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Decomposition of energy efficiency and energy-saving potential in China: A three-hierarchy meta-frontier approach

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ABSTRACT

Considering both regional heterogeneity and industrial heterogeneity, this paper proposes a three-hierarchy meta-frontier data envelopment analysis (DEA) to decompose energy efficiency and energy-saving potential into three components, i.e., industrial structure, regional balance development, and management. Based on this approach, the paper then analyses the historical evolution and current status of energy efficiency in China. The results show the following. (1) From 2001 to 2015, Mainland China's energy efficiency increased by a factor of 2.48, primarily because of technological progress and the optimization of its industrial structure. (2) Nonetheless, the current energy efficiency in Mainland China remains very low and energy inefficiency is as high as 0.5922, indicating that 59.22% of total energy consumption is invalidly used. Severe industrial structure inefficiency and regional balance development inefficiency are the two main factors responsible for the very low energy efficiency. (3) By promoting industrial restructuring, regional balance development, and management improvement, Mainland China is expected to save, respectively, 13.67%, 24.54%, and 61.73% of its current total invalid energy consumption. Based on the estimation results, this paper formulates strategies to improve energy efficiency and save energy for China's provinces based on their specific situations, considering not only the direction of industrial restructuring in both the short and long terms but also the path to improved energy efficiency. In addition, a brief discussion about the applicability and the preconditions for an application of the multi-hierarchy meta-frontier approach is given at the end of the paper.

1. Introduction

Since China's reform and opening up, energy resources, as a key production factor, have been a powerful driving force in the nation's economic development. With the continuous development of China's society and economy, its energy demands have soared. According to BP (2017), China overtook the United States as the world's largest energy consumer as early as 2009. Because energy in China is dominated by coal, which is non-renewable and not clean, China is now facing increasing pressure from both international and domestic entities to promote improvements in energy efficiency and energy savings. In this context, research on the factors that contribute to energy efficiency changes, energy inefficiency, and energy-saving potential are of vital importance for China's sustainable development.

The study aims to conduct an empirical analysis of energy efficiency and energy-saving potential in China, using a proposed three-hierarchy meta-frontier DEA. This study's main contributions are as follows: (i) it proposes a three-hierarchy meta-frontier DEA in which both regional heterogeneity and industrial heterogeneity are considered to measure energy efficiency; (ii) it presents and analyses China's historical and current performance in energy efficiency from the perspectives of technology, industrial structure, regional balance development, and management; and (iii) it formulates provincial strategies for improving energy efficiency and saving energy, accounting for the direction of industrial restructuring and the path to improved energy efficiency.

The remainder of this paper is organized as follows. The relevant

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Table 1
Full name of abbreviations.

Abbreviation	Full name
DEA	Data envelopment analysis
DMU	Decision-making unit
EE	Energy efficiency
SE	Industrial structure efficiency
RE	Regional balance development efficiency
ME	Management efficiency
CRS & VRS	Constant and variable returns to scale
EI & EP	Energy inefficiency and energy-saving potential
SI & SP	Industrial structure inefficiency and industrial energy-saving potential
RI& RP	Regional balance development inefficiency and regional balance development energy-saving potential
MI & MP	Management inefficiency and management energy-saving potential
GM index	Global Malmquist index
GTCH	Changes in technology
PECH	Pure efficiency change
SECH	Changes in industrial structure efficiency
RECH	Changes in regional balance development efficiency
MECH	Changes in management efficiency

literature is reviewed in Section 2. The extended DEA models for decomposing energy efficiency are briefly introduced in Section 3. Section 4 describes the panel data. The results are presented and analysed in Sections 5.1 and 5.2. Section 5.3 details the strategies for improving energy efficiency and saving energy in China's 30 provinces. Section 6 provides conclusions and corresponding policy implications.

Because our paper uses numerous abbreviations, we summarize them below in Table 1.

2. Literature review

In the existing literature, two main types of indicators are used for China's economy-wide energy efficiency studies: single-factor indicators (e.g., energy intensity, which is measured by energy consumption per output) and total-factor indicators (e.g., total-factor energy efficiency, which is mainly measured using DEA). In recent years, single-factor indicators have been widely used to explore the factors responsible for energy efficiency changes by combining decomposition methods (Ang and Zhang, 2000; Su and Ang, 2012). As many scholars have argued, single-factor indicators have certain limitations due to their neglect of other, non-energy inputs, such as labour and capital (e.g., Hu and Wang, 2006). Therefore, this approach cannot account for the substitution effect among factors, the underlying production technology, and actual energy-saving potential (Wilson et al., 1994). In response to these shortcomings, Hu and Wang (2006) proposed a total-factor energy efficiency indicator using DEA techniques, choosing energy, labour, and capital as the inputs and using gross domestic product as the output. DEA-based total-factor indicators are measured based on a total-factor framework, into which energy inputs, non-energy inputs, and outputs are incorporated, and thus can overcome the above-referenced defects. Following Hu and Wang (2006), Hu and Kao (2007) and Honma and Hu (2008) respectively applied this total-factor framework for energy efficiency analysis of APEC economies and Japan.

In addition, because energy efficiency usually depends on region-specific characteristics, e.g., economic development (Shao, 2017), an increasing number of scholars have tried to analyse China's economy-wide energy efficiency using a DEA-based total-factor framework with a regional perspective (Meng et al., 2016). For example, using this DEA-based total-factor indicator, Wei et al. (2009) examined the energy efficiency of 29 Chinese provinces and the influencing factors for the period 1997–2006. Wang (2011) analysed the sources of energy productivity growth and its distribution in Mainland China for the period 1990–2005. Wang et al. (2012) applied the DEA-based total-factor framework to analyse China's regional industrial energy efficiency and found that there is considerable room for improvement in China's western provinces. Song et al. (2013) examined energy efficiency and energy saving in China using a bootstrap DEA approach and found that although energy efficiency in China has gradually improved, there is considerable room for further improvement.

A common feature of the above studies is that they did not consider undesirable outputs (e.g., CO_2 emissions). In real-world production practices, desirable outputs are always accompanied by undesirable ones in the production process. If undesirable outputs are not considered, efficiency estimations may be biased (Watanabe and Tanaka, 2007). Thus, scholars have begun to take undesirable outputs into consideration when evaluating China's regional energy efficiency. For example, by incorporating industrial waste gas and CO_2 emissions into DEA-based total-factor frameworks, Shi et al. (2010) and Wu et al. (2012), respectively, studied China's regional industrial energy efficiency. Li and Hu (2012) took CO_2 and SO_2 emissions into account when they examined China's regional ecological energy efficiency. Zhang and Choi (2013) applied a slacks-based DEA to measure the environmental energy efficiency of China's regions, considering CO_2, SO_2, and chemical oxygen demand emissions. Wang et al. (2014a) considered wastewater, waste gas and solid waste in their global DEA model to analyse regional energy efficiency in China from both static and dynamic perspectives. Wu et al. (2015) evaluated China's regional energy and environmental performance for the period 2006–2010, taking into account the undesirable output of waste gas. Song et al. (2016) proposed a DEA model that can measure resource and environmental efficiency based on resource inputs, undesirable outputs and desirable outputs; their empirical results suggest that resource and environmental efficiency in China must be further improved.

The above-mentioned energy efficiency studies assumed that all of China's regions share the same or similar production technology. This assumption is contradicted by China's current situation. Due to uneven levels of economic development, resource endowment, etc., regional production technology heterogeneities are inevitable. Ignoring these heterogeneities might lead to biased estimations (Wang et al., 2013). To take regional production technology heterogeneities into consideration, the meta-frontier concept has been introduced into many Chinese regional energy efficiency studies. For example, using meta-frontier DEA-based models, Wang et al. (2014b) conducted an empirical analysis of energy efficiency and energy-saving potential in China; Zhang et al. (2015) analysed regional ecological energy efficiency in China for the 2001–2010 period; Hang et al. (2015) explored the sources of China's urban energy inefficiency; Li and Lin (2015a) examined China's regional energy efficiency based on CO_2 emissions; Fei and Lin (2016), Lin and Zhao (2016), and Lin and Zheng (2017) measured energy efficiency in China's regional agricultural sector, textile industry, and paper industry, respectively; and Feng and Wang (2017a,b) examined regional energy efficiency of China's industrial sector and building industry.

The above-listed studies successfully identified regional heterogeneities but ignored the significance of industrial heterogeneities. To fill this research gap, the present paper builds a three-hierarchy meta-frontier approach by that considers both regional and industrial heterogeneities. It allows us to decompose energy efficiency changes into four components: a technological effect, a structural effect, a balanced development effect, and a