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The Measurement of Satisfaction Degree with Controllable and Uncontrollable Based on DEA Approach

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Abstract

Data envelopment analysis (DEA) has gained great popularity in environmental performance measurement because it can provide a synthetic, standardized environmental performance index when pollutants are suitably incorporated into the traditional DEA framework. This paper applies the DEA approaches to evaluate the CO_2 emission performance and measure its satisfaction degree of 40 countries and regions from 2008 to 2009. We use the input variables of capital, energy consumption and population and the output variables of gross domestic product (GDP) and the amount of fossil-fuel CO_2 emissions. Past studies about the application of DEA to environmental performance measurement have not considered uncontrollable factors. In this paper, we present the DEA formulas with controllable and uncontrollable factors to measure environment performance and its satisfaction degree. We first define and construct the environmental production technologies with desirable and undesirable outputs. The degree of environment satisfaction performance based on the DEA approach can be computed by solving a series of data envelopment analysis formulas. A case study of 40 countries and regions applying the DEA approach is also presented.

Key words: DEA; CO_2 Emissions; Environment Performance; Controllable; Uncontrollable

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INTRODUCTION

Carbon dioxide has long been a great problem to the global ecology, and in recent years, the situation has become even worse (Ang et al. 2011). It is commonly understood that carbon dioxide makes the greatest contribution to greenhouse gas. In the past century, the global climate has undergone significant change, ushering in new issues for leaders and decision makers (Yang and Pollitt, 2009). The increasing global temperature, the rising sea level, and diminishing grain output, among countless other issues, all contribute to the need for action and counteraction for human perseverance and prosperity. Scientists have documented the increasing global temperature; in the last 30 years, for instance, the average global temperature has risen by .48 degrees C (Yu, 2004; Wei et al, 2004; Tone, 2001). Humans make a great contribution to the global temperature through the use of fossil fuels (coal, petroleum, etc.) in daily living and industrial production (Zaim, 2004; Scheel, 2001). The resulting greenhouse gases absorb long-wave radiation in the atmosphere, trapping heat and driving global climate change. Given the current trend of atmospheric change, it is estimated that the global temperature will rise 1.4-5.8 degrees C before the year of 2100. In addition, experts have found that grain reduction also has a positive correlation with the global warming, and they predict this tendency will continue for many years.

Global attention about climate change has increased in recent years, and the need to control and mitigate greenhouse gas emission is likely to be an imminent and integral part of the worldwide policy agenda. Therefore, it is worthwhile to benchmark country by country performance of carbon dioxide output and assess potential for CO_2 emission reduction.

Data envelopment analysis (DEA) is a popular tool to measure the relative efficiency of a homogeneous decision making unit (DMU) with multiple inputs and outputs. DEA has been widely applied in many fields since it was first introduced by Charnes et al (1978). In the context of environmental performance measurement, DEA-based models have become increasingly popular in recent years, and the DEA method has been considered as an efficient tool for environment performance evaluation by many previous scholars. A large number of scholars focus their research on the DEA theory field and apply the DEA-models to the environment performance at the macro level. In the production theory approaches, pollutants (also called undesirable outputs) and desirable outputs are assumed to be generated in the same production process, which cannot be modeled by traditional DEA approach (Fare et al. 1989). In particular, carbon emission performance at the regional or national level has been studied widely (Zhou et al., 2008a). Various partial indicators have been proposed to model national carbon emission performance, such as the carbonization index, energy intensity, CO_2 emission intensity and CO_2 emission per capital (Mielnik and Goldemberg, 1999; Tol et al., 2009). Allowing for incomplete evaluation of partial indicators, the DEA approach is applied to combine all the relevant indicators in macro production systems into an overall index to reflect a more holistic view of performance evaluation. For instance, Zofio and Prieto (2001) developed a hyperbolic efficiency measure to calculate the CO_2 emission efficiency of OECD countries under regulatory scenarios. Zhou et al (2008) proposed a slacks-based environmental DEA model for modeling CO_2 emission performance that accounts for economic inefficiency. Zhou et al (2010) studied the total CO_2 emission performance of the top 18 emitters in the world in a time series using Malmquist index analysis. Wang et al (2010) applied the methodology of Zhou et al (2010) to the CO_2 emission performance of Chinese provinces. Ang et al. (2011) estimates the potential for reducing CO_2 emission in over 100 countries through improving generation efficiency and increasing the share of non-fossil fuel generation. Zhou (2012) analyzed the energy and CO_2 emission performance in electricity generation using a non-radial directional distance function approach.

As noted, many studies have utilized environmental DEA technology (Fare et al. 2004; Seiford and Zhu, 2005), but a gap in current literature still exists. Previous scholars applying DEA methods to measure environmental performance first incorporate undesirable outputs in the DEA framework, and then calculate the DMU's efficiency (Zhou et al, 2008). No studies have evaluated the DMU's performance with controllable and uncontrollable output. It is therefore worthwhile to extend the DEA approach with controllable and uncontrollable factors. The paper also proposes a measurement of degree of satisfaction and presents a case study of 60 OECD countries and regions using this proposed measurement.

In this paper, we review the introduction and related prior studies that have influenced this field of study in the first section, then propose the research DEA approach that includes the description and variable selection in Section 2. Section 3 provides the empirical results and interpretations, and the conclusion will be presented at the end.

1. RESEARCH METHOD

In this section, we will discuss the DMUs' efficiency and degree of satisfaction performance with controllable and uncontrollable outputs. Most pollution issues arise from the joint production of desirable and undesirable outputs; for example, the emission of CO_2 is inevitable when electricity is generated by burning coal (Zhou et al., 2008).

Noting $x \in A^m$ can produce output $y \in A^s$ for DMU_j(j=1,2.....n), DEA models are related to a production possibility set which is uniquely determined by a system of postulates. The production possibility set is given by (Wei and Fan, 2004):

$$T = \{(x, y) \mid x \in A^m, x \ge 0, y \in A^s, y \ge 0\}$$

Banker et al (1984) make an assumption of variable return to scale (VRS) in data envelopment analysis, which is different from the constant return to scale (CRS) assumption proposed by Charnes et al in 1978. Based on the BCC model proposed by Banker et al, the production possibility set P (convex) can be present as follows:

$$P = \{(x, y) \mid \lambda X \le x, \lambda Y \ge y, e\lambda = 1, \lambda \ge 0\}$$

Suppose we have a set of independent homogeneous DMU_j (j=1, 2…..n). Denote DMU_j can using different amounts of m inputs x_{ij} produce different amounts of output y_{ij} .λ_j is the weight of DMU_j . The efficiency of a specific DMU_O can be evaluated by the "BCC model" of DEA as introduced in Banker et al. (1984). The "envelopment form" is present as follows:

$$\begin{aligned}
\min \quad & \phi_o \\
s.t. \quad & \textstyle\sum_{j=1}^{n} \lambda_j x_{ij} \le \phi_o x_{i0}, \quad i = 1,2.....m \\
& \textstyle\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0}, \quad i = 1,2.....s \\
& \textstyle\sum_{j=1}^{n} \lambda_j = 1, \quad j = 1,2.....n \\
& \lambda_j \ge 0, \qquad\qquad j = 1,2.....n
\end{aligned}$$

As noted in the above envelopment form DEA model, we confine it is the input oriented version of radial measure model. λ_j is the weight of DMU_j, which can be auto generated by the DEA models. We don't set the value in advance, so the efficiency of DMU_j will not be subjective affected. This is a big advantage of DEA methods. DMU_o is DEA efficiency when ϕ_o is equal to 1 and DEA inefficiency when $\phi_o$is less than 1.The DEA model proposed by Cooper et al. (2009) for any DMU_j when ignoring the relationship between undesirable and desirable outputs can be given by model 1. Model 1 can evaluate the performance of DMU with controllable and uncontrollable inputs. x_{ij}^{c} represents the controllable inputs variable vector of DMU_j. x_{i0}^{uc} represents the uncontrollable inputs variable vector of DMU_j. The other variable is the same with the variable mentioned above.

$$\begin{aligned}
&\min \quad \phi \\
&s.t. \quad \sum\nolimits_{j=1}^{n} \lambda_j x_{ij} \le \phi x_{i0}^{c}, \quad i=1,2.....m \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j x_{ij}^{v} \le x_{i0}^{uc}, \quad i=1,2.....m \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0}, \quad i=1,2.....s \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j = 1, \quad j=1,2.....n \\
&\qquad \lambda_j \ge 0, \qquad j=1,2.....n
\end{aligned} \tag{1}$$

Model (1) is constructed based on the assumption of maximizing the output and minimizing the input for each DMU_j. This value of ϕ^* provides a measure of what is referred to as "technical efficiency" in economics. The minimization identifies a value $(1-\phi^*)x_{io}$, which represents the amount by which each input may be reduced without changing the proportions in which these inputs were used. Because ϕ^* is minimal, the proportional reduction in all inputs represented by $(1-\phi^*)$ is maximized.

The variable return to scale (VRS) model based on undesirable outputs proposed by Seiford and Zhu (2002) for any DMU_j can be given by model (2). b_{tj} is the *tth* undesirable output for DMU_j. The other variable is the same with the variable above.

$$\begin{aligned}
&\min \quad \theta \\
&s.t. \quad \sum\nolimits_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{i0} \quad i=1,2.....m, \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j x_{ij}^{v} \le x_{i0}^{v}, \quad i=1,2.....m \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0} \quad i=1,2.....s, \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j b_{tj} = \theta b_{t0} \quad t=1,2.....l, \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j = 1, \\
&\qquad \lambda_j \ge 0, \qquad j=1,2.....n
\end{aligned} \tag{2}$$

DMU_j is DEA efficient if and only if ϕ_j=1.DMU_j is DEA inefficient when $\phi_j \le 1$, which means DMU_j has inadequate production capability by using existing levels of inputs.

The above model is applied to evaluate the performance of DMU_j from technical efficiency. We define $\theta^{\min}$ and $\theta^{\max}$ as follow:

$$\theta^{\max} = \max\{\theta_j, j=1,2....n\}$$

$$\theta^{\min} = \min\{\theta_j, j=1,2....n\}$$

We assume that we have N (N=K_1+ K_2) DMUs in the sample. K_1 represents the number of DMUs which have an efficiency value less than 1. K_2 represents the number of DMUs where efficiency value is equal to 1. Then we define a virtual maximum value η (Stephan and Ivan, 2006), which can be obtained by the following formula:

$$\frac{1-\theta_{\min}}{K_1} = \frac{\eta-\theta_{\min}}{N}$$

So the virtual value range of θ is enlarge from interval [$\theta^{\min}$, 1] to [$\theta^{\min}$, η].

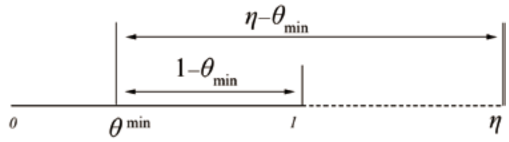

Figure 1
Definition of Virtual Maximum Value
η

We define the satisfaction interval value $\alpha=\eta-\phi^{\min}$ and gain satisfaction $\beta=\sigma-\phi^{\min}+\varepsilon$

We assume that ε is equal to 10^{-6} in this paper. The parameter ε aims to insure that β is not equal to zero. α and β are both positive values. We can define the DMU's degree of satisfaction as γ based on the definition. The bigger value of γ means more satisfaction compare to other DMUs.

$$\gamma(\sigma) = \frac{\beta}{\alpha} = \frac{\sigma-\phi^{\min}+\varepsilon}{\eta-\phi^{\min}}$$

Since the definition of satisfaction degree is given above, we can establish some formulas based on the definition. The models based on undesirable and desirable outputs for measuring the degree of satisfaction of each DMU_j * MERGEFORMAT can be given as follow.

$$\begin{aligned}
&\max \gamma_0 \\
&s.t. \quad \sum\nolimits_{j=1}^{n} \lambda_j x_{ij} \le \sigma_0(\gamma_0) x_{i0}, \quad i=1,2.....m \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j x_{ij}^{v} \le x_{i0}^{v}, \quad i=1,2.....m \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0}, \quad i=1,2.....s \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j b_{tj} = \sigma_0(\gamma_0) b_{t0}, \quad t=1,2.....l \\
&\qquad \sigma_0(\gamma_0) = [\gamma_0 * (\eta-\phi^{\min}) + \phi^{\min} - \varepsilon] \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j = 1, \\
&\qquad k_0 = 0,1 \\
&\qquad \lambda_j \ge 0, \qquad j=1,2.....n
\end{aligned} \tag{3}$$

2. AN EMPIRICAL STUDY

In this section, we apply the DEA approach to study the carbon emission performances and its satisfaction performance of 40 countries and regions (34 OECD countries and 6 world regions) during 2008 and 2009. CO_2 emission, which poses a great risk through its potential effects on world climate, sea level, etc, is the most important element of atmospheric concentration (Jose and Angel, 2001). Recently, there has been a growing concern about global climate change due to worldwide carbon dioxide emissions (Tol, 2005). Several input and output indicators are widely used to monitor a country and region's performance in CO_2 emissions (Chio and Ang, 2001; Ang and Chio, 2002; Ang, 2011). Xiao et al (2011) use capital, population, and energy consumption as inputs and GDP and CO_2 emission as outputs to calculate the CO_2 emission reduction of 29 provinces in China. Chu et al (2012) use the same indicators to evaluate 29 provinces' CO_2 emission performance. Zhou et al (2007) use the input indicators of capital and population as inputs and GDP and CO_2 emission as outputs to compute the environmental efficiency of OECD countries. For the purposes of discussing CO_2 emission environmental performance, this paper use capital (billion US$), population (million) and total primary energy supply (petajoules) as inputs, and we use CO_2 emissions (million tons) and GDP (billion US$) as outputs to evaluate the CO_2 emission performance. Total Primary Energy Supply (TPES) is the controllable factor. We use population as an uncontrollable factor because the population number cannot change in a short period of time. In this paper we claim that CO_2 emission is an undesirable output and GDP is a desirable output. The data characteristic is shown in Table 1 and the data source is International Energy Agency (2011).

Table 1
Data Characteristic of 40 Countries and Regions in 2008 and 2009

2008	Capital	TPES	Population	GDP	CO_2
Max	2861.273	95335	2177.6	11668.5	6549
Min	32.236	175	0.3	9.3	2.2
Mean	558.556	1249.03	167.085	961.768	710.158
Std.dev	797.444	22458.29	419.733	1949.355	1412.647
2009	Capital	TPES	Population	GDP	CO_2
Max	3290.464	95126	2207.8	1135.1	6877.2
Min	32.377	165	0.3	8	2
Mean	591.303	12373.1	169.01	991.8575	699.6205
Std.dev	885.615	22588.51	425.16684	1955.052	1417.834

Table 2 shows the ϕ and θ for measuring the performance of CO_2 emission of 40 countries and regions obtained in 2008 and 2009 by using the DEA approaches in section 2. The degree of satisfaction of 40 countries and regions γ is also presented in the table 2. Table 2 shows the results obtained.

Table 2
ϕ, θ and γ of 40 Countries and Regions in 2008-2009

DMU	***Country***	ϕ^*		θ^*		γ^*	
		2008	**2009**	**2008**	**2009**	**2008**	2009
1	Canada	0.9009	0.8807	0.3613	0.3268	0.252059	0.234541
2	Chile	0.7439	0.7357	0.2328	0.2356	0.141815	0.154548
3	Mexico	0.7796	0.7921	0.4229	0.3556	0.304907	0.259802
4	United States	1	1	1	1	0.800017	0.825015
5	Australia	1	1	0.2685	0.2501	0.172443	0.167266
6	Israel	0.995	1	0.3638	0.3716	0.254204	0.273836
7	Japan	1	1	1	1	0.800017	0.825015
8	Korea	0.7585	0.7765	0.33	0.2883	0.225206	0.200772
9	New Zealand	0.6433	0.6207	0.3032	0.3235	0.202213	0.231646
10	Austria	0.824	0.7815	0.4815	0.5055	0.355182	0.391281
11	Belgium	0.7253	0.6867	0.3568	0.3776	0.248198	0.279098
12	Czech Republic	0.8524	0.8617	0.1026	0.1033	0.030113	0.038505
13	Denmark	0.9825	0.9781	0.5522	0.533	0.415837	0.415402
14	Estonia	1	1	0.1243	0.3376	0.04873	0.244014
15	Finland	0.7194	0.6832	0.4003	0.3775	0.285518	0.279011
16	France	0.7008	0.5959	1	0.8853	0.800017	0.72441
17	Germany	0.8513	0.9017	0.3219	0.5788	0.218257	0.455574
18	Greece	1	1	0.2704	0.2732	0.174073	0.187527
19	Hungary	0.6407	0.6319	0.1749	0.1768	0.092141	0.102973
20	Iceland	1	1	1	1	0.800017	0.825015
21	Ireland	1	1	0.4686	0.474	0.344115	0.363652
22	Italy	0.9353	0.8939	0.6572	0.5925	0.50592	0.467591
23	Luxembourg	1	1	1	1	0.800017	0.825015
24	Netherlands	0.8689	0.8266	0.4617	0.4271	0.338195	0.322516
25	Norway	1	1	1	1	0.800017	0.825015
26	Poland	0.9955	1	0.1177	0.123	0.043068	0.055785
27	Portugal	0.7202	0.7321	0.3548	0.3426	0.246482	0.248399
28	Slovak Republic	0.6283	0.6472	0.1447	0.1476	0.066232	0.077362
29	Slovenia	0.7337	0.7604	0.2708	0.2702	0.174417	0.184896
30	Spain	0.8305	0.8179	0.5124	0.4926	0.381692	0.379967
31	Sweden	0.8367	0.7739	1	1	0.800017	0.825015

To be continued

Continued

DMU	***Country***	ϕ^*		θ^*		γ^*	
		2008	**2009**	**2008**	**2009**	**2008**	2009
32	Switzerland	1	1	1	1	0.800017	0.825015
33	Turkey	0.8784	0.8681	0.2436	0.2259	0.151081	0.14604
34	United Kingdom	1	0.9521	0.9121	0.7739	0.724605	0.626699
35	Latin American region	0.6712	0.6571	0.5058	0.4356	0.37603	0.329971
36	Non-OECD Europe and Eurasia region	0.8739	0.8809	0.0675	0.0594	0.0483	ε
37	Middle East region	0.8998	0.9241	0.1171	0.1029	0.042553	0.038155
38	China region	1	1	0.1212	0.1021	0.046071	0.037453
39	Asia region	0.7186	0.7297	0.2136	0.1732	0.125343	0.099816
40	Africa region	0.4663	0.4616	0.2116	0.1956	0.123627	0.119463

* Asia excludes China

The values of ϕ^* or θ^* provide a measure of what is referred to as "technical efficiency" in economics. $(1-\phi^*)\, x_{io}$ and $(1-\theta^*)\, x_{io}$represent the amount by which each input may be reduced without changing the proportions in which these inputs were used. Thus, the bigger value of θ^*means the better performance of data making units (DMU). The table above shows that in the case of ϕ there are 12 and 13 DEA efficient countries that have the CO_2 emission performance score of "1" in 2008 and 2009, respectively. In the case of θ there are 8 and 7 DEA countries in 2008 and 2009, respectively. It is interesting that China is DEA efficient in the case of ϕ in both 2008 and 2009, but in the case of θ the efficiency value is 0.1212 in 2008 and 0.1021 in 2009. It shows that China has a much smaller CO_2 emission performance when taking uncontrollable factors into consideration. The results show that in the case of ϕ and θ, the United States, Japan, Iceland, Luxembourg, Norway, and Switzerland are DEA efficient in both 2008 and 2009. It shows in table 2 that the worst performer in the case of ϕ is the Africa region (0.4663) in 2008 and the Africa region (0.4616) 2009. However, in the case of θ, the worst performer is the "Non-OECD Europe and Eurasia" region (0.0675) in 2008 and the "Non-OECD Europe and Eurasia" region (0.0594) in 2009.

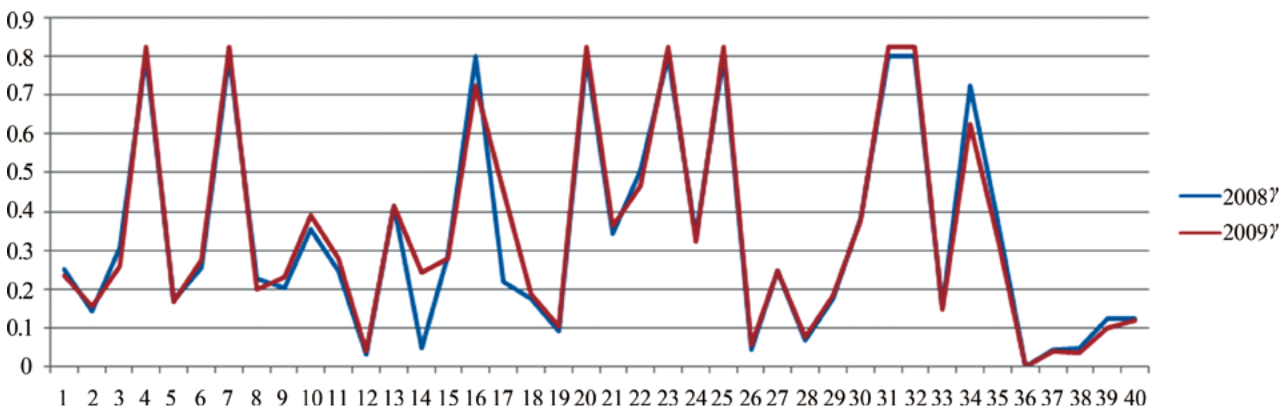

Figure 2
γ Value of 40 Countries and Regions

Figure 2 provides some information on the trend of the degree of satisfaction of 40 countries and regions. The ordinate is the value of γ, and the abscissa is number of 40 countries and regions, which can be found in table 2. Interestingly, the results show that the values of DMUs' satisfactions are distributed in the interval between zero and one. Also, we can clearly know the ranking of DMU through the value of satisfaction. Roughly speaking, in the case of γ, it is found that the 34 OECD countries have better CO_2 emission performance satisfaction than the other 6 regions.

The value of γ for the United States is 0.800017 in 2008 and 0.825015 in 2009, meaning it is the best performing country in both 2008 and 2009. The "Non-OECD Europe and Eurasia" region is 0.0594 in 2008 and 0.0483 in 2009, making it the worst performing region. China's γ is 0.046071 in 2008 and 0.037453 in 2009. There is a little decline in its degree of satisfaction in 2009 compared to 2008. Interestingly, it is found that the countries with a higher γ are better performers in CO_2 emission performance. We can conclude the ranking of countries and regions' CO_2 emission degree of satisfaction based on the result in table 2. The result is presented in table 3.

Table 3
Ranking of 40 Countries and Regions' Degree of Satisfaction in 2008-2009

DMU	Ranking		DMU	Ranking	
	2008	2009		2008	2009
Canada	20	24	Ireland	15	15
Chile	30	30	Italy	10	10
Mexico	17	21	Luxembourg	5	4
United States	1	1	Netherlands	16	17
Australia	28	29	Norway	6	5
Israel	19	20	Poland	37	36
Japan	2	2	Portugal	22	22
Korea	23	26	Slovak Republic	34	35
New Zealand	25	25	Slovenia	26	28
Austria	14	13	Spain	12	14
Belgium	21	18	Sweden	7	6
Czech Republic	39	37	Switzerland	8	7
Denmark	11	12	Turkey	29	31
Estonia	35	23	United Kingdom	9	9
Finland	18	19	Latin American	13	16
France	3	8	Non-OECD Europe and Eurasia	40	40
Germany	24	11	Middle East	38	38
Greece	27	27	China	36	39
Hungary	33	33	Asia	31	34
Iceland	4	3	Africa	32	32

We can find that France is ranked 3rd in 2008 and 8th in 2009. The CO_2 emission satisfaction performance declined significantly in 2009 compared to 2008. Estonia Republic is ranked 35th in 2008 but ranked 23rd in 2009; the CO_2 emission satisfaction performance increases appreciably compared to 2008. Estonia Republic had a big improvement in CO_2 emission performance in 2009. We also can find that the "Non-OECD Europe and Eurasia" region is the worst satisfaction performer in both 2008 and 2009. The ranking of other countries and regions don't change significantly in 2008 and 2009, which means that in 2008 and 2009 there is not much change in CO_2 emission degree of satisfaction.

CONCLUSION

In recent years, data envelopment analysis efficiency approaches that integrate the concept of environmental DEA technology have gained popularity in environmental performance evaluation because they can provide a synthetic, standardized environmental performance index when pollutants are suitably incorporated into the traditional DEA framework. There are no previous studies that evaluate the CO_2 emission performance while taking both controllable and uncontrollable factors into consideration. This paper applies the DEA approaches to evaluate the CO_2emission performance and measure the degree of satisfaction of 40 countries and regions from 2008 to 2009. Among the countries included in the study, in the case of ϕ and θ, the United States, Japan, Iceland, Luxembourg, Norway, and Switzerland are DEA efficient practitioners in 2008 and 2009. We then applied model 3 to measure the degree of satisfaction. In the case of γ, it shows that the United States is the best performer country in 2008 and 2009. The value of γ * MERGEFORMAT for the United States is 0.800017 in 2008 and 0.825015 in 2009. That means the United States makes a great effort to improve economic results and the environment. The "Non-OECD Europe and Eurasia" region is the worst satisfaction performer of all countries and regions in 2008 and 2009.

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