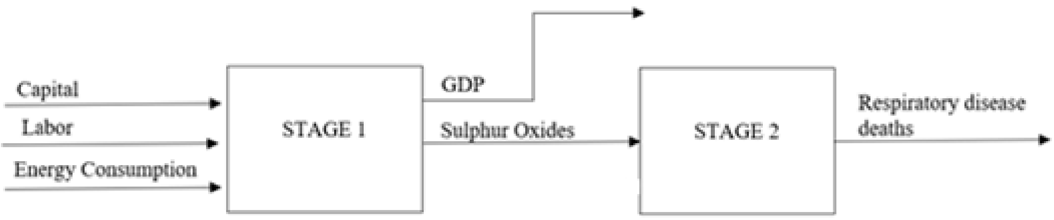

Figure 3: The presentation of the proposed two stage model

The above presentation shows that labor force, capital stock, and energy use are treated as inputs in the first stage. GDP serves as the desirable output. This output comes from the first stage. SO_x are treated as undesirable output. They turn into an input of the second stage. Also, production respiratory disease deaths are used as undesirable output coming from the second stage. It would be essential to note that smoking is the most common cause of respiratory disease. Notwithstanding, sulfur oxides is another core source for respiratory disease.

The modification processed by Halkos & Argyropoulou (2021b) concerning the multiplicative Kao and Hwang (2008) model is presented in the following lines. Let us denote as:

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[2] The sources of the data used were the following:

- European commission (https://ec.europa. eu/economy_finance/ameco/user/serie/ResultSerie.cfm)
- World Bank database (https://data.worldbank.org/)
- Eurostat (https://ec.europa.eu/eurostat/tgm/table.do?tab=table&plugin=1&language=en&pcode=sdg_07_11)
- The OECD (https://stats.oecd.org/)
- Our world in data (https://ourworldindata.org/grapher/respiratory-disease-deaths-by-age?country=GRC)

X_{ij}, the i-th input of j-th DMU (j=1,…,n)

Z_{dj}^{D}, the d-th desirable intermediate variable of j-th DMU (j=1,…,n)

Z_{kj}^{U}, the k-th undesirable intermediate variable of j-th DMU (j=1,…,n)

Y_{rj}^{U}, the r-th undesirable output of j-th DMU (j=1,…,n)

After transforming the Seiford and Zhu (2002) of the undesirable variables, the Kao and Hwang (2008) model is transformed as:

$$E_p = Max \frac{\sum_{r=1}^{S} w_r Y_{rp}^{U}}{\sum_{i=1}^{m} v_i X_{ip}} \tag{7}$$

$$\text{s.t.} \quad \frac{\sum_{r=1}^{S} w_r Y_{rj}^{U}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1, j = 1, \dots, n$$

$$\frac{\sum_{d=1}^{D} h_d Z_{dj}^{D} + \sum_{k=1}^{K} u_k Z_{kj}^{U}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1, j = 1, \dots, n$$

$$\frac{\sum_{r=1}^{S} w_r Y_{rj}^{U}}{\sum_{k=1}^{K} u_k Z_{kj}^{U}} \leq 1, j = 1, \dots, n$$

$$w_r, v_i, h_d, u_k \geq a, r = 1, \dots, s; i = 1, \dots, m; d = 1, \dots, D; k = 1, \dots, K$$

$$E_p^1 = Max \frac{\sum_{d=1}^{D} h_d Z_{dp}^{D} + \sum_{k=1}^{K} u_k Z_{kp}^{U}}{\sum_{i=1}^{m} v_i X_{ip}} \tag{8}$$

$$\text{s.t.} \quad E_p = \frac{\sum_{r=1}^{S} w_r Y_{rp}^{U}}{\sum_{i=1}^{m} v_i X_{ip}}$$

$$\frac{\sum_{r=1}^{S} w_r Y_{rj}^{U}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1, j = 1, \dots, n$$

$$\frac{\sum_{d=1}^{D} h_d Z_{dj}^{D} + \sum_{k=1}^{K} u_k Z_{kj}^{U}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1, j = 1, \dots, n$$

$$\frac{\sum_{r=1}^{S} w_r Y_{rj}^{U}}{\sum_{k=1}^{K} u_k Z_{kj}^{U}} \leq 1, j = 1, \dots, n$$

$$w_r, v_i, h_d, u_k \geq a, r = 1, \dots, s; i = 1, \dots, m; d = 1, \dots, D; k = 1, \dots, K$$

The transformations of Charnes and Cooper's (1962), modify models (7) and (8) into the next linear programs (LP) for solution:

$$E_p = Max\ \sum_{r=1}^{S} w_r Y_{rp}^{U} \tag{9}$$

$$\text{s.t. } \sum_{i=1}^{m} v_i X_{ip} = 1$$

$$\sum_{r=1}^{S} w_r Y_{rj}^{U} - \sum_{i=1}^{m} v_i X_{ij} \leq 0, j = 1, \dots, n$$

$$\sum_{d=1}^{D} h_d Z_{dj}^{D} + \sum_{k=1}^{K} u_k Z_{kj}^{U} - \sum_{i=1}^{m} v_i X_{ij} \leq 0, j = 1, \dots, n$$

$$\sum_{r=1}^{S} w_r Y_{rj}^{U} - \sum_{k=1}^{K} u_k Z_{kj}^{U} \leq 0, j = 1, \dots, n$$

$$w_r, v_i, h_d, u_k \geq a, r = 1, \dots, s; i = 1, \dots, m; d = 1, \dots, D; k = 1, \dots, K$$

$$E_p^1 = Max\ \sum_{d=1}^{D} h_d Z_{dp}^{D} + \sum_{k=1}^{K} u_k Z_{kp}^{U} \tag{10}$$

$$\text{s.t. } \sum_{i=1}^{m} v_i X_{ip} = 1$$

$$\sum_{r=1}^{S} w_r Y_{rp}^{U} - E_p \cdot \sum_{i=1}^{m} v_i X_{ip} = 0$$

$$\sum_{r=1}^{S} w_r Y_{rj}^{U} - \sum_{i=1}^{m} v_i X_{ij} \leq 0, j = 1, \dots, n$$

$$\sum_{d=1}^{D} h_d Z_{dj}^{D} + \sum_{k=1}^{K} u_k Z_{kj}^{U} - \sum_{i=1}^{m} v_i X_{ij} \leq 0, j = 1, \dots, n$$

$$\sum_{r=1}^{S} w_r Y_{rj}^{U} - \sum_{k=1}^{K} u_k Z_{kj}^{U} \leq 0, j = 1, \dots, n$$

$$w_r, v_i, h_d, u_k \geq a, r = 1, \dots, s; i = 1, \dots, m; d = 1, \dots, D; k = 1, \dots, K$$

After computing E_p and E_p^1 from models (9) and (10), the efficiency of the second stage is calculated as $E_p^2 = \frac{E_p}{E_p^1}$.

The test results of the two stage DEA application have been published in Air Quality, Atmosphere and Health by Springer (Halkos and Argyropoulou, 2021b)

3.3 SDG indexes

The performance of the 3rd Sustainable Development Goal titled 'Good health and well-being' at the country level is estimated by adopting the following methods:

- The simple mean Bertelsmann Index – BI (Lafortune et al., 2018; Sachs et al., 2018)
- The OECD's Distance Measure Index – DMI (OECD, 2017)

3.3.1 The methods

i) Bertelsmann Index (Lafortune et al., 2018; Sachs et al., 2018)

Sachs et al. (2018) use the following rescaling equation to achieve the normalization for comparability. We apply this approach and rescale the individual indicators from 0 to 100:

$$R = \frac{R_j - \min(R)}{\max(R) - \min(R)}$$

Where R_j the value of indicator j

After this rescaling process concerning the variables, their weighting and concentration is demanded to calculate the SDG index.

There are many procedures to aggregate. For instance, the Leontief production function, geometric mean, and arithmetic mean. Halkos & Argyropoulou (2022) used the widely known arithmetic mean method, because of its simplicity and explication, adopting the following type:

$$T_i^I = \sum_{j=1}^{N} \frac{1}{N_i} \cdot \frac{R_{ij} - \min(R_{ij})}{\max(R_{ij}) - \min(R_{ij})}$$

where N_i is the number of SDG's indicators for country i,

R_{ij} is the value of indicator j in country i

According to the Bertelsmann Index (BI) simple mean formula the normalization of the calculated scores to the 0-1 scale is preceded. The higher the BI score, the better the country's performance, and vice versa.

The results of the BI scores have been published in Ecological Economics by Elsevier (Halkos and Argyropoulou, 2022)

ii) The Distance Measure Index (OECD, 2017)

This measure concerns a country's distance from a certain (specified) target score with reference to that indicator. To calculate this index for an SDG target, a country's distance from each indicator's specified target score is first calculated. The quotient of this distance to the standard deviation of the index scores across all countries is then calculated. The maximum value between this quotient and zero is found. This maximum estimator is then divided by the number of indices and lastly these are added.

Thus, we have the following formula:

$$T_i^{II} = \sum_{j=1}^{N} \frac{1}{N_i} \max\left\{\frac{S_{ij} - K_j}{SD_j}, 0\right\}$$

where S_{ij} is the score value of indicator j for country i,

K_j is the target score for indicator j

N_i is the number of indicators

SD_j is the Standard Deviation of indicator j in all countries.

$T_i^{II} = 0$ means for a country that its target score has been achieved.

After the computation of the above indexes, Halkos & Argyropoulou (2022) have made forecast of the DMI scores for each country to decide which specific countries will have zeroed them by 2030.

This index measures each country's distance from its targeted goal. Therefore, the smaller the Distance Measure Index (DMI), the better the country's performance, and vice versa. As a target has been set the reduction of each variable by 40%.[3] (Halkos & Argyropoulou, 2022)

The results of the DMI scores have been published in Ecological Economics by Elsevier (Halkos and Argyropoulou, 2022)

3.3.2 The empirical Application

This paper concerns the SDG target 3.9: “By 2030, substantially reduce the number of deaths and illnesses from hazardous chemicals and air, water and soil pollution and contamination”

Target 3.9 is linked with the following three indicators:

- **Indicator 3.9.1:** “Mortality rate attributed to household and ambient air pollution”.
- **Indicator 3.9.2:** “Mortality rate attributed to unsafe water, unsafe sanitation and lack of hygiene”.
- **Indicator 3.9.3:** “Mortality rate attributed to unintentional poisoning.”

[3] This percentage has been chosen since this is an achievable target (neither too strict, nor too lax).

Thus, the following variables have been used in the analysis:

a) Death Rate from air pollution

b) Death Rate from poisonings

c) Death Rate from poor sanitation

d) Death Rate from unsafe water

The data[4] used concern 107 countries (Table 4) for the period 1990 to 2017. The countries were selected based on the countries' income classification defined by the World Bank for 2020-2021, in order to facilitate the comparison of results and useful conclusions based on each country's income to be drawn. This classification includes the following four income categories:

i) Low income <1.036

ii) Lower – middle income 1.036 – 4.045

iii) Upper – middle income 4.046 – 12.535

iv) High income >12.535

Thus, as shown on Table 4 below, there are 14 low income countries, 22 lower – middle income countries, 24 upper – middle income countries and 47 high income countries.

Low income countries	Lower-middle income countries	Upper-middle income countries	High income countries	
Afghanistan	Albania	Angola	Australia	Korea, Rep.
Burkina Faso	Algeria	Argentina	Austria	Kuwait
Burundi	Bangladesh	Armenia	Bahrain	Latvia
Eritrea	Bolivia	Azerbaijan	Barbados	Lithuania
Ethiopia	Cabo Verde	Belarus	Belgium	Luxembourg
Haiti	Cameroon	Bosnia and Herzegovina	Canada	Malta
Liberia	India	Brazil	Chile	Netherlands
madagascar	Kenya	Bulgaria	Croatia	New Zealand
Mali	Mauritania	China	Cyprus	Norway
Mozambique	Moldova	Georgia	Czech Republic	Oman
Sierra Leone	Mongolia	Guatemala	Denmark	Panama
Sudan	Morocco	Indonesia	Estonia	Poland
Tajikistan	Nepal	Iraq	Finland	Portugal
Uganda	Nicaragua	Jordan	France	Qatar
	Nigeria	Kazakhstan	Germany	Romania
	Pakistan	Malaysia	Greece	Saudi Arabia
	Philippines	Maldives	Hungary	Singapore
	Senegal	Montenegro	Iceland	Slovak Republic
	Tunisia	North Macedonia	Ireland	Slovenia
	Ukraine	Peru	Israel	Spain
	Uzbekistan	Russian Federation	Italy	Sweden
	Zimbabwe	Serbia	Japan	Switzerland
		Thailand		United Kingdom
		Turkey		United States
				Uruguay

Table 4 The list of the 107 countries by income category

[4] The source of the data used is: https://Ourworldindata.org

4 Conclusions

Below are the conclusions for each methodology described, as according to Halkos & Argyropoulou (2021, 2021, 2022) have been derived.

4.1 The simple DEA model

Based on the bias corrected scores the core conclusions that can be drawn are (Halkos & Argyropoulou, 2021a):

- In the first specification model the higher efficient countries over the years are Sweden, Finland and France.
- Concerning the second model, Slovenia, Denmark, UK, Netherlands, Sweden and France proved to be most efficient countries over the years.
- Sweden is the most efficient having on average the maximum efficiency scores.
- In the first specification, Slovak Republic, Hungary, Poland and Greece are the less efficient countries having on average the highest rates of mortality and very low levels of GDP/c.
- In the second specification, Slovak Republic, Hungary, Poland, Greece and Estonia are the less efficient countries having on average the highest rates of mortality and very low levels of GDP/c.
- Countries that have the GDP/c can achieve greater overall health, wellbeing and healthcare/medical status (standards). Thus, the above conclusions could be justified by the fact that the richer the country is, the lower death rates from air pollution. (Ritchie and Roser, 2017)
- On the contrary, countries with low GDP/c levels may have lower overall health and healthcare quality resulting in a higher burden because of pollution-related disease (Akhtar et al., 2002).
- Finally, the following Table shows that there is a small percentage difference between the two models in the mean efficiency scores. Thus, the effect of environmental tax revenue on the efficiency scores seems to be negligible.

Table 2 Summary of the mean efficiency scores

	Mean efficiency scores		
	Model 1	Model 2	% Change
2000	0.703031	0.754217	7.28
2005	0.660469	0.696471	5.45
2010	0.706183	0.704951	−0.17
2014	0.6916	0.693486	0.27
2015	0.614446	0.588087	−4.29
2016	0.611766	0.589112	−3.70

4.2 The two-stage DEA model

Based on the data statistics, although SO_X is reduced, in most of the cases, in most of the countries, the respiratory disease deaths are rising from 1990 to 2017. This situation can be explained by other determinants (factors) that may create respiratory illnesses, for instance, the $PM_{2.5}$, or smoking, in which there is also a reduction over time. Linking together all these factors increases in deaths can be noted due to respiratory diseases. (Halkos & Argyropoulou, 2021b)

According to the efficiency scores, no country demonstrates efficiency in overall terms, since $E_p<1$. For all of the countries efficiency levels decreases over the years. Considering the last three years, the performance of the 23 selected countries in producing is better than in reusing the undesirable pollutant output (SO_X). ($E_p^1>E_p^2$)

4.3 SDG indexes

4.3. i) Simple mean Bertelsmann index

The average value of the BI is greater for low-income countries than high-income countries in the period of years considered. Hence BI and income are positively related. (Halkos & Argyropoulou, 2022). In addition, the average BI for the two lowest income categories shows a downward trend, in contrast to the upward trend of the average BI noted in the other two highest income categories. (Halkos & Argyropoulou, 2022).

4.3. ii) Distance Measure Index

According to the DMI scores, countries' DMI performance and their income are negatively related. Additionally, the majority of the countries are closely reaching the target set for reducing the variables by 40%, since the DMI decreases over the time. Halkos & Argyropoulou (2022) have forecast that the majority of countries will approach their goal until 2030 belong to the upper – middle- and high-income categories.

Overall, it can be said that countries' performance with high income are better on both indexes compared to low-income countries. Thus, high-income countries have a better chance to meet the Sustainable Development health goals linked to environment related issues by 2030.

Comparing the two indexes, Halkos & Argyropoulou (2022) drew the following conclusions:

- BI seems to be more reliable compared to DMI, since BI gives a clearer relationship between the index and income (high income countries are in first place, low-income countries are in last place). Based on the DMI some countries appear in the first place despite the fact that they belong to the third income category, whereas other countries appear in the last place despite belonging to the second income category.

- The BI is more objective than DMI which is considers the subjective goal that is each time determined, depending on how strict or relaxed is the preferable.

- On average the two indexes confirm each other and both of them confirm the relationship between the two indexes with per capita income. This is illustrated in an antisymmetric relationship between them.

Consequently, environmental performance is better for wealthy countries than for poor countries. Ineffective policies or their hesitation to handle the issues derived from air pollution could be an explanation for this lower index evaluation concerning the performance countries with low income (Halkos & Argyropoulou, 2022)

5 Discussion and Policy Implications

This paper summarizes the methodologies used in the research by Halkos & Argyropoulou (2021a, 2021b, 2022). The goal is for researchers dealing with these issues to acquire the tools they need, so that depending on their needs they can refer to the appropriate methodology. For this purpose, the capabilities, advantages and disadvantages of the above methodologies are summarized below.

The methods described are used to measure efficiency. Their main differences consist in the information we can get from their results.

The simplest method is that of simple DEA model, which, like the two-stage DEA model, allows us to handle undesirable outputs, using the Seiford & Zhu (2002) transformation as described above. In addition, with bias correction, the results are becoming more reliable.

Two-stage DEA model also handles undesired outputs. But the information we get from this is greater, as in addition to the overall efficiency's scores, it also gives us the individual of each stage efficiency's scores. For instance, as aforementioned, Halkos & Argyropoulou (2021a), in their research, compared the efficiency scores of stage 1 with these of stage 2, concluding that countries perform better in producing than in reusing the pollutant output, as Ep1>Ep2. While the overall efficiency scores (Ep) lead to the conclusion that there is no overall efficient country. Consequently, it is obvious that the information is greater and the conclusions more targeted.

The use of BI and DMI indexes are relatively simple as their calculation is based on simple formulas. They are comparable to each other, since as proved by Halkos & Argyropoulou (2022) there is an antisymmetric relationship between them. In addition, they give useful information from the prediction of their values, while allowing the researcher to investigate factors that may affect the achievement of the defined goals. In Halkos & Argyropoulou's (2022) application this factor was income. Alternatively, factors such as geographic location or educational level could be added. Even more, they may be related to issues of cultural dimensions (Halkos & Petrou, 2019), waste management (Halkos & Aslanidis, 2024) as well as to qualitative aspects of the effect of stress and dissatisfaction on employees during any crisis, economic (Halkos & Bousinakis, 2017) or environmental (Halkos & Polemis, 2016).

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