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SciVerse ScienceDirect
Procedia Environmental Sciences 13 (2012) 2256 – 2263
Procedia Environmental Sciences

The 18th Biennial Conference of International Society for Ecological Modelling

Study of the Energy and Environmental Efficiency of the Chinese economy based on a DEA Model

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Abstract

Energy and environmental efficiency were analyzed for each province in China by developing a Data Envelopment Analysis (DEA) model using real-time data available for 30 provinces. The Malmquist Index was selected to illustrate the dynamic characteristics of energy and environment efficiency and the tobit model was used to regress the factors affecting efficiency. The results indicated that Beijing and other southeast coastal provinces are relatively efficient while provinces in the central and western regions of China are inefficient. The gap between Beijing and low energy-environment efficient provinces is significant and is continuously increasing. Gross Domestic Product (GDP) per capita, the proportion of tertiary industry and the urbanization rate were found to be the key elements that affect energy/environment efficiency with the former two factors exhibiting significant positive correlations and the latter factor exhibiting a negative correlation.

Keywrds: Data envelopment analysis; Energy saving and emission reduction; Efficiency evaluation;China

1. Introduction

The Chinese economy has grown aggressively in the past three decades resulting in severe environmental pollution and an acute shortage of energy supply. According to the Statistical Review of World Energy 2011, China has replaced the US as the largest energy consumer, contributing to 20.3% of global energy consumption. To construct a resource-conserving and environment-friendly society, China's

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 doi:10.1016/j.proenv.2012.01.214

11th five-year plan, launched in 2006, stipulates that all government divisions must reduce energy consumption by 20% and reduce primary pollution by 10% by 2010. However, several differences exist at the provincial level with regards to the level of economic growth, industrial structure and resource capital indicating that the potential contribution to energy saving and emission reduction of each province will be different. This has, in fact, been observed by comparing the accomplished levels of energy saving and emission reduction in the last five years to the actual targets of each province.

Since the policy of energy saving and emission reduction was launched in 200, many scholars have explored the performance of this policy. The key issues of energy and environmental efficiency have been widely analyzed using models such as Data Envelopment Analysis (DEA). Hu and Wang introduced a new index called the total-factor energy efficiency using the DEA model [1] and found that this index can represent the ground-level scenario in 29 Chinese provinces between 1996 and 2002 more operative. However, the environmental efficiency, an indicator of the environmental cost of economic development, was not determined in this report. This is also the case with several other studies that either calculated the energy efficiency alone without taking environment factors into account or vice versa [2-3]. Therefore, this study combines the input of energy and environmental factors to calculate the total energy/environmental efficiency of each province in China from 2003-2009, the years after the energy-saving and emission-reduction policy was launched.

2. Methodology

2.1. The DEA model

DEA is a well-established methodology to evaluate the relative efficiencies of a set of comparable entities by specific mathematical modelling. These entities, often called Decision Making Units (DMUs), perform the function of transforming multiple inputs into outputs. The main advantage of DEA is that it does not require any prior assumptions of the underlying functional relationships between inputs and outputs [4]. It is therefore a nonparametric approach. In addition, DEA is a data-driven frontier analysis technique that floats a piecewise linear surface to rest on top of the empirical observations [5].

Assume that there are n DMUs, and each of them has M inputs and N outputs. Further assume that DMU_j consumes $x_{i,j} \geq 0$ of input m to produce $y_{sj} \geq 0$ of output s. v and u are N*1 weight vectors of inputs and outputs, respectively. Then there are:

$$x_j = (x_{1j}, x_{2j}, ..., x_{mj})^T \tag{1}$$

$$y_j = (y_{1j}, y_{2j}, ..., y_{sj})^T \tag{2}$$

$$v = (v_1, v_2, ..., v_m)^T \tag{3}$$

$$u = (u_1, u_2, ..., u_s)^T \tag{4}$$

The efficiency of DMU_j would be the optimized solution of the following programming model:

$$\begin{aligned} \max \quad & h_{j_0}(u,v) = \sum_{r=1}^{s} u_r y_{rj_0} / \sum_{i=1}^{m} v_i x_{ij_0} \\ s.t. \quad & \sum_{r=1}^{s} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \leq 1 \\ & u_r, v_i \geq 0, i = 1, ..., m; = 1, ...n; r = 1, ..., s \end{aligned} \tag{5}$$

The Charnes-Cooper Transform can turn the fractional programming into a linear one as following:

$$\begin{aligned} &\min \quad \theta \\ &s.t. \quad \sum_{j=1}^{n} \lambda_j X_j \le \theta X_{j_o} \\ &\qquad \sum_{j=1}^{n} \lambda_j X_j \ge Y_{j_o} \\ &\qquad \sum_{j=1}^{n} \lambda_j = 1 \\ &\qquad \lambda_j \ge 0, j = 1,...,n \end{aligned} \tag{6}$$

In equation 6, λ_j represent the coefficient of input X_j. The resolution of the linear programming (i.e., eqn. 6) is considered as the efficiency of DMU_{jo}.

2.2. The Malmquist Index

The bilateral Malmquist index (MI) is used to compare the production technology of two economies [6]. The MI is based on the concept of the production function, which is a function of the maximum possible production from a set of inputs pertaining to capital and labour.

If S_a is the set of labour and capital inputs that affect the production function Q of Economy A, then $Q=f_a(S_a)$. Next, to calculate the MI of economy A with respect to economy B, the labour and capital inputs of economy A must substituted into the production function of B, and vice versa. Therefore, MI is calculated as:

$$MI = \sqrt{(Q_1 Q_2)/(Q_3 Q_4)} \tag{7}$$

Where $Q_1=f_a(S_a), Q_2=f_a(S_b), Q_3=f_b(S_a),$ *and* $Q_4=f_b(S_b)$.

When it refers to the relative efficiency between times *t* and *t*+1, MI can be derived from the following equation [7,8]:

$$M(x_{t+1}, y_{t+1}, x_t, y_t) = \sqrt{\frac{D^t(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} * \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^{t+1}(x_t, y_t)}} \tag{8}$$

If MI>1, it means that the production efficiency has improved.

2.3. The tobit regression model

The tobit regression model delineates the relationship between a non-negative dependent variable and an independent variable. It has previously been employed to study the relationship of energy efficiency to factors [9].The analysis comprises two stages: In stage 1, the non-parametric DEA is used to calculate the efficiency with which output is produced from physical inputs. In stage 2, an econometric model is generated to relate efficiency scores to factors, i.e., exogenous variables that influence efficiency. This second stage analysis, where the efficiency scores obtained by DEA are subsequently modelled against exogenous variables, has previously been described [10-13].

The efficiency scores belonging to [0, 1] it means that they are limited independent variables. It's inappropriate to employ ordinary least squares. The most-often encountered approach to model the DEA scores against exogenous variables is the tobit regression, which is suitable when the dependent variables are either censored or corner solution outcomes [14]. Often in stage 2, the regression procedure used is two-limit tobit (2LT) with limits at zero and unity.

The energy-environment efficiency of each region can be calculated by the DEA model, which are determined by the factors beyond the input and output indicators. He and Li hold that the impact of economic growth on energy consumption could be divided to scale effect, structure effect, and technical effect [15]. Zhang and He independently analyzed the impact of upgrading industrial structure on energy efficiency [16, 17]. And other studies point out the economic scale, the opening degree, and regional factors affect the environment efficiency [2, 3].

Factors that affected energy and environment efficiencies were considered to be the independent variables of the econometric model and included economic development, industrial structure, technological effects, and resource capital. The econometric model was determined as follows:

$$EE = \beta_0 + \beta_1 \ln G_i + \beta_2 S_i + \beta_3 U_i + \beta_4 Mi + \beta_5 P_i + \varepsilon_i \quad (9)$$

Where EE is the energy/environment efficiency, β_0 is a constant, β_1~β_5 is the regression coefficient of each independent variable, ε_i is the error term, G_i is the Gross Domestic Product (GDP) per capita, S_i is the industrial structure representing the proportion of tertiary industry in GDP, U_i is the urbanization rate, M_i is the ratio of environment protection investment to the regional GDP, and P_i is the population density.

2.4. Data compilation and DEA models specific to this study

For empirical measurements, the 30 provinces in China were regarded as individual DMUs (Tibet was excluded because energy-use and environmental statistics were not available). A province-level database from 2003-2009 was established using data obtained from China's Statistical Yearbook (2004-2010), China Environmental Statistical Yearbook (2004-2010), and China Energy Statistical Yearbook (2004-2010). The input indicators included COD emissions and SO_2 emissions in addition to energy consumption, because China set a 10% volume reduction target for emissions of SO_2 and COD in its 11th Five-Year Plan. The GDP of each province served as the output of each DMU and was calculated according to the constant price of the year 2003.

The most widely used models in DEA are the CCR model and BCC model. The former assumes that the constant returns to scale, while the latter assumes that the variable returns to scale. According to the yearbook records, the energy consumption elasticity coefficient varied greatly every year while the cost of emission reduction increased due to its augmented difficulty. Therefore, the input-oriented BCC model was used to calculate energy/environment efficiency.

3. Results

3.1. Energy/environment efficiency

BCC-type DEA models were developed using the DEAP software developed by Tim Coelli. This program constructed DEA frontiers for the calculation of technical and cost efficiencies, and the Malmquist indices. The resultant efficiency scores from 2003 to 2009 for each province are shown in Fig. 1. Beijing was the most energy-efficient province in China, keeping ranking first every year along with provinces like Guangdong, Hainan, Zhejiang, Shanghai, Fujian, and Jiangsu that are located along the southeastern coast of China. Among them, Guangdong in 2004-2005 and Hainan in 2003-2005 all the most efficient provinces with a score 1.However, the gap between these provinces and Beijing has increased in recent years. Alternately, the provinces of Qinghai, Guizhou, Shanxi, and Ningxia had low energy efficiencies. The DEA scores for these provinces were less than 0.3 with the lowest being 0.17, with a trend further away from the most efficient provinces. This means that for every unit of GDP produced in these provinces, the amount of energy consumed and pollutants emitted was 4 to 6 times more than that of Beijing.

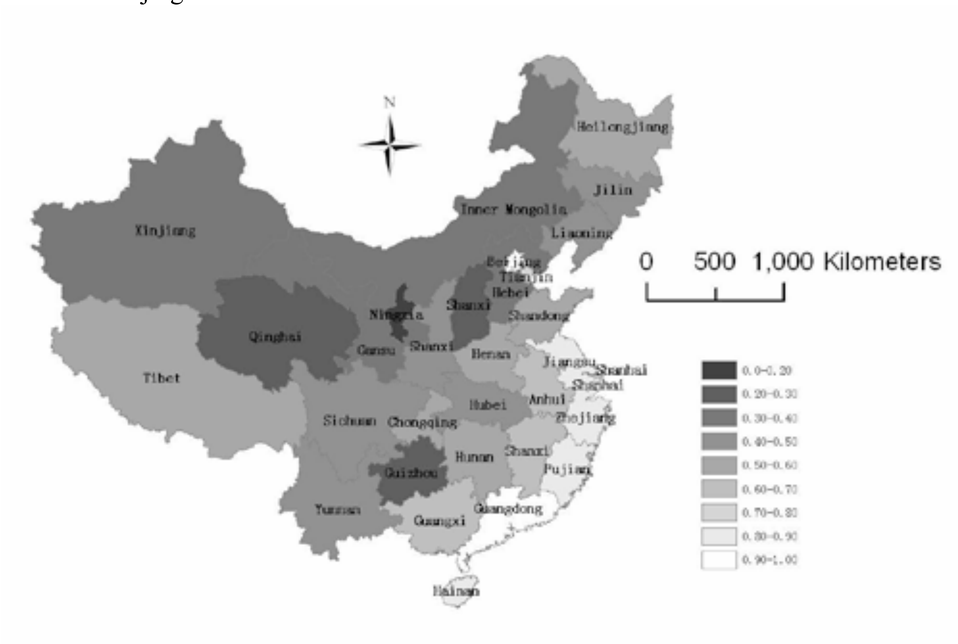

Figure 1. Map of the energy/environment efficiency in different provinces in China from 2003-2009. The value for Tibet represents the average of the other provinces, i.e., the average energy/environment efficiency of China.

3.2. The dynamic characteristics of energy/environment efficiency

Malmquist indices were calculated for different periods of time to determine the dynamic characteristics of the energy/environment efficiencies (Table 1). In the years 2003-2005, the energy-environment efficiency decreased for all provinces. However, since the 11th five year plan was launched in 2006, the energy efficiency of the entire nation increased at a rate of 4.7% per year. Beijing, in particular, was not only the most energy efficient, but also had the fastest increase rate of 15.9% per year. Qinghai with a rate of 3.4% and Xinjiang with a rate of 2.3% showed the slowest rates of improvement. This could be attributed to compare the dynamic characteristics of energy/environment efficiency in different provinces.

3.3. Regression analysis of factors affecting energy/environment efficiency

Four factors were regressed as independent variables to analyze their correlation with the energy/environment efficiency, including GDP per capita, the proportion of tertiary industry in GDP, urbanization rate and the ratio of environmental protection investment to regional GDP. The analysis showed that GDP per capita and the proportion of tertiary industry in GDP of a province had positive correlations with the energy/environment efficiency. In contrast, the urbanization rate and ratio of environmental protection investment to the regional GDP had a weak negative or no correlation with the energy-environment efficiency.

Table 1. The dynamic characteristics of energy/environment efficiency from 2003 to 2009

	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2005-2009	2003-2009
Beijing	1.11	1.145	1.138	1.194	1.209	1.099	1.159	1.148
Tianjin	1.102	1.111	1.041	1.037	1.15	1.079	1.076	1.086
Hebei	1.016	1.041	1.041	1.051	1.074	1.064	1.057	1.048
Shanxi	0.862	0.981	1.026	1.047	1.067	1.074	1.053	1.007
Inner Mongolia	0.952	1.018	1.033	1.043	1.072	1.063	1.053	1.029
Liaoning	0.81	0.941	1.036	1.047	1.069	1.058	1.052	0.989
Jilin	1.065	1.005	1.02	1.047	1.08	1.061	1.052	1.046
Heilongjiang	0.821	0.878	1.035	1.046	1.072	1.054	1.052	0.979
Shanghai	1.061	1.006	1.044	1.057	1.039	1.065	1.051	1.045
Jiangsu	1.011	1.159	1.035	1.046	1.053	1.066	1.050	1.061
Zhejiang	0.929	1.017	1.037	1.044	1.059	1.057	1.049	1.023
Anhui	1.017	0.999	1.027	1.042	1.052	1.076	1.049	1.035
Fujian	0.938	0.915	1.036	1.044	1.062	1.054	1.049	1.006
Jiangxi	0.897	0.996	1.032	1.042	1.068	1.053	1.049	1.013
Shandong	0.862	1.025	1.031	1.043	1.054	1.066	1.048	1.011
Henan	0.947	0.975	1.035	1.048	1.063	1.047	1.048	1.018
Hubei	0.926	0.834	1.035	1.046	1.052	1.058	1.048	0.988
Hunan	1.014	1.023	1.034	1.043	1.051	1.062	1.047	1.038
Guangdong	0.901	1.004	1.033	1.044	1.063	1.047	1.047	1.014
Guangxi	1.011	1.073	1.037	1.042	1.054	1.053	1.046	1.045
Hainan	1.28	0.988	1.01	1.037	1.072	1.067	1.046	1.072
Chongqing	1.032	1.199	1.031	1.042	1.068	1.043	1.046	1.068
Sichuan	0.979	1.02	1.033	1.046	1.042	1.062	1.046	1.030
Guizhou	1.099	1.027	1.035	1.043	1.048	1.056	1.045	1.051
Yunnan	0.908	0.949	1.015	1.041	1.051	1.048	1.039	1.000
Shaanxi	1.008	0.971	1.03	1.033	1.045	1.045	1.038	1.022
Gansu	0.848	0.977	1.033	1.037	1.039	1.04	1.037	0.993
Qinghai	0.91	0.976	1.026	1.034	1.041	1.046	1.037	1.004
Ningxia	0.924	0.904	0.993	1.031	1.044	1.068	1.034	0.992
Xinjiang	0.923	0.993	1.011	1.032	1.033	1.015	1.023	1.000
Average	0.952	0.996	1.033	1.044	1.057	1.055	1.047	1.022

Table 2. The regression of factors that affect energy/environment efficiency

The factor	Coefficient	Std err.	Significance
Ln (GDP per capita)	0.0072	0.691*E-3	>99%
The proportion of tertiary industry	0.0156	0.0026	>95%
The urbanization rate	-0.0049	0.0028	>90%
Ratio of environmental protection investment to the regional GDP	0.1045	0.0900	No

4. Discussion

Since Beijing's successful bid to host the Olympic Games in 2008, it has become the most energy-efficient province in China. The Beijing governing body has continuously implemented the Clear Air Action Plan, sped up the adjustment of its industrial structure and eliminated backward production capacity. Thus, the energy consumption and pollution emission per GDP in Beijing is the lowest in China and this was reflected in our analysis (Fig. 1 and Table 1). In contrast, the Central and Western provinces like Qinghai, Guizhou, and Shanxi exhibited low energy efficiency due to their poor industrial structure and resource capital. Importantly, these provinces have the highest potential to save energy and reduce emissions making them the prime focus areas for future ecological development. Because China's overall energy efficiency and pollutant emissions are far behind the levels of developed countries, the provinces with high efficiency, even Beijing and the Southeast coastal provinces, should also continue to reduce energy consumption and pollution emission

The regression analysis determined that GDP per capita is an important contributor to energy/environment efficiency (Table 2). In the economically developed provinces, technology is more advanced, energy efficiency higher, and the demand for good environment quality urgent. Also, these regions can afford to make bigger investments in energy engineering and pollutant emission reduction projects. In the process of industrial change, the economically developed regions gradually turn into the high-end of the industry chain. These provinces tend to introduce low energy consumption and environment-friendly enterprise. The proportion of tertiary industry in GDP was another important factor that impacted energy efficiency. This indicates that the development of tertiary industry results in value addition, low energy consumption and low emission at the provincial level, and should be utilized to…

5. Conclusions

This report presents the energy and environment efficiencies of each province in China (except Tibet) between 2003 and 2009, by using the DEA model. The results showed that the efficiency values were consistent with the spatial distribution of development in China. Beijing and the southeast coastal provinces shared high efficiency, while the central and western provinces were poorly efficient. The gap between the energy-efficient and –inefficient provinces was quite significant and appeared to increase with time. Next, the trend of energy and environment efficiency in 2003-2009 was calculated using the MI. The energy/environment efficiency was low until 2005, but showed an upward trend since the 11th five-year plan was launched in 2006, specifically after the implementation of the policy of energy-saving and emission reduction. Regression analysis showed that GDP per capita and the proportion of tertiary industries contributing to GDP were the key elements that positively regulated energy/environment efficiency whereas urbanization rate had a weak negative correlation with the energy/environment efficiency.

However, it is necessary to point out that there are a few limitations to employing the DEA methodology. For example, the DEA model requires a large volume of accurate and reliable data. Also, the DEA identifies the weights that maximize the efficiency score of an evaluated unit in comparison with a group of similar units. This could result in certain units to appear to be efficient even though they perform a single, relatively unimportant function [18].

Acknowledgements

This study was supported by grants from the National Natural Science Foundation of China under Grant No. 40801229.

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