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The improvement gap in energy intensity: Analysis of China's thirty provincial regions using the improved DEA (data envelopment analysis) model

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ABSTRACT

Enacting a reduction target for energy intensity in provinces has become an important issue for the central and local governments in China. But the energy intensity index has provided little information about energy efficiency improvement potential. This study re-estimates the TFEE (total-factor energy efficiency) using an improved DEA (data envelopment analysis) model, which combines the super-efficiency and sequential DEA models to avoid “discriminating power problem” and “technical regress”, and then used it to calculated the TEI (target for energy intensity). The REI (improvement potential in energy intensity) is calculated by the difference between TEI and the actual level of energy intensity. In application, we calculate the REIs for different provinces under the metafrontier and group-frontier respectively, and their ratios are the technology gaps for energy use. The main result shows that China's REIs fluctuate around 21%, 7.5% and 12% for Eastern, Central and Western China respectively; and Eastern China has the highest level of energy technology. These findings reveal that energy intensities of China's provinces do not converge to the optimal level. Therefore, the target of energy-saving policy for regions should be enhancing the energy efficiency of the inefficient ones, and thereby reduce the gap for improvement in energy intensity across regions.

1. Introduction

Energy intensity, or energy use over economic output [GDP (gross domestic product) for a country or GRP (gross regional product) for a region/province], has become a core index for China's energy conservation policy, and the government aims to pursue sustainable development by keeping it on a downward trend. Based on current practice, the central government enacts a reduction target of energy intensity for the whole country, which is then enforced by provinces, industries and other key energy units. For example, the twelfth Five-Year-Plan (12th FYP, 2011–2015) calls for an energy intensity reduction of 16% in 2015 relative to the 2010 level. The central government enacts the targets for the various provinces in a comprehensive work plan for energy conservation and emissions abatement during 2011–2015 based on the above target. However, whether the targets for provinces are reasonable or not is debatable. According to the above plan, the targets for the eastern provinces, which are higher than 16%, are higher than those of the central and western provinces. The government may have considered that the central and western provinces have relatively low level of development, and high energy-saving targets may be disadvantageous for economic growth. However, energy intensities in the eastern provinces are lower than those in other regions. So the above targets may cause the energy efficiency gap among the regions to be wide, thereby harming the aggregate energy intensity target.

China's energy intensity has declined rapidly since 1978. This spurs considerable inquiries into the major factors responsible for the decline in order to find a sustainable way to reduce it [1–7]. Lin and Moubarak [8] adopted the cointegration model to estimate the energy saving potential in China's paper industry by determining energy intensity under different scenarios. Similarly, Lin and Zhang [9] analyzed the electricity saving potential of the nonferrous metals industry in China. However, energy intensity in these

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studies is a partial-factor energy efficiency indicator because it takes energy as the only input factor. Hu and Wang [10] argued that energy must be combined with other inputs such as capital and labor to produce outputs, hence, a multiple-input model should be adopted to evaluate energy efficiency. In addition, Chang [11] believed that the energy intensity index did not provide any information about the realizable improvement gap in energy efficiency.

The above shortcomings can be overcome by using distance function such as the DEA (data envelopment analysis) in energy efficiency measurement. The original work on DEA was conducted by Charnes et al. [12], who constructed a multiple input–output pattern to find the best practice frontier or the efficient frontier, and measure the efficiency score of a DMU (decision making unit) by its distance from the efficient frontier. The main advantages of DEA are that it does not require i) any prior assumptions on the underlying functional relationships between inputs and outputs, and ii) any data and information about price of inputs and outputs.

Hu and Wang [10] and Hu and Kao [13] introduced a new index, namely TFEE (total-factor energy efficiency) based on the DEA approach, to measure energy efficiency. Since the TFEE index is constructed as the ratio of the target energy inputs to the actual energy inputs, it reflects the room for improvement in energy savings, it is a popular means of estimating overall energy efficiency [14]. There are many studies that adopted the TFEE to analyses China's energy efficiency [15–18].

Some studies present the potential for energy savings in China using the DEA model. Lee et al. [15] adopted the DEA model with a single output (GDP) and five inputs (labor, real capital stock, coal consumption, gasoline oil consumption, and electricity consumption) to calculate the saving potential of electricity, coal, and gasoline oil for 27 provinces in China during 2000–2003. Bian et al. [16] estimated the potential energy savings and CO_2 emission reduction for 31 provinces using a non-radial DEA model.

Chang [11] presented an indicator of the improvement gap in energy intensity by measuring the difference between the target level of energy intensity that is suggested from DEA and the actual energy intensity, and then investigated the improvement potential for 27 EU (European Union) members. This original research inspires us to further study this subject.

As stated earlier, China's energy conservation policy is effective, but it ignores the significant differences in energy intensity across regions. More importantly, it cannot evaluate whether the reduction targets of provinces are realistic. We believe it is important for energy policy-makers to know the target level of energy intensity and the potential for energy intensity reduction. The answers to the question have significant implications for energy policy-makers to enact energy-saving targets for provinces in China.

The contribution of this study is twofold. Firstly, we present an improved DEA model to estimate the TFEE in Chang [11], and thereby the target level of energy intensity. The innovation is that we combine the super-efficiency and sequential DEA models to avoid "discriminating power problem" and "technical regress" when evaluating TFEE using the conventional DEA model. Secondly, we adopt the above method in the meta-frontier analysis framework to reflect the technology heterogeneities across regions in China. Therefore, the target level of energy intensity will have a stronger discriminating power and could provide more reasonable evaluation results that characterize the regions. From an application perspective, we first estimate the target level of energy intensity and the improvement gap in energy intensity in China.

The remainder of this paper is organized as follows. Section 2 discusses the methodology of the study. Section 3 presents the description of the data. Section 4 discusses the empirical results and discussion. The final section concludes the research findings.

2. Methods

2.1. The analysis framework

The AEI (actual energy intensity) of DMUs, which are the provinces in this paper, is defined as energy use over economic output, say GRP, namely

$$\mathrm{AEI} = \mathbf{e}/\mathbf{y} \tag{1}$$

where **e** is the amount of the energy use, and **y** is GRP. High energy intensity implies low energy use efficiency for converting energy into GRP, and vice verse. Many studies adopt Eq. (1) to measure China's energy efficiency, and analyze its trend and determinants [1–3]. However, energy intensity in this form provides no idea of the potential for improvement in energy saving, and it is also inadequate to analyze the impact of changing energy use over time since it is a partial-factor energy efficiency indicator [10,11,13]. Boyd and Pang [19] believed that energy efficiency improvement relied on total-factor productivity improvement. Therefore, measuring energy efficiency under the total-factor analysis framework became the mainstream in the energy economics field.

The TFEE (total-factor energy efficiency) index, which wasoriginally proposed by Hu and Wang [10] and calculated by the DEA approach, is closely related to energy-saving potential. Hu and Wang [10] expressed TFEE as:

$$\mathrm{TFEE} = 1 - \mathrm{ESTR} \tag{2}$$

$$\mathrm{ESTR} = \mathrm{EST}/\mathrm{AEC} \tag{3}$$

where ESTR is the energy-saving target ratio, EST is the energy-saving target, and AEC is the actual energy consumption. Eq. (2) is a relative value of energy efficiency, and it is defined in terms of the ratio with which a best practice operation—its energy efficiency is unity in the model—compares with an actual operation. According to Eq. (2) and Eq. (3), the EST (energy-saving target) is

$$\mathrm{EST} = \mathrm{AEC} \times (1 - \mathrm{TFEE}) \tag{4}$$

The TFEE index introduced by Hu and Wang [10] is based on the no-output growth model. They assume that output is fixed at an original level in order to conveniently calculate the TFEE index. Based on the distance function, Chang [14] provided a more general model in which the TFEE index was calculated by considering the output could be adjusted to the optimal level. The rationale is that outputs are produced by all inputs, and hence there is the best allocation efficiency level among energy input and other inputs. Compared with this best level, the inefficient ones can use fewer energy inputs to generate more outputs. In order to define the distance function formally for the model, we define the input requirement set $\boldsymbol{F}$ as follow,

$$F_t(y_{it}) = \{(e_{it}, x_{it}) : (e_{it}, x_{it}, y_{it}) \in T_t\}, \quad e_{it} \in \mathbb{R}_h^+, x_{it} \in \mathbb{R}_m^+, y_{it} \in \mathbb{R}_s^+ \tag{5}$$

where $\boldsymbol{T}$ is the set of feasible production vectors under best practice or the reference technology, e is a vector of energy inputs, x is a vector of non-energy inputs, and y is a vector of outputs. i is individual (provinces) and t is periods (years). The best practice technology is common to all provinces but may change over time. Then the distance function for DMU k is defined as: