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IS IT FEASIBLE FOR CHINESE THERMAL POWER PLANTS TO IMPROVE CO_2 EMISSION? TOTAL-FACTOR PRODUCTIVITY AND CARBON INTENSITY INDICATOR APPROACH

This paper proposes non-radial directional distance functions for a low-carbon productivity analysis in the field of fossil fuel electricity generation. It is used to measure the low-carbon productivity performance of thermal electric power plants. Based on the approach, we develop a total-factor carbon intensity (TCI) indicator in the total-factor productivity viewpoint and provide an empirical analysis of thermal power plants in China belonging to various power companies. The results show significant differences in total-factor carbon intensity across power companies. TCI indicator is lower for state-owned power companies than for private ones. This suggests that Chinese government should consider private incentives and deregulation for its state-owned enterprises.

Keywords: *thermal power plants, non-radial directional distance function, total-factor carbon intensity indicator, China.*

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ЧИ СКОРОТЯТЬ КИТАЙСЬКІ ТЕПЛОВІ ЕЛЕКТРОСТАНЦІЇ ВИКИДИ CO_2? СУКУПНА ФАКТОРНА ПРОДУКТИВНІСТЬ І ПІДХІД ДО ПОКАЗНИКІВ ПИТОМИХ ВИКИДІВ

У статті запропоновано нерадіальну спрямовану функцію відстані для аналізу виробництва електроенергії на низьковуглецевому викопному паливі. Її можна використовувати дла вимірювання показників низьковуглецевого виробництва теплових електростанцій. На основі даного підходу розроблено сукупний факторний індикатор питомих викидів (TCI) з точки зору сукупної факторної продуктивності, що дає можливість емпіричного аналізу теплових електростанцій в Китаї, які належать різним енергетичним компаніям. Отримані результати показали значні відмінності в сукупних факторних питомих викидах в енергетичних компаніях. Показник TCI виявився нижчим для державних енергетичних компаній, ніж для приватних. Передбачається, що китайський уряд повинен розглянути приватні засоби заохочення і дерегулювання для державних підприємств.

Ключові слова: теплові електростанції, нерадіальна спрямована функція відстані, сукупний факторний показник питомих викидів, Китай.

Табл. 5. Форм. 7. Літ. 22.

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СОКРАТЯТ ЛИ КИТАЙСКИЕ ТЕПЛОВЫЕ ЭЛЕКТРОСТАНЦИИ ВЫБРОСЫ CO_2? СОВОКУПНАЯ ФАКТОРНАЯ ПРОИЗВОДИТЕЛЬНОСТЬ И ПОДХОД К ПОКАЗАТЕЛЯМ УДЕЛЬНЫХ ВЫБРОСОВ

В статье предложена нерадиальная направленная функция расстояния для анализа производства электроэнергии на низкоуглеродистом ископаемом топливе. Ее можно использовать для измерения показателей низкоуглеродистого производства тепловой электроэнергии. На основе данного подхода разработан совокупный факторный индикатор удельных выбросов (TCI) с точки зрения совокупной факторной

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производительности, что дает возможность обеспечивать эмпирический анализ тепловых электростанций в Китае, принадлежащих различным энергетическим компаниям. Полученные результаты показали значительные различия в совокупных факторных удельных выбросах в энергетических компаниях. Показатель TCI оказался ниже для государственных энергетических компаний, чем для частных. Предложено китайскому правительству использовать частные средства поощрения и дерегулирования для государственных предприятий.

Ключевые слова: *тепловые электростанции, нерадиальная направленная функция расстояния, совокупный факторный показатель удельных выбросов, Китай.*

I. Introduction.

In China as the biggest CO_2 emitter in the world, the power sector accounted for about 48% of CO_2 emissions in 2010 (Liu, Wang, 2011) and thus played an important role in reducing China's total CO_2 emissions. It is crucial for fossil fuel power plants in China to improve their energy efficiency to reduce CO_2 emissions. By taking proactive strategies to improve energy efficiency, power generation companies are able to not only reduce CO_2 regulation risks, but also improve their economic competitiveness through reductions in abatement costs. However, it is not easy to handle all the positive as well as negative input and output factors simultaneously. In order to include all these diverse issues together and to propose more field-oriented implications, this paper aims to develop a total-factor carbon intensity indicator for benchmarking the CO_2 emission performance of Chinese thermal power plants.

Various indicators have been developed and applied to monitor CO_2 emissions. For instance, Mielnik and Goldemberg (1999) propose 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 changes. Ang (1999) argues that energy intensity (energy consumption per unit of GDP) is as useful as the carbonization index in the study of climate changes. Sun (2005) highlights the usefulness of CO_2 emission intensity in measuring de-carbonization and assessing energy policies at the national level. More specifically, several studies were conducted to estimate potential emission reduction in electricity generation through benchmarking analysis (Maruyama, Eckelman, 2009). These studies often assumed that the fossil-fuel electricity generation efficiency by fuel type could reach a certain percentile level of all the sampling countries/regions. Unfortunately, the single indicator approach and benchmarking studies focus on the single-factor CO_2 emissions performance. However, electricity generation is a multi-factor production process that utilizes both energy and non-energy inputs including labor force and capital to produce desirable and undesirable outputs. It is therefore meaningful to analyze energy and CO_2 performance of electricity generation within the total-factor production framework, which could provide valuable information regarding how emission reduction potentials may be achieved.

Many studies have utilized production efficiency to analyze energy and environmental performance (Zhou et al., 2008). Even in the electric power industry, a number of studies have employed the data envelopment analysis (DEA) technique to analyze the efficiency of fossil fuel electricity generation (Yang, Pollitt, 2010; Sozen et al., 2010; Jaraite, Maria, 2012; Sueyoshi, Goto, 2011; Zhou et al., 2012). However, few have focused on the use of the directional distance function (DDF) for analyzing the efficiency of the electric power industry. In comparison to traditional DEA models, the DDF measures efficiency by increasing desirable outputs (electricity) and reducing undesirable ones (CO_2 emissions) simultaneously.

The conventional DDF reduces undesirable outputs (inputs) and increases desirable outputs at the same rate and thus it may be regarded as a radial approach with several limitations. One limitation is that a radial measure may overestimate efficiency when there are some slacks (Fukuyama, Weber, 2009). Several studies have extended the DDF to the non-radial DDF (NDDF) by incorporating slack into efficiency measurement (Fukuyama, Weber, 2009; Fare, Grosskopf, 2010; Barros et al., 2012). Zhou et al. (2012) define an NDDF with desirable mathematical properties by taking an axiomatic approach to efficiency measurement.

This paper proposes a new NDDF named energy-carbon non-radial DDF (ECNDDF) to measure the CO_2 emissions performance of fossil fuel power plants in China. This paper employs the plant-level data for China, whereas Zhou et al. (2012) use the country-level data only. To the authors' knowledge, this paper is the first study to empirically measure carbon intensity on the fossil fuel power plant level in China, and thus it will bring more field-oriented implications.

The rest of this paper is organized as follows: Section 2 describes the methodology. Section 3 empirically estimates the total-factor carbon intensity indicator of fossil fuel power plants in China and presents the results, and Section 4 concludes this study.

2. Methodology.

2.1. Environmental production technology. Suppose that there are N thermal power plants and that each plant uses capital (K), labor (L), and fossil fuel (F) as inputs to generate electricity (E), the desirable output, and CO_2 emissions (C), the undesirable out. The multi-output production technology can be described as follows:

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

where T is often assumed to satisfy the standard axioms of production theory (Fare, Grosskopf, 2005). That is, inactivity is always possible, and finite amounts of inputs can only produce finite amounts of outputs. In addition, inputs and desirable output are often assumed to be strongly or freely disposable. For a reasonable model of the joint-production technology, as described in Fare et al. (1989), the weak-disposability and null-jointness assumptions should be imposed on T. Technically, these two assumptions can be expressed as follows:

(1) If $(K,L,F,E,C)\in T$ and $0\le\theta\le 1$, then $(K,L,F,\theta E,\theta C)\in T$,

(2) If $(K,L,F,E,C)\in T$ and $C=0$, then $E=0$.

The weak-disposability assumption indicates that reducing CO_2 emissions is not free but costly in terms of a proportionate reduction in electricity generation, and the null-jointness assumption implies that CO_2 emissions are unavoidable in fossil fuel electricity generation and that the only way to remove all CO_2 emissions is to stop operating electric power plants.

Once the environmental production technology T is specified, the nonparametric DEA method can be used to specify the environmental production technology. Based on Zhou et al. (2012), the environmental production technology T for N power plants exhibiting constant returns to scale can be expressed as follows:

$$T=\left\{\begin{array}{l}(K,L,F,E,C):\sum_{n=1}^{N}z_nK_n\le K,\sum_{n=1}^{N}z_nL_n\le L,\\ \sum_{n=1}^{N}z_nF_n\le F,\sum_{n=1}^{N}z_nE_n\ge E,\sum_{n=1}^{N}z_nC_n=C,z_n\ge 0,n=1,2,\cdots,N\end{array}\right\}. \tag{2}$$

Based on this nonparametric piecewise linear production frontier for the environmental production technology, we can apply the NDDF.

2.2. Non-radial directional distance function. The DDF is a relatively new methodology for measuring performance. Chung et al. (1997) is the first to use the DDF to examine environmental efficiency. Here, the traditional DDF is defined such that it seeks to maximize desirable outputs while reducing undesirable ones simultaneously:

$$\vec{D}(K,L,F,E,C;g)=\sup\{\beta:((K,L,F,E,C)+g\cdot\beta))\in T\}. \tag{3}$$

Because the radial DDF in equation (3) does not take slack into account, it has the potential to reduce inefficiencies and thus may overestimate the efficiency score. Another limitation of the radial DDF derives from the fact that the radial DDF cannot distinguish environmental performance with operational ones because radial DDF can only give the same rate of inefficiency (Sueyoshi, Goto, 2011). Therefore, it is difficult to obtain carbon performance by using the radial DDF. Non-radial efficiency measures are often advocated to overcome this limitation because of their advantages (Zhou et al., 2007; Chang, Hu, 2010; Choi et al., 2012). Recently, Zhou et al. (2012) provide a formal definition of the non-radial DDF with undesirable outputs. Following Zhou et al. (2012), we define the non-radial DDF as follows:

$$\vec{D}(K,L,F,E,C;g)=\sup\{w^T\beta:((K,L,F,E,C)+g\cdot diag(\beta))\in T\}, \tag{4}$$

The symbol diag refers to diagonal matrices, where $\mathbf{w}^T=(w_K, w_L, w_F, w_E, w_C)^T$ denotes the normalized weight vector relevant to the numbers of inputs and outputs; $g=(-g_K,-g_L,-g_F,g_E,-g_C)$ is the explicit directional vector; and $\beta=(\beta_K,\beta_L,\beta_F,\beta_E,\beta_C)^T\ge 0$ denotes a vector of scaling factors representing individual inefficiency measures for each input/output.

The NDDF value, denoted as $D(K,L,F,E,C;g)$, can be computed by solving the following DEA-type model:

$$\vec{D}(K,L,F,E,C;g)=\max w_K\beta_K+w_L\beta_L+w_F\beta_F+w_E\beta_E+w_C\beta_C \tag{5}$$

$$\text{s.t.}\sum_{n=1}^{N}z_nK_n\le K-\beta_Kg_K$$

$$\sum_{n=1}^{N}z_nL_n\le L-\beta_Lg_L$$

If $D_T(K,L,F,E,C;g)=0$, then the power plant to be evaluated is located on the production frontier by g direction.

$$\sum_{n=1}^{N} z_n F_n \le F - \beta_F g_F$$
$$\sum_{n=1}^{N} z_n E_n \ge E + \beta_E g_E$$
$$\sum_{n=1}^{N} z_n C_n = C - \beta_C g_C$$
$$z_n \ge 0, n = 1,2,\cdots,N$$
$$\beta_K, \beta_L, \beta_F, \beta_E, \beta_C \ge 0.$$

We can then develop an indicator to measure the unified performance in the context of electricity generation. Because there are 3 inputs, one desirable output, and one undesirable output, we set the weight vector as (1/9, 1/9, 1/9, 1/3, 1/3). For measuring the environmental performance of fossil fuel power plants it is better to fix the non-energy inputs. By setting the directional vector as $g = (0,0,-g_F,g_E,-g_C)$ and the weight vector as (0, 0, 1/2, 1/4, 1/4), we remove the diluting effects of capital and labor from the objective function and constraints. We define this non-radial distance function as the energy-carbon non-radial DDF (ECNDDF). The ECNDDF value, denoted as $D_E(K,L,F,E,C;g)$, can be calculated by solving the following DEA model:

$$\vec{D}_E(K,L,F,E,C;g) = \max w_F\beta_F + w_E\beta_E + w_C\beta_C \tag{6}$$
$$\text{s.t.} \sum_{n=1}^{N} z_n K_n \le K$$
$$\sum_{n=1}^{N} z_n L_n \le L$$
$$\sum_{n=1}^{N} z_n F_n \le F - \beta_F g_F$$
$$\sum_{n=1}^{N} z_n E_n \ge E + \beta_E g_E$$
$$\sum_{n=1}^{N} z_n C_n = C - \beta_C g_C$$
$$z_n \ge 0, n = 1,2,\cdots,N$$
$$\beta_F, \beta_E, \beta_C \ge 0.$$

Once equation (6) is solved, we can obtain the optimal solutions β^*_F, β^*_E, and β^*_C, and following Zhou et al. (2012) we define the total-factor carbon intensity (TCI) indicator as the ratio of potential target carbon intensity to actual carbon intensity (C/E), which can be expressed by

$$TCI = \frac{(C - \beta_C^* C)/(E + \beta_E^* E)}{C/E} = \frac{1 - \beta_C^*}{1 + \beta_E^*} \tag{7}$$

Clearly, TCI indicator lies between zero and unity. The higher the TCI is, the better is the carbon intensity performance. If the TCI is equal to unity, then the observation reflects the best efficiency located on the electricity generation technology frontier.

3. Empirical Analysis and the Results.

3.1. Data. Based on the methodology described above, we estimate the carbon intensity indicator for fossil fuel power plants in China. The sample consists of 260 thermal power plants operating as of 2010. Table 1 provides detailed information on these plants. About half belong to 5 main state-owned companies referred to as "five big groups": DATANG, GUODIAN, HUANENG, HUADIAN, and POWER INVESTMENT. Local companies also account for a large percentage of power plants (38.8%). In addition to these "five big groups" and local companies, CR power, GUOHUA, and SDIC are also large private power companies in China. As the 5 main state-owned companies are major suppliers of electricity, it is meaningful to compare the unified efficiency of these companies with private and local companies.

The next subsection discusses the empirical results for the unified efficiency and environmental performance of all these companies to assess differences in their performance.

Table 1. **Classification of thermal power plants of companies**

Code	Electric Power Companies	# of Plants	%
1	China DATANG Corporation	34	13.1%
2	China GUODIAN Corporation	37	14.2%
3	China HUANENG Group	36	13.8%
4	China HUADIAN Corporation	25	9.6%
5	China POWER INVESTMENT Corporation	7	2.7%
6	China Resources Power Holdings Company	7	2.7%
7	SHENHUA GUOHUA power	10	3.8%
8	SDIC Power Holdings	3	1.2%
9	Local Power Companies	101	38.8%

The electricity output (*E*) of each power plant is measured by the gross amount of electricity generated and the capital input (*K*) and the fossil fuel input (*F*) by the installed generating capacity and fuel consumption, respectively, in standard coal equivalent. The labor input (*L*) is measured by the number of employees for each power plant. All data are obtained from the China Electric Power Yearbook 2011 (*E* and *K*), the Chinese Industrial Enterprises Database (*L*), and the China Electric Power Industry Statistical Analysis (*F*). According to Yang and Pollitt (2010), CO_2 emissions of fossil fuel power plants can be estimated using the IPCC carbon emission factors by fuel type. Table 2 shows the descriptive statistics for input and output variables. The total installed capacity of the sample plants reached 404,274 MW, accounting for about 57.2% of China's total installed fossil fuel capacity in 2010. Total CO_2 emissions of the sample plants are 2,150.2 mln. tons. The sample of our empirical test (260 fossil fuel power plants) accounts for 25.8% of China's total CO_2 emissions.

Table 2. **Descriptive statistics**

Variable	Unit	Mean	Standard Deviation	Maximum	Minimum
E	103 GWh	7.84	3.59	26.6	0.51
C	106 tons	8.27	3.73	27.99	5.26
K	MW	1554.90	608.80	4800	1000
L	Persons	654	264	2016	201
F	106 tons	24.39	10.89	84.59	1.53

3.2. Empirical results. Table 3 shows the results for total-factor carbon intensity indicator. The TCI for all power plants ranges from 0.306 to 1 with the average of

0.776. This implies that, on average, 260 power plants together can achieve a 22.4% decrease in their carbon intensity if they all operate along the production technology frontier. Local companies such as Baosteel and Waigaoqiao2 (of Shanghai), Ligang (Jiangsu) and Taizhou (Zhejiang) show the highest TCI indicator of 1. This result reflects the fact that economically well developed provinces such as Shanghai and Zhejiang are more likely to show greater efficiency even in terms of low carbon performance (Choi et al., 2012).

Table 3. **Total-factor carbon intensity indicator of companies and total plants**

Company	TCI			
	Mean	Std. Dev	Minimum	Maximum
DATANG	0.778	0.068	0.522	0.846
GUODIAN	0.784	0.073	0.461	0.846
HUANENG	0.764	0.105	0.306	0.847
HUADIAN	0.774	0.055	0.636	0.842
POWER INVEST	0.689	0.157	0.455	0.845
CR Power	0.814	0.073	0.649	0.847
GUOHUA	0.785	0.121	0.446	0.848
SDIC Power	0.811	0.008	0.803	0.819
Local Power Companies	0.785	0.075	0.457	1.00
Total Plants	0.776	0.082	0.306	1.00

At the company level, CR Power shows the highest average TCI indictor value of 0.814. POWER INVEST shows the lowest average TCI value of 0.689. These results may be due to the fact that private companies such as CR Power in Hong Kong are more motivated to improve management performance in terms of carbon intensity than state-owned companies such as POWER INVEST. It might be interpreted as private companies tend to incorporate the environmental strategy proactively into their business management to avoid carbon risk and obtain the competitive advantage of climate change.

SDIC Power shows the lowest standard deviations for TCI indicator, indicating that its power plants operate under relatively similar technology conditions. On the other hand, the power plants of POWER INVEST show the highest standard deviations, indicating a relatively large technology gap between the individual power plants of this company. State-owned companies such as POWER INVEST result in bad performance in their innovation capacity and thus require much more incentive to enable their individual power plant to promote and share technological innovations.

The average TCI value for "five big groups" is 0.772, whereas the average for other companies is 0.818. This indicates that these 5 state-owned companies show poor carbon performance than other companies. Therefore, state-owned companies need to be innovated with more management incentives as well as R&D investment for better low carbon-oriented governance.

As shown in Table 4, we employ the Kruskal-Wallis rank-sum test to determine any significant differences in TCI indicator between different companies. The results reject the null hypothesis at the 10% level, and it means rank differences in two indices between the sample groups of companies.

Table 4. **Kruskal-Wallis test of companies**

Index	Null Hypothesis (H_o)	KW Statistics	p-value
TCI	$Mean(TCI_1)=Mean(TCI_2)=... Mean(TCII_9)$	14.38	0.076

The total-factor carbon intensity of power plants is examined in Table 5 by provinces. Because the sample covers most regions in China, a provincial comparison shall provide important implications. In terms of TCI, Tianjin shows the highest average value of 0.839. On the other hand, Jilin shows the lowest performance values (average = 0.684). Because Tianjin is more economically developed than Jilin, these results indicate that the level of economic development may be positively related to economic and environmental efficiency of power plants. Economic development enhances infrastructure and puts greater pressure on environmental issues, and therefore power plants in these provinces should make more effort to meet these conditions.

Table 5. **TCI of power plants by province**

Provinces	# of Plants	TCI
Anhui	13	0.831
Fujian	7	0.706
Gansu	3	0.725
Guangdong	20	0.789
Guangxi	4	0.832
Guizhou	8	0.775
Hainan	1	0.800
Hebei	14	0.817
Henan	17	0.774
Heilongjiang	5	0.706
Hubei	9	0.738
Hunan	8	0.740
Jilin	5	0.684
Jiangsu	26	0.815
Jiangxi	6	0.757
Liaoning	9	0.774
Inner Mongolia	16	0.742
Ningxia	4	0.798
Shandong	18	0.807
Shanxi	18	0.813
Shaanxi	10	0.770
Shanghai	10	0.734
Sichuan	3	0.750
Tianjin	5	0.839
Xinjiang	1	0.754
Yunan	5	0.767
Zhejiang	14	0.752
Chongqing	1	0.728

4. Conclusion.

Many previous studies used DEA to measure the environmental efficiency of fossil fuel power plants, but few have employed the DDF for this. This paper develops energy-carbon non-radial DDFs to measure the low carbon performance of fossil fuel electricity generation. Based on the ECNDDF, we compute the total-factor carbon intensity indicator from the viewpoint of total-factor productivity of fossil fuel electric power plants.

The empirical results show significant differences in total-factor carbon intensity indicators across power companies as well as provinces. The power plants of state-owned companies show poorer carbon performance than other companies, which suggests that privately motivated innovation plays a more important role in enhancing overall as well as environment-friendly performance. Chinese government should emphasize more on incentives of private companies indirectly and deregulation for state-owned companies directly for better governance of innovation in power sector.

This study has some limitations in that the empirical analysis is based only on the cross-sectional data for 2010. Although the efficiency of electricity generation is not likely to change in the short term, the empirical implications can be enhanced by considering time series data. Given data availability, future research should include a longer period of time to better assess the CO_2 emission performance of China's fossil fuel electricity generation.

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Стаття надійшла до редакції 31.01.2013.