An additive two-stage DEA approach creating sustainability efficiency indexes

George Halkos and Nickolaos Tzeremes

University of Thessaly, Department of Economics

February 2013

An additive two-stage DEA approach creating sustainability efficiency indexes

By

George E. Halkos, Nickolaos G. Tzeremes, Stavros A. Kourtzidis

Laboratory of Operations Research, Department of Economics, University of Thessaly, Korai 43, 38333, Volos, Greece

Abstract

In this paper we apply an additive two-stage data envelopment analysis (DEA) estimator on a panel of 27 Annex I countries for the time period 2006-2010 in order to create sustainability efficiency indexes. The sustainability efficiency indexes are decomposed into economic and eco-efficiency indicators. The results reveal inequalities among the examined countries between the two stages. The eco-efficiency stage is characterized by large inequalities among countries and significantly lower efficiency scores than the overall or/and the economic efficiency stage. Finally, it is reported that a country's high economic efficiency level does not ensure a high eco-efficiency performance.

Keywords: Additive two-stage DEA; Sustainability efficiency index; Annex I countries.

JEL Codes: C14; O44; Q50

1. Introduction

Environmental degradation and pollution due to human economic activities have entered the public and political dialogue the last few decades. The major environmental problems such as global warming, ozone depletion, contamination of air and water and acidification are complex and can not be dealt with by a single nation, therefore international cooperation is needed. Tol (2001) claimed that separate individual attempts are unlikely to have a significant impact on the environment.

In the past, traditional policies dealt with the environmental problems by applying an ex-post management which is likely to cause devastating and irreversible outcomes to the environment (Zofio and Prieto, 2001). This situation began to change from the Earth Summit in Rio in June 1992. From then on, a great number of nations have adapted sustainable development and sustainability principals (Callens and Tyteca, 1999). Sustainability is multidimensional and envelops socio-economic, biological and ecological aspects. According to Brundtland's report (1987) sustainable development refers to the "*development that meets the needs of the present without compromising the ability of future generations to meet their own needs*".

An important instrument of sustainable development is eco-efficiency. Kuosmanen and Kortelainen (2005) define eco-efficiency as the ability to produce the maximum level of economic output while causing the least possible environmental deterioration. It is clear that the notion of eco-efficiency encompasses both economic and ecological aspects and it can be applied either at firm or national level. Huppes and Ishikawa (2005) note that eco-efficiency is a misinterpreted concept and describe the four possible types of eco-efficiency, that are: environmental productivity, environmental intensity, environmental cost improvement and environmental cost effectiveness. Environmental productivity is the ratio of economic output to environmental pressure while environmental intensity is exactly the opposite ratio, thus environmental pressure to economic output. In addition, environmental cost improvement is the ratio of environmental improvement cost divided by environmental improvement while environmental cost effectiveness is exactly the inverse ratio. In this study we use the notion of environmental intensity to assess eco-efficiency.

Judging from the above indices, one might think that a rise in economic activity is considered as a negative factor for the environment which is a rather static view of the reality (Porter and van der Linde, 1995). In a dynamic point of view this may not be the case. Tyteca (1996) notes that there are a large number of firms which have realized the benefits they might gain by building a more environmental friendly profile. This concept is in line with dynamic competitiveness (Porter and van der Linde, 1995) which defines a firm as a competitive if it constantly makes advancements and innovations in every sector, such as the environment.

In order for a firm, an organization, a country or a multinational panel of countries to achieve dynamic competitiveness, it must embrace sustainable development. To this end, researchers have to provide the policy makers with the appropriate tools for measuring sustainability and eco-efficiency. Consequently, measures of economic performance have to be adjusted in order to incorporate environmental impacts. A widely used approach is the construction of environmental indices by using data envelopment analysis (DEA). DEA is an appropriate tool for efficiency measurement when there is a need to aggregate multiple inputs and outputs, which are measured in different units, into a single index. DEA evaluates the efficiency of simple structures, decision making units, which utilize inputs to produce outputs. When the situation demands complex structures there is a need for more sophisticated models such as two-stage DEA models.

In this paper we see the environmental sustainability problem as a composite problem consisting by economic and eco-efficiency. In order to create countries' sustainability efficiency indexes we apply the additive two-stage DEA model (Chen et al., 2009) at a group of 27 Annex I countries.[1] We construct an index of economic efficiency at the first stage and an index of eco-efficiency in the second stage, which are combined into an overall sustainability efficiency index.

The remainder of this paper is organized as follows. Section 2 is a review of the DEA literature on environmental indices and on two-stage DEA models. Section 3 introduces the data and the methodology of two-stage DEA models while in Section 4 the empirical application is provided. The last section concludes the paper.

2. Literature review

2.1. DEA environmental indices

In order for a model to represent the true production process, the joint production of desirable and undesirable outputs is necessary (Pasurka, 2006). The most challenging aspect in constructing an environmental DEA index is the incorporation of undesirable outputs. Traditional DEA models can not deal with undesirable outputs because in such a model we can only decrease inputs and increase outputs, hence we can not decrease an output even if it is not desirable. Here we present a number of approaches which deal with undesirable outputs. For a more detailed review Tyteca (1996) presents environmental performance at a firm base and Zhou et al. (2008a) review DEA techniques on energy and environment.

[1] Annex I countries are industrialized countries which are members of the OECD and economies in transition, who have signed the Kyoto protocol.

We can categorize the available environmental DEA models either by their reference technology or by the type of the efficiency measurements (Zhou et al., 2008a). Relatively to the reference technology one can apply a monotone decreasing transformation, such as the use of the outputs' reciprocals (Lovel et al., 1995) and the data translation at undesirable outputs while assuming strong disposability for inputs, desirable outputs and the transformed undesirable outputs (Seiford and Zhu, 2002, 2005).

The other approach is to apply weak disposability at undesirable outputs proposed by Fare et al. (1989). The weak disposability implies that in order to decrease undesirable outputs we must also decrease desirable outputs proportionally[2]. In a different approach, Sueyoshi and Goto (2012a, b) introduce the concept of natural and managerial disposability into DEA analysis. Natural disposability refers to the case where a firm reduces its inputs in order to reduce its undesirable outputs as a negative reaction to a change in environmental regulation. Managerial disposability refers to the case where a firm increases its inputs in order to exploit the business opportunity after a change in environmental regulation.

Relatively to the type of efficiency, radial efficiency measurements imply proportional increases or decreases for both desirable and undesirable outputs (Zhou et al., 2008b; Sueyoshi and Goto, 2012c). Non-radial efficiency measurements imply non-proportional change in both types of outputs (Zhou et al., 2007; Sueyoshi and Goto, 2011). Hyperbolic efficiency measurements allow for a simultaneous increase in desirable outputs and decrease in undesirable outputs (Färe et al., 1989; Zaim and Taskin, 2000; Zofio and Prieto, 2001; Taskin and Zaim, 2001). Directional distance function efficiency measurements allow for a simultaneous increase in desirable

[2] For an interesting discussion regarding weak disposability see the works by Kuosmanen (2005), Färe and Grosskopf (2009), Kuosmanen and Podinovski (2009) and Kuosmanen and Matin (2011).

outputs and decrease in undesirable outputs based on a predetermined direction vector (Chung et al., 1997; Picazo-Tadeo et al., 2005; Picazo-Tadeo and Prior, 2009; Picazo-Tadeo et al., 2012; Halkos and Tzeremes, 2013).

Specifically, Zhou et al. (2008b) apply a radial DEA model with non-increasing returns to scale (NIRS) and variable returns to scale (VRS) at eight world regions. They employ energy to produce GDP as a desirable output and CO_2 as an undesirable output. Sueyoshi and Goto (2012c) utilize a radial DEA model to assess the efficiency of US coal fired power plants. CO_2, SO_2 and NO_X are the air pollutants which are considered in the model. Conversely, Zhou et al. (2007) employ a non-radial model to measure the environmental performance of 26 OECD countries and a non-radial Malmquist Productivity Index to assess the efficiency over time. The authors use labor force and primary energy consumption as inputs, GDP as desirable output and CO_2, SO_X, NO_X and CO as undesirable outputs. Furthermore, they argue that since non-radial model has higher discriminating power, it is more appropriate to be used in assessing environmental efficiency. Sueyoshi and Goto (2011) evaluate the efficiency of Japanese fossil fuel power generation by utilizing a non-radial DEA model with separation between desirable and undesirable outputs and also between energy and non-energy inputs. The authors use CO_2 as the only bad output.

Färe et al. (1989) construct a hyperbolic environmental efficiency measure which satisfies weak disposability. Thus this model seeks to simultaneously increase the good output and decrease the bad output. Zaim and Taskin (2000) apply hyperbolic efficiency model to OECD countries for the period 1980-1990, using capital stock and total labor as inputs, GDP as desirable output and CO_2 as the only undesirable output. Zofio and Prieto (2001) study 14 OECD countries and mark the significance of carbon dioxide in air pollution which along with the other greenhouse gases (CH_4, N_2O and CFCs) is responsible for global warming. Taskin and Zaim (2001) use Zaim and Taskin's (2000) model and investigate the existence of the environmental Kuznets curve (EKC).

EKC hypothesis implies an inverted U-shaped relationship between income per capita and environmental quality and takes its name from Kuznets (1955). An increase in income per capita results into environmental degradation up to a certain threshold beyond which an additional increase in income per capita results into an increase in environmental quality. This can be explained by the demand of relatively wealthy people for environmental quality. Taskim and Zaim (2001) confirm EKC hypothesis and they also find significant impact of trade openness on environmental quality.

Halkos and Tzeremes (2009) employ a DEA window analysis and investigate the existence of EKC for 17 OECD countries. The authors use sulphur emissions as an undesirable variable and they find no evidence of support for the EKC hypothesis. In fact, Dinda (2004) in a detailed review of the literature draws the conclusion that specific air pollutants like sulphur dioxide, suspended particulate matters, carbon monoxide and nitrous oxides exhibit an inverted U-shaped relationship while other pollutants such as carbon dioxide does not. Particularly, carbon dioxide reveals a monotonic increase as per capita income increases.

The directional distance function (DDF) approach originates from Luenberger (1992). Chung et al. (1997) utilize a DDF to construct a Malmquist-Luenberger productivity index which is then applied at Swedish paper and pulp industry. This novel index allows to credit for contractions in undesirable outputs. Picazo-Tadeo et al. (2005) examine the Spanish ceramic tile industry and argue the DDF provides the necessary flexibility for the cost assessment of pollution restrictive rules. Picazo-

Tadeo and Prior (2009) examine the case that the biggest producer of the good output is not the biggest polluter of the bad output. In this scenario, the appropriate environmental policy can result in a pollution decrease while maintaining the desirable output at the same level.

Picazo-Tadeo et al. (2012) apply the DDF at Spanish olive growing farms and consider alternative scenarios for the direction vector which may correspond to alternative targets and policies. In a novel approach, Halkos and Tzeremes (2013) incorporate bad outputs in the conditional directional distance function proposed by Simar and Vanhems (2012) and measure the regional environmental efficiency in the UK. The authors use total labor force and capital stock as inputs, GDP as good output and three greenhouse gases (CO_2, CH_4 and N_2O) as bad outputs.

All the above approaches consider pollutants as undesirable outputs because they are by-products of the production of the desirable outputs. In contrast with this traditional view, a number of researchers treat pollutants as undesirable inputs. Reinhart et al. (2000) employ DEA and stochastic frontier analysis (SFA) and use undesirable inputs, to study Dutch diary firms. Hailu and Veeman (2001) extend Chavas-Cox transformation to DEA approach with the incorporation of undesirable outputs which are treated as inputs. This approach has caused some debate about its validity (Färe and Grosskopf, 2003; Hailu, 2003). De Koeijer et al. (2002) investigate Dutch sugar beet growers and argue that the incorporation of detrimental inputs supports the construction of a sustainability index. Lansik and Bezlepkin (2003) include CO_2 as undesirable input in their DEA model and examine the environmental efficiency of greenhouse firms in the Netherlands. Seiford and Zhu (2002) argue that the treatment of undesirable outputs as inputs violates the true production procedure.

The vast majority of the above studies construct the environmental indices in order to measure eco-efficiency and consequently sustainability. Specifically, according to Huppes and Ishikawa's (2005) definition, most studies use environmental productivity to measure eco-efficiency, which is the ratio of economic output to environmental pressure. Typical examples of this approach are, among others, the models of Korhonen and Luptacik (2004), Färe et al. (2004), Zhang et al. (2008), Picazo-Tadeo et al. (2011).

Alternatively, Zaim (2004) utilizes distance functions to construct an index of desirable outputs and an index of undesirable outputs. The first index reveals the ability of a decision making unit (DMU) to expand the good output while maintaining the level of inputs stable. The second index shows the ability of a DMU to reduce the environmental pressures while maintaining the level of good output stable. The ratio of the second index to the first index gives a pollution intensity index. The author use capital and labor as inputs, gross state product as good output and SO_X, NO_X and CO as bad outputs. Wursthorn et al. (2011) employ a pollution intensity index to assess the eco-efficiency of German industry. The authors argue that an environmental intensity index offers the opportunity of simultaneously being used as a decoupling indicator. Decoupling indicators measure the ability of an economy to expand without damaging the environment.

It is clear that sustainability consists of economic efficiency and ecological efficiency which can be seen as two different stages. The above studies adapt this complex two-stage structure to a unified framework of one stage DEA type models. In a similar case, Chen et al. (2012) construct a two-stage DEA model to assess the sustainable product design performances of automobile industry. In the first stage, the model evaluates the industrial design module efficiency and in the second stage evaluates the bio design efficiency. The first stage is the typical design procedure where the traditional inputs are converted into outputs. This is equivalent to the economic efficiency. The second stage measures the environmental intensity of the design process. This is equivalent to the eco-efficiency. The authors use a centralized cooperative two-stage DEA model introduced by Liang et al. (2008). Hwang et al. (2013) introduce simultaneous rise in desirable outputs and decrease in undesirable outputs into the above centralized model.

2.2. Multistage DEA models

Typical DEA models evaluate the efficiency of a DMU while treating its internal structures as a "black box" which utilizes inputs to produce outputs without considering the internal structures, an assumption which is usually sufficient (Sexton and Lewis, 2003). However in some cases DEA models consist of multiple stages which are linked with intermediate variables. These variables are considered as inputs in one stage and outputs in the other stage. We can classify these models into four categories. First, standard DEA models which evaluate the efficiency of each stage separately, without considering the interaction and possible conflicts between the two stages. Second, models which consider the interaction between the stages. The third category is about network DEA models and the last is about game theoretic two-stage DEA models.

Seiford and Zhu (1999) were the first to study two-stage DEA models. They use standard DEA methodology to evaluate the profitability in the first stage and the marketability in the second stage of the top commercial banks in the USA. The drawback of this methodology is that it fails to incorporate the interactions between the two stages. This shortcoming is corrected by the VRS model of Chen and Zhu (2004) which evaluates only the overall efficiency. Multiplicative models (Kao and

Hwang, 2008) and additive models (Chen et al., 2009) capture the interactions between the two stages by treating the intermediate variables in a simultaneous manner and in addition they can evaluate the efficiencies of the individual stages. Network DEA is rather a group of models which share some common attributes. Färe and Grosskopf (1996) developed a series of models in which exogenous inputs are allowed, final outputs may exist in any stage and the model may consists of more than two stages.

Liang et al. (2006, 2008) investigate the two stage DEA problem under the view of game theory where the two stages can be considered as two players. The authors construct a centralized cooperative model where the two players wish to simultaneously increase both the overall and the individual efficiencies and a non-cooperative Stackelberg type model where one player is the leader and the other is the follower. According to Cook et al. (2010) the cooperative model is equivalent to the multiplicative model of Kao and Hwang (2008). Similarly, in this paper we model for the first time countries' sustainability efficiency levels by applying the additive two-stage DEA model introduced by Chen et al. (2009).

3. Variable description and methodology

3.1. Variable description

For the needs of our analysis we use data collected from the World Bank[3] and the United Nations Framework Convention on Climate Change (UNFCC)[4] for the time period 2006-2010. The data refer to a list of 27 Annex I countries. As we have already presented, our model consists of two stages. In the first stage, the economic efficiency stage, we utilize the economic output which is a good output and two

---

[3] Available from: http://databank.worldbank.org/ddp/home.do?Step=2&id=4&hActiveDimensionId=WDI_Series
[4] Available from: http://unfccc.int/ghg_data/items/3800.php

inputs. The first stage inputs are capital stock and total labor force. Capital stock is not available, therefore we have calculated it following the perpetual inventory model (Feldstein and Foot, 1971; Epstein and Denny, 1980) as:

$$K_t = I_t + (1- \delta) K_{t-1}$$

where K_t is the gross capital stock in current year, K_{t-1} is the gross capital stock in the previous year, I_t is the gross fixed capital formation and δ is the depreciation rate of capital stock. Here, we follow Zhang et al. (2011) and set δ to 6%. Real Gross Domestic Product (GDP) in 2000 prices is the intermediate variable in our model and it is used as a good and the only output in the first stage and as an input in the second stage.

In the second stage, the eco-efficiency stage, we incorporate the environmental pressures which are bad outputs and we use the real GDP as input. In this study we use the most important greenhouse gases (GHGs) as a measure for environmental pressures which are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) and fluorinated greenhouse gases (F-gases)[5], all measured in gigagrams of CO_2 equivalent including land use, land-use change and forestry. GHGs absorb and re-emit thermal radiation which causes a number of dangerous situations such as global warming. In addition, Tol (2001) notes that GHGs are responsible for making the planet more vulnerable to climate change.

According to IPCC (2007), in 2004 the 77% of GHGs was accounted to CO_2, 14% to CH_4, 8% to N_2O and 1% to F-gases. Although it may seems that CO_2 is the primary and only responsible gas for greenhouse gas effect, if we exam the Global Warming Potential[6] (GWP) of each gas we can make a better understanding of the

[5] F-gases are a family of three man-made gases HFCs, PFCs and SF6.

[6] GWP is a relative measure of the heat that a GHG traps in the atmosphere for 20, 100 or 500 years. GWP for CO_2 is 1 and if one gas has GWP of 10 for 100 years it means that this gas traps 10 times more heat in the atmosphere over a period of 100 years.

situation. The GWP for 100 years of CO_2 is 1, of CH_4 is 21, of N_2O is 310 and of F-gases ranges from 140 to 23,900[7]. With this information in mind, one can easily understand the magnitude of the ecological and economic consequences of GHGs. For a detailed review about the marginal costs of greenhouse gas emissions and the economic impact of climate change see Tol (2008) and for the F-gases see Halkos (2010).

Finally, we use Seiford and Zhu (2002) transformation, f(U) = -U +β, to deal with undesirable outputs. U is the vector of undesirable outputs which is incorporated as a vector of desirable outputs by multiplying it with -1. Then, a proper translation vector β is added in order for the variables to become positive, thus f(U)>0. Table 1 gives the descriptive statistics of the data.

Table 1: Descriptive statistics of the variables used

		Total Labour Force (in thousands $)	Capital Stock (in million $)	GDP (in million $)	CO_2	CH_4	N_2O	F-gases
2006	Mean	22,082	3,855,340	1,059,945	461,132	71,891	35,579	10,496
	St. Dev.	32,577	9,445,671	2,318,478	943,939	151,064	65,215	26,457
	Min	2,128	114,966	48,534	13,528	3,798	3,152	456
	Max	155,132	44,595,279	11,442,690	4,908,648	664,637	336,824	138,830
2007	Mean	22,297	3,850,405	1,086,874	468,132	71,539	35,433	10,817
	St. Dev.	32,843	9,333,435	2,363,197	962,269	150,252	65,099	27,201
	Min	2,190	122,739	52,368	14,966	3,797	3,177	637
	Max	156,352	44,131,876	11,660,927	5,010,317	656,194	334,939	143,075
2008	Mean	22,520	3,839,358	1,085,954	446,927	71,519	34,686	10,797
	St. Dev.	33,124	9,202,590	2,351,600	928,997	152,404	62,407	26,445
	Min	2,199	129,869	53,572	8,577	3,876	3,194	728
	Max	158,012	43,568,326	11,619,054	4,836,805	667,881	317,080	139,100
2009	Mean	22,589	3,800,511	1,041,516	413,194	70,107	33,425	10,264
	St. Dev.	33,073	9,015,812	2,261,228	852,209	150,153	60,186	24,959
	Min	2,151	129,252	45,643	7,290	3,816	3,120	625
	Max	157,816	42,705,955	11,209,195	4,437,958	672,205	304,034	131,520
2010	Mean	22,653	3,767,440	1,073,417	432,823	70,990	33,168	11,031
	St. Dev.	33,022	8,845,244	2,334,175	890,245	151,895	60,183	27,061
	Min	2,126	129,023	47,515	12,496	3,816	3,081	635
	Max	157,493	41,926,217	11,547,905	4,631,685	666,543	306,243	142,665

[7] Available from: http://unfccc.int/ghg_data/items/3825.php

3.2. Methodology

Our model consists of two stages. We name the first stage efficiency as the economic efficiency index and the second stage efficiency as the eco-efficiency index. In the second stage we use environmental intensity to measure eco-efficiency as defined by Huppes and Ishikawa (2005). Environmental intensity is the ratio of environmental pressure to economic output. The overall efficiency of the two-stage model is a sustainability efficiency index. The sustainability index in our model serves as a decoupling indicator as defined by Wursthorn et al. (2011) because it measures the ability of an economy to expand without damaging the environment and as such it fulfils the concept of sustainability. We approach this two-stage structure with a two-stage DEA model, specifically the additive model of Chen et al. (2009).

Next, we present the additive two-stage DEA models imposing the VRS assumption and in order to account for any scale effects between the countries. According to Chen et al. (2009) the overall efficiency E_0 is evaluated as follows:

$$E_0 = \xi_1 \cdot \frac{\sum_{d=1}^{D} w_d \cdot z_{d0}}{\sum_{i=1}^{m} v_i \cdot x_{i0}} + \xi_2 \cdot \frac{\sum_{r=1}^{s} u_r \cdot y_{r0}}{\sum_{d=1}^{D} w_d \cdot z_{d0}}$$

where ξ_1 and ξ_2 are the weights which represent the significance of each stage. Instead of an arbitrary specification of these weights, the authors propose that a measure for the significance of each individual stage is their size, which can be proxied by the total inputs of each stage. Thus, the overall size is $\sum_{i=1}^{m} v_i \cdot x_{i0} + \sum_{d=1}^{D} w_d \cdot z_{d0}$ which is the sum of the first stage size $\sum_{i=1}^{m} v_i \cdot x_{i0}$ and the second stage size $\sum_{d=1}^{D} w_d \cdot z_{d0}$. Therefore, the significance of each stage is calculated as:

$$\xi_1 = \frac{\sum_{i=1}^{m} v_i \cdot x_{i0}}{\sum_{i=1}^{m} v_i \cdot x_{i0} + \sum_{d=1}^{D} w_d \cdot z_{d0}} \text{ and } \xi_2 = \frac{\sum_{d=1}^{D} w_d \cdot z_{d0}}{\sum_{i=1}^{m} v_i \cdot x_{i0} + \sum_{d=1}^{D} w_d \cdot z_{d0}} \tag{1}$$

Under proper calculations the VRS additive two-stage DEA model of Chen et al. (2009) for overall efficiency is the following:

$$max \sum_{d=1}^{D} w_d \cdot z_{d0} + \sum_{r=1}^{s} u_r \cdot y_{r0} + u^1 + u^2 \tag{2}$$

$$s.t. \quad \sum_{i=1}^{m} v_i \cdot x_{i0} + \sum_{d=1}^{D} w_d \cdot z_{d0} = 1,$$

$$\sum_{d=1}^{D} w_d \cdot z_{dj} - \sum_{i=1}^{m} v_i \cdot x_{ij} + u^1 \leq 0, \qquad j = 1,2,\ldots,n,$$

$$\sum_{r=1}^{s} u_r \cdot y_{rj} - \sum_{d=1}^{D} w_d \cdot z_{dj} + u^2 \leq 0, \qquad j = 1,2,\ldots,n,$$

$$u_r, v_i, w_d \geq 0, \; i = 1,2,\ldots,m, \quad r = 1,2,\ldots,s, \quad d = 1,2,\ldots,D.$$

where u^1 and u^2 are free in sign.

Optimal weights in model (2) may not be unique and as a result the decomposition of the overall efficiency E_0 into the individual efficiencies, E_0^1 and E_0^2, may not be unique either. Chen et al. (2009) propose the maximization of one of the individual efficiencies, say E_0^1, while maintaining the overall efficiency at E_0 as calculated in model (2). The other individual efficiency E_0^2 is calculated as $E_0^2 = \frac{E_0 - \xi_1^* \cdot E_0^1}{\xi_2^*}$, where ξ_1^* and ξ_2^* are the optimal weights calculated in model (2) as defined in (1). In our model we choose to give priority at the eco-efficiency and so we first calculate the efficiency of the second stage E_0^2 as:

$$E_0^2 = max \sum_{r=1}^{s} u_r \cdot y_{r0} + u^2 \tag{3}$$

$$s.t. \quad \sum_{d=1}^{D} w_d \cdot z_{d0} = 1,$$

$$\sum_{d=1}^{D} w_d \cdot z_{dj} + \sum_{r=1}^{s} u_r \cdot y_{r0} - E_0 \cdot \sum_{i=1}^{m} v_i \cdot x_{i0} + u^1 + u^2 = E_0,$$

$$\sum_{d=1}^{D} w_d \cdot z_{dj} - \sum_{i=1}^{m} v_i \cdot x_{ij} + u^1 \leq 0, \qquad j = 1,2,\ldots,n$$

$$\sum_{r=1}^{s} u_r \cdot y_{rj} - \sum_{d=1}^{D} w_d \cdot z_{dj} + u^2 \leq 0, \qquad j = 1,2,\ldots,n$$

$$u_r, v_i, w_p \geq 0, \quad i = 1,2,\ldots,m, \quad r = 1,2,\ldots,s, \quad d = 1,2,\ldots,D.$$

where u^1 and u^2 are free in sign. Then, the first stage efficiency E_0^1 is calculated as $E_0^1 = \dfrac{E_0 - \xi_2^* \cdot E_0^2}{\xi_1^*}$.

4. Empirical results

We solve the additive two-stage DEA model (2) and model (3) for the time period 2006-2010. In each model we calculate the overall efficiency which is the sustainability efficiency index, the first stage which is the economic efficiency and the second stage efficiency which is the eco-efficiency. As we already mentioned, we give pre-emptive priority at second stage. In addition, we provide the mean efficiency and the rankings for each country. The results in Table 2 indicate these four countries are overall efficient in every year and that are Ireland, New Zealand, Norway and Ukraine. Also, Czech Republic and Sweden achieve maximum efficiency for one and four years respectively. Other countries which achieve very high mean overall efficiency above 90% are Switzerland, Hungary and Finland. In contrast, Spain achieves the lowest score in overall efficiency with a mean value of 0.365. Furthermore, six other countries fail to achieve mean overall efficiency above 0.500 and that are Italy, Greece, the Netherlands, Australia, France and Germany.

Table 2: The results of the additive model for years 2006-1010.

	2006			2007			2008		
Countries	Sustainability Efficiency Index	Economic Efficiency Index	Eco-Efficiency Index	Sustainability Efficiency Index	Economic Efficiency Index	Eco-Efficiency Index	Sustainability Efficiency Index	Economic Efficiency Index	Eco-Efficiency Index
Australia	0.475	0.826	0.096	0.474	0.806	0.100	0.482	0.825	0.100
Austria	0.681	0.666	0.702	0.674	0.676	0.671	0.664	0.697	0.617
Belgium	0.585	0.788	0.381	0.593	0.744	0.378	0.605	0.770	0.374
Canada	0.507	1.000	0.057	0.504	0.975	0.061	0.506	0.972	0.062
Czech Republic	1.000	1.000	0.873	0.968	0.968	0.727	0.939	1.000	0.710
Denmark	0.821	0.820	0.833	0.875	0.778	1.000	0.882	0.791	1.000
Finland	0.895	0.884	1.000	0.921	0.889	1.000	0.942	0.915	1.000
France	0.485	0.926	0.034	0.484	0.916	0.035	0.488	0.923	0.036
Germany	0.488	0.940	0.026	0.489	0.940	0.026	0.495	0.958	0.026
Greece	0.465	0.465	0.463	0.470	0.476	0.378	0.478	0.487	0.362
Hungary	0.921	0.921	1.000	0.931	0.931	1.000	0.937	0.925	1.000
Ireland	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Italy	0.441	0.755	0.045	0.441	0.751	0.046	0.442	0.750	0.047
Japan	0.505	1.000	0.011	0.505	0.995	0.016	0.506	1.000	0.011
Netherlands	0.468	0.757	0.136	0.472	0.768	0.132	0.482	0.795	0.131
New Zealand	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Norway	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Poland	0.721	0.987	0.254	0.711	1.000	0.246	0.699	1.000	0.238
Portugal	0.519	0.428	1.000	0.555	0.457	1.000	0.588	0.486	1.000
Russia	0.589	1.000	0.128	0.585	1.000	0.128	0.579	0.994	0.124
Spain	0.363	0.526	0.077	0.363	0.525	0.076	0.368	0.533	0.077
Sweden	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Switzerland	0.944	0.882	1.000	0.951	0.898	1.000	0.964	0.925	1.000
Turkey	0.605	0.893	0.155	0.598	0.885	0.155	0.592	0.883	0.156
Ukraine	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
United Kingdom	0.508	1.000	0.030	0.509	1.000	0.030	0.509	1.000	0.031
United States	0.502	1.000	0.004	0.502	1.000	0.004	0.502	1.000	0.005

Table 2: The results of the additive model for years 2006-1010 (continue).

	2009			2010			Mean			
Counries	Sustainability Efficiency Index	Economic Efficiency Index	Eco-Efficiency Index	Sustainability Efficiency Index	Economic Efficiency Index	Eco-Efficiency Index	Sustainability Efficiency Index	Economic Efficiency Index	Eco-Efficiency Index	**Rankings**
Australia	0.484	0.856	0.083	0.474	0.821	0.087	0.478	0.827	0.093	20
Austria	0.638	0.679	0.577	0.650	0.693	0.591	0.661	0.682	0.632	9
Belgium	0.602	0.791	0.354	0.611	0.783	0.351	0.599	0.775	0.368	10
Canada	0.505	0.974	0.054	0.499	0.956	0.054	0.504	0.975	0.058	16
Czech Republic	0.936	0.994	0.790	0.889	0.978	0.683	0.946	0.988	0.756	4
Denmark	0.867	0.819	1.000	0.878	0.860	1.000	0.865	0.814	0.967	7
Finland	0.935	0.902	1.000	0.956	0.931	1.000	0.930	0.904	1.000	6
France	0.489	0.931	0.031	0.486	0.922	0.032	0.486	0.924	0.034	19
Germany	0.491	0.944	0.024	0.493	0.954	0.024	0.491	0.947	0.025	18
Greece	0.473	0.483	0.348	0.473	0.481	0.365	0.472	0.478	0.384	22
Hungary	0.938	0.938	1.000	0.944	0.944	1.000	0.934	0.932	1.000	5
Ireland	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Italy	0.437	0.742	0.045	0.438	0.741	0.045	0.440	0.748	0.046	23
Japan	0.505	1.000	0.011	0.506	1.000	0.011	0.506	0.999	0.012	15
Netherlands	0.479	0.788	0.125	0.484	0.799	0.125	0.477	0.781	0.130	21
New Zealand	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Norway	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Poland	0.682	1.000	0.209	0.670	1.000	0.206	0.697	0.997	0.231	8
Portugal	0.614	0.511	1.000	0.639	0.531	1.000	0.583	0.483	1.000	12
Russia	0.551	0.911	0.115	0.549	0.920	0.114	0.571	0.965	0.122	13
Spain	0.366	0.535	0.071	0.363	0.526	0.073	0.364	0.529	0.075	24
Sweden	1.000	1.000	1.000	0.796	1.000	0.558	0.959	1.000	0.912	2
Switzerland	0.964	0.925	1.000	0.968	0.933	1.000	0.958	0.913	1.000	3
Turkey	0.583	0.786	0.270	0.587	0.910	0.138	0.593	0.871	0.175	11
Ukraine	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
United Kingdom	0.508	1.000	0.029	0.508	1.000	0.029	0.508	1.000	0.030	14
United States	0.502	1.000	0.004	0.502	1.000	0.004	0.502	1.000	0.004	17

Figure 1 presents graphically the geographical dispersion of efficiency scores. In Subfigure 1a[8] we provide a visual representation of these results for the mean sustainability index scores. As it is shown Scandinavian countries along with all other countries which perform at least 90% appear with bright or dark green colour which means they have very high efficiency scores. On the contrary, Central and Southern European countries along with Australia appear with yellow colour which means they achieve below average results. All the other countries perform average results and they appear with bright or dark turquoise colour.

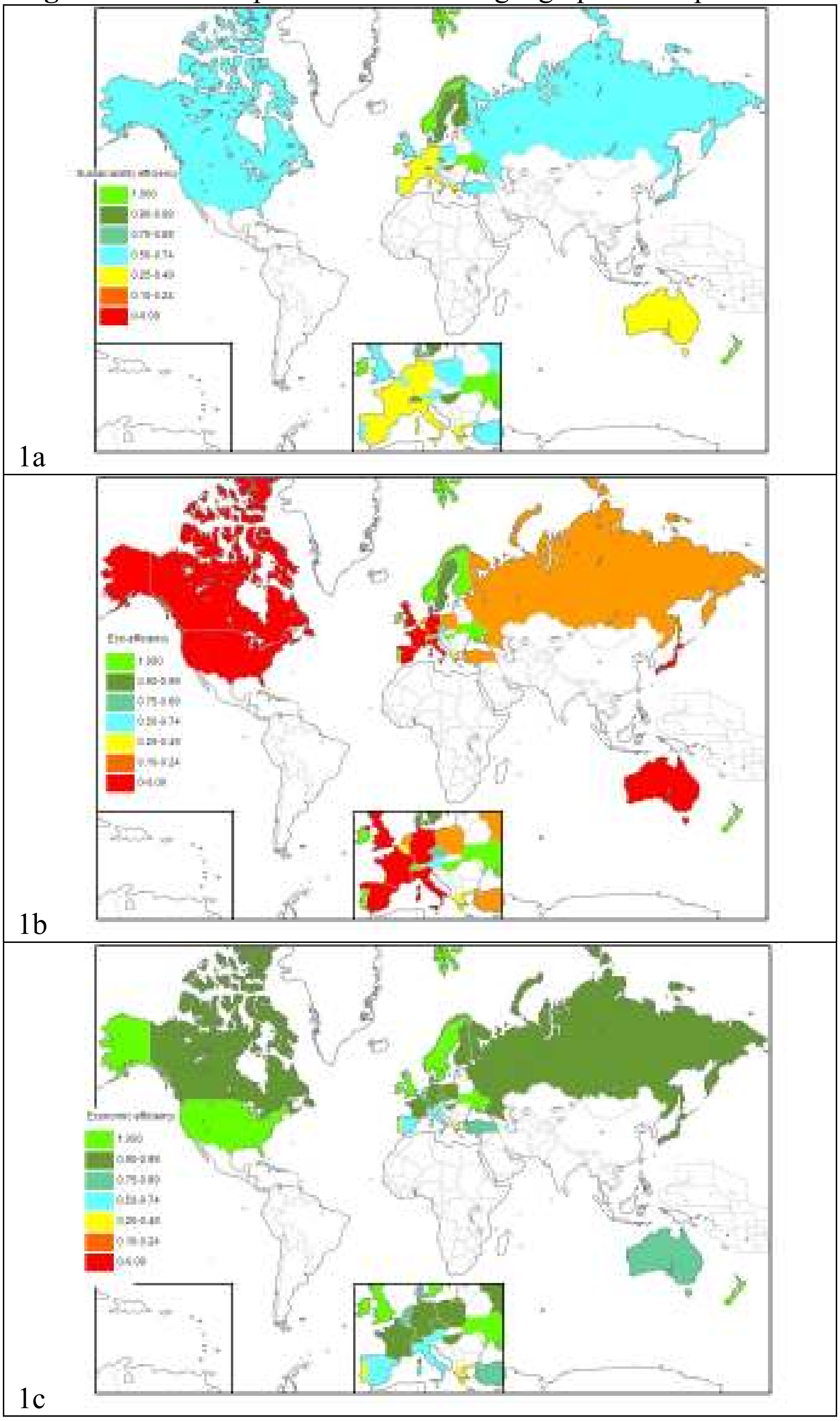
Concerning the eco-efficiency stage which we gave pre-emptive priority, apart from the overall efficient countries, four other countries achieve unity and these are Finland, Hungary, Portugal and Switzerland. Very close to maximum mean efficiency are Denmark and Sweden with 0.967 and 0.912 respectively. On the opposite side, the United Kingdom achieves the worst mean eco-efficiency (0.030) and eight other countries appear to be under 10% efficient (Australia, Canada, France, Germany, Italy, Japan, Spain, the United States).

In Subfigure 1b, we demonstrate these results graphically. It is clear from this figure that there are large inequalities in eco-efficiency among countries. Again, Scandinavian countries perform very high results along with seven other countries which appear with bright or dark green colour. Only two countries achieve average results (bright or dark turquoise colour) and all the other countries appear with orange or red colour which implies very low efficiency scores.

---

[8] The classes in Figure 1 were chosen based on the nature of the results. At first, fully efficient countries were made distinct with bright green colour. Furthermore, a lot of observations are concentrated at the first and at the last 10% of the efficiency score, so we created these two groups in order to highlight the best and worst performing countries. For the best performing countries we selected the dark green color while for the worst performing countries we selected the red colour. We chose a range of 0.15 for all the other classes and starting from the better performing countries we selected dark turquoise, bright turquoise, yellow and orange respectively.

Figure 1: Visual representation of the geographical dispersion of efficiency scores.

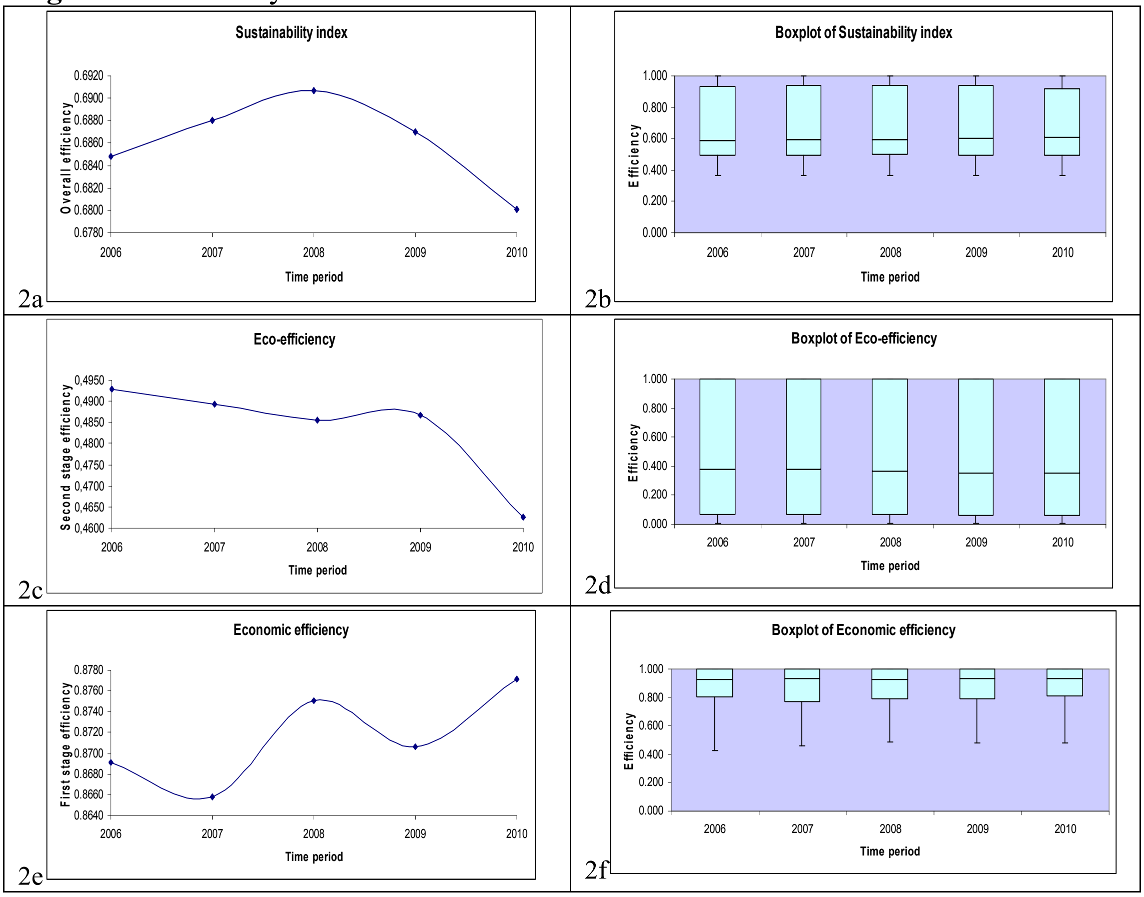


Regarding the economic efficiency stage, besides the four overall efficient countries, Sweden, the United Kingdom and the United States appear to be efficient. Ten other countries achieve very high mean economic efficiency over 90% (Canada, Czech Republic, Finland, France, Germany, Hungary, Japan, Poland, Russia and

Switzerland). On the contrary, Greece is the least economic efficient country (0.478) with Portugal at close range (0.483). As it is shown in Subfigure 1c, the results of economic efficiency stage are more balanced than the results of eco-efficiency stage. The majority of countries perform very high efficiency scores and only two countries (Greece and Portugal) fail to achieve results above average. Furthermore, Southern European countries and Australia do not perform so well relative to the other countries. In general, eighteen countries perform better at economic stage than at eco-efficiency stage.

Another interesting aspect to investigate is how the mean efficiencies change over time. This is shown in Figure 2. Specifically, in Subfigure 2a we present how the overall efficiency changes over time. The curve has an inverted U-shape and specifically it rises until 2008 and declines from then on. In Subfigure 2b we present the boxplot of the overall efficiencies and we can deduce that the fluctuations over time are rather insignificant. Changes in eco-efficiency over time appear in Subfigure 2c. A negative trend is present and becomes more rapid after 2009. A more careful examination based on the boxplot in Subfigure 2d shows that not only the decline is not rapid but also it barely exists. Subfigure 2e is about the changes of mean economic efficiency over time. Although the curve rises and declines consecutively, a positive trend appears to exist in general. Boxplot in Subfigure 2f illustrates that although there is no change at median values, lower scores (which are found at the first quartile) appear to be slightly improved. Moreover, if we examine the boxplots in Subfigures 2d and 2f together we confirm that the economic efficiency scores are highly concentrated as we already see at Subfigure 1c while there are large inequalities in eco-efficiency scores as we already see at Subfigure 1b. From boxplot in Subfigure 2b we can see that overall efficiency scores are also concentrated in fair degree and 75% of them are found at the efficiency range 0.500-1.000.

Figure 2: Efficiency results over time



5. Summary and concluding remarks

In this paper we construct a sustainability efficiency index using a two-stage DEA model. To our knowledge, this is the first time a two-stage DEA model is employed for the assessment of countries' sustainability levels. We apply the additive efficiency two-stage DEA model (Chen et al., 2009) and we constructed a two stage structure where in the first stage we measure the economic efficiency and in the second stage we measure the eco-efficiency. The overall efficiency of the model is the proposed sustainability efficiency index. The advantage of this index is that it serves as a decoupling indicator as defined by Wursthorn et al. (2011) because it measures the ability of an economy to expand without damaging the environment and as such it fulfils the concept of sustainability.

In addition, our model provides more information than a typical DEA model as it can evaluate both the sustainability efficiency (overall efficiency) and the individual efficiencies of each of the two stages. Furthermore, it defines the concepts of economic and eco-efficiency in a more distinct way and explores the connection among them.

The model is applied in a panel of 27 Annex I countries for the time period 2006-2010. The results indicate that eco-efficiency stage is characterized by large inequalities among countries with significant lower efficiency scores compared to the overall sustainability and economic efficiency levels. Finally, it appears that a country's high economic efficiency level does not ensure a high eco-efficiency level.

Acknowledgements

We would like to thank Professor Joe Zhu for his valuable advice about the computational part of the model.

References

Brundtland, H., 1987. Our common future. World Commission on Environment and Development, United Nations.

Callens, I., Tyteca, D., 1999. Towards indicators of sustainable development for firms: A productive efficiency perspective. Ecol. Econ. 28, 41-53.

Chen, Y., Zhu, J., 2004. Measuring information technology's indirect impact on firm performance. Inf. Techn. Manage 5, 9-22.

Chen, Y., Cook, W.D., Li, N., Zhu, J., 2009. Additive efficiency decomposition in two-stage DEA. Eur. J. Oper. Res. 196, 1170-1176.

Chen, C., Zhu, J., Yu, J-Y., Noori, H., 2012. A new methodology for evaluating sustainable product design performance with two-stage network data envelopment analysis. Eur. J. Oper. Res. 221, 348-359.

Chung, Y.H., Fare, R., Grosskopf, S., 1997. Productivity and undesirable outputs: A directional distance function approach. J. Environ. Manage 51, 229-240.

Cook, W.D., Liang, L., Zhu, J., 2010. Measuring performance of two-stage network structures by DEA: A review and future perspective. Omega 38, 423-430.

De Koeijer, T.J., Wossink, G.A.A., Struik, P.C., Renkema, J.A., 2002. Measuring agricultural sustainability in terms of efficiency: the case of Dutch sugar beet growers. J. Environ. Manage 66, 9-17.

Dinda, S., 2004. Environmental Kuznets Curve Hypothesis: A survey. Ecol. Econ. 49, 431-455.

Epstein, L., Denny, M. 1980. Endogenous capital utilization in a short run production model. J. Econometrics 12, 189-207.

Färe, R., Grosskopf, S., Lovell, C.A.K., Pasurka, C., 1989. Multilateral productivity comparisons when some outputs are undesirable: A nonparametric approach. The Rev. Econ. Statistics 71, 90-98.

Färe, R., Grosskopf, S., 1996. Intertemporal production frontiers: with dynamic DEA. Kluwer Academic Publishers, Boston.

Färe, R., Grosskopf, S., 2003. Nonparametric productivity analysis with undesirable outputs: Comment. Am. J. Agr. Econ. 85, 1070-1074.

Färe, R., Grosskopf, S., 2009. A comment on weak disposability in nonparametric production analysis. Am. J. Agr. Econ. 91, 535-538.

Färe, R., Grosskopf, S., Hernandez-Sancho, F., 2004. Environmental performance: an index number approach. Resour. Energy Econ. 26, 343-352.

Feldstein, M., Foot, D., 1971. The other half of gross investment: replacement and modernization. Rev. Econ. Statistics 53, 49-58.

Hailu, A., 2003. Nonparametric productivity analysis with undesirable outputs: Reply. Am. J. Agr. Econ.85, 1075-1077.

Hailu, A., Veeman, T.S., 2001. Non-parametric productivity analysis with undesirable outputs: An application to the Canadian pulp and paper industry. Am. J. Agr. Econ. 83, 605-616.

Halkos, G.E., Tzeremes, N.G., 2009. Exploring the existence of Kuznets curve in countries' environmental efficiency using DEA window analysis. Ecol. Econ. 68, 2168-2176.

Halkos, G.E., 2010. Construction of abatement cost curves: The case of F-gases. MPRA Paper 26532, University Library of Munich, Germany.

Halkos, G.E., Tzeremes, N.G., 2013. A conditional directional distance function approach for measuring regional environmental efficiency: Evidence from UK regions. Eur. J. Oper. Res. 227, 182-189.

Huppes, G., Ishikawa, M., 2005. Eco-efficiency and its terminology. J. Ind. Ecol. 9, 43-46.

Hwang, S-H., Chen, C., Chen, Y., Lee, H-S., Shen, P-D., 2013. Sustainable design performance evaluation with applications in the automobile industry: Focusing on inefficiency by undesirable factors. Omega 41, 553-558.

IPCC, 2007. Climate change 2007: Mitigation of climate change, in: Metz, B., Davidson, O.R., Bosch, P.R., Dave, R. and Meyer, L.A. (Eds.), Contribution of Working Group III to Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, USA.

Kao, C., Hwang, S., 2008. Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance in Taiwan. Eur. J. Oper. Res. 185, 418-429.

Korhonen, P.J., Luptacik, M., 2004. Eco-efficiency analysis of power plants: An extension of data envelopment analysis. Eur. J. Oper. Res. 154, 437-446.

Kuosmanen, T., 2005. Weak disposability in nonparametric production analysis with undesirable outputs. Am. J. Agr. Econ. 87, 1077-1082.

Kuosmanen, T., Kortelainen, M., 2005. Measuring eco-efficiency of production with data envelopment analysis. J. Ind. Ecol. 9, 59-72.

Kuosmanen, T., Podinovski, V., 2009. Weak disposability in nonparametric production analysis: A reply to Fare and Grosskopf. Am. J. Agr. Econ. 91, 539-545.

Kuosmanen, T., Matin, R.K., 2011. Duality of weak disposable technology. Omega 39, 504-512.

Lansink, A.O., Bezlepkin, I., 2003. The effect of heating technologies on CO2 and energy efficiency of Dutch greenhouse firms. J. Environ. Manage 68, 73-82.

Liang, L., Yang, F., Cook, W.D., Zhu, J., 2006. DEA models for supply chain efficiency evaluation. Ann. Oper. Res. 145, 35-49.

Liang, L., Cook, W., Zhu, J., 2008. DEA models for two-stage processes: Game approach and efficiency decomposition. Nav. Res. Log. 55, 643-653.

Lovell, C.A.K., Pastor, J.T., Turner, J.A. 1995. Measuring macroeconomic performance in the OECD: A comparison of European and non-European countries. Eur. J. Oper. Res. 87, 507-518

Luenberger, D., 1992. Benefit functions and duality. J. Math. Econ. 21, 461-481.

Pasurka, C.A., 2006. Decomposing electric power plant emissions within a joint production framework. Energ. Econ. 26-43.

Picazo-Tadeo, A.J., Reig-Martinez, E., Hernandez-Sancho, F., 2005. Directional distance function and environmental regulation. Resour. Energy Econ. 27, 131-142.

Picazo-Tadeo, A.J., Prior, D., 2009. Environmental externalities and efficiency measurement. J. Environ. Manage 90, 3332-3339.

Picazo-Tadeo, A.J., Gomez-Limon, J.A., Reig-Martinez, E., 2011. Assessing farming eco-efficiency: A data envelopment analysis approach. J. Environ. Manage 92, 1154-1164.

Picazo-Tadeo, A.J., Beltran-Esteve, M., Gomez-Limon, J.A., 2012. Assessing eco-efficiency with directional distance functions. Eur. J. Oper. Res. 220, 798-809.

Porter, M.E., van der Linde, C., 1995. New conception of the environment-competitiveness relationship. J. Econ. Perspect. 9, 97-118.

Reinhard, S., Lovell, C.A.K., Thijssen, G.J., 2000. Environmental efficiency with multiple environmentally detrimental variables, estimated with SFA and DEA. Eur. J. Oper. Res. 121, 287-303.

Seiford, M., Zhu, J., 1999. Profitability and marketability of the top 55 U.S. commercial banks. Manage Sci 45, 1270-1288.

Seiford, L.M., Zhu, J., 2002. Modeling undesirable factors in efficiency evaluation. Eur. J. Oper. Res. 142, 16-20.

Seiford, L.M., Zhu, J., 2005. A response to comments on modeling undesirable factors in efficiency evaluation. Eur. J. Oper. Res. 161, 579-581.

Sexton, T., Lewis, H., 2003. Two-stage DEA: An application to major league baseball. J. Prod. Anal. 19, 227-249.

Simar, L., Vanhems, A., 2012. Probabilistic characterization of directional distances and their robust versions. J. Econometrics 166, 342-354.

Sueyoshi, T., Goto, M., 2011. DEA approach for unified efficiency measurement: Assessment of Japanese fossil fuel power generation. Energ. Econ. 33, 292-303.

Sueyoshi, T., Goto, M., 2012a. Weak and strong disposability vs. natural and managerial disposability in DEA environmental assessment: Comparison between Japanese electric power industry and manufacturing industries. Energ. Econ. 686-699.

Sueyoshi, T., Goto, M., 2012b. Returns to scale and damages to scale on U.S. fossil fuel power plants: Radial and non-radial approaches for DEA environmental assessment. Energ. Econ. 34, 2240-2259.

Sueyoshi, T., Goto, M., 2012c. Environmental assessment by DEA radial measurement: U.S. coal-fired power plants in ISO (Independent System Operator) and RTO (Regional Transmission Organization). Energ. Econ. 34, 663-676.

Taskin, F., Zaim, O., 2001. The role of international trade on environmental efficiency: a DEA approach. Econ. Model. 18, 1-17.

Tol, R.S.J., 2001. Equitable cost-benefit analysis of climate policies. Ecol. Econ. 36, 71-85.

Tol, R.S.J., 2008. The economic impact of climate change. Economic and Social Research Institute, Working Paper No. 255.

Tyteca, D., 1996. On the measurement of the environmental performance of firms: A literature review and a productive efficiency perspective. J. Environ. Manage 46, 281-308.

Wursthorn, S., Poganietz, W-R., Schebek, L., 2011. Economic-environmental monitoring indicators for European countries: A disaggregated sector-based approach for monitoring eco-efficiency. Ecol. Econ. 70, 487-496.

Zaim, O., Taskin, F., 2000. Environmental efficiency in carbon dioxide emissions in the OECD: A non-parametric approach. J. Environ. Manage 58, 95-107.

Zaim, O., 2004. Measuring environmental performance of state manufacturing through changes in pollution intensities: a DEA framework. Ecol. Econ. 48, 37-47.

Zhang, B., Bi, J., Fan, Z., Yuan, Z., Ge, J., 2008. Eco-efficiency analysis of industrial system in China: A data envelopment analysis approach. Ecol. Econ. 68, 306-316.

Zhou, P., Poh, K.L., Ang, B.W., 2007. A non-radial DEA approach to measuring environmental performance. Eur. J. Oper. Res. 178, 1-9.

Zhou, P., Ang, B.W., Poh, K.L., 2008a. A survey of data envelopment analysis in energy and environmental studies. Eur. J. Oper. Res. 189, 1-18.

Zhou, P., Ang, B.W., Poh, K.L., 2008b. Measuring environmental performance under different environmental DEA technologies. Energ. Econ. 30, 1-14.

Zofio, J.L., Prieto, A.M., 2001. Environmental efficiency and regulatory standards: the case of CO2 emissions from OECD countries. Resour. Energy Econ. 23, 63-83.