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POTENTIAL REDUCTION OF CO_2 EMISSIONS IN G20 COUNTRIES: THE PRODUCTION-EFFICIENCY APPROACH

This paper attempts to develop a CO_2 emissions performance index and potential CO_2 emissions reduction index based on the production efficiency point of view. An empirical study is conducted to assess carbon performance of G20 countries. The results demonstrate that developed countries in Europe, North America, and Japan, which enjoy the highest level of economic development, also evidence the best carbon performance. The potential level of carbon emission reduction is estimated. Tobit regression is used to identify the influence factors of carbon performance. Some policy implications are suggested.

Keywords: *G20 countries; data envelopment analysis (DEA); CO_2 emissions, production efficiency.*

Юнрок Чой

ПОТЕНЦІЙНЕ ЗНИЖЕННЯ ВИКИДІВ CO_2 В КРАЇНАХ "ВЕЛИКОЇ ДВАДЦЯТКИ": ПІДХІД ДО ЕФЕКТИВНОГО ВИРОБНИЦТВА

У статті зроблено спробу використовувати показники якості викидів CO_2 і потенційного зниження викидів CO_2 з точки зору ефективного виробництва в країнах "великої двадцятки". Результати показали, що країни з високим рівнем економічного розвитку, такі як країни Європи, Північної Америки і Японія, показують високий рівень вироблення вуглецю. Оцінено потенційний рівень зниження викидів CO_2. Використано тобіт-регресію для визначення впливу чинників вироблення CO_2. Надано рекомендації з розробки відповідної політики.

Ключові слова: *країни "великої двадцятки", аналіз середовища функціонування, викиди CO_2, ефективне виробництво.*

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Юнрок Чой

ПОТЕНЦИАЛЬНОЕ СНИЖЕНИЕ ВЫБРОСОВ CO_2 В СТРАНАХ "БОЛЬШОЙ ДВАДЦАТКИ": ПОДХОД К ЭФФЕКТИВНОМУ ПРОИЗВОДСТВУ

В статье сделана попытка использовать показатели качества выбросов CO_2 и потенциального снижения выбросов CO_2 с точки зрения эффективного производства в странах "большой двадцатки". Результаты показали, что страны с высоким уровнем экономического развития, такие как страны Европы, Северной Америки и Япония, также показывают высокий уровень выработки углерода. Оценен потенциальный уровень снижения выбросов CO_2. Использована тобит-регрессия для определения влияния факторов выработки CO_2. Даны рекомендации по разработке соответствующей политики.

Ключевые слова: *страны "большой двадцатки", анализ среды функционирования, выбросы CO_2, эффективное производство.*

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I. Introduction. Carbon dioxide (CO_2) emissions are currently a growing concern in the context of climate change theory. Many organizations and governments have introduced special measures to reduce the effects of climate change, including GHG reporting programs, carbon taxes, and emissions trading schemes (ETS). These measures emphasize the urgent need for understanding and assessing economic performance with carbon emissions in different countries, both developed and developing. One of the most outstanding efforts is the Kyoto protocol. 38 countries participating in the Kyoto protocol in Annex I have made efforts to cut their levels of carbon emission to 5.2% below the baseline year of 1990, on average, for 2008-2012.

Depending on the efforts by participating countries, the CO_2 emission trends varied markedly between 2008 and 2009. The CO_2 emissions of non-Annex I countries grew by 6%, while those of the Annex I countries decreased by 2%; as a result, the aggregate emissions of developing countries have overtaken those of developed countries during this period. 2/3 of the world emissions originated just from 10 top level countries in 2009, with the shares contributed by China and the United States far outstripping those of all the others. Combined, these 2 countries alone generated 12.1 Gt of CO2, corresponding to approximately 41% of the world CO_2 emissions (IEA, 2011).

However, it is somewhat difficult for these countries to lower their CO_2 emissions levels because of the trade-off between the level of CO_2 emissions and economic performance. As a result of this trade-off, the United States withdrew from the Kyoto protocol in 2001, even though they account for a significant portion of the global CO_2 emissions. Not only the United States, but many other countries, including non-Annex-I countries, are reluctant to extend or renew the Kyoto protocol in 2012. Since global warming is a global concern, the G20 summit has taken a leading role in ameliorating the environmental crisis as well. In response to the proposal by Korean government, the G20 agreed to establish the Global Green Growth Institute (GGGI) to take appropriate measures to understand, assess, and mitigate the effects of CO_2 emissions globally. The objective of GGGI is not to avoid the environmental crisis, but to use new opportunities to develop renewable energies and meet new challenges in environmental protection.

For the sustainable, eco-friendly development several indicators have been developed to assess CO_2 performance. For instance, Mielnik and Goldemberg (1999) introduced a carbon factor (level of CO_2 emissions per unit of energy consumption) to evaluate the effects of climate change in developing countries. Ang (1999) demonstrated that energy intensity (energy consumption per unit of GDP) is a useful tool to study climate changes. Tol et al. (2009) demonstrated that both energy intensity and carbon emission per person can prove to be useful information. However, each of these indicators only provides partially useful information. Therefore, it is necessary to use a multiple-factors model to correctly assess the total factor productivity of low carbon economy (Zhou et al., 2010). The principal objective of this paper is to empirically utilize the data envelopment analysis (DEA) to deal with these multi-factorial inputs and outputs to determine the implications and suggestions for the G20 countries.

II. Methodology. Data envelope analysis (DEA) is a widely used methodological approach for measuring total factor productivity (TFP) at the macroeconomic level. It generates a synthetic productivity index with multiple inputs and outputs. As global climate change attracts serious concerns regarding sustainable economy, DEA approaches may provide a platform for the assessment of diverse inputs and outputs, even in the cases in which they contraindicate each other to suggest some important implications. A variety of methods have been proposed to incorporate undesirable carbon outputs into DEA models, as demonstrated by Zhou et al. (2008a) in their survey study. Generally, these methods can be divided into 2 groups.

The first method treats undesirable outputs as inputs in the traditional DEA model; it assumes they have the same characteristics of "the less the better" in the production process (Hu and Lee, 2008; Zhang, 2008). Hu and Lee (2008) used the DEA-CCR model to estimate the total factor productivity of Chinese industrial sector. However, undesirable output is not an input during the production process, but rather a by-product of production. Thus, this method is too simple to be considered reflective of the actual production process.

The second method of disposing the undesirable output is based on the simple data translation and the use of traditional DEA models. Lovell et al. (1995) took the reciprocals of the undesirable outputs, and then treated them as normal outputs. Seiford and Zhu (2002) developed a radial undesirable output DEA model; in their model, negative signs were assigned to all undesirable outputs and were applied to a suitable transition vector by linear programming. Yeh et al. (2010) evaluated the total factor efficiency of energy utilization with GHG emissions. They treated undesirable GHG emissions via the methods devised by Seiford and Zhu (2002). The weakness of this method is that the original data is changed in the way that would never arise from actual economic activity.

Almost all of these studies adhere to the concept of the radial DEA model, which has a weak discriminating power in ranking and comparing decision-making units (DMUs) when many DMUs have the same efficient score of 1. Additionally, the radial model adjusts all undesirable outputs and inputs by the same proportion to the efficient target, which may not be preferred by decision makers (Choi and Zhang, 2011). The principal concern regarding carbon reduction adjustment is not based on labor or capital reduction issues. Under these circumstances, our approach may fill the gaps of previous studies by introducing a carbon-adjustment focused framework based on the slack measures, which are directly constructed from the slack variables in inputs and outputs with a high degree of discriminating power.

Another limitation of the previous literature derives from carbon performance in different countries. Most studies have focused on the high-income OECD or developed countries. In this paper, however, we consider G20 countries that also include developing countries. Together, these countries constitute almost 80% of the world's total CO2 emissions, and thus will convey the generally applicable implications.

In this section, our objective is to develop a framework that can estimate the potential carbon reductions (PCR) and carbon efficiency (CE) of different countries. DEA frameworks are used because it is based on the slacks-based measure (SBM), developed by Tone (2001), upgraded by Zhou et al. (2006), and utilized by Lozano and Gutierrez (2011) considering the undesirable factors.

The SBM-DEA is a non-radial and non-oriented model, and directly employs input and output slacks to produce an efficiency measure. We assume that producing more outputs relative to less input resources is a criterion for efficiency. In the presence of undesirable outputs, technologies with more good (desirable) outputs and less bad (undesirable) outputs relative to less input resources should be recognized as efficient. Suppose that there are *n* countries and that each has 3 factors-inputs, good outputs, and carbon emissions which are denoted by 3 vectors:

$x \in R^m$, $Y \in R^{s1}$ and $c \in R^{s1}$, respectively. Define the matrices *Y, C*, and *X* as

$$Y = [y_{ij}] = [y_1,\ldots,y_n] \in R^{s1\times n},$$
$$C = [c_{ij}] = [c_1,\ldots,c_n] \in R^{s\times n},$$
$$X = [x_{ij}] = [x_1,\ldots,x_n] \in R^{m\times n},$$

respectively. The production possibility set (PPS) is as follows:

$$P(x) = \{(y,c)/x \ produce\ (y,c),\ x \ge X\lambda, y \le Y\lambda, c \ge C\lambda, \lambda \ge 0\} \tag{1}$$

where λ is the non-negative intensity vector, indicating that the above definition corresponds to the constant returns to scale (CRS) situation. Our objective is to estimate the potential carbon reduction and carbon performance.

The undesirable outputs SBM-DEA model can be measured as follows:

$$\rho_0^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_{i0}^-}{x_{i0}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_{r0}^y}{y_{ro}} + \sum_{r=1}^{s_2}\frac{s_{r0}^c}{c_{r0}}\right)}$$

S.T.

$$\begin{aligned} x_0 &= X\lambda + s_0^- \\ y_0 &= Y\lambda - s_0^y \\ c_0 &= C\lambda + s_0^c \\ s_0^- \ge 0, s_0^y &\ge 0, s_0^c \ge 0, \lambda \ge 0 \end{aligned} \tag{2}$$

The vector s^y denotes the shortage of good outputs, whereas vectors s^- and s^c correspond to excesses of inputs and CO_2 outputs, respectively. The DMU is efficient in the presence of undesirable outputs if $\rho^*=1$, indicating that all the slacks variables are 0, ($s^-=0$, $s^y=0$, $s^c=0$) but the object model (2) is not a linear function. Using the transformation suggested by Tone (2001), we can establish an equivalent linear programming for t, ϕ, s^{-*}, s^c and s^y as follows:

$$r_0^* = \min t - \frac{1}{m}\sum_{i=1}^{m}\frac{s_{i0}^-}{x_{i0}}$$

S.T.

$$1 = t + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{s_{r0}^{y}}{y_{r0}} + \sum_{i=1}^{s_1}\frac{s_{r0}^{c}}{c_{ro}}\right)$$
$$x_0 t = X\varphi + S_0^{-} \tag{3}$$
$$y_0 t = Y\varphi - S_0^{y}$$
$$c_0 t = C\varphi + S_0^{c}$$
$$S_0^{-} \geq 0, S_0^{y} \geq 0, S_0^{c} \geq 0, \varphi \geq 0, t > 0$$

Let the optimal solution of linear programming model (3) be (t^*, ϕ^*, S^{-*}, S^{c*} and S^{y*}), where

$$\rho^* = t^*, \lambda^* = \frac{\varphi^*}{t^*}, s^{-*} = \frac{s^{-*}}{t^*}, s^{y*} = \frac{s^{y*}}{t^*}, s^{c*} = \frac{s^{c*}}{t^*}$$

from model (2). Model (3) can guarantee the solution of (t^*, ϕ^*, S^-, S^c, S^y) with $t^*>0$. A similar LP solution idea of solving undesirable SBM-DEA can be found in Zhou et al. (2006), and Lozano and Gutierrez (2011). The potential carbon reduction (PCR) of each country is estimated by the slack variable s_0^c, indicating the excess of carbon emissions, and the carbon efficiency *(CE)* of each country is estimated as:

$$\text{CE= (Target carbon emission/Real carbon emission)} = \frac{c_0 t - s_0^c}{c_0 t}$$

This "Target carbon emission per real carbon emission" idea was introduced by Hu and Wang (2006) in "Target energy input per real energy input" to estimate energy efficiency, and developed by Zhou and Ang (2008) for undesirable carbon outputs.

III. Empirical results.

1. Data collection. Choi et al. (2010) used 3 indicators to assess economic performance: gross domestic product (GDP), industrial value added, and the employment rate. According to Choi et al. (2010), the real GDP is selected, based on the year 2000 constant price to represent the only desirable output. In fact, this number has also been selected in a variety of previous studies (Hu and Wang, 2006; Bian and Yang, 2010; Yeh et al., 2010). Labor and capital are selected as 2 basic non-resource inputs and all types of energy consumption as the resource inputs. CO_2 emissions are the only bad output in the model. Data on GDP, labor, and capital stock are collected from World Development Indicators 2011. The data regarding energy consumption and CO_2 emissions were gathered from the BP Statistical Review of World Energy (2011). Table 1 shows the descriptive statistics of the data. The variables fluctuate substantially. Thus, it will be good to see whether large inputs are relevant to carbon performance.

Table 1. **Descriptive statistics of inputs and outputs in 2010 (n = 20)**

	Units	Minimum	Maximum	Mean
GDP	bln US$	193.9	14564.2	2368.7
Labor force	mln workers	9.56	873.16	154.95
fixed capital	bln US$	0.07	1961.24	426.60
Energy	mln TOE	72.31	2081.03	506.06
CO_2	mln tons	67.75	7718.46	1308.8

[a]TOE means tons of oil equivalents.

Table 2 shows the correlation matrix of outputs and inputs. It clearly demonstrates that the correlation coefficients are all significantly positive and this indicates that when inputs are added, the outputs will also increase.

Table 2. **Correlation matrices for inputs and outputs**

	GDP	LF	CS	EC	CE
GDP	1.000				
LF	0.263*	1.000			
CS	0.936*	0.499*	1.000		
EC	0.787*	0.676*	0.901*	1.000	
CE	0.715*	0.782*	0.856*	0.985*	1.000

* represents the significance at the 5% level.

2. Results and discussion. From the countries' perspectives in Table 3, Australia, the US, Japan and Italy show the highest efficient carbon efficiency score, while Russia had the lowest carbon efficiency scores of 0.10. China and South Africa had the low carbon efficiency scores at 0.15. South Korea evidenced a carbon efficiency of 0.44, indicating a 56% reduction potential of CO_2.

Table 3. **Potential carbon reduction, carbon efficiency, and target carbon**

DMU	PCR	CE	TC
Australia	0.00	1.00	68.75
United States	0.00	1.00	5941.87
Japan	0.00	1.00	1222.07
Italy	0.00	1.00	434.84
Germany	24.59	0.97	771.01
Argentina	8.73	0.95	155.50
France	29.09	0.93	369.59
European Union	350.12	0.91	3715.77
United Kingdom	62.70	0.88	466.35
Mexico	180.79	0.59	256.03
Brazil	269.65	0.55	333.03
Canada	271.80	0.55	330.90
Turkey	124.37	0.53	139.69
South Korea	369.17	0.44	294.17
Indonesia	287.47	0.26	101.01
India	1193.07	0.22	345.98
Saudi Arabia	439.74	0.18	97.86
China	6370.61	0.15	1147.84
South Africa	397.47	0.15	71.09
Russia	1379.84	0.10	155.50

(Unit: MT CO_2, %)

The results also demonstrate that China should reduce about 6,370.61 mln tons of CO_2 emission potentially to become a carbon-efficient country. For India, 1,193 mln tones of CO_2 should be potentially reduced. The potential carbon reduction in all G20 countries will be 11,759 mln tons in total.

In order to evaluate the influence factors of carbon efficiency, we employ the tobit regression model as many researchers did for the relations between carbon efficiency, capital intensity (capital/GDP), energy intensity (energy/GDP), and GDP. The graphical illustration in Figure1 and Table 4 shows that the capital intensity and energy intensity exert a significant negative impact on carbon efficiency, whereas the role of GDP is not significant.

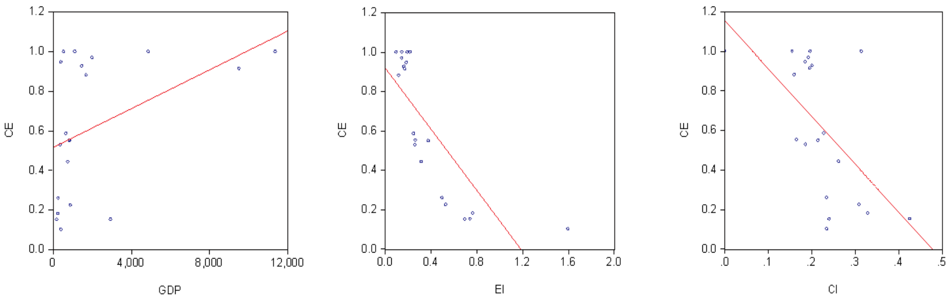

Figure 1. **Tobit regression results**

Table 4. **Tobit regression results**

Variables	coefficient	Std. Error	P-value
Carbon intensity	-1.17	0.577	0.06
Energy intensity	-0.59	0.143	0.00
GDP	2.44E-05	1.49E-05	0.12
Constant	1.06	0.132	0.00

IV. Conclusions. This study presents a new carbon-adjustment DEA approach - specifically, a non-radial measurement — to estimate carbon emission performance and potential carbon emission reductions in G20 economies. The results demonstrate that Australia, Japan, Italy, and the US evidenced the highest carbon efficiency score of 1, whereas Russia had the lowest carbon efficiency scores of 0.10. Most developing countries, including China, India, South Africa, and South Korea, have relatively lower carbon efficiency scores. This implies that sustainable development could be attained without imposing arbitrary measures. That is, the higher economic performance a country achieves, the lower the carbon emissions it yields. However, this conclusion should be drawn with caution, as the eco-friendly final assembling may be carried out in developed countries with a public inefficiency burden transferring to developing ones under the conditions of interdependent intra-firm international trade. Therefore, economic support should be provided for "green growth" in developing countries, because of this unfair collaboration across the countries. It should be the vision of G20 countries to promote the mutual benefit of eco-friendly sustainable development.

The potential carbon reduction in all G20 countries will be 11,759 mln tons in total. Tobit regression demonstrated that capital intensity and energy intensity have a significant negative impact on carbon efficiency, whereas the GDP's role is not significant. This suggests that energy intensity should be significantly reduced, while its efficiency should be increased simultaneously. This was the main theme of the Global Green Growth Summit 2012 in Seoul hosted by OECD and Korean government. As proposed on that conference, now is the time for more than just discussion; decisive actions should be taken to secure a better, more sustainable future.

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