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BENCHMARKING LOW-CARBON MANAGEMENT PERFORMANCE: AN EMPIRICAL STUDY OF G20 COUNTRIES

This paper introduces a new DEA framework based on the slacks-based measure (SBM) to assess low-carbon management performance (LCMPI) in 20 major developing and developed countries' economies of the world. The results show that developed countries in Europe, North America and Japan which enjoy the highest level of economic development, also have the highest low-carbon management performance; on the other hand, China shows the lowest low-carbon management performance scores because of its huge energy consumption and CO2 emissions.

Keywords: *low-carbon economy; management performance; DEA; total factor productivity; G20.*

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БЕНЧМАРКІНГ УПРАВЛІННЯ НИЗЬКОВУГЛЕЦЕВОЮ ПРОДУКТИВНІСТЮ ЕКОНОМІКИ: ЕМПІРИЧНЕ ДОСЛІДЖЕННЯ КРАЇН “ВЕЛИКОЇ ДВАДЦЯТКИ”

У статті введено новий метод аналізу середи функціонування на основі резервостворювальної міри ефективності (SBM) для оцінювання управління низьковуглецевою продуктивністю економіки (LCMPI) в 20 найбільших економіках світу, розвинених і таких, що розвиваються. Результати показують, що розвинені країни Європи, Північної Америки і Японія, які знаходяться на найвищому рівні економічного розвитку, також мають найвищий рівень управління низьковуглецевою продуктивністю, а з іншого боку, Китай показує низький рівень управління низьковуглецевою продуктивністю економіки через величезний вжиток енергії і викиди CO2.

Ключові слова: *низьковуглецева економіка; управління продуктивністю; DEA; сукупна продуктивність чинників виробництва; країни “великої двадцятки”.*

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БЕНЧМАРКИНГ УПРАВЛЕНИЯ НИЗКОУГЛЕРОДНОЙ ПРОИЗВОДИТЕЛЬНОСТЬЮ ЭКОНОМИКИ: ЭМПИРИЧЕСКОЕ ИССЛЕДОВАНИЕ СТРАН “БОЛЬШОЙ ДВАДЦАТКИ”

В статье введен новый метод анализа среды функционирования на основе резервообразующей меры эффективности (SBM) для оценки управления низкоуглеродной производительностью экономики (LCMPI) в 20 крупнейших развивающихся и развитых экономик мира. Результаты показывают, что развитые страны Европы, Северной Америки и Япония, которые находятся на самом высоком уровне экономического развития, также имеют самый высокий уровень управления низкоуглеродной производительностью, а с другой стороны, Китай показывает низкий уровень управления низкоуглеродной производительностью экономики из-за его огромного потребления энергии и выбросов CO2.

Ключевые слова: *низкоуглеродная экономика; управление производительностью; DEA; совокупная производительность факторов производства; страны “большой двадцатки”.*

Introduction. There is a growing concern regarding carbon dioxide (CO2) emissions; in fact, CO2 emissions account for the largest proportion of atmospheric greenhouse gas (GHG) emissions that lead to global climate change. Recently, inter-

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national organizations and national governments have set GHG emissions reduction targets for the next several decades (e.g., EU by 20% by 2020, UK by 2050; both targets are relative to the 1990 emissions levels). These organizations and governments have also introduced special measures to meet these targets including GHG reporting programs, carbon taxes, and emission trading schemes (ETS). Consequently, these factors emphasize the need for understanding and assessing economic performance and carbon emissions among different countries.

Several indicators have been developed to assess each country's national CO2 performance. For instance, Mielnik and Goldemberg (1999) introduced a carbon factor (the level of CO2 emissions per unit of energy consumption) to assess the climate change effect in developing countries. Ang (1999) showed that energy intensity (energy consumption per unit of GDP) is a useful tool in the study of climate change. Tol et al. (2009) showed 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. Since economic activity is a joint process, it utilizes various inputs such as labor, capital and resources to produce desirable economic outputs; however, it also simultaneously provides undesirable GHG emissions. Therefore, it is necessary to use a multiple-factor model to correctly assess the low-carbon management performance (Zhou et al., 2010).

Data envelopment analysis (DEA) is a technology that is widely used to measure total factor performance (TFP) at the macroeconomic level; it can provide a synthetic productivity index with multiple inputs and outputs. Fung et al. (1996) noted that DEA evaluates the industrial performance in terms of both outputs and inputs; they suggested that this evaluation process could be applied as an alternative to the conventional TFP approach. Many researchers employed the DEA framework to calculate the TFP index. These researchers include Jha et al. (2000) and Aldaz et al. (2003), who used this approach to analyze the regional productivity of Spanish agriculture and Indian farming, respectively. Sufian and Shah Habibullah (2009) used DEA to examine the impact of M&A on the technical performance of Malaysian banking sector. Chen et al. (2010) also used DEA to measure management performance of financial holding companies in Taiwan. Lin et al. (2010) used DEA to analyze the debt-paying management performance of Taiwan's shipping industry. Although these studies used DEA to measure the performance of multiple DMUs, they did not consider the environmental impact from the sustainable perspective. Chen et al. (2010) suggested a three-stage DEA method incorporating environmental factors, but their study was not empirically proved, but just a theoretical proposition.

As environmental issues such as global climate change attract serious concerns about the sustainable economy, DEA has also received a great deal of publicity regarding their measurements of multidimensional economic productivity incorporating undesirable outputs such as industrial pollutants. Therefore, a variety of methods have been proposed to incorporate undesirable outputs into DEA models as Zhou et al. (2008a) summarized in their survey study. Generally, these methods can be divided into two groups. The first method of disposing undesirable output is based on the simple data translation and utilization of traditional DEA models. Lovell et al. (1995) took the reciprocals of 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 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 based on the methods devised by Seiford and Zhu (2002). The weakness of this method is that the original data is changed in a way that would never exist in actual economic activity.

The second method treats undesirable outputs as inputs in the traditional DEA model; it assumes that they have the same characteristics of "the less the better" in the production process (e.g., Hu and Lee, 2008; Zhang, 2008). Hu and Lee (2008) used the DEA-CCR method to estimate the total factor productivity of Chinese industrial sector. Zhang (2008, 2009) employed DEA to assess the productivity of Chinese agriculture and industrial sector, respectively. Clearly, the treatment of undesirable outputs simply as inputs can incorporate pollutants into the traditional DEA. However, undesirable output is not an input during a production process, but a by-product of production. Thus, this method is too simple to reflect the actual production process.

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 efficient targets, which may not be preferred by decision makers. Under the circumstances, the approach may fill the gaps of previous studies by introducing a non-radial DEA framework based on the slack-based measures (SBM-DEA), which are constructed directly from the slack variables in inputs and outputs with a high discriminating power. In the previous literature based on DEA, the focus is on the high income OECD countries. This paper, however, considers G20[1] countries that also include developing countries. Furthermore, these countries contribute to almost 80% of the world's total CO2 emissions with the proportion of 77.70%, 77.89%, 77.01%, 77.01%, 77.52%, 76.69% respectively from 2003 to 2008 (see Table 1). And among hem developed and developing countries take about 50% of these CO2 emissions, respectively (See Table 2). So it is meaningful to compare the carbon performance among G20 countries to reduce their carbon emissions.

Table 1. **Cumulative carbon dioxide emissions of G20 countries in 2003-2008**

	2003	2004	2005	2006	2007	2008
France	0.11	0.11	0.11	0.10	0.10	0.10
Japan	0.34	0.34	0.34	0.34	0.34	0.33
UK	0.15	0.15	0.15	0.15	0.14	0.14
US	1.55	1.58	1.59	1.56	1.59	1.55
Germany	0.23	0.23	0.22	0.22	0.21	0.21
Italy	0.13	0.13	0.13	0.13	0.13	0.12
EU	0.29	0.30	0.29	0.29	0.29	0.28
Argentina	0.04	0.04	0.04	0.05	0.05	0.05
Australia	0.09	0.10	0.10	0.10	0.10	0.11
Canada	0.15	0.15	0.15	0.15	0.15	0.15
Brazil	0.09	0.09	0.10	0.10	0.10	0.11

[1]The memberships have been increased since the EU grouped. To keep the data consistent, here the EU includes Austria, Belgium, Denmark, Finland, Greece, Ireland, Luxembourg, the Netherlands, Portugal, Spain and Sweden.

The End of *Table 1*

	2003	2004	2005	2006	2007	2008
Mexico	0.11	0.11	0.12	0.12	0.12	0.13
Turkey	0.06	0.06	0.06	0.07	0.08	0.08
South Korea	0.13	0.13	0.13	0.13	0.14	0.14
Saudi Arabia	0.09	0.09	0.10	0.10	0.11	0.12
South Africa	0.10	0.11	0.11	0.11	0.12	0.12
Indonesia	0.09	0.09	0.09	0.09	0.10	0.11
Russia	0.43	0.44	0.44	0.46	0.45	0.47
India	0.35	0.37	0.38	0.41	0.44	0.48
China	1.23	1.44	1.58	1.75	1.85	1.92
Sum of G20	5.75	6.06	6.23	6.43	6.62	6.71
Global	7.40	7.78	8.09	8.35	8.54	8.75

Data source: CDIAC, doi10.3334/CDIAC/00001

Table 2. **Distribution of CO2 emissions in G20 countries during 2003-2008**

	2003	2004	2005	2006	2007	2008
Developed countries	3.26	3.31	3.31	3.27	3.30	3.25
Developing countries	2.41	2.66	2.83	3.06	3.21	3.31

Methodology. The basic CCR or BCC-DEA is a kind of radial and input- or output-oriented approach which may lead to estimation bias as mentioned above. The SBM-DEA is a non-radial and non-oriented approach, and it directly employs input and output slacks to produce an efficiency measure. We assume that one criterion for productivity is that a country must produce more outputs relative to less input resources. In the presence of bad outputs, technologies with more good (GDP) outputs and less bad (CO_2 emissions) 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 bad outputs, which are denoted by 3 vectors: $x \in R^m$, $y^g \in R^{s1}$ and $y^b \in R^{s2}$ respectively. Define the matrices Y_g, Y_b and X as

$$Y^g = [y^g_{ij}] = [y^g_1, \cdots, y^g_n] \in R^{s1 \times n},\ Y^b = [y^b_{ij}] = [y^b_1, \cdots, y^b_n] \in R^{s2 \times n}$$

and $X = [x_{ij}] = [x_1, \cdots, x_n] \in R^{m \times n}$ respectively. The production possibility set (PPP) is as follows:

$$P(x) = \{(y^g, y^b) \mid x \text{ produce } (y^g, y^b),\ x \geq X\lambda,\ y^g \geq Y^g\lambda,\ y^b \leq Y^b\lambda,\ \lambda \geq 0\}$$

where λ is the non-negative intensity vector indicating that the above definition corresponds to the constant returns-to-scale (CRS) assumption.

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

$$\varphi^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_g + s_b}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b}\right)}$$

$$S.T. \qquad (1)$$

$$x_0 = X\lambda + s^-$$

$$y_0^g = Y^g\lambda - s^g$$

$$y_0^b = Y^b\lambda + s^b$$

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0,$$

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

$$\begin{gathered} r^* = \min t - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}} \\ 1 = t + 1 + \frac{1}{s_g + s_b}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right) \\ S.T. \\ x_0 t = X\delta + s^- \\ y_0^g = Y^g\delta - s^g \\ y_0^b = Y^b\delta + s^b \\ s^- \ge 0, s^g \ge 0, s^b \ge 0, \delta \ge 0, t \ge 0 \end{gathered} \qquad (2)$$

Let an optimal solution of the model (2) be $(t^*, \delta^*, s^{-*}, s^{g*}, s^{b*})$ to solve the optimizing model (1) defined by $\rho^* = t^*, \delta^* = \frac{\delta}{t^*}, s^{-*} = \frac{s^-}{t^*}, s^{g*} = \frac{s^g}{t^*}, s^{b*} = \frac{s^b}{t^*}$. The existence of $(t^*, \delta^*, s^{-*}, s^{g*}, s^{b*})$ with t*>0 is guaranteed by the model (2). A similar idea can be found in Cook and Seiford's (2009) research. This framework can evaluate the low-carbon management performance considering the bad outputs of CO_2 emissions.

Results.

Data collection. 3 indicators were used to assess the economic productivity: gross domestic product (GDP), industrial value added, and the employment rate. Considering that this research focuses on the comparison of the global economy, we selected the real GDP based on the year 2000 constant prices to represent the only desirable output. In fact, this number was also selected in many previous studies (e.g., Hu and Wang, 2006; Bian and Yang, 2010; Yeh et al., 2010). Labor and capital are two basic non-resource inputs; all kinds of energy consumption are selected as the resource input. CO_2 emissions are the only bad output in the model. The empirical period is selected from 2003 to 2008. (G20 was founded in 2003.) Data for GDP, labor and capital stock are collected from World Development Indicators (2010). The data for energy consumption and CO_2 emissions were gathered in the BP Statistical Review of World Energy (2010). Table 3 shows the descriptive statistics of the data. The variables fluctuate substantially; thus, it will be good to see whether large inputs are important for productivity analysis.

Table 4 shows the correlation matrix of outputs and inputs. It clearly shows that the correlation coefficients between our outputs and inputs are all significantly positive; it indicates that when inputs are added, the outputs will also increase.

Table 3. **Descriptive statistics of inputs and outputs, 2003-2008**

Variable	Variable	Units	Mean	Max	Min
Capital stock	CS	Mln USD	428498.5	2238989.8	23878.5
Labor force	LF	Mln workers	110.7	776.8	7.7
Energy consumption	EC	Mln TOE[a]	491.6	2361.5	58.7
Real GDP	GDP	Mln USD	1989235.1	11671492.9	145692.9
CO_2 emissions	CE	Mln tons	1366.2	6907.9	129.6

[a]TOE stands for tons of oil equivalents

Table 4. **Correlation matrices for inputs and outputs, 2003-2008**

	GDP	LF	CS	EC	CE
GDP	1.000				
LF	0.203*	1.000			
CS	0.987*	0.321*	1.000		
EC	0.859*	0.569*	0.896*	1.000	
CE	0.792*	0.661*	0.846*	0.987*	1.000

* represents the significance at 5% level

Results and discussions. The Lingo package was employed to estimate the linear programming. The results of low-carbon management performance (LCMP) are as follow (see Table 5):

Table 5. **Low-carbon management performance of G20 countries, 2003-2008**

DMU	Continent	2003	2004	2005	2006	2007	2008	AVG.
France	EU*	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Japan	AS*	1.00	1.00	1.00	1.00	1.00	1.00	1.00
UK	EU	1.00	1.00	1.00	1.00	1.00	1.00	1.00
US	NA*	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Germany	EU	0.75	0.76	0.76	0.74	0.75	0.71	0.75
Italy	EU	0.73	0.71	0.71	0.70	0.68	0.68	0.70
EU	EU	0.65	0.64	0.64	0.63	0.60	0.60	0.63
Argentina	SA*	1.00	1.00	0.57	0.56	0.54	0.52	0.70
Australia	AU*	0.50	0.49	0.48	0.46	0.45	0.45	0.47
Canada	NA	0.52	0.51	0.49	0.47	0.45	0.45	0.48
Brazil	SA	0.65	1.00	1.00	1.00	1.00	0.45	0.85
Mexico	NA	0.47	0.46	0.45	0.43	0.40	0.40	0.43
Turkey	EU	0.44	0.42	0.40	0.38	0.37	0.39	0.40
South Korea	AS	0.36	0.37	0.37	0.38	0.37	0.38	0.37
Saudi Arabia	AS	0.38	0.39	0.36	0.34	0.30	0.28	0.34
South Africa	AF*	0.33	0.31	0.30	0.29	0.29	0.26	0.30
Indonesia	AS	0.27	0.26	0.25	0.27	0.27	0.25	0.26
Russia	EU	0.24	0.24	0.23	0.23	0.22	0.20	0.23
India	AS	0.23	0.21	0.21	0.21	0.20	0.19	0.21
China	AS	0.18	0.17	0.18	0.17	0.17	0.17	0.17
G20	-	0.59	0.60	0.57	0.56	0.55	0.52	0.56

* EU, AS, NA, SA, AU, and AF stand for Europe, Asia, North America, South America, Australia, and Africa, respectively.

First, we examine the results from the countries' view. We reviewed the results during 2003 to 2008, as well as during the whole research period. We found that France, Japan, the UK, and the US showed the highest efficient TFCEP scores "1". Brazil received an efficient TFCEP score "1" in 4 years (from 2004 to 2007), and Argentina received the highest score in two years (2003 and 2004). However, China had the lowest TFCEP scores of 0.17 or 0.18.

Second, we examine the results from the continental view. We found that the average low-carbon management performance scores of South America were the highest, with an average of 0.77. Europe showed the second highest TFCEP scores of 0.67, followed by North America with 0.64, Australia with 0.47, and Asia with 0.39, respectively. Africa showed the worst TFCEP score with 0.30.

As a comparison, Lindmark (2004) argued that less developed areas with a lower income are likely to have fewer industries, thus, they will tend to experience less pollution emissions and higher sustainable performance than more developed countries. Our study partially supports his studies, as we did find that developing countries of Brazil and Argentina showed higher TFCEP as well. However, our results also suggest that TFCEP of developed areas such as Europe and North America were higher than those of developing areas in general. Thus, the results of our study contradict the argument of Lindmark (2004). This may be a result of the fact that Lindmark's method is a partial carbon productivity index and our approach is a more integrated approach with much more information. Zhou et al. (2008b)'s results showed that TFCEP of China is about 0.53, which is an average level in the world; however, according to our results, China showed the worst TFCEP scores. The explanation could be simple: in Zhou et al.'s work, the energy consumption is the only input, but our study includes labor and capital inputs together with energy consumption. China has a huge labor market and capital inputs, which lead to low TFCEP scores. In addition, China's total energy consumption and carbon emissions are both the highest in the world, which can also lead to its low TFCEP score.

These results can have many significant implications. As an example, in more developed areas, a government can allocate more capital derived from the area's rapid economic growth to the area's environmental governance and energy usage technology for sustainable development. Thus, the area's economic growth and environment governance is harmonious. Governments of developing countries may need to pursue selective concentration policies to improve their low-carbon management performance by placing more emphasis on economic development. This may help to achieve their role of developing government to fill the missing links in rapid development (Choi and Lee, 2009). To harmonize this disparity in carbon productivity over the world, we argue that G20 countries could enact a partner emission trade scheme (ETS) into the global market system, setting the maximum level of emissions for different countries. With such emission trade scheme, emissions can be further reduced; in turn, less developed countries could benefit from this trading system.

Conclusions. This study contributes to the existing body of relevant literature by assessing low-carbon management performance of G20 countries employing the proposed non-radial SBM-DEA model from 2003 to 2008. The results demonstrated that developed countries in Europe, North America and Japan which enjoy the highest level of economic development, also had the highest low-carbon management performance; China showed the lowest low-carbon management performance scores because of its huge energy consumption and CO_2 emissions. During our study, we also learned that Africa showed a poor low-carbon management performance score because of its lagged economy and low technologies.

Thus, we suggest that each government pursue a different type of policy to improve its low-carbon management performance. Instead of implementing a selective concentration of economic policies, we believe that governments of developing countries should focus on harmonizing the trade-off situation on low-carbon management performance, where different countries could have different levels of allowable carbon emissions.

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