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Accessing provincial energy efficiencies in China's transport sector

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ABSTRACT

The transport sector is attracting increasingly attention in the context of climate change and sustainable development, for its rapidly growing demand for energy and heavy reliance on oil products. Especially in China, where the demands for transportation are tremendous and ever-increasing, it is worthy to explore the provincial variations in energy efficiency in the transport sector, in order to enhance energy efficiency and to promote energy savings in this sector. By using stochastic frontier analysis (SFA) approach, this paper calculates the provincial energy efficiency as well as energy saving potential in China's provincial transport sector over 2007–2016. Results suggest that China's national average energy input efficiency in the transport industry is 0.673 during the sample period, which implied that relatively large degree of non-efficiency exists in this sector. Besides, the increase of government support (GS), the improvement of road condition (RC) and public transport (PT) are influencing factors for the improvement of China's provincial energy efficiency in the transport industry. Additionally, energy saving potential in the transport sector is also estimated in this paper. It is shown that, although energy efficiency in the eastern China is the highest (much higher than the country-wide level), the estimated absolute amount of the energy saving potential in the eastern area is significantly larger than those in the central area and western area due to the fact that the eastern area contributes to the largest share of the total energy consumption in this sector.

1. Introduction

Transport sector is crucial to economic and social development, as mobility is generally known as one of the basic and vital needs for human. It provides moving from one location to another for passengers and frights, and expedites the economic activities in the industrial world (Atabani et al., 2011). A sophisticated mobility system plays a role as a catalyst in the development of economy.

However, in recent years, transport sector consumes a high portion of total primary energy globally (Ong et al., 2011). Energy use in transport sector is growing especially fast in the emerging countries like China and part of Latin America (Yan and Crookes, 2007). Based on the statistics from Asia Pacific Energy Research Centre (APERC), energy consumption in China's transport industry raised from 15.0 Mtoe in 1980 to 166.5 Mtoe in 2010 (i.e., with a growth rate of 8.4% per annual), which made transport one of the fastest growing sectors in terms of energy consumptions. According to Wang et al. (2014), the global energy consumption in transport sector accounted for one-third of the world's consumption in 2013, while such a proportion in China reached 20%.

Moreover, the world is currently facing the challenge of global warming and environmental pollution in consequence of continuous growth in energy use. Emissions and pollutants produced by different economic sectors have negative impact on the environmental protection, sustainable development and the public health (Mahlia, 2002). The transport sector, among the entire economic sectors, has been seen as one of the main contributors to the environmental degradation and the deterioration of human health due to its excessive reliance on fossil fuels and high greenhouse gas (GHG) emissions (Pucher et al., 2005; Gasparatos et al., 2009; Liu et al., 2013; etc.).

With more and more attentions being paid on environmental problems and energy issues worldwide, evaluating environmental performance and energy efficiency has become crucial (Zhou et al., 2014; Wang et al., 2018b). Energy efficiency as well as energy-saving potential in transport sector are addressing increasing attention worldwide, which are significant for relieving energy shortage and improving the environment (Xie and Hawkes, 2015; Xie et al., 2016).

The remainder of this article is divided into the following sections: Section 2 presents a literature review; Section 3 describes methodologies and data processing in the manuscript; Section 4 discusses the

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model findings; and Section 5 concludes the paper and provides policy implications.

2. Literature review

Why improving energy efficiency is of significant? According to Cullen et al. (2011), the improvement of energy efficiency could contribute to relieving energy shortage, saving energy costs, and reducing CO_2 emissions. Patterson (1996) elaborated different kinds of definitions and indicators on energy efficiency. According to Lovins (2004), energy efficiency is defined as the ratio of the product (including any value or service) supplied to the energy that needed to supply it.

"Broadly, any ratio of function, service, or value provided to the energy converted to provide it." It is well known that there are plenty of indicators measuring energy efficiency. According to Hu and Wang (2006), these indicators are simply concluded as two types: one is the partial factor energy efficiency (PFEE) index, the other is the total-factor energy efficiency (TFEE) index.

PFEE mainly measures the relationship of energy input and energy output, and energy is usually regarded as an input factor during the production process. PFEE index simply denotes a proportional relation between energy input and output without considering the contribution of other production factors like capital and labor to the output generation, as a result, it has been criticized in recent years. Given this, Hu and Wang (2006) raised the category of TFEE for the first time. Under the frame of neo-classical production theory, TFEE takes into consideration not only the energy factor, but also the production factors of labor and capital, when evaluating energy efficiency. In addition, the substitution effects between different input factors are also included in the efficiency analysis. The framework of TFEE can be summarized as follows: (i) Firstly, defines the production possibility set (given production technology level); (ii) Secondly, builds a production frontier using the input and output data of each decision-making unit; (iii) Finally, analyzes the relationship between each production unit and the production frontier. When a production unit deviates from the production frontier, it suggests that resources in this production unit have not been fully utilized and there is room for Pareto improvement. To be specific, TFEE is regarded as the ratio of the theoretically minimum energy input to the real energy input. After Hu and Wang (2006), a wide variety of literature conducted empirical analysis on the energy efficiency performance in many countries/areas using different TFEE indexes, among which the data envelopment analysis (DEA) and the stochastic frontier analysis (SFA) are the most popular research methodologies. Both DEA and SFA are frontier approaches on the basis of distance function (Coelli et al., 2005). The measured efficiency is a relative efficiency, which is strongly comparable within the sample but has poor comparability among different samples.

The basic idea of DEA is to describe the production possibility set by using the smallest convex set. The frontier of production possibility set is a technological frontier, which reflects the optimum production state under given technology level. In practice, DEA builds the technological frontier by linear programming technique, thus to determine the evaluation benchmark and conduct the efficiency analysis. From this prospective, DEA is a nonparametric approach with following advantages: (i) it does not require an assumed form of production function or distance function, which can avoid the risk of model misspecification; (ii) the flexible setting of DEA model (with many types) can be applied to the estimation of most efficiency evaluation models. As a result, DEA is widely used in the estimation of TFEE. In spite of the above-mentioned advantages, DEA has obvious disadvantages. DEA model does not take into consideration the impacts of statistical error and other random errors, and is easily affected by the quality of sample data. As a result, there may be deviation in the efficiency estimation.

Given that considerable statistical noise may exist in macroeconomic data, the frontier method of SFA is recommended to overcome this problem. For example, Boyd (2008) and Zhou et al. (2012) built a SFA model to estimate the energy efficiency on the basis of energy distance function. DEA regards the deviation part between decision-making unit and the technological frontier, as inefficiency. Different from DEA, SFA divides this deviation part into two sections: one section is caused by inefficiency; while the other is caused by random errors. Therefore, SFA can measure energy efficiency while eliminating the impact of statistical noise. In addition, as a parameter estimation approach based on statistics, SFA allows statistical tests for model settings. Due to the advantages mentioned above, SFA has been widely applied into evaluating national/industrial energy efficiency performance.

For example, Filippini and Hunt (2012) adopted SFA to analyze the residential energy efficiency of the United States over 1995–2007. Hu and Honma (2014) estimated energy efficiency for the ten industries in the fourteen developed countries for the time period of 1995–2005 based on SFA. By adopting panel data parametric frontier technique, Honma and Hu (2014) measured energy efficiency in Japan. Lundgren et al. (2016) estimated the energy efficiency and energy demand in Swedish manufacturing sectors in a company level through the SFA technique. Based on the input-oriented Shephard distance function, He (2011) constructed to a SFA model and conducted an empirical study on energy efficiency and its impact factors for China's 36 industrial sectors over 1994–2008. The results suggested the average industrial efficiency was 0.76 over the research period, and the opening-up policy was a contributing factor for the increase of energy efficiency while the state-owned property right was the opposite. Lin and Du (2013) measured China's provincial energy efficiency over 1997–2010, by utilizing the SFA approach similar to Zhou et al. (2012). Lin and Wang (2014) adopted SFA to analyze energy efficiency in the iron & steel sector in China. By using a similar method, Lin and Long (2015) evaluated energy efficiency in the chemical sector in China. Ouyang et al. (2018) measured factor price distortions and estimate their impact on energy efficiency based on an empirical analysis of 30 provinces of China using the SFA.

There are also many papers focusing on the meta-frontier which could take regional heterogeneity into consideration. For example, Feng and Wang (2017) analyzed the total-factor energy efficiency and energy savings potential in China's provincial industrial sectors by using a meta-frontier DEA. Wang et al. (2018a) evaluated carbon reduction efficiency of technologies on project level through employing a meta-frontier DEA approach.

On the basis of distance function, this paper builds a stochastic frontier model regarding excessive energy input, to estimate the energy input efficiency and the corresponding energy-saving potential, as well as the influencing factors in China's provincial transport sectors.

When measuring the energy-saving potential, a proper benchmark is that the given energy service level cannot be degraded, which means to reduce the amount of energy consumption on the premise of achieving at least the same level of output; or in other words, to achieve equivalent or more energy services with the same amount of energy input. The frontier analysis based on distance function provides a practicable approach for measuring energy input efficiency under given output (different from the energy efficiency represented by energy intensity) and energy-saving potential.

3. Method and data

3.1. Methodology

Referring to Zhou et al. (2012), a production possibility set (T) that reflects the production technology is built in our paper. Three factors including labor (L), capital (K) and energy (E) are taken as input factors, while the gross domestic product (Y) is viewed as the single output.

$$T = \{(L, K, E, Y): Input\,(L, K, E)\, is\ able\ to\ provide\, Y\} \quad (1)$$

We define the Shephard energy distance function as follows, in