



# Estimation of industrial energy efficiency and corresponding spatial clustering in urban China by a meta-frontier model

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## ABSTRACT

Energy efficiency is an important measure of the energy utilization performance, which should be evaluated in industrial production. This paper proposes an improved slacks-based data envelopment analysis (DEA) and spatial clustering analysis to investigate urban efficiency considering regional technological heterogeneity and the presence of carbon emissions. The technological and managerial inefficiencies of industrial energy utilization are first explored by considering neighboring performance. The proposed method is applied to an empirical study including data on 277 cities in China during 2007–2014. Some conclusions can be drawn: (1) there are significant spatial disparities in the energy efficiency, technology gap rate and managerial inefficiency in cities. Improvements in technology and management should be decided on depending upon the urban conditions. (2) There is evident spatial clustering in energy efficiency, technology gap rate and managerial inefficiency for partial cities. Importantly, management improvement has a more positive effect on the energy saving than technological improvement, except for cities in the low-low clustering pattern. (3) The negative technology gap rate reflects resource misallocation for technological improvement. For some underdeveloped cities, investment in technology should be controlled.

## 1. Introduction

China's drastic economic development highly depends on energy consumption, which makes China the world's largest energy consumer currently. In 2016, China had massive energy consumption which accounting for 23% of global consumption (BP, 2017). This massive energy consumption also generates excessive carbon emissions, which can result in the greenhouse effect and natural hazards (Shi, Chen, & Shen, 2017). Given this circumstance, China's government has made a commitment of 45% carbon intensity reduction from 2005 to 2020 (Wu, Zhu, & Liang, 2016). To reduce the carbon emissions, the energy saving should be addressed by all levels of government: national, regional and municipal (Melica et al., 2018). Moreover, energy is a core resource in economic production, which can affect the sustainability of economic growth. Energy saving should also be addressed to ensure energy supply security (Ang, Mu, & Zhou, 2010). Notably, industrial production, especially for energy-intensive industries, is an important consumer of fossil fuel, accounting for 69.41% of China's total energy consumption in 2014. To achieve the sustainability, China's industrial sectors should undertake the substantial task of saving energy.

In practice, China's government has launched serial policies of energy saving in industrial production. In China's 12th five-year-plan, the

policies of controlling the growth of energy-intensive industries, and improving technologies, management, and regulations for energy saving are advocated. Some detailed solutions are also proposed, for example, updating the industrial structure by discarding partial energy-intensive and heavy-pollutant sectors, advocating adjustment of the energy consumption structure, and promoting technological innovations for energy saving (Jiang, Sun, Liu, Jin, & Zhang, 2010). In this circumstance, an important question has been raised: how to evaluate the impact of proposed solutions? Since the energy cannot be consumed by itself, but with all the production factors. A single-factor evaluation (e.g., energy intensity, a ratio of energy consumption to GDP output) is not sufficient. A comprehensive measure should be proposed as an important start for improving the energy performance (Poggi, Firmino, & Amado, 2017). Energy efficiency, an important total-factor proxy of the energy utilization performance, is adopted in this study. The energy efficiency has several definitions in literature (Hu & Wang, 2006; Patterson, 1996). It is defined as a conversion ratio by using less energy to produce the same amount of services or useful output in production (Patterson, 1996) in this study.

This study aims to propose the general energy-efficiency estimation for any regional size and analyze the inefficiency improvement based on regional locations, which is seldom considered in existing literature.

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To achieve this, an improved method framework incorporating the meta-frontier setting and slacks-based data envelopment analysis (DEA) model is developed. A local Moran's index is used to detect the spatial clustering of energy inefficiencies. An empirical study is also applied to test the effectiveness of the proposed method, which is based on China's 277 cities during 2007–2014.

The main objectives can be summarized into two aspects. First, the industrial energy efficiency estimation for all of China's cities should be conducted by an improved meta-frontier model. The industrial carbon emissions included in the total-factor estimation at the city level can be regarded as the first attempt. Second, this paper combines the DEA method and a local Moran's index to investigate the spatial clustering of urban inefficiency scores. The spatial clustering analysis of technological inefficiency and management inefficiency and detailed efficiency improvement solutions are further provided for cities considering the neighboring performance.

The remaining parts of this paper are as follows. Section 2 is the literature review. In Section 3, the improved methodological framework is introduced to calculate energy efficiencies and the corresponding spatial clustering conditions. Section 4 illustrates variables, data sources, corresponding empirical results, the further discussion and suggestions. Conclusions follows in Section 5.

## 2. Literature review

Data envelopment analysis (DEA), a popular total-factor performance evaluation method, is widely accepted for energy efficiency estimations (Hu & Wang, 2006; Wang & Wei, 2014; Wu, Fan, Zhou, & Zhou, 2012), for the merit of not imposing any functional form on total-factor efficiency evaluations (Choi, Zhang, & Zhou, 2012). The existing research on industrial energy efficiency estimations by DEA at the macro level can be summarized as two main streams. The first stream refers to the efficiency estimations in regional production systems such as countries or regions. For example, Wu et al. (2012) constructed both static and dynamic performance indices to estimate industrial energy efficiency in China during 1997–2008. Feng and Wang (2017) extended the dynamic perspective to analyze energy efficiency and potential energy savings for China's provincial industrial sectors by a meta-frontier model. The energy and environmental performance among China's provincial industries during 2008–2012 was explored by Wang, Zhao, and Zhang, (2016) in a non-radial DEA model. The second stream is related to the efficiency estimation of different industrial sub-sectors, especially energy-intensive industrial sectors. For instance, the energy efficiency estimations of sub-industrial sectors in Beijing and Canada were evaluated using DEA by Wang, Shi, and Zhang, (2017) and Olanrewaju, Jimoh, and Kholopane, (2012), respectively. Detailed characteristics of energy efficiencies are also analyzed by DEA. For example, the impacts of influencing factors on energy efficiency were estimated for China's provincial industry sectors and sub-industrial sectors by He, Liao, and Zhou (2018) and Wang, Shi et al. (2017), respectively. Carbon emission abatement costs based on regional industrial energy efficiency in China during 2006–2010 were measured by Wang and Wei (2014). Han, Long, Geng, and Zhang (2017) determined that potential carbon reduction can improve energy efficiency in China's industrial departments.

Based on China's vast territory and diverse regional economic levels, the spatial disparities in energy efficiency can exist. In the literature, the existence of urban disparities can be caused from natural resource endowments, energy consumption structures, industrial structures, economic development (Wang, Shi et al., 2017), and energy-saving characteristics (Wang & Wei, 2014). In this study, the disparities of energy utilization performance can be summarized in terms of three causes. The first is from the industrial sector structure, which is diverse among China's regions. Regional industrial production dominated by the heavy-industrial sector (e.g., steelmaking and thermal power generation) can result in more energy consumption than the light-industrial

sector (e.g., textile manufacturing and paper making). The second refers to the technology level gap. Energy consumption and carbon emissions are highly correlated with the technology level in industrial production (Sueyoshi & Goto, 2014). The technology level, affected by the advanced machinery, high educated labor, and lean management, can induce the spatial disparities of energy utilization performance. The third is the energy consumption structure. For some of China's provinces with abundant coal reserves, such as Shanxi and Guizhou, it is economical to consume coal as the main energy in industrial production (Bian, He, & Xu, 2013). This can form a coal-dominant energy structure. The regional energy utilization performance can vary for the energy structure. To that end, this paper aims to illustrate the existence of spatial disparities in energy efficiency based on a spatial clustering analysis. In the existing literature, the local Moran's index is a popular method for analyzing spatial hotspot or identifying spatial clusters (Zhang, Luo, Xu, & Ledwith, 2008), which is adopted in this study. More information on local Moran's index can be found in Anselin (2013) and Lesage and Pace (2009).

Furthermore, there exist several studies examining the spatial disparities in industrial energy efficiency at the provincial level or within the province (Feng & Wang, 2017; Wang, Zhao et al., 2016). For example, Keirstead (2013) measured energy efficiency in 198 urban administrative units in UK. Hu, Chang, and Tsay, (2017) estimated urban energy efficiencies by a congestion efficiency model. The energy efficiency of 285 cities in China during 2008–2012 was explored by Wang, Lv, Bian, and Cheng (2017) considering carbon dioxide emissions abatement costs. Wu et al. (2017) analyzed energy use efficiency in crop production among cities of Anhui Province from 1990 to 2014 by DEA. The emission-reduction and energy-conservation (EREC) efficiency of 211 cities in China was measured by Sun, Wang, and Li, (2018).

To the best of our knowledge, research on industrial energy efficiency estimation at the city level is scarce. The only exception is Zhou, Wang, Su, Zhou, and Yao, (2016), who proposed a DEA-Malmquist analysis to measure the energy conservation and emission reduction performance for China's 214 urban industrial sectors. However, the undesirable output of carbon emissions is lacking in the literature, which makes the total-factor evaluation insufficient. Besides, Chen, Xu, Song, and Liu, (2018) investigated energy productivity and spatial clustering among China's 248 cities, which is a related issue. Unfortunately, energy productivity in Chen et al. (2018) is focused on urban overall production, not urban industrial production. Carbon emissions and the diverse regional production technologies are also ignored. To fill the gap, an industrial efficiency estimation extension is discussed in this study.

## 3. Methodology

In this section, a meta-frontier and slacks-based measure (SBM) incorporating the linkage between gross domestic product (GDP) output and carbon emissions is proposed to measure the industrial energy efficiency. The local Moran's index is also incorporated to analyze the spatial clustering of efficiencies. This combination provides an improved methodological framework which is different from the existing literature.

### 3.1. Energy efficiency estimation in SBM-DEA model

Assume that there are  $n$  decision-making units (DMUs), which represent the regional industrial production systems ( $RS_j$ ,  $j = 1, \dots, n$ ). The production process is regarded as one that invests the inputs of labor ( $XL$ ), capital ( $XK$ ) and energy ( $XE$ ) to produce the desirable output of economic output ( $YG$ ) and the undesirable output of carbon emissions ( $YC$ ). A similar variable setting was also adopted by Wang, Lv et al. (2017).

As a non-radial DEA model, the SBM model can effectively discover

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