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China's regional natural resource allocation and utilization: a DEA-based approach in a big data environment

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A B S T R A C T

China's economic reform and opening policy has resulted in China's rapid growth, especially in terms of economy. The growth, however, is mainly based on huge consumption of natural resources, and that consumption should be reduced by significant amounts to protect global ecosystems. Emerged in 1980s, "big data" has developed very quickly in recent years, bringing new perspectives and opportunities for all kinds of academic fields, especially in DEA since it is a research highly based on data. In this paper, we propose a SBM-DEA model based on natural resource input orientation to evaluate the efficiency of natural resource utilization for 26 provincial regions in mainland China from 2005 to 2012. A DEA-based approach is developed to allocate a reduced total of natural resources among the 26 provincial regions. Drawing support from the developments of "big data", we use each provincial region's previously observed production data to characterize its own production technology, which allows a better analysis of how the production will change after allocations of natural resources are reduced. Our empirical study shows that most provincial regions perform well in terms of efficiency in utilizing natural resources, but that is based on huge consumption of natural resources. From an area perspective, the eastern area of China achieved the highest average efficiency value, followed by the central and western areas. Our study also indicates that the most effective allocation of the natural resources requires about half of the 26 provincial regions to reduce their natural resource consumption while the remaining ones can maintain their original consumption.

1. Introduction

Great development as a result of mainland China's economic reform and opening policy starting in 1978 has brought China into a new era with both opportunities and challenges. For example, on one hand, according to the National Bureau of Statistics of China (NBSC), the average annual growth rate of China's gross domestic product (GDP) has increased 15.73% from 1979 to 2013, which has given China the second largest economy in the world following the United States (Zhang and Yang, 2013; Wu et al., 2014b; Song et al., 2013). On the other hand, the scale-driven economic development mode is based on a great deal of natural resource utilization (Nordström and Vaughan, 1999; Zhang et al., 2008; Wang et al., 2013a; Wu et al., 2015b). Facing a new round of industrialization and urbanization during the 12th five year plan (2011–2015), the pressure of natural resource shortages has already become the most important constraint on economic growth and social development in China (Wu et al., 2014a).

In order to balance rational utilization of natural resources and sustainable development, many resource regulations have been strengthened by the central Chinese government. For instance, the Chinese government set the targets of reducing the energy consumption of per unit of GDP by 20% and 16% in the 11th and 12th five-year plans effective from 2006 to 2010 and 2011–2015 respectively (Wang et al., 2013b; Wu et al., 2015c). Although the regional authorities have been required to adjust their natural resource utilization and restructure their policies, this may not guarantee that local efforts in natural resource saving are in line with the national target (Wang et al., 2013b). In addition, lack of accountability for reduction efforts in emission and energy at the provincial level may lead to poor implementation of the national policy. Therefore, it is particularly important for the national Chinese government to determine the natural resource allocation among China's provincial regions.

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Data envelopment analysis (DEA) was firstly developed by Charnes et al. (1978). As a non-parametric method, DEA is used to evaluate the relative performance of a group of homogenous decision making units (DMUs), especially a group with multiple inputs and multiple outputs (Cooper et al., 2007; Cook and Seiford, 2009; Wu et al., 2015a). DEA does not need any prior functional form and also does not require the many assumptions that arise from the use of statistical methods for function estimation, yet it gives good results when used to measure efficiency (Cook and Seiford, 2009; Wu et al., 2015c; Wu et al., 2016a). To date, DEA has been extensively applied in the performance evaluation and benchmarking of hospitals (Biørn et al., 2003), universities (Fandel, 2007), supply chains of enterprises (Tajbakhsh and Hassini, 2014; An et al., 2015b), and banks (An et al., 2015a). In addition to efficiency evaluation, DEA has been widely used in solving the problem of resource allocation (Korhonen and Syrjanen, 2004; Lozano and Villa, 2004; Du et al., 2014).

The research about resource allocation by DEA may be classified into different categories. One category encompasses resource allocation and target setting. Mandell (1991) firstly proposed two related bi-criteria mathematical methods to identify the trade-offs between overall output and equity from alternative allocations of service resources among different public service delivery sites. Athanassopoulos (1995) integrated resource allocation and target setting in multilevel planning problems to allocate central grants to Greek local authorities. Amirteimoori and Tabar (2010) proposed an approach to allocate resources based on the assumption that output targets are set beforehand. Based on a parallel production system, Bi et al. (2011) presented a DEA-based approach for resource allocation and target setting.

Another category focuses on centralized resource allocation. Lozano and Villa (2004) were the first to propose DEA-based models for centralized resource allocation, giving two types. One type of model seeks radial reductions of the total consumption of every input while the other type seeks separate reduction for each input according to a preference structure. After that, Asmild et al. (2009) suggested modifying one of the centralized models to only consider adjustment of inefficient units. Fang (2013) extended Lozano and Villa's (2004) and Asmild et al.'s (2009) models to a more general case. Recently, Fang and Li (2015) formulated a centralized model to reallocate resources based on an extended revenue model. Under a centralized decision-making environment, Fang (2015) proposed a new approach for resource allocation based on efficiency analysis.

In addition, there are other categories that approach the problem from different perspectives. Cook and Kress (1999) made the first attempt to propose a DEA-based method to allocate fixed costs and resources, which was based on two principles: invariance and Pareto-optimality. Beasley (2003) proposed an alternative DEA-based approach by maximizing the average efficiency of all units and adding additional constraints to obtain a unique allocation scheme. Cook and Zhu (2005) extended Cook and Kress's (1999) model from CCR to BCC (Banker et al., 1984), and from input orientation to output orientation, giving a feasible allocation scheme. Korhonen and Syrjänen (2004) proposed a DEA-based multiple-objective linear programming (MOLP) method to maximize the values of multiple output variables when allocating fixed resources. Their approach is based on two assumptions: one is that all units are able to modify their production in the current production possibility set formed by efficient units; the other is that the units can modify their production plans without changing their efficiency. Recently, Wu et al. (2013) proposed a DEA-based approach by considering both economic and environmental factors for resource allocation. Du et al. (2014) developed a DEA-based iterative approach to allocating fixed costs and resources.

Reviewing the literature, we find that existing DEA approaches to resource allocation often have strong assumptions about the individual production after resource allocation. The main limitations can be concluded that: (i) the first assumption on the individual production is that each DMU's production efficiency stays constant after the fixed resource is allocated. Most of the researches based on this assumption indicated that the production possibility set may be altered. (ii) The other assumption is that the efficiency for each DMU is changeable after the fixed resource is allocated. Most of the researches based on this assumption indicated that the productions of all DMUs are efficient after resource allocation. Based on these two assumptions, Fang (2015) indicated that it is particularly difficult for the DMUs to achieve their target efficiencies when their efficiencies keep constant or changeable. Actually, the key point in dealing with resource allocation problem is the new production of all DMUs after the fixed resource has been allocated. In other words, with input resource increases or decreases, how does the output change? In practice, all DMUs have to do their new production using their own existing technology. Therefore, how to define each DMU's own technology plays an important role in solving resource allocation problems.

Although it was emerging in 1980s, the concept of “big data” was officially launched in an EMC World 2011 conference talk entitled “Cloud Meets Big Data”. Then, McKinsey Global Institute defined big data as “datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze” (Manyika et al., 2011). Since then, big data has become a hot issue in the computer industry and financial businesses, and it also draws the attention of governments. The emergence of the big data phenomenon over the past few years, with its increased volume, velocity, variety, and value, plus a requirement for agile development of data-driven applications, has created a new set of challenges and opportunities (Baru et al., 2013). In this context, the evolving science of “big data” can potentially be used to help scientists, policy makers, and city planners develop policies, strategies, procedures, and practices. Ohlhorst (2012) and Tien (2013) indicated that “big data” is an all-encompassing term for any collection of data sets which are large and complex. Michael and Miller (2013) emphasized that “big data” approaches can be used to perform the kinds of comprehensive analyses that are needed to support the development of improved policy regime-based systems. Recently, “big data” approaches, integrated with other new managerial approaches, have been applied to industrial pollution reduction and pollutant treatment, improved health care, and other applications (Cao, 2014; Maughan et al., 2014). In the DEA field, “big data” brings many problems for researchers. For example, the huge number of DMUs in the “big data” context is the biggest issue. In addition, complex relationships may need to be considered when the number of DMUs is big enough. Addressing these problems is worthwhile, however, since DEA on big data brings new perspectives. For example, when the observed production data for one DMU is available and big enough, we can utilize that data to estimate its production more precisely when inputs change. Therefore, this advantage through support from “big data” is applied in our study.

The aim of this paper is to disaggregate China's national natural resource reduction target into targets for the regional level. The contributions of our study can be summarized as follows. First, we develop a SBM-DEA model based on natural resource input orientation to measure the natural resource utilization efficiency of 26 provincial regions in mainland China during the period 2005–2012. With these efficiency values, we can know not only each provincial region's efficiency in utilizing natural resources but also the efficiency change trends. To combat high consumption of natural resources, the Chinese government sets targets for reducing