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Constructing slacks-based composite indicator of sustainable energy development for China: A meta-frontier nonparametric approach

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ABSTRACT

This paper proposes a meta-frontier nonparametric approach to construct the slacks-based composite indicator considering heterogeneity. The meta-frontier approach is useful to control and study the impact of potential heterogeneity in constructing composite indicator. In virtue of the Malmquist index, we further study tracking the evolvement of the constructed meta-frontier slacks-based composite indicator over time, and quantifying the driving forces behind the change. The proposed approach has been applied to assess China's regional sustainable energy utilization capacity during 2005–2010. Our empirical results show that all the three regions, i.e. the eastern, central and western, in China experience deterioration in sustainable energy development level. The best practice gap change and technology gap change are identified as the main contributors to the declining trend. Hence, improving the general production technology and enhancing technology diffusion among regions can help to promote China's overall sustainable energy development level. At the provincial level, Beijing is found to maintain a good balance in improving efficiency and absorbing advanced technology, while other provinces show diverse performance during this time period. More results and discussions are presented in this paper.

1. Introduction

Along with the rapid economic development, China's energy consumption has increased substantially in the past years, as well as the related CO_2 emissions. This trend has caused severe resource and environmental problems, e.g. the haze appearing more frequently and the accelerating climate change. To reduce the energy consumption and CO_2 emissions while maintaining the economic development, a possible way is to realize the sustainable energy development. Various measures have been implemented in China to achieve this goal. For instance, China's central government has issued the Energy Development Strategic Action Plan (2014–2020) to facilitate improving energy efficiency and refining energy mix. To better understand the effectiveness of these measures, it is worthwhile to evaluate China's sustainable energy development level. Essentially this is a MCDA (multi-criterion decision analysis) problem since multiple aspects involved, such as energy consumption, CO_2 emissions and economic development. A key tool to solve such question is *CI* (composite indicator) [1]. The principle strength of *CI* is to transform the information embedded in sub-indicators into a single indicator, which can comprehensively represent entities' characteristics in multiple dimensions. For example, the Human Development Index evaluates countries' performance in three aspects of human development, and the Global Competitiveness Index measures the competitiveness landscape of economies across the world considering 12 components. In energy and environmental areas, *CI* has been widely used in various environmental impact assessments to assist policy making, e.g. the life cycle impact assessment and Strategic Environmental Assessment [2]. Two examples of *CI* in this field are the ESI (Environmental Sustainability Index) [3] and the EPI (Environmental Performance Index) [4].

In constructing *CI*s, a key process is to weight and aggregate sub-indicators. In the literature, a number of weighting and aggregating approaches have been applied to construct *CI* [5]. Some commonly

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used approaches are PCA (Principle Component Analysis) [6,7], AHP (Analytic Hierarchy Process) [8], Conjoint Analysis [9,10]and DEA (Data Envelopment Analysis). All they can appropriately weight and transform a set of sub-indicators into a composite indicator. For instance, EPI uses the PCA to weight and aggregate 25 sub-indicators, while ESI equally weights 21 sub-indicators. Of the four weighting approaches, the first three require prior or external information to determine the weights for sub-indicators. However, the determination of weights is usually too subjective, which makes these approaches criticized frequently. On the other hand, DEA is essentially a nonparametric approach, mainly used to evaluate DMUs' (Decision Making Units') technical efficiency [11]. An important feature of DEA is that it doesn't need any prior information to weight sub-indicators. Instead, it is able to endogenously optimize the weights for DMUs. Due to this advantage, DEA has been widely studied and applied in productivity and efficiency analysis [12]. For example, by using DEA model, Hu and Wang [13], Wang et al. [14], Wang et al. [15] and Zhang et al. [16]evaluate the total-factor energy efficiency for China, Honma and Hu [17] for Japan, and Xie et al. [18] for OECD and BRIC countries. In the *CI* literature, DEA has also attracted increasing attention as it can resolve the problem of subjectivity as aforementioned. For example, Zhou et al. [19]propose some DEA-type models to derive the differentiated weights that allow DMUs to choose their own most preferred weights. After obtaining the weights, they construct a *CI* in the additive form. Along this line of research, Zhou et al. [20], Zhou and Ang [21] and Zhou et al. [22] further study/compare weighting and aggregating methods to constructing *CI*. As an extension, Zhou et al. [23] study weighting and aggregating sub-indicators in the multiplicative form, and the proposed approach is applied in Blancard and Hoarau [24]. In addition to the differentiated weighting approach, Hatefi and Torabi [25] study how to derive the common weights to weighting sub-indicators, which implies that all DMUs share the same set of weights. More recently, Wang [26] proposes a *SBCI* (slacks-based composite indicator) from the perspective of distance function, which facilitates the dynamic studies on *CI* as well as identifying improvement potential for DMUs.

In constructing *CI*s, heterogeneity is likely to exist with the number of entities or sub-indicators growing. In particular, such heterogeneity might be significant when evaluation is at global level or for large developing countries such as China and India. For instance, Ma [27] documents the existence of strong heterogeneity at regional and sectoral dimensions for China's energy consumption pattern. Thus, the heterogeneity might substantially bias the performance assessment using *CI*. However, as far as we are aware, it is lacking a formal study to address this question in the *CI* literature. To bridge this gap, this paper attempts to propose a nonparametric approach to construct *CI* aiming to account for the potential heterogeneity.

In the literature, heterogeneity is usually studied by using the meta-frontier approach within the nonparametric framework [28]. For example, Oh [29], Oh and Lee [30] and Chiu et al. [31] measure the heterogeneity among economies in terms of productivity and efficiency, while Wang et al. [32] evaluate the regional heterogeneity in China's energy efficiency and production technology. At the firm level, Zhang and Choi [33] and Zhang et al. [34]study the power generation plants' environmental efficiency/productivity in China and Korea, respectively. It can be seen from these example studies that the meta-frontier approach can effectively capture the impact of heterogeneity. Hence, we shall employ this technique to study constructing *CI*, both statically and dynamically. More specifically, we shall propose a meta-frontier DEA approach to construct *CI* while accounting for potential heterogeneity. Moreover, by using the Malmquist index, we shall further study the evolvement of *CI* over time while considering heterogeneity, and explore the underlying driving forces behind the change in *CI*. As such, this paper would contribute to the literature in that it firstly presents an approach to account for potential heterogeneity in constructing *CI*. The proposed approach is then applied to assess China's sustainable energy development level during 2005–2010. As aforementioned, regions in China show significant heterogeneity in energy consumption and emission patterns. Moreover, China becomes the biggest energy consumer and CO_2 emitter over the world, which makes it more pressured in sustainable development. The proposed approach can therefore be meaningfully verified by evaluating China's sustainable capacity in energy utilization.

The rest of this paper is organized as follows. Section 2 discusses the methodological issues in constructing *CI* using the meta-frontier nonparametric approach. Section 3 presents an empirical study using the proposed method to evaluate China's regional sustainable energy development level. Section 4 concludes the study.

2. Methodology

2.1. Weighting sub-indicators

As the foregoing analysis shows, two types of weights are usually used in constructing *CI*s, i.e. the common weights and differentiated weights. The advantage of the common weights is that it can set a fair baseline to compare DMUs' performance, while differentiated weights can help DMUs achieve their best performance for further comparison. In large-scale comparisons, both the two extremes might not be suitable due to the potential existence of heterogeneity among DMUs. Hence, neither common weights nor differentiated weights can generate unbiased outputs. In such circumstance, we shall follow Wang [26] to first category all DMUs into some predefined groups according to certain criterion, and then to derive common weights within each group, which can be varying among groups. The weights obtained in this manner can be termed as “common but differentiated” weights.

Suppose K DMUs are under consideration, which can be further divided into H groups due to the heterogeneity in certain dimensions. In the hth group ($h = 1,\ldots,H$), assume that here are R_h entities, and $\sum_{h=1}^{H} R_h = K$. As to sub-indicators, suppose there are n input-type indicators, $x_i(i = 1,\ldots,n)$, and m output-type indicators, $y_j(j = 1,\ldots,m)$.To cope with the different units and varying value scales of sub-indicators, we shall normalize all sub-indicators first. Then the following DEA-type model can be used to yield a set of weights for DMUs in each group.

$$
\begin{aligned}
&\min L\\
&s.t. L \geq \max(d_{kh}),\ \forall k,h\\
&\sum_{i=1}^{n} w_{hi}^{1} x_{ikh} + \sum_{j=1}^{m} w_{hj}^{1} y_{jkh} + d_{kh} = 1, k = 1,\ldots,R_h, h = 1,\ldots,H\\
&\sum_{i=1}^{n} w_{hi}^{1} + \sum_{j=1}^{m} w_{hj}^{1} = 1,\ \forall h\\
&w_{hi}^{1} \geq \varepsilon, w_{hj}^{1} \geq \varepsilon,\ \forall i,j,h
\end{aligned}
\tag{1}
$$

where d is slacks and w_{hi}^{1} is the weight for the ith sub-indicator in the hth DMU group. ε is an arbitrary small positive number, which helps to keep the weights for each sub-indicator non-zero. Essentially, model (1) aims to decrease the slacks for all DMUs by optimizing the weights in each DMU group. In this manner, the weights obtained can ensure the whole set of DMUs to achieve a satisfactory performance. Thus, the results obtained can be considered as the ‘best’ weights.