Energy Economics 32 (2010) 194–201

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Total factor carbon emission performance: A Malmquist index analysis

P. Zhou [a,*], B.W. Ang [b], J.Y. Han [b]

[a] College of Economics and Management, Nanjing University of Aeronautics and Astronautics, 29 Yudao Street, Nanjing 210016, China
[b] Department of Industrial and Systems Engineering, National University of Singapore, 10 Kent Ridge Crescent, Singapore 119260, Singapore

ARTICLE INFO

Article history:
Received 11 May 2009
Received in revised form 21 September 2009
Accepted 3 October 2009
Available online 13 October 2009

JEL classification:
C61
D24
Q43
Q54

Keywords:
Carbon dioxide emissions
Malmquist index
Data envelopment analysis
Total factor productivity
Bootstrap

ABSTRACT

This paper introduces a Malmquist CO_2 emission performance index (MCPI) for measuring changes in total factor carbon emission performance over time. The MCPI is derived by solving several data envelopment analysis models. Bootstrapping MCPI is proposed to perform statistical inferences on the MCPI results. Using the index the emission performance of the world's 18 top CO_2 emitters from 1997 to 2004 is studied. The results obtained show that the total factor carbon emission performance of the countries as a whole improved by 24% over the period and this was mainly driven by technological progress. The results of a cross-country regression analysis to investigate the determinants of the resulting MCPI are presented.

1. Introduction

Global awareness on climate change has created much interest in analyzing the trends of world energy use and carbon dioxide (CO_2) emissions. Policy makers have realized the importance of considering CO_2 emissions in formulating national economic and energy policies. Internationally, it is apparent that the post-Kyoto climate policy will put more emphasis on the reduction of global CO_2 emissions in order to mitigate climate change. These facts bring the need for understanding the patterns of CO_2 emissions and monitoring the emission performance in different countries.

Various indicators have been developed and applied to monitor national CO_2 emission performance trends. For instance, Mielnik and Goldemberg (1999) propose the use of a “carbonization index” (the level of CO_2 emissions per unit of energy consumption) to assess the evolution patterns of developing countries with regard to climate change. Ang (1999) shows that energy intensity (energy consumption per unit of GDP) is as useful as the carbonization index in the study of climate change. Sun (2005) highlights the usefulness of CO_2 emission intensity in measuring decarbonization and assessing energy policies at the national level. Tol et al. (2009) show that both CO_2 emission intensity and CO_2 emissions per person can be considered as a function of per capita income.

The indicators mentioned above may be interpreted as partial indicators since they can only reflect partial aspects of CO_2 emission performance. Ramanathan (2002) points out that a more holistic view is to use the data envelopment analysis (DEA) technique to combine all the relevant indicators such as energy consumption, economic activity and CO_2 emissions into an overall index for performance comparisons. DEA, a nonparametric frontier approach to efficiency evaluation, has been widely applied to assess the relative performance of various entities.[1] Recently, the use of DEA has also been extended to model and analyze CO_2 emission performance. For example, Zaim and Taskin (2000) develop a hyperbolic efficiency measure to calculate the CO_2 emission efficiency of OECD countries. Zofio and Prieto (2001) study the CO_2 emission performance of OECD manufacturing industries by considering several different regulatory scenarios. Zhou et al. (2006) propose a slacks-based efficiency measure for modeling CO_2 emission performance that accounts for economic inefficiency.

A limitation of these previous studies is that they usually study CO_2 emission performance within a cross-sectional data framework and not over time. It is therefore worthwhile to develop a tool for carrying out a formal time-series analysis of CO_2 emission performance. It is for

[1] In energy economics, DEA has also been applied to areas such as energy efficiency measurement and productivity analysis of energy sectors. Examples of such studies include Abbott (2006), Barros (2008), Barros and Peypoch (2008), Mukherjee (2008), and Ramos-Real et al. (2009). A recent literature review of DEA in energy and environmental analysis can be found in Zhou et al. (2008a).

* Corresponding author. Tel.: +86 25 84896261; fax: +86 25 84892751.
E-mail address: cemzp@nuaa.edu.cn (P. Zhou).

0140-9883/$ – see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.eneco.2009.10.003

this purpose that in this paper we introduce a Malmquist CO_2 emission performance index (MCPI) for measuring changes of CO_2 emission performance over time. The MCPI may be considered as an extension to the Malmquist productivity index that is a popular approach to computing total factor productivity index. For this reason, the MCPI may be termed as a total factor carbon emission performance index.

Compared to partial indicators, the MCPI measures the relative CO_2 emissions performance from the viewpoint of production efficiency. It ranks countries based on their dynamic behavior towards the empirical production frontiers. In application, the derivation of MCPI can be done by solving several DEA type models. Considering the fact that DEA is a deterministic programming technique, we further propose bootstrapping MCPI for sensitivity analysis and statistical inferences on the index scores. In empirical application, most previous studies focus on the OECD countries. In this study, we consider the world's top 18 CO_2 emitters which include non-OECD countries. They together contribute to over 70% of the world's total energy-related CO_2 emissions.

The remainder of this paper is organized as follows. Section 2 introduces the methodology, which consists of the concept of environmental DEA technology, the development of MCPI, and bootstrapping of MCPI. In Section 3, we use the approach described in Section 2 to study the carbon emission performance of the world's top 18 CO_2 emitters from 1997 to 2004. A cross-country regression analysis is also carried out to study factors that may influence MCPI. Section 4 concludes this study.

2. Methodology

2.1. Environmental DEA technology

Consider a production process where each country employs capital stock (K), labor force (L), and energy (E) as inputs to generate gross domestic product (Y) as desirable output and CO_2 emissions (C) as undesirable output.[2] The production technology set can be defined as:

$$T = \{(K, L, E, Y, C) : (K, L, E) \text{ can produce } (Y, C)\}. \tag{1}$$

In production theory, T is often assumed to be a closed and bounded set, which implies that finite inputs can only generate finite outputs. Also, inputs and desirable outputs are supposed to be strongly or freely disposable. That is to say, if $(K, L, E, Y, C) \in T$ and $(K', L', E') \geq (K, L, E)$ (or $Y' \leq Y$) then $(K', L', E', Y, C) \in T$ (or $(K, L, E, Y', C) \in T$).

In order to reasonably model a production technology that produces both desirable and undesirable outputs, several additional assumptions need to be imposed. A simple one is to treat undesirable outputs as inputs (Seiford and Zhu, 2002). However, Førsund (2008) shows that treating undesirable outputs as inputs leads to a conflict with the material balance equation. On the other hand, Färe et al. (1989) propose to impose the weak disposability of undesirable outputs on the production technology set, which can be used to capture the opportunity cost of reducing undesirable outputs. The weak disposability assumption implies that the reduction of undesirable outputs is not free but a proportional reduction in both desirable and undesirable outputs is feasible. In addition, the nulljointness condition also needs to be imposed, which implies that some undesirable outputs must be generated in order to produce desirable outputs. Technically, the two assumptions can be formulated as

(i) If $(K, L, E, Y, C) \in T$ and $0 < \theta \leq 1$, then $(K, L, E, \theta Y, \theta C) \in T$.
(ii) If $(K, L, E, Y, C) \in T$ and $C = 0$, then $Y = 0$.

[2] A similar production framework excluding CO_2 emissions has been widely adopted to investigate the casual relationship between energy consumption and economic growth. Several recent examples among the bulk of literature are Soytas and Sari (2007), Lee et al. (2008) and Wolde-Rufael (2009).

Up to now, the production technology for modeling the joint production of Y and C has been well defined in concept but it cannot be directly used in empirical analysis. In the literature a common practice is to characterize the production technology within a nonparametric framework, which can be done by using the piecewise linear combinations of the observed data. Suppose that there are $i = 1, 2, \ldots, I$ countries and for country i the vector of inputs, desirable, and undesirable outputs is $(K_i, L_i, E_i, Y_i, C_i)$. The piecewise linear production technology can be formulated as

$$T = \{(K, L, E, Y, C) : \begin{array}{l} \sum_{i=1}^{I} z_i K_i \leq K \\ \sum_{i=1}^{I} z_i L_i \leq L \\ \sum_{i=1}^{I} z_i E_i \leq E \\ \sum_{i=1}^{I} z_i Y_i \geq Y \\ \sum_{i=1}^{I} z_i C_i = C \\ z_i \geq 0, i = 1, 2, \Lambda, I. \end{array} \tag{2}$$

Since the piecewise linear production technology T is formulated in a DEA framework, it may be referred to as the environmental DEA technology. It can be verified that T exhibits constant returns to scale. Characterizations of other types of environmental DEA technologies can be found in Zhou et al. (2008b). In energy and environmental studies, the usefulness of environmental DEA technology has been widely explored. See, for example, Zaim and Taskin (2000), Zofio and Prieto (2001), Zhou et al. (2006, 2008b), Lozano and Gutiérrez (2008), and Lozano et al. (2009).

2.2. Malmquist CO_2 emission performance index

Many earlier studies, for example those listed in Zhou et al. (2008a), deal with the development of models for measuring environmental performance based on the environmental DEA technology. Among the different models, the undesirable outputs orientation DEA efficiency index proposed by Tyteca (1997) is particularly attractive. Theoretically, the index is the reciprocal of the Shephard input distance function for undesirable outputs. Following Tyteca (1997), we define the Shephard input distance function for CO_2 emissions (hereafter referred as the Shephard carbon distance function) as

$$D_c(K, L, E, Y, C) = \sup\{\lambda : (K, L, E, Y, C/\lambda) \in T\}. \tag{3}$$

Eq. (3) seeks to measure the maximal possible reduction in CO_2 emissions, which can be used to measure the CO_2 emissions performance of each country at a certain period of time. To study the change in CO_2 emissions performance over time, we extend the Malmquist productivity index and propose a Malmquist CO_2 emission performance index (MCPI) for application purposes.

The Malmquist productivity index was first developed by Caves et al. (1982) as a ratio of two distance functions for the measurement of productivity. Färe et al. (1994) extend it by considering technical inefficiency in productivity measurement and calculating the Malmquist productivity index within a nonparametric framework. The nonparametric Malmquist productivity index has since then been widely applied in different areas. Applications specific to energy can be found in Førsund and Kittelsen (1998), Abbott (2006), Kumar (2006), Pombo and Taborda (2006), Wei et al. (2007), Barros (2008), and Kortelainen (2008).

Following the spirit of the nonparametric Malmquist productivity index, we propose a MCPI for assessing the change in CO_2 emission performance over time. Let t and s $(t<s)$ denote two time periods. Assume that $D_c^t(K_i^t, L_i^t, E_i^t, Y_i^t, C_i^t)$ and $D_c^s(K_i^t, L_i^t, E_i^t, Y_i^t, C_i^t)$ are the Shephard carbon distance functions of country i based on its inputs and outputs at period t for the production technology at t and s, respectively. Further assume that $D_c^t(K_i^s, L_i^s, E_i^s, Y_i^s, C_i^s)$ and $D_c^s(K_i^s, L_i^s, E_i^s, Y_i^s, C_i^s)$ are respectively the Shephard carbon distance functions of country i based on its inputs and outputs at period s for the production technology at t and s. We define the MCPI as follows:

$$MCPI_i(t,s) = \left[\frac{D_c^t(K_i^t, L_i^t, E_i^t, Y_i^t, C_i^t)\cdot D_c^s(K_i^t, L_i^t, E_i^t, Y_i^t, C_i^t)}{D_c^t(K_i^s, L_i^s, E_i^s, Y_i^s, C_i^s)\cdot D_c^s(K_i^s, L_i^s, E_i^s, Y_i^s, C_i^s)}\right]^{1/2}. \quad (4)$$

$\mathrm{MCPI}_i(t, s)$ can be used to measure the change in CO_2 emissions performance of country i from period t to period s. $\mathrm{MCPI}_i(t, s)>1$ (or $\mathrm{MCPI}_i(t, s)<1$) indicates that the CO_2 emissions performance has improved (or deteriorated). Like Malmquist productivity index, MCPI can also be decomposed into two components, namely efficiency change and technological change, respectively given by

$$EFFCH_i(t,s) = \frac{D_c^t(K_i^t, L_i^t, E_i^t, Y_i^t, C_i^t)}{D_c^s(K_i^s, L_i^s, E_i^s, Y_i^s, C_i^s)} \quad (5)$$

$$TECHCH_i(t,s) = \left[\frac{D_c^s(K_i^t, L_i^t, E_i^t, Y_i^t, C_i^t)\cdot D_c^s(K_i^s, L_i^s, E_i^s, Y_i^s, C_i^s)}{D_c^t(K_i^t, L_i^t, E_i^t, Y_i^t, C_i^t)\cdot D_c^t(K_i^s, L_i^s, E_i^s, Y_i^s, C_i^s)}\right]^{1/2}. \quad (6)$$

The efficiency change component measures the catch-up effect, which reflects the change in relative CO_2 emission performance with regard to country i's production frontiers at period t and s. The technological change component measures the frontier-shift effect, which quantifies the shift in the production technology of country i over time from period t to period s.

Fig. 1 shows a simple graphical illustration of MCPI. Assume that the regions OABCD and OA′B′C′D′ respectively represent the environmental DEA technologies for period t and s. Further assume that a country uses the same amounts of inputs to produce different amounts of output pairs at t and s which are represented by point M and N. Then the efficiency change component of MCPI is equal to $\frac{DM/DF}{GN/GH}$. The technological change component is equal to $\left[\frac{DM/DE}{DM/DF}\cdot\frac{GN/GH}{GN/GK}\right]^{1/2} = \left[\frac{DF}{DE}\cdot\frac{GK}{GH}\right]^{1/2}$, which measures the shift of the production frontiers at the GDP levels of OD and OG.

To estimate MCPI and its two contributing components, we compute four Shephard carbon distance functions, i.e. $D_c^{l_1}(K_i^{l_2}, L_i^{l_2}, E_i^{l_2}, Y_i^{l_2}, C_i^{l_2})$, $l_1, l_2 \in \{s, t\}$. According to Eq. (3) and the environmental DEA technology given by Eq. (2), we compute $D_c^{l_1}(K_i^{l_2}, L_i^{l_2}, E_i^{l_2}, Y_i^{l_2}, C_i^{l_2})$ by solving the following DEA model:

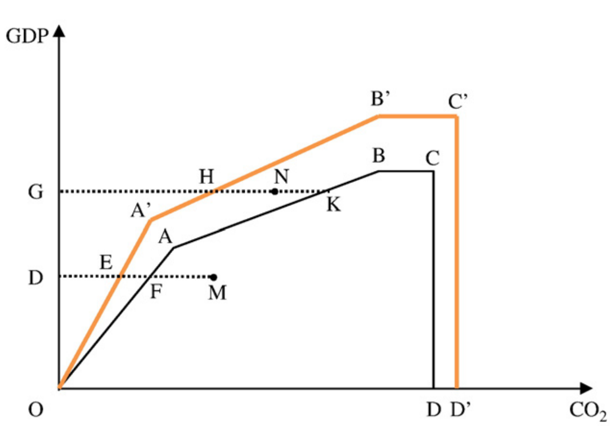

Fig. 1. Graphical illustration of Malmquist CO_2 emission performance index.

$$\begin{aligned}
[D_c^{l_1}(K_i^{l_2}, L_i^{l_2}, E_i^{l_2}, Y_i^{l_2}, C_i^{l_2})]^{-1} = \; & \min\theta \\
\text{s.t.} \; & \sum_{i=1}^{I} z_i K_i^{l_1} \le K_i^{l_2} \\
& \sum_{i=1}^{I} z_i L_i^{l_1} \le L_i^{l_2} \\
& \sum_{i=1}^{I} z_i E_i^{l_1} \le E_i^{l_2} \\
& \sum_{i=1}^{I} z_i Y_i^{l_1} \ge Y_i^{l_2} \\
& \sum_{i=1}^{I} z_i C_i^{l_1} = \theta C_i^{l_2} \\
& z_i \ge 0, i = 1, 2, \Lambda, I
\end{aligned} \quad (7)$$

Note that Eq. (7) is based on the environmental DEA technology exhibiting constant returns to scale, which is the most commonly adopted practice in the literature. According to Førsund and Kittelsen (1998), the Malmquist productivity index based on the constant returns to scale production technology can be interpreted as a total factor productivity index. As a result, the MCPI derived from Eq. (7) may be interpreted as a total factor carbon emission performance index.

2.3. Bootstrapping Malmquist CO_2 emission performance index

Since MCPI is derived from the Shephard carbon distance functions that are calculated based on the estimate of the true production frontier, it will be subjected to uncertainties due to the sampling variation of the obtained production frontier. It is therefore meaningful to assess the sensitivity of MCPI with respect to the sampling variation by bootstrapping the index. The theory and algorithm of bootstrapping nonparametric DEA efficiency scores are developed by Simar and Wilson (1998), which are extended by Simar and Wilson (1999) to bootstrap the Malmquist productivity index. Recent developments on the use of the bootstrap method in nonparametric frontier models can be found in Daraio and Simar (2007).

We adopt the algorithm developed by Simar and Wilson (1999) to bootstrap MCPI by considering CO_2 emissions. Compared to bootstrapping DEA efficiency scores, time-dependent structure of the data must be taken into account in bootstrapping MCPI. The simplified process for bootstrapping MCPI is summarized as follows:

(1) Compute $MCPI_i(t, s)$ for $i=1,2,\ldots,I$ by solving Eqs. (7) and (4).
(2) Use the bivariate kernel density estimator and the reflection method as introduced in Simar and Wilson (1999) to generate two pseudo datasets $\{K_i^t, L_i^t, E_i^t, Y_i^t, C_i^{t*}\}, i=1,2,\ldots,I$ and $\{K_i^s, L_i^s, E_i^s, Y_i^s, C_i^{s*}\}, i=1,2,\ldots,I$.[3]
(3) Compute the bootstrap estimate of $MCPI_{i,b}^*(t, s)$ of $MCPI_i(t, s)$ for $i=1,2,\ldots,I$ by solving Eqs. (4) and (7) based on the environmental DEA technologies constructed from the pseudo datasets obtained in Step 2.
(4) Repeat steps 2–3 B times to provide B estimates $\{MCPI_{i,b}^*(t, s), b=1,2,\ldots,B\}$ for $i=1,2,\ldots,I$.[4]

[3] The density estimated from only the bivariate kernel estimator is inconsistent and asymptotically biased as the Shephard carbon distance functions are bounded from unity. The use of the reflection method can help to overcome this problem. The technical details on the reflection method can be found in Simar and Wilson (1999).

[4] The size of B may vary from one study to another study. For instance, B is set as 1000 in Simar and Wilson (1998) while 2000 is used in Simar and Wilson (1999). In their recent study, Daraio and Simar (2007) suggest that B should be at least equal to 2000.

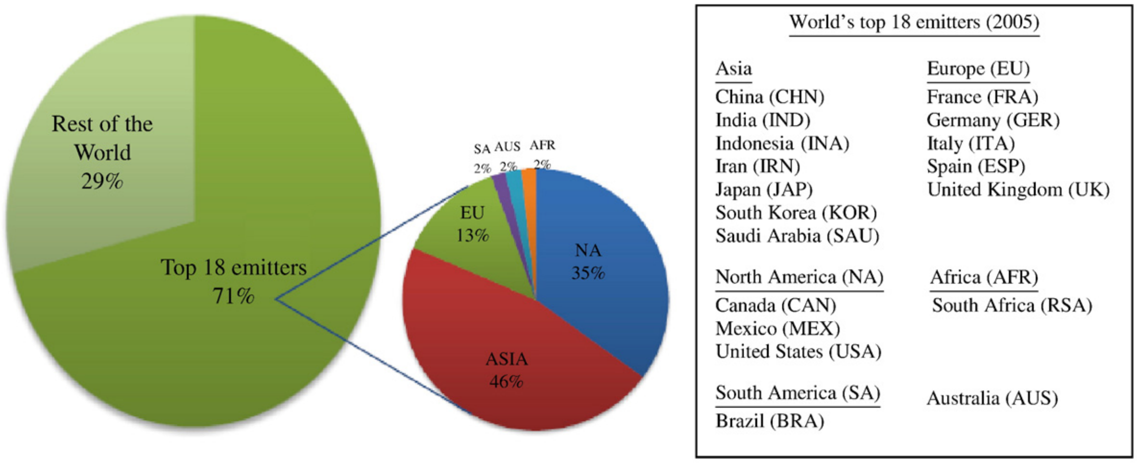

Fig. 2. Distribution of CO_2 emissions for the top 18 emitters in 2005.

The bootstrapping estimates of MCPI obtained can then be used to construct confidence intervals and perform statistical inferences. The information from the confidence intervals is useful in identifying whether the improvement or deterioration indicated by the total factor carbon emission performance index is significant or not at the desired significance level. At the same time, we can also use the estimates to test the significance of the contributing components of MCPI, e.g. technical efficiency change and technological change.

3. Empirical application

3.1. Data

The approach described in Section 2 is applied to study the total factor carbon emission performance of the world's top energy-related CO_2 emitters in 2005. Of the top 20 emitters, Russia and Ukraine are excluded due to data limitations. We shall refer to the remaining 18 countries as the world's top 18 emitters. Fig. 2 lists the countries and shows the distribution of CO_2 emissions in 2005.[5] The 18 countries together contributed to 71% of the world's CO_2 emissions.

The data for capital stock, labor force, energy consumption, GDP, and CO_2 emissions are collected and compiled for a ten-year period from 1995 to 2004. The data for aggregate labor force are gathered from World Bank (2007) and for total primary energy consumption from BP (2008). The data for capital stock are estimated using the perpetual inventory method based on the inputs from the *Penn World Tables Version 6.2* (Heston et al., 2006).[6] The data for GDP, measured in PPP and 2000 prices, are also collected from Heston et al. (2006). For consistency, the CO_2 emission data are estimated using the energy data from BP (2008).[7] Table 1 shows the summary statistics of the data collected and compiled.

3.2. Dynamic CO_2 emission performance analysis

The CO_2 emission efficiency scores of the 18 countries from 1997 to 2004 are first calculated by using Eq. (3) in which all the data on inputs and outputs are for the same years. Table 2 displays the results obtained. Compared to the MCPI, the CO_2 emission efficiency scores given in Table 2 could be referred to as static CO_2 emission performance indices as they are computed only based on cross-sectional data. These static CO_2 emission performance indices provide information on the rankings of the countries in terms of their relative CO_2 emission efficiency.

To assess the dynamic CO_2 emission performance of the 18 countries, we compute the MCPI for each of the 18 countries. For each consecutive two-year period, four linear programming (LP) models are solved. In a mix-period LP problem, the production frontier constructed by the observations from a period may not enclose all the observations from another period. As a result, some mix-period LP problems may be infeasible. We therefore follow Färe et al. (2007) to use the three-year “windows” approach to constructing the

Table 1
Summary statistics of inputs and outputs for the 18 countries studied (average, 1995–2004).

Variable	Name	Unit	Mean	Std. dev.
K	Capital stock	US$ trillion	3.07	3.85
L	Total labor force	Million workers	100.61	183.91
E	Total primary energy consumption	Million tons of oil equivalent (Mtoe)	368.07	527.49
Y	Gross domestic product	US$ billion	1925.04	2361.23
C	Carbon dioxide emissions	Million tons (Mt)	1036.97	1546.14

Table 2
The static CO_2 emission performance scores of 18 countries, 1997–2004.

Country	1997	1998	1999	2000	2001	2002	2003	2004
AUS	0.4228	0.4206	0.4221	0.4145	0.4105	0.3976	0.4272	0.4239
BRA	1.0000	0.9629	0.9589	1.0000	1.0000	1.0000	1.0000	1.0000
CAN	0.3913	0.3942	0.4032	0.4028	0.3926	0.3880	0.3852	0.4016
CHN	0.4516	0.5116	0.5124	0.5152	0.5350	0.5419	0.4673	0.4251
ESP	0.7930	0.7766	0.7486	0.7137	0.7308	0.7094	0.7147	0.6876
FRA	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
GER	0.6494	0.6892	0.7263	0.7127	0.6831	0.6995	0.6862	0.7151
INA	1.0000	0.9668	0.8647	0.9413	1.0000	0.9786	0.9186	0.8055
IND	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
IRN	0.3236	0.3215	0.3449	0.3414	0.3322	0.3363	0.3338	0.3022
ITA	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
JAP	0.7381	0.7540	0.6999	0.6654	0.6491	0.6274	0.6096	0.6131
KOR	0.4056	0.4210	0.4148	0.3997	0.3919	0.3871	0.3806	0.3810
MEX	0.7122	0.6230	0.6911	0.7659	0.7230	0.6885	0.5807	0.5793
RSA	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
SAU	1.0000	0.7521	0.9086	1.0000	0.9468	0.9825	0.8616	1.0000
UK	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
USA	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

[5] The emission data are taken from IEA (2007). Note that the 18 emitters include both developed and developing countries, which means that there may exist the problem of heterogeneous sample. Therefore, the results obtained from this empirical analysis should be interpreted with this limitation in mind.

[6] Although the source provides capital stock estimates for a number of countries, the data for some of the top 18 emitters in several recent years of the study period are not available. We therefore re-estimate the capital stock data for all the 18 countries in this study.

[7] A comparison shows little difference between our estimated CO_2 emissions and the IEA emission data.

Table 3
Changes in MCPI from 1997/1998 to 2003/2004.

Country	1997/1998	1998/1999	1999/2000	2000/2001	2001/2002	2002/2003	2003/2004
AUS	1.0170	1.0406	1.0451	1.0376*	1.0199	1.1152**	1.1034**
BRA	0.9597	0.9795	1.1120**	1.0863**	1.0010	1.2410**	1.0254
CAN	1.0037	1.0637	1.0758	1.0203	1.0387	1.0099	1.0862**
CHN	1.0799	1.0020	1.0029	1.0241	1.0198	0.9102**	0.9158*
ESP	0.9933	1.0125	1.0393*	1.1120**	1.0593	1.0573	1.0531
FRA	1.1295**	1.2267**	1.0335	1.0244	1.0218	1.0069	1.0178
GER	1.0630	1.1160**	1.0736	1.0425**	1.1118**	1.0319	1.1262**
INA	0.9664	0.8849**	1.0614	1.0307	1.0016	1.0451	0.9151**
IND	1.0321	1.0464	1.0000	1.0323	1.0026	1.0486	1.0015
IRN	0.9862	1.0695	1.0131	0.9838*	1.0410	1.0390	0.9802**
ITA	1.0034	1.0073	1.0185	1.0371	1.0283	1.0000	1.0245
JAP	1.0231	0.9860	1.0391*	1.0434	1.0298	1.0037	1.0581
KOR	1.0386	1.0071	1.0139**	1.0210	1.0362	1.0155	1.0431
MEX	0.8918*	1.1638*	1.2149**	0.9829**	1.0184	1.0005**	1.0952**
RSA	1.0102	1.0317	1.0645	0.9735	1.0315	0.9970	0.9974
SAU	0.7528**	1.1781**	1.2096**	0.9471	1.0389	0.8764**	1.1089**
UK	1.0208	1.0353	1.0257	1.0233	1.0499	1.0295	1.0251
USA	1.0471	1.0551	1.0605	1.0406	1.0432	1.0848**	1.1030**
A. Mean	1.0010	1.0504	1.0613	1.0257	1.0330	1.0285	1.0378
G. Mean	0.9977	1.0475	1.0597	1.0251	1.0327	1.0259	1.0360

* The MCPI index is significantly different from unity at the 0.10 level.
** The MCPI index is significantly different from unity at the 0.05 level.

Table 4
Efficiency change component of MCPI from 1997/1998 to 2003/2004.

Country	1997/1998	1998/1999	1999/2000	2000/2001	2001/2002	2002/2003	2003/2004
AUS	0.9949	1.0034	0.9822	0.9901	0.9687*	1.0743**	0.9924
BRA	0.9629	0.9959	1.0428	1.0000	1.0000	1.0000	1.0000
CAN	1.0075	1.0227	0.9992	0.9746*	0.9884	0.9926	1.0428
CHN	1.1327**	1.0016	1.0055	1.0384	1.0129	0.8623**	0.9097*
ESP	0.9793	0.9640	0.9533*	1.0240	0.9708*	1.0075	0.9620
FRA	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
GER	1.0613**	1.0539	0.9812	0.9585**	1.0240	0.9811	1.0421
INA	0.9668	0.8944**	1.0885**	1.0624**	0.9786	0.9387**	0.8768*
IND	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
IRN	0.9937	1.0726**	0.9898	0.9732*	1.0121	0.9926	0.9054**
ITA	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
JAP	1.0215	0.9283*	0.9507*	0.9755	0.9666	0.9717	1.0057
KOR	1.0379	0.9853	0.9636**	0.9806	0.9877	0.9831	1.0010
MEX	0.8748**	1.1092**	1.1083*	0.9440**	0.9522*	0.8434**	0.9977
RSA	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
SAU	0.7521**	1.2081**	1.1006**	0.9468**	1.0376	0.8769**	1.1607**
UK	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
USA	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
A. Mean	0.9881	1.0133	1.0092	0.9927	0.9944	0.9736	0.9942
G. Mean	0.9850	1.0112	1.0082	0.9923	0.9942	0.9719	0.9925

* The efficiency change component is significantly different from unity at the 0.10 level.
** The efficiency change component is significantly different from unity at the 0.05 level.

environmental DEA technologies. In the three-year "windows" approach, the environmental DEA technology in period t is constructed from the 54 observations in period t, $t-1$ and $t-2$. We can then use the environmental DEA technology to assess the observations for the year $t+1$ or $t-1$. Having obtained the MCPI results for seven two-pairs from 1997/1998 to 2003/2004 for each country, we apply the bootstrap procedure as described in Section 2.3 to construct the confidence intervals of the original MCPI values for testing their significant differences from unity. Table 3 shows the original MCPI estimates and the statistical testing results.

Table 3 shows that different conclusions may be drawn based on the original MCPI estimates and their bootstrapping results. The original MCPI estimates indicate that all the countries have a change (most likely an improvement) in their total factor carbon emission performance for each consecutive two-year period. However, the bootstrapping results show that in most cases the change is not significant. For instance, in 2001/2002 although all the countries seem to have an improvement in CO_2 emission performance, only the improvement in Germany is found to be significant. In 1997/1998, of the six countries that have a drop in performance, only two, i.e. Saudi Arabia and Mexico, are found to be significant.

We have also decomposed the MCPI estimates (including their bootstrapping results) into their efficiency change and technological change components using Eq. (5) and (6). Table 4 shows the efficiency change components obtained. Six countries, namely France, Italy, India, South Africa, UK, and USA, did not experience changes in their technical efficiency over time. Based on the bootstrapping results, we may conclude that technical efficiency change is also not significant for Brazil.

Table 5 shows the results of the technological change component. Of the 126 entries, the original estimates show that 18 registered negative shift in technology. The bootstrap results, however, reveal that only two (China in 1997/1998 and Saudi Arabia in 2003/2004) are significantly less than unity. The results do not show significant technological regress in the remaining 16 entries. On the other hand, most countries have been found to register a positive shift in technology. Among them, about a third has shown significant technological improvement.

From Tables 4 and 5 we may find that improvement in total factor carbon emission performance is largely attributable to technological improvement. The efficiency change effect seems to have little influence on the improvement in CO_2 emission performance. In fact, the overall efficiency change of the 18 countries registered a negative shift (below unity) from 2000/2001 to 2003/2004.

Table 6 summarizes the findings from the bootstrapping results of MCPI, efficiency and technological change components for 1997/1998, 2000/2001 and 2003/2004. Although a number of countries are found to experience changes in MCPI, efficiency and technological change effects based on the original estimates, they are not significant in most cases. Therefore, the CO_2 emission performance comparisons among countries based on the original MCPI estimates need to be interpreted with caution.

To study the overall emission performance changes of the 18 countries from 1997 to 2004, we have also calculated the cumulative MCPI and its contributing components in 2004. Table 7 shows the

Table 5
Technological change component of MCPI from 1997/1998 to 2003/2004.

Country	1997/1998	1998/1999	1999/2000	2000/2001	2001/2002	2002/2003	2003/2004
AUS	1.0221	1.0371	1.0641	1.0479*	1.0529	1.0381	1.1118*
BRA	0.9967	0.9836	1.0663**	1.0863**	1.0010	1.2410**	1.0254
CAN	0.9962	1.0401	1.0767**	1.0469	1.0510	1.0175	1.0416
CHN	0.9534*	1.0004	0.9974	0.9862	1.0069	1.0554**	1.0067*
ESP	1.0143	1.0504**	1.0901*	1.0860**	1.0912**	1.0494	1.0947*
FRA	1.1295**	1.2267**	1.0335	1.0244	1.0218	1.0069	1.0178
GER	1.0017	1.0589**	1.0942**	1.0877**	1.0858**	1.0518	1.0808**
INA	0.9996	0.9894	0.9751	0.9702	1.0235	1.1134**	1.0437*
IND	1.0321	1.0464	1.0000	1.0323	1.0026	1.0486	1.0015
IRN	0.9924	0.9971	1.0235	1.0109	1.0286	1.0467	1.0826**
ITA	1.0034	1.0073	1.0185	1.0371	1.0283	1.0000	1.0245
JAP	1.0016	1.0622**	1.0930*	1.0696**	1.0654**	1.0330	1.0521
KOR	1.0007	1.0222	1.0521**	1.0413	1.0491	1.0329	1.0420
MEX	1.0194	1.0492	1.0962**	1.0412*	1.0695**	1.1863**	1.0977**
RSA	1.0102	1.0317	1.0645**	0.9735	1.0315	0.9970	0.9974
SAU	1.0009	0.9752	1.0991**	1.0003	1.0012	0.9993	0.9553**
UK	1.0208	1.0353	1.0257**	1.0233	1.0499	1.0295	1.0251
USA	1.0471	1.0551**	1.0605**	1.0406*	1.0432	1.0848**	1.1030**
A. Mean	1.0134	1.0371	1.0517	1.0336	1.0391	1.0573	1.0447
G. Mean	1.0129	1.0359	1.0510	1.0331	1.0387	1.0556	1.0438

* The technological change component is significantly different from unity at the 0.10 level.
** The technological change component is significantly different from unity at the 0.05 level.

Table 6
Number of countries experiencing MCPI, efficiency and technological changes based on the original and bootstrapping results.

	1997/1998			2000/2001			2003/2004		
	Original estimate	Significance		Original estimate	Significance		Original estimate	Significance	
		5%	10%		5%	10%		5%	10%
Change in MCPI									
Improvement	12	1	0	14	3	1	14	5	0
Decline	6	1	1	4	1	1	4	2	1
Stagnation	0	0	0	0	0	0	0	0	1
EFCH									
Improvement	5	2	0	3	1	0	5	1	0
Decline	7	2	0	8	3	2	6	1	2
Stagnation	6	0	0	7	0	0	7	0	0
TECHCH									
Improvement	13	1	0	15	4	3	16	4	4
Decline	5	0	1	3	0	0	2	1	0
Stagnation	0	0	0	0	0	0	0	0	0

Table 7
Cumulative Malmquist CO_2 emission performance index and its decomposition in 2004 (1997 = 1).

Country	Cumulative MCPI	Efficiency change	Technological change	Rank
AUS	1.4402**	1.0027	1.4364**	5
BRA	1.4466**	1.0000	1.4466**	4
CAN	1.3354**	1.0265	1.3009**	8
CHN	0.9448*	0.9413*	1.0037	17
ESP	1.3709**	0.8670**	1.5812**	7
FRA	1.5361**	1.0000	1.5361**	2
GER	1.7157**	1.1012**	1.5580**	1
INA	0.8961**	0.8055**	1.1126*	18
IND	1.1738	1.0000	1.1738**	12
IRN	1.1144*	0.9339**	1.1933**	14
ITA	1.1246**	1.0000	1.1246**	13
JAP	1.1961*	0.8306**	1.4400**	10
KOR	1.1885**	0.9393*	1.2654**	11
MEX	1.3832**	0.8134**	1.7004**	6
RSA	1.1078	1.0000	1.1078**	15
SAU	1.0258*	1.0000	1.0258*	16
UK	1.2290**	1.0000	1.2290**	9
USA	1.5220**	1.0000	1.5220**	3
A. Mean	1.2639	0.9590	1.3199	–
G. Mean	1.2459	0.9556	1.3038	–

* The index is significantly different from unity at the 0.10 level.
** The index is significantly different from unity at the 0.05 level.

results obtained with 1997 taken as the base year, i.e. the 1997 value is set equal to 1, for calculating the cumulative MCPI index. It is found that the sample countries as a whole show an improvement in CO_2 emission performance by over 24% from 1997 to 2004. China and Indonesia are the only two that experienced a decline in total factor carbon emission performance. In addition, Table 7 shows that most of the countries experienced significant changes in their CO_2 emission performance from 1997 to 2004 but the results for each consecutive two-year period are found to be insignificant. This should be mainly attributed to the cumulative effect and the bootstrapping may also play a role through affecting the variance of MCPI.

Among the 18 countries, Germany, France, USA, Brazil and Australia are found to be the best performers, while Indonesia, China, Saudi Arabia, South Africa and Iran the worst and based on the cumulative MCPI value. Figs. 3 and 4 respectively depict the cumulative MCPI trends for the top and bottom five performers from 1997 to 2004.

The results for the technological change component given in Table 5 signify a shift in the frontier technology around each country over time. However, a value for a particular country greater than one does not indicate that this country play a role in shifting the frontier. By using the set of criteria as defined by Färe et al. (1994) and used by Kumar (2006), we may identify the "innovators" which contribute to the frontier shift over each consecutive two-year period. The results

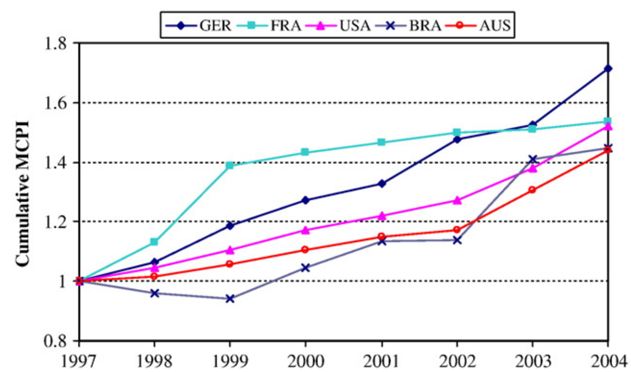

Fig. 3. The cumulative MCPI trends for the top five performers over time.

obtained are shown in Table 8, which show that the "innovators" include France, USA and Brazil.

3.3. A cross-country regression analysis

We investigate if there exists a relationship between some country-specific variables and MCPI. A cross-country multiple linear regression model with the United States taken as the base country is built for this analysis. The dependent variable is the cumulative MCPI, and the explanatory variables considered include GDP per capita, energy intensity and the ratification of the Kyoto Protocol. The first explanatory variable has often been adopted in previous literature, e.g. Kumar (2006). The second variable is included as intuitively it may affect a country's CO_2 emission performance. The third variable is used to examine whether rectifying Kyoto Protocol plays a role in improving total factor CO_2 emission performance.[8] Data for the real GDP per capita is obtained from the World Bank (2007), while Kyoto Protocol ratification dates are taken from the United Nations Framework Convention on Climate Change (UNFCCC) website.

Each of the three factors identified is likely to affect the pattern and level of CO_2 emissions in a country. The association with GDP per capita will determine the impact of income growth on the total factor carbon emission performance (Kumar, 2006). Energy intensity is included to capture the impact of economic structure as the latter has direct impacts on the amounts of energy use and CO_2 emissions. For example, a shift from energy-intensive sectors to less energy-intensive sectors would result in a decline in CO_2 emissions. The

[8] It is clear that there are other explanatory variables that may be included. A problem we faced is that for these variables a complete data set for all the 18 countries is often not available, and the data needed are often not available for some non-OECD countries. We therefore limit our study to only the three identified variables.

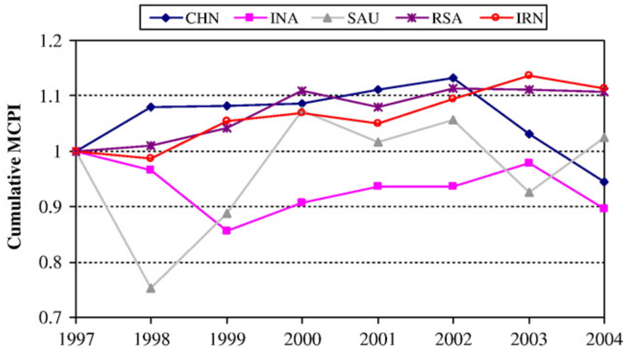

Fig. 4. The cumulative MCPI trends for the bottom five performers over time.

Table 8
Countries shifting the production frontier.

Year	Innovators
1997–1998	France
1998–1999	France
1999–2000	USA, Brazil
2000–2001	USA, Brazil
2001–2002	USA
2002–2003	USA, Brazil
2003–2004	–

Kyoto Protocol variable may provide an indication on the effectiveness of international and national efforts in regulating CO_2 emissions.

Let *CMCPI*, *GDPPC* and *EI* denote the cumulative MCPI, GDP per capita and energy intensity, respectively. Let *RATDATE* denote the dummy variable that takes a value of one for the years after a country rectified the Kyoto Protocol (otherwise a value of zero). Let $COUNTRY_i$ be a dummy variable that takes a value of one to signify the country in evaluation (otherwise a value of zero).[9] The multiple regression equation to describe the relationship between total factor carbon emission performance and its determinants can be formulated as follows

$$CMCPI = \beta_0 + \beta_1 GDPPC + \beta_2 EI + \beta_3 RATDATE + \sum_{i=1}^{18} \gamma_i COUNTRY_i + \varepsilon \quad (8)$$

where ε is a random disturbance term such that $\varepsilon \sim N(0, \sigma_\varepsilon^2)$.[10]

Table 9 summarizes the main regression results. All the three determinant factors are statistically significant. The coefficient of determination, denoted by R^2 or R^2(adj), shows that the regression model fits the data reasonably well. The coefficient of GDP per capital is positive which is consistent with the conclusion drawn by most previous studies. Not surprisingly, energy intensity is found to have a negative relationship with MCPI. The coefficient of the dummy Kyoto Protocol variable is positive and highly significant, which may provide an empirical support on the effectiveness of the ratification of the Kyoto Protocol on improving the CO_2 emission performance. As to the coefficients for the dummy COUNTRY variables, the coefficients for the top performers in MCPI are not significantly different from zero. This is not surprising as the United States has been shown to be among the list of top performers. The bottom performers generally have a negative coefficient with a very small *p*-value, which indicates that they are worse than the United States in emission performance.

[9] In the case of the United States, $COUNTRY_i$ ($i = 1,\cdots,18$) are all equal to zero as it is taken as the base country for comparisons.

[10] The regression equation is essentially a model with constant slopes and variable intercepts. Such models are common in analyzing panel data as they provide simple but reasonable alternatives to the models with constant slopes and intercepts for all agents at all times (Hsiao, 2003). Our analysis shows that the error terms are not correlated with the country dummies, which provides further justification on the use of cross-country regression analysis. A better alternative would be to use a panel data approach as described in Hsiao (2003) and to examine whether the model is a fixed or random effect one.

Table 9
Determinants of the Malmquist CO_2 emissions performance index.

Variable	Coefficient	*P*-value
CONSTANT	0.6859	0.013
GDPPC	0.3413	0.002
EI	−2.6969	0.000
RATDATE	0.0642	0.003
AUS	0.1467	0.136
BRA	0.5828	0.072
CAN	0.5204	0.000
CHN	−0.7416	0.027
ESP	0.1913	0.308
FRA	0.2741	0.354
GER	0.1983	0.308
INA	−0.4023	0.027
IND	0.5847	0.126
IRN	−1.0054	0.000
ITA	−0.0610	0.716
JAP	−0.0030	0.983
KOR	0.5171	0.008
MEX	0.6273	0.042
RSA	0.9053	0.001
SAU	0.7343	0.000
UK	−0.0329	0.809

Note: $R^2 = 0.76$ and $R^2(\text{adj}) = 0.72$.

4. Conclusion

Addressing the problems arising from global climate change calls for a better understanding of the patterns of CO_2 emissions and national emission performance over time. Many of the indicators proposed in previous studies can only reflect partial aspects of CO_2 emission performance. In this study, we introduce a MCPI that measures the dynamic CO_2 emission performance of different countries. The MCPI may be interpreted as a total factor carbon emission performance index as it is constructed from a total factor production perspective. The derivation of MCPI can be done by solving several DEA type models. We also propose bootstrapping MCPI in order to perform statistical inferences on MCPI.

We apply the proposed approach to studying the total factor carbon emission performance of the world's 18 top CO_2 emitters from 1997 to 2004. It is found that the total factor carbon emission performance of these countries improved by 24% from 1997 to 2004 and this was due mainly to technological progress. Among the countries studied, Germany ranks first while China and Indonesia have seen deteriorations in CO_2 emission performance. In addition, bootstrapping MCPI is found to be a useful complement of MCPI in performance comparisons. The results from a cross-country regression analysis show that GDP per capita and the ratification of the Kyoto Protocol have a positive while energy intensity has a negative effect on total factor carbon emission performance.

Finally, it should be noted that the results of the empirical study presented are dependent on the countries included and the variables and data set used. As the study covers several developing countries, we encountered some problems in data collection and as such simplification and assumptions are incorporated in certain parts of the analysis. Further research may be carried out to improve and extend this study by covering a greater number of countries, using time series over a longer time period, and including more relevant variables and data of better quality.

Acknowledgements

The authors would like to thank two anonymous reviewers for their invaluable comments on an earlier draft of this paper. P. Zhou is also grateful to the financial support provided by the National Natural Science Foundation of China under Grant Nos. 70903031 and 70873058 as well as the Major Program of the National Social Science Foundation of China under Grant No. 08&ZD046.

References

Abbott, M., 2006. The productivity and efficiency of the Australian electricity supply industry. Energy Economics 28, 444–454.
Ang, B.W., 1999. Is the energy intensity a less useful indicator than the carbon factor in the study of climate change? Energy Policy 27, 943–946.
Barros, C.P., 2008. Efficiency analysis of hydroelectric generating plants: a case study for Portugal. Energy Economics 30, 59–75.
Barros, C.P., Peypoch, N., 2008. Technical efficiency of thermoelectric power plants. Energy Economics 30, 3118–3127.
BP, 2008. Statistical Review of World Energy. Available at: http://www.bp.com/statisticalreview.
Caves, D.W., Christensen, L.R., Diewert, W.E., 1982. Multilateral comparisons of output, input and productivity using superlative index numbers. The Economic Journal 92, 73–86.
Daraio, C., Simar, L., 2007. Advanced Robust and Nonparametric Methods in Efficiency Analysis: Methodology and Applications. Springer.
Färe, R., Grosskopf, S., Lovell, C.A.K., Pasurka, C., 1989. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. The Review of Economics and Statistics 71, 90–98.
Färe, R., Grosskopf, S., Norris, M., Zhang, Z., 1994. Productivity growth, technical progress and efficiency change in industrialized countries. American Economic Review 84, 66–83.
Färe, R., Grosskopf, S., Pasurka Jr., C.A., 2007. Pollution abatement activities and traditional productivity. Ecological Economics 62, 673–682.
Førsund, F.R., 2008. Good modeling of bad outputs: pollution and multiple-output production. Memo, No. 30/2008. Department of Economics, Oslo University.
Førsund, F.R., Kittelsen, S.A.C., 1998. Productivity development of Norwegian electricity distribution utilities. Resource and Energy Economics 20, 207–224.
Heston, A., Summers, R., Aten, B., 2006. Penn World Table Version 6.2. University of Pennsylvania, Philadelphia.
Hsiao, C., 2003. Analysis of Panel Data, Second edition. Cambridge University Press.
International Energy Agency (IEA), 2007. CO2 Emissions from Fuel Combustion: 1971–2005. OECD, Paris.
Kortelainen, M., 2008. Dynamic environmental performance analysis: a Malmquist index approach. Ecological Economics 64, 701–715.
Kumar, S., 2006. Environmentally sensitive productivity growth: a global analysis using Malmquist–Luenberger index. Ecological Economics 56, 280–293.
Lee, C.C., Chang, C.P., Chen, P.F., 2008. Energy-income causality in OECD countries revisited: the key role of capital stock. Energy Economics 30, 2359–2373.
Lozano, S., Gutiérrez, E., 2008. Non-parametric frontier approach to modelling the relationships among population, GDP, energy consumption and CO_2 emissions. Ecological Economics 66, 687–699.
Lozano, S., Villa, G., Brannlund, R., 2009. Centralised reallocation of emission permits using DEA. European Journal of Operational Research 193, 752–760.
Mielnik, O., Goldemberg, J., 1999. The evolution of the "carbonization index" in developing countries. Energy Policy 27, 307–308.
Mukherjee, K., 2008. Energy use efficiency in U.S. manufacturing: a nonparametric analysis. Energy Economics 30, 76–96.
Pombo, C., Taborda, R., 2006. Performance and efficiency in Colombia's power distribution system: effects of the 1994 reform. Energy Economics 28, 339–369.
Ramanathan, R., 2002. Combining indicators of energy consumption and CO_2 emissions: a cross-country comparison. International Journal of Global Energy Issues 17, 214–227.
Ramos-Real, F.J., Tovar, B., Iootty, M., de Almeida, E.F., Pinto Jr., H.Q., 2009. The evolution and main determinants of productivity in Brazilian electricity distribution 1998–2005: an empirical analysis. Energy Economics 31, 298–305.
Seiford, L.M., Zhu, J., 2002. Modeling undesirable factors in efficiency evaluation. European Journal of Operational Research 142, 16–20.
Simar, L., Wilson, P.W., 1998. Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. Management Science 44, 49–61.
Simar, L., Wilson, P.W., 1999. Estimating and bootstrapping Malmquist indices. European Journal of Operational Research 115, 459–471.
Soytas, U., Sari, R., 2007. The relationship between energy and production: evidence from Turkish manufacturing industry. Energy Economics 29, 1151–1165.
Sun, J.W., 2005. The decrease of CO_2 emission intensity is decarbonization at national and global levels. Energy Policy 33, 975–978.
Tol, R.S.J., Pacala, S.W., Socolow, R.H., 2009. Understanding long-term energy use and carbon emissions in the USA. Journal of Policy Modeling 31, 425–445.
Tyteca, D., 1997. Linear programming models for the measurement of environmental performance of firms — concepts and empirical results. Journal of Productivity Analysis 8, 183–197.
Wei, Y.M., Liao, H., Fan, Y., 2007. An empirical analysis of energy efficiency in China's iron and steel sector. Energy 32, 2262–2270.
Wolde-Rufael, Y., 2009. Energy consumption and economic growth: the experience of African countries revisited. Energy Economics 31, 217–224.
World Bank, 2007. World Development Indicators. World Bank, Washington.
Zaim, O., Taskin, F., 2000. A Kuznets curve in environmental efficiency: an application on OECD countries. Environmental and Resource Economics 17, 21–36.
Zhou, P., Ang, B.W., Poh, K.L., 2006. Slacks-based efficiency measures for modeling environmental performance. Ecological Economics 60, 111–118.
Zhou, P., Ang, B.W., Poh, K.L., 2008a. A survey of data envelopment analysis in energy and environmental studies. European Journal of Operational Research 189, 1–18.
Zhou, P., Ang, B.W., Poh, K.L., 2008b. Measuring environmental performance under different environmental DEA technologies. Energy Economics 30, 1–14.
Zofio, J.L., Prieto, A.M., 2001. Environmental efficiency and regulatory standards: the case of CO_2 emissions from OECD industries. Resource and Energy Economics 23, 63–83.