

Chapter 2

Data Envelopment Analysis for Measuring Environmental Performance

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Abstract Environmental performance measurement provides an analytical foundation for environmental policy analysis and decision making. As a popular performance evaluation tool, Data Envelopment Analysis (DEA) has been applied to construct environmental performance index in different ways, where modeling undesirable outputs and the choice/construction of efficiency measures are the main steps. This chapter gives an introductory text on applications of DEA to environmental performance measurement by describing the formulation of environmental DEA technologies as well as radial and non-radial DEA models for constructing pure environmental efficiency/productivity index. A case study on measuring the environmental performance of OECD countries is presented. Future directions of DEA applications to environmental modeling are discussed with reference to several recent developments in this area.

Keywords Data envelopment analysis • Environmental performance • Aggregation • Malmquist productivity index

2.1 Introduction

Environmental performance measurement has received increasing attention at different levels due to the global concern about environmental issues and sustainable development. At firm level, the improvement of environmental performance may lead to better financial performance and therefore bring stakeholders huge potential benefits. As such, the measurement of environmental performance has been regarded as the centre of the theoretical framework for business environmental

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management (Tyteca 1996). At macro level, the measurement of environmental performance measurement helps to make environmental policy analysis and decision making more quantitative, empirically grounded and systematic (Hsu et al. 2014).

Technically speaking, the measurement of environmental performance often involves converting a set of indicators to a composite environmental index. Many studies have so far been reported on the construction of composite environmental index, which deal with cases that range from a specific environmental theme to the whole economic-energy-environmental system, and from a single country/region to multiple countries/regions (Zhou et al. 2006a). Of the various methods for constructing composite environmental index, data envelopment analysis (DEA) as a well-established non-parametric approach to efficiency evaluation has been widely employed. The review study by Cook and Seiford (2009) provides a sketch of the historical developments for DEA in the past three decades. As reported by Zhou et al. (2008a) in their survey study on the applications of DEA to energy and environmental analysis, about a quarter of studies dealt with environmental performance measurement.

This chapter discusses the use of DEA in environmental performance measurement. It is not our intention to provide a very comprehensive review of this area, which has been done by several earlier review studies like Zhou et al. (2008a) and Song et al. (2012). On the contrary, we only focus on the theoretical foundation (i.e. environmental DEA technology) and several basic DEA models for measuring environmental efficiency and productivity, while some recent developments have also been sketched. A case study is also presented in Sect. 2.4 to illustrate the applicability of the models. Finally, we end this chapter by some concluding remarks on the possible future research agenda about the use of DEA for environmental performance measurement.

2.2 Environmental DEA Technology

The application of DEA to environmental performance measurement starts from the incorporation of undesirable outputs into production technology (or production possibility set). It is aware that many production activities will inevitably generate undesirable (or bad) outputs as byproducts of desirable (or good) outputs. For instance, the emissions of carbon dioxide and sulphur dioxide are inevitable when coal is burned to generate electricity in a fossil-fired power plant. In DEA, the issue of undesirable outputs may be referred to as data irregularity (Zhu and Cook 2007). For the conventional DEA models, all the outputs are assumed to be of benefit type, i.e. more outputs are expected to be produced given the constraints of inputs. This assumption, however, does not hold for undesirable outputs in view of its ‘undesirable’ feature, which need to appropriately modeled into DEA framework.

A large number of methods for modeling undesirable outputs in the DEA framework have been proposed to deal with this situation (Scheel 2001). In addition

to treating undesirable outputs as inputs, there are two popular groups of methods for handling undesirable outputs. One is based on the translation invariance property in DEA, for which we first multiply undesirable outputs by “−1” and then add a sufficiently large number to them to make all the undesirable outputs become positive. The study by Ali and Seiford (1990) found that additive DEA model and its variant are translation invariant under variable returns to scale (Banker et al. 1984). Later, Seiford and Zhu (2002) developed an approach to incorporating undesirable outputs into BCC–DEA model by using the concept of classification invariance. The other group uses the original data but is based on the concept of weak disposable reference technology introduced by Färe et al. (1989). The weak disposable reference technology, also known as environmental production technology or polluting technology, can be characterized in a nonparametric or parametric way. If it is characterized within a DEA framework, the resulting piece-wise linear production technology is often referred to as environmental DEA technology (Färe and Grosskopf 2004; Zhou et al. 2008b). Since the concept of environmental DEA technology is more frequently used for modeling environmental performance, in this chapter we shall only introduce environmental DEA technology and the relevant DEA models for environmental performance measurement.

Suppose that $\mathbf{x} \in \mathbf{R}_+^N$, $\mathbf{y} \in \mathbf{R}_+^M$ and $\mathbf{u} \in \mathbf{R}_+^J$ are respectively the vectors of inputs, desirable outputs and undesirable outputs. Then the environmental production technology can be represented by the following output set (Chung et al. 1997)

$$P(\mathbf{x}) = \{(\mathbf{y}, \mathbf{u}) : \mathbf{x} \text{ can produce } (\mathbf{y}, \mathbf{u})\} \quad (2.1)$$

According to Färe and Grosskopf (2004), $P(\mathbf{x})$ is often imposed the weak disposability and null-jointness assumptions as follows:

1. If $(\mathbf{y}, \mathbf{u}) \in P(\mathbf{x})$ and $0 \leq \theta \leq 1$, then $(\theta\mathbf{y}, \theta\mathbf{u}) \in P(\mathbf{x})$.
2. If $(\mathbf{y}, \mathbf{u}) \in P(\mathbf{x})$ and $\mathbf{u} = 0$, then $\mathbf{y} = 0$.

The first property says that a proportional reduction in desirable outputs and undesirable outputs is feasible. The second property implies that ceasing production activities is the only choice to eliminate all the undesirable outputs.

In application, the data on inputs and outputs for all the decision making units (DMUs) are required in order to make the environmental DEA technology be applicable. Assume that there are $k = 1, 2, \dots, K$ DMUs and for DMU_{*k*} the observed data on the vectors of inputs, desirable outputs and undesirable outputs are respectively $\mathbf{x}_k = (x_{1k}, x_{2k}, \dots, x_{Nk})$, $\mathbf{y}_k = (y_{1k}, y_{2k}, \dots, y_{Mk})$ and $\mathbf{u}_k = (u_{1k}, u_{2k}, \dots, u_{Jk})$. Under the constant returns to scale (CRS), the environmental DEA technology can be characterized by the following output set

$$\begin{aligned}
P_{CRS}(\mathbf{x}) = \{(\mathbf{y}, \mathbf{u}) : & \sum_{k=1}^K z_k x_{nk} \leq x_n, \quad n = 1, 2, \dots, N \\
& \sum_{k=1}^K z_k y_{mk} \geq y_m, \quad m = 1, 2, \dots, M \\
& \sum_{k=1}^K z_k u_{jk} = u_j, \quad j = 1, 2, \dots, J \\
& z_k \geq 0, \quad k = 1, 2, \dots, K\}
\end{aligned} \tag{2.2}$$

As summarized in Zhou et al. (2008a), most of the studies on environmental performance measurement are based on the CRS environmental DEA technology. However, in actual situations the production technology may not always exhibit CRS and other cases like variable returns to scale (VRS) are likely to be observed (Tyteca 1996). Under the context of VRS, it is not appropriate to simply add the constraint of intensity variables being equal to one like the classical BCC–DEA model. As discussed in Färe and Grosskopf (2004) and Zhou et al. (2008b), the VRS environmental DEA technology may be characterized by the following production output set:

$$\begin{aligned}
P_{VRS}(\mathbf{x}) = \{(\mathbf{y}, \mathbf{u}) : & \sum_{k=1}^K z_k x_{nk} \leq x_n, \quad n = 1, 2, \dots, N \\
& \sum_{k=1}^K z_k y_{mk} \geq \alpha y_m, \quad m = 1, 2, \dots, M \\
& \sum_{k=1}^K z_k u_{jk} = \alpha u_j, \quad j = 1, 2, \dots, J \\
& \sum_{k=1}^K z_k = 1 \\
& \alpha \geq 1, \quad z_k \geq 0, \quad k = 1, 2, \dots, K\}
\end{aligned} \tag{2.3}$$

where α is a parameter which allows the output set to satisfy the weak disposability assumption.

A graphical comparison between the CRS and VRS environmental DEA technologies is given by Zhou et al. (2008b). While (2.3) is theoretically consistent with the weak disposability and null-jointness properties, the resulting DEA models are nonlinear and difficult to solve. The study by Chen (2013) showed that the linear formulation of VRS environmental DEA technology given by Kuosmanen (2005), i.e. (2.4), is more appropriate for application, especially when the additive DEA models are used to measure environmental performance.

$$\begin{aligned}
P_{VRS}(\mathbf{x}) = \{(\mathbf{y}, \mathbf{u}) : & \sum_{k=1}^K (z_k + \lambda_k) x_{nk} \leq x_n, \quad n = 1, 2, \dots, N \\
& \sum_{k=1}^K z_k y_{mk} \geq y_m, \quad m = 1, 2, \dots, M \\
& \sum_{k=1}^K z_k u_{jk} = u_j, \quad j = 1, 2, \dots, J \\
& \sum_{k=1}^K (z_k + \lambda_k) = 1 \\
& z_k \geq 0, \quad \lambda_k \geq 0, \quad k = 1, 2, \dots, K\}
\end{aligned} \tag{2.4}$$

It should be noted that in literature most of DEA models for environmental performance measurement are based on the CRS environmental DEA technology. Despite of the fact, several recent studies also adopt either (2.3) or (2.4) form of the VRS environmental DEA technology in their empirical analysis. An example is Chen (2013) who employs (2.4) to examine the energy efficiency of EU states.

2.3 Models for Measuring Environmental Performance

A large number of DEA models have been developed for environmental performance measurement under the constraint of environmental DEA technology. Most of them are built upon the CRS environmental DEA technology, e.g. Tyteca (1996, 1997), Färe et al. (2004), Zaim (2004), and Zhou et al. (2006a, b, 2007a, b, 2010a, b, 2012). Therefore, in this section we only introduce several typical DEA models for measuring environmental performance under the CRS environmental DEA technology. However, these models can be easily adapted to the case of VRS environmental DEA technology as mentioned above.

2.3.1 Environmental Efficiency Index

A standardized environmental efficiency index, which lies between zero and one, is often derived when multilateral comparison of environmental performance is concerned. Of the various DEA models for constructing environmental efficiency index, the undesirable outputs-oriented DEA model, i.e. (2.5), is particularly attractive (Tyteca 1997). In (2.5), undesirable outputs are reduced as much as possible by the same rate, while the constraint of environmental DEA technology is not violated.

$$\begin{aligned}
EEI_1 = \min \lambda \\
\text{s.t. } \sum_{k=1}^K z_k x_{nk} \leq x_n, \quad n = 1, 2, \dots, N \\
\sum_{k=1}^K z_k y_{mk} \geq y_m, \quad m = 1, 2, \dots, M \\
\sum_{k=1}^K z_k u_{jk} = \lambda u_j, \quad j = 1, 2, \dots, J \\
z_k \geq 0, \quad k = 1, 2, \dots, K
\end{aligned} \tag{2.5}$$

Obviously, (2.5) offers a standardized index for evaluating the environmental efficiency of each DMU. A DMU with larger EEI_1 is believed to have a better environmental performance compared with other DMUs.

While (2.5) as a radial DEA model holds some desirable properties, it has relatively weak discriminating power. In addition, it cannot incorporate additional information offered by decision/policy makers regarding their individual preferences on different undesirable outputs. The weighted non-radial DEA model proposed by Zhu (1996) and Seiford and Zhu (1998) may be used to overcome the limitations. Zhou et al. (2007a, b) incorporate undesirable outputs into Zhu's non-radial DEA framework and develop the following non-radial DEA model for constructing an environmental efficiency index:

$$\begin{aligned}
EEI_2 = \min \sum_{j=1}^J w_j \lambda_j \\
\text{s.t. } \sum_{k=1}^K z_k x_{nk} \leq x_n, \quad n = 1, 2, \dots, N \\
\sum_{k=1}^K z_k y_{mk} \geq y_m, \quad m = 1, 2, \dots, M \\
\sum_{k=1}^K z_k u_{jk} = \lambda_j u_j, \quad j = 1, 2, \dots, J \\
z_k \geq 0, \quad \lambda_j \leq 1, \quad k = 1, 2, \dots, K; \quad j = 1, 2, \dots, J
\end{aligned} \tag{2.6}$$

where w_j ($j = 1, 2, \dots, J$) refers to a set of normalized user-specified weights for adjusting the undesirable outputs, which may reflect the preference of decision/policy makers in adjusting each undesirable output. If there is only one undesirable output, (2.6) will be exactly the same as (2.5).

In (2.6), there is a constraint $\lambda_j \leq 1$ which is not included by Zhou et al. (2007a, b). The additional constraint indicates that no undesirable outputs are allowed to increase, while in Zhou et al. (2007a, b) some undesirable outputs are allowed to be expanded in order to achieve higher overall reduction of undesirable outputs as a whole. In (2.6), the determination of the weights is also a controversial and difficult issue. In addition to the information on policy/decision makers' preference, the

marginal abatement costs or shadow prices of undesirable outputs are also valuable in determining the weights. As shown in the recent study by Zhou et al. (2014b), DEA also plays a significant role in estimating the shadow prices of undesirable outputs.

Finally, it should be pointed out that a DMU with EEI_1 or EEI_2 equal to one may not be technical efficient since the slacks/surplus for certain inputs and desirable outputs may not be zero. As such, it might be appropriate to interpret EEI_1 and EEI_2 as pure environmental efficiency indexes.

2.3.2 Environmental Productivity Index

The environmental efficiency indexes described in Sect. 2.3.1 are static ones which are mainly for environmental performance comparisons between different DMUs at a certain point (period) of time. In addition to cross-section comparisons, decision/policy makers are also keen to track or monitor the trends in environmental performance of each DMU over time. While there are several formal time series analysis methods in DEA, a popular practice is to adapt the Malmquist productivity index initiated by Caves et al. (1982) and developed by Färe et al. (1994) to construct environmental productivity index. Originally, Malmquist productivity index is defined as a ratio of two distance functions. In the case of radial DEA models, the Shephard distance function is nicely the reciprocal of efficiency score. In virtue of this relationship, the environmental productivity index can be directly defined from efficiency scores with time index.

Let t and s ($t < s$) denote two time indexes. Suppose that EEI_p^q ($p, q = s, t$) refers to the environmental efficiency index of a DMU derived from its input–output pairs for period of time p and the environmental DEA technology for period q . As described in Zhou et al. (2007b, 2010), the Malmquist environmental productivity index (EPI) of DMU_0 can be calculated by

$$EPI = \left[\frac{EEI_s^t}{EEI_t^t} \frac{EEI_s^s}{EEI_t^s} \right]^{1/2} \quad (2.7)$$

Using EPI, we can then measure the environmental productivity change of each DMU to monitor its dynamic environmental performance over time. When $EPI > 1$, it indicates that an improvement of environmental performance from t to s is observed for the DMU being evaluated. When $EPI < 1$, a deterioration of environmental performance from t to s is identified for it.

Like the conventional Malmquist productivity index, we can also investigate the mechanism of environmental productivity changes by decomposing (2.7) into the following two contributing components:

$$EPI = \frac{EEI_s^s}{EEI_t^t} \times \left[\frac{EEI_s^t}{EEI_s^s} \frac{EEI_t^t}{EEI_t^s} \right]^{1/2} \quad (2.8)$$

where the first term of the right-hand side measures the environmental efficiency change (EEFCH), and the second term measures the shift of environmental DEA technology, i.e. technological change (TECH). It should be pointed that EPI and its contributing components can be derived from either radial or non-radial DEA model introduced in Sect. 2.3.1. For the latter, the studies by Zhou et al. (2007a, b) and Meng et al. (2013) provide two application examples. When there is only one undesirable output, choosing radial or non-radial DEA models will lead to the same environmental productivity index. Examples of such studies can be found in Zhou et al. (2010a, b) who developed a total factor carbon performance index for monitoring CO₂ emission performance over time.

2.3.3 Other Developments

The several DEA models mentioned above represent only the basic and typical ones for environmental performance measurement. Recent years have also seen a number of new developments in this field. Since the radial and non-radial DEA models described earlier do not incorporate slacks/surplus in inputs and desirable outputs, some scholars have attempted to model environmental performance by incorporating these slacks/surplus. For example, Zhou et al. (2006b) adapted the slacks-based measure (SBM) proposed by Tone (2001) to measure the economic-environmental performance and estimate the impacts of environmental regulations. Bian and Yang (2010) used the weighted SBM based on Shannon's entropy to measure energy and environmental performance simultaneously. Sueyoshi and Goto (2012) applied range-adjusted measure (RAM), a weighted sum of slack variables, to measure environmental performance under different disposability assumptions. Wang et al. (2013) employed the RAM-DEA model to examine the environmental performance of different provinces in China.

Directional distance function (DDF) as a new direction in efficiency and productivity analysis has also received increasing attention in environmental performance measurement (Färe and Grosskopf 2005). Chung et al. (1997) developed Malmquist-Luenberger productivity index by considering undesirable outputs in DDF. Boyd and McClelland (1999) used DDF to measure the impact of environmental regulations on productivity growth. Picazo-Tadeo et al. (2005) employed DDF to examine the impact of environmental regulation on firm's performance. The study by Managi and Jena (2008) analyzed the environmental productivity in India with DDF. Recently, Zhou et al. (2012) employed the non-radial directional distance function, which is closely linked to the slacks-based DEA models, to assess the energy and carbon performance in electricity generation.

Note that environmental efficiency or productivity index is basically a composite indicator aggregated from several underlying sub-indicators. DEA as a data weighting and aggregation tool has also received increasing attention in constructing composite indicators. Zhou et al. (2007a) developed a linear programming approach comprising two DEA-like models for constructing composite indicators. Since geometric aggregation is superior to arithmetic aggregation in terms of information loss, Zhou et al. (2010a, b) extended their earlier study and proposed a multiplicative DEA model for constructing composite indicators, which has been empirically used in a recent study by Blancard and Hoarau (2013).

Yet, there are still many other developments in the applications of DEA to environmental performance measurement, e.g. the incorporation of material balance condition into DEA models for measuring environmental performance (Coelli et al. 2007). However, it is not the purpose of this chapter to enumerate them in a complete way. Interested readers may refer to the survey study by Zhou et al. (2008a, b) and Song et al. (2012) for identifying more relevant studies.

2.4 Case Study

In this section, we apply the radial and non-radial DEA models as described in Sect. 2.3 to calculate the environmental efficiency index (EEI) and environmental productivity index (EPI) of 29 OECD countries from 2000 to 2011 under the CRS environmental DEA technology. It should be pointed out that the case study is mainly for illustrating purpose so that the policy and managerial implications of our modeling results as well as the data and model biases will not be discussed in detail.

2.4.1 Data

Capital stock and labor force are employed as two inputs and gross domestic production (GDP) is taken as desirable outputs. In the case of undesirable outputs, we choose carbon dioxide (CO₂) emissions, methane (CH₄) emissions and nitrous oxide (N₂O) emissions for use since they are major air pollutants causing global warming and having adverse health effects. The data on all the variables but capital stock were collected from the World Bank Group (WBG) and OECD Statistics (<http://stats.oecd.org/>). The data on capital stock are calculated by using perpetual inventory method based on the data of gross fixed capital formation. Table 2.1 shows the descriptive statistics of collected data for the six variables.

Table 2.1 Descriptive statistics of inputs and outputs for 29 OECD countries, 2000–2011

Indicators	Units	Max	Min	Mean	S.D.
Capital stock	Constant 2005 billion US\$	213,138.49	71.36	13,873.82	31,290.39
Labor force	Ten thousand workers	15,800.00	16.60	1672.48	2933.48
Gross domestic product	Constant 2005 billion US\$	138,000.00	98.40	11,389.07	24,105.53
Carbon dioxide (CO ₂)	1000 tons	6,119,317.83	2773.28	414,084.18	1,058,109.36
Methane (CH ₄)	1000 tons of CO ₂ eq	610,114.02	437.00	43,949.50	106,083.55
Nitrous oxide (N ₂ O)	1000 tons of CO ₂ eq	362,415.56	441.27	27,683.95	62,109.40

2.4.2 Results and Discussions

2.4.2.1 EEI Analysis

Table 2.2 shows the EEI results derived from the radial DEA model (2.5). It can be seen from Table 2.2 that the EEI values of nine countries are always equal to 1, which indicates that they had a better environmental performance than other countries. On the other hand, several countries like Slovak Republic, Czech Republic and Estonia have relatively lower EEI values, which might be an indication of poor environmental performance in these countries.

Table 2.3 shows the EEI results derived from the non-radial DEA model (2.6) by setting equal weights for undesirable outputs. It is not surprising that the EEI values from non-radial DEA model are lower than those from radial one since the former has a more relaxed constraint. Compared to the radial DEA model, non-radial DEA model has higher discriminating power since fewer countries had EEI values equal to one. Meanwhile, the EEI values for countries like Slovak Republic, Czech Republic and Estonia are still the lowest. However, there are two exception cases including Australia and New Zealand that have quite low non-radial EEI scores, whereas their radial EEI scores are equal to one as shown in Table 2.2. In addition to the data bias, one possible reason is that that the two countries did not perform well in certain dimension of undesirable outputs (like CH₄).

Figure 2.1 shows the average EEIs for OECD countries from both radial and non-radial DEA models over time. Not surprisingly, the average EEI₁ value is always above the average EEI₂ value, which comes from the fact that non-radial DEA model has a relaxed constraint than radial one. It could also be an indication that the radial DEA model may overestimate environmental efficiency since they only allow the reduction of undesirable outputs at the same rate. It can also be seen that the average EEIs for OECD countries are relatively stable, no matter whether radial or non-radial DEA model is used.

Table 2.2 Radial EEs of 29 OECD countries, 2000–2011

Countries	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Mean
Australia	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Austria	0.567	0.550	0.551	0.520	0.492	0.510	0.529	0.542	0.568	0.560	0.533	0.559	0.540
Belgium	1.000	1.000	1.000	1.000	1.000	0.845	0.645	0.582	0.599	0.622	0.586	0.554	0.786
Canada	0.471	0.463	0.460	0.412	0.380	0.386	0.399	0.335	0.301	0.310	0.302	0.291	0.376
Czech Republic	0.107	0.110	0.113	0.123	0.126	0.125	0.130	0.130	0.134	0.136	0.144	0.138	0.126
Denmark	1.000	1.000	1.000	0.903	0.977	0.691	0.599	0.639	0.673	0.638	0.667	1.000	0.816
Estonia	0.106	0.116	0.113	0.110	0.112	0.123	0.131	0.130	0.135	0.129	0.115	0.127	0.121
Finland	0.543	0.588	0.688	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.476	0.511	0.817
France	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Germany	0.628	0.599	0.615	0.608	0.603	0.608	0.639	0.641	1.000	1.000	1.000	1.000	0.745
Greece	0.351	0.338	0.331	0.338	0.330	0.326	0.332	0.266	0.264	0.276	0.274	0.238	0.305
Hungary	0.240	0.257	0.261	0.262	0.305	0.269	0.272	0.262	0.255	0.258	0.267	0.261	0.264
Iceland	0.946	1.000	0.847	0.921	0.935	1.000	1.000	1.000	1.000	1.000	0.648	0.647	0.912
Ireland	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Italy	0.607	0.558	0.533	0.503	0.484	0.465	0.482	0.449	0.454	0.468	0.491	0.473	0.497
Japan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Luxembourg	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Netherlands	0.482	0.470	0.449	0.454	0.459	0.470	0.486	0.545	0.790	0.804	0.814	0.785	0.584
New Zealand	1.000	1.000	1.000	1.000	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	1.000	1.000	1.000	1.000
Portugal	0.404	0.447	0.430	0.520	0.479	0.476	0.510	0.473	0.524	0.559	0.674	0.677	0.514
Slovak Republic	0.150	0.147	0.156	0.169	0.176	0.185	0.198	0.214	0.219	0.234	0.231	0.286	0.197
Slovenia	0.256	0.246	0.264	0.287	0.296	0.297	0.297	0.295	0.307	0.296	0.307	0.288	0.286
Spain	0.424	0.428	0.391	0.422	0.393	0.376	0.389	0.361	0.403	0.438	0.479	0.412	0.410
Sweden	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

(continued)

Table 2.2 (continued)

Countries	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Mean
Switzerland	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Turkey	0.659	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.972
United Kingdom	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
United States	0.417	0.368	0.365	0.394	0.375	0.329	0.330	0.305	0.331	0.334	0.328	0.325	0.350

Table 2.3 Non-radial EELs of 29 OECD countries, 2000–2011

Countries	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Mean
Australia	0.155	0.153	0.158	0.163	0.162	0.164	0.161	0.159	0.162	0.167	0.171	0.162	0.162
Austria	0.458	0.457	0.455	0.445	0.466	0.466	0.473	0.474	0.481	0.488	0.487	0.481	0.469
Belgium	0.487	0.468	0.489	0.517	0.516	0.508	0.514	0.513	0.510	0.500	0.464	0.496	0.498
Canada	0.293	0.278	0.278	0.263	0.246	0.241	0.238	0.208	0.198	0.207	0.191	0.184	0.235
Czech Republic	0.105	0.109	0.113	0.118	0.118	0.123	0.126	0.128	0.133	0.134	0.134	0.130	0.122
Denmark	0.617	0.582	0.562	0.542	0.561	0.589	0.541	0.512	0.495	0.454	0.456	0.473	0.532
Estonia	0.096	0.103	0.107	0.108	0.109	0.119	0.127	0.121	0.114	0.110	0.102	0.107	0.110
Finland	0.429	0.409	0.406	0.404	0.420	0.455	0.435	0.455	0.474	0.404	0.396	0.428	0.426
France	0.610	0.590	0.573	0.570	0.563	0.551	0.543	0.520	0.511	0.530	0.497	0.505	0.547
Germany	0.545	0.539	0.545	0.546	0.541	0.555	0.582	0.592	0.625	0.632	0.658	0.664	0.585
Greece	0.306	0.309	0.299	0.308	0.301	0.294	0.302	0.256	0.250	0.255	0.242	0.218	0.278
Hungary	0.142	0.143	0.152	0.155	0.156	0.159	0.165	0.146	0.154	0.154	0.154	0.191	0.156
Iceland	0.455	0.476	0.478	0.509	0.530	0.516	0.415	0.397	0.384	0.363	0.355	0.412	0.441
Ireland	0.237	0.261	0.291	0.317	0.319	0.322	0.326	0.330	0.312	0.312	0.306	0.309	0.303
Italy	0.571	0.547	0.516	0.492	0.470	0.456	0.467	0.436	0.437	0.439	0.446	0.431	0.476
Japan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Luxembourg	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Netherlands	0.427	0.434	0.440	0.447	0.453	0.468	0.481	0.505	0.604	0.602	0.584	0.589	0.503
New Zealand	0.216	0.208	0.213	0.207	0.197	0.186	0.174	0.166	0.157	0.176	0.168	0.155	0.185
Norway	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Portugal	0.259	0.268	0.257	0.272	0.261	0.258	0.266	0.257	0.265	0.270	0.283	0.269	0.265
Slovak Republic	0.128	0.127	0.127	0.134	0.138	0.147	0.151	0.162	0.171	0.178	0.183	0.251	0.158
Slovenia	0.193	0.196	0.203	0.213	0.218	0.220	0.222	0.223	0.235	0.227	0.230	0.219	0.217
Spain	0.328	0.342	0.342	0.343	0.343	0.349	0.351	0.339	0.367	0.369	0.368	0.351	0.349
Sweden	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

(continued)

Table 2.3 (continued)

Countries	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Mean
Switzerland	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Turkey	0.236	0.236	0.271	0.308	0.359	0.376	0.325	0.350	0.381	0.331	0.368	0.389	0.327
United Kingdom	0.692	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.974
United States	0.276	0.259	0.262	0.273	0.272	0.259	0.254	0.242	0.253	0.252	0.251	0.247	0.258

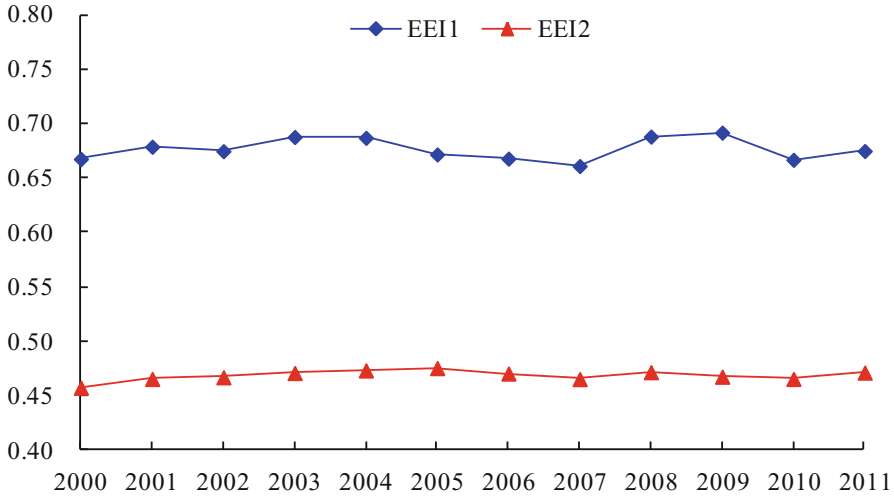


Fig. 2.1 Trends in the average EEI values from radial and non-radial DEA models

2.4.2.2 EPI Analysis

In order to assess how the environmental performance of OECD countries changed over time, we further employ (2.7) to calculate the EPI values for the countries. In this process, both radial and non-radial DEA models are employed. Table 2.4 shows the cumulative EPI values for all the countries in 2011 with 2000 as the base year. Equation (2.8) is used to compute the two contribution components of EPI and the cumulative results for 2011 are also shown in Table 2.4. If radial DEA model is used, the environmental productivity index decreased by 3.3 % from 2000 to 2011, which was mainly driven by the shift of environmental DEA technology. On the other hand, the environmental efficiency of OECD countries as a whole increased by 21.7 %. With non-radial DEA model, the environmental productivity of OECD countries decline by more during the period of time and the shift of environmental DEA technology was still the main contributing factor to the deterioration.

Table 2.5 shows the average EPI values as well as their contribution components derived from non-radial DEA models for OECD countries as a whole for every two consecutive years. It is found that from 2000 to 2009 the environmental productivity of OECD countries as a whole showed a declining trend mainly driven by the degeneracy of environmental production technology. However, in 2009–2011 the environmental productivity of these countries increased, which was mainly due to the growth of environmental efficiency while the situation of technology deterioration also became better. On the other hand, the environmental efficiency showed an increasing trend with the average growth rate equal to 1.9 % during the sample period.

Table 2.4 Cumulative EPI and their components, 2011

Countries	Radial DEA			Non-radial DEA		
	Cumulative EPI	EEFCH	TECH	Cumulative EPI	EEFCH	TECH
Australia	0.862	1.084	0.795	1.210	1.046	1.157
Austria	1.234	0.983	1.256	1.213	1.050	1.155
Belgium	0.578	0.761	0.760	0.455	1.301	0.350
Canada	0.191	1.102	0.174	0.227	1.003	0.226
Czech Republic	1.597	1.285	1.243	1.559	1.245	1.252
Denmark	1.221	1.000	1.221	0.339	1.076	0.315
Estonia	1.321	1.251	1.056	1.305	1.147	1.138
Finland	0.912	0.937	0.974	0.432	1.289	0.336
France	0.823	1.000	0.823	0.321	1.239	0.259
Germany	0.407	2.508	0.162	0.414	1.689	0.245
Greece	0.387	0.946	0.410	0.451	0.998	0.452
Hungary	1.428	1.085	1.316	1.103	1.486	0.742
Iceland	0.635	0.695	0.913	0.605	1.073	0.564
Ireland	0.713	1.166	0.612	1.619	1.301	1.245
Italy	0.705	0.979	0.720	0.598	1.023	0.584
Japan	1.012	1.000	1.012	1.012	1.000	1.012
Luxembourg	0.927	1.000	0.927	0.907	1.000	0.907
Netherlands	0.849	1.552	0.547	0.562	1.597	0.352
New Zealand	0.995	1.000	0.995	0.482	0.921	0.524
Norway	1.000	1.000	1.000	1.000	1.000	1.000
Portugal	1.930	1.672	1.154	1.302	1.040	1.252
Slovak Republic	2.379	1.900	1.252	2.396	1.921	1.247
Slovenia	1.352	1.125	1.201	1.391	1.139	1.221
Spain	1.242	0.972	1.278	1.334	1.070	1.246
Sweden	0.988	1.000	0.988	0.351	1.477	0.238
Switzerland	1.000	1.000	1.000	0.999	1.000	0.999
Turkey	0.373	2.562	0.146	0.397	2.305	0.172
United Kingdom	0.307	1.739	0.176	0.130	2.255	0.058
United States	0.679	0.985	0.689	0.919	0.984	0.934
Mean	0.967	1.217	0.855	0.863	1.265	0.730

2.5 Conclusion

DEA has been applied to model environmental performance at both macro and micro levels. This chapter first introduces the concepts and formulations of environmental DEA technologies, which highlights the fundamental role of modeling undesirable outputs in environmental performance measurement. We then present both radial and non-radial DEA models for measuring environmental efficiency and productivity. A case study of OECD countries for 2000–2011 is proposed to illustrate the use of different DEA models. While only several basic DEA models

Table 2.5 Non-radial EPI estimates and their components

	EPI	EFFCH	TECH
2000/2001	0.925	1.013	0.913
2001/2002	0.948	1.053	0.900
2002/2003	0.943	1.022	0.923
2003/2004	0.965	1.047	0.922
2004/2005	0.972	1.015	0.958
2005/2006	0.981	1.010	0.971
2006/2007	0.985	1.014	0.971
2007/2008	0.963	0.978	0.984
2008/2009	0.933	0.968	0.964
2009/2010	1.007	1.037	0.971
2010/2011	1.043	1.049	0.994
Mean	0.969	1.019	0.952

are introduced in this chapter, a quick summary of some other developments in this area is also provided.

This chapter is by far not a comprehensive review of DEA models for environmental performance measurement. In the last decade, many studies on the applications of DEA to environmental performance measurement have been reported. While a number of studies focused on the application aspect, others attempted to refine the existing DEA models in order to cater for their particular purposes, e.g. the incorporation of the slacks for specific variables. Indeed, DEA can easily handle different situations depending on the user targets, whereas the interpretation of the DEA results needs to be more careful. It is expected that this introductory text helps to invoke the attention of energy and environmental analysts to use DEA to model environmental issues for informing policy and decision making. In the future, one interesting topic is to examine the issue of carbon dioxide emissions with DEA as a result of the growing concern about climate change and global warming. This includes not only the measurement of carbon performance but also many other topics, e.g. the allocation of CO₂ emission allowance in emission trading. A recent example is Zhou et al. (2014a) in which the optimal path as well as policy strategies for controlling CO₂ emissions in China is derived through DEA modeling. Another interesting direction is to use DEA to benchmark corporate environmental performance as done by Chen and Delmas (2012), which helps to identify top performers with their competitive advantages for business strategy management. In this line of research, unpredicted data features may bring difficulty in the use of DEA and the interpretation of modeling results while are capable of generating more interesting works.

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