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Analysis of energy efficiency and its influencing factors in China's transport sector

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ABSTRACT

With the rapid development of the Chinese economy, demand for transportation has increased dramatically, which cause high energy consumption in the transport sector. Energy conservation and emission reduction is currently a long and arduous task for China. Thus, it is of great significance to study the inter-provincial energy efficiency and its influencing factors in China's transport sector. We use the new energy efficiency model that integrates output growth and energy conservation to measure provincial energy efficiency in China's transport sector. The results show that energy efficiency shows a distinctly ladder-like distribution with the eastern province having the highest level, followed by the central and western provinces, and the energy efficiency gap among the provinces is narrowing. In addition, we use the censored model and truncated model to analyze the relevant factors impacting energy efficiency and propose relevant policy recommendations on how to improve energy efficiency.

1. Introduction

Compared with other countries in the world, China's economic development is relatively fast. Meanwhile, urbanization and industrialization are gradually advancing in an orderly manner. In this process, the transport sector which provides basic services shows a rapidly rising trend of energy consumption. In line with the data provided by NBSC (National Bureau of Statistics of China), oil consumption in the transport sector accounted for about 37.255% of all sectoral oil consumption in 2015. It becomes an imminent and urgent problem to reduce energy consumption and CO_2 emission. Therefore, the study of energy efficiency is the first step in exploring energy conservation and CO_2 abatement in China's transport sector. It is practically significant to evaluate the regional energy efficiency and analyze its related influencing factors. This can provide a reasonable basis for formulating energy-saving policies.

After measuring energy efficiency, we naturally think of what factors affect energy efficiency and how they do. Through the regression analysis of energy efficiency on its related influencing factors, we reveal the extent to which these factors affect energy efficiency, and then analyze how energy efficiency can be improved.

Different provinces have different economic development level, transport infrastructure, industrial structure and technical level. As a result, energy efficiency in the transport sector differs across provinces. China's transportation is far from meeting the increasing social needs. We should not only take into account energy conservation and environmental protection but also pay attention to the strong growth of transport output. In order to more intuitively and accurately quantify the energy efficiency of China's transport sector, we use the new energy efficiency model (Wang et al., 2013b) that integrates energy conservation and output growth to measure it, and then employ Tobit bilateral censored regression and bilateral truncated regression to analyze the relevant factors that have impacts on energy efficiency.

The remainder of this article is arranged as follows. In part two, we review the relevant literature on energy efficiency. Part three presents the energy efficiency model integrating energy conservation and output growth. Part four is the data source and processing. Part five provides the empirical results and discussion, which include the calculation of energy efficiency and the study of

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its influencing factors. Part six is the conclusion and policy suggestion of this article.

In order to simplify the reading of this article, we made the abbreviated form (see Table 1).

2. Literature review

Energy intensity, as a SFEE indicator, has a serious flaw and it only considers energy as a single input element. Therefore, Hu and Wang (2006) first elaborated the concept of TFEE based on DEA model. TFEE is the ratio of the target energy input to the actual energy input, which is the relative efficiency index for energy use. According to this definition, the target energy input is frequently less than or equal to the actual one, so TFEE is less than or equal to 1.

$$0 \leq \frac{Target\ \ energy\ \ input}{Actual\ \ energy\ \ input} \leq 1 \tag{1}$$

The study of energy efficiency issues generally revolves around industry and regional dimensions. Based on the substitution or complementary relationship between energy and other inputs, Mukherjee (2008) used four DEA models to calculate the energy efficiency of the six energy-intensive sectors in the US manufacturing industry. The results show that the energy use of the paper sector is the most efficient, while that of the metallurgy sector is the least efficient. Azadeh et al. (2007) combined the DEA model with principal component analysis and numerical taxonomy to explore the characteristics of energy efficiency for high energy-consuming manufacturing industries in Iran and the OECD countries, and pointed out that it is difficult to identify the special relationship among energy consumption, output growth and structural change at the industry level by only relying on the DEA model. Zhang et al. (2013) used a meta-frontier DEA model to measure energy efficiency and CO_2 emission performance in South Korea's power plants, and they found that power plants using coal as fuel have higher energy efficiency than oil-fired ones. Lin and Tan (2016) employed slack-based DEA model to analyze energy efficiency in China's high energy-consuming industries and they found that there were significant regional differences.

At the regional level, some scholars used DEA model to sort the energy efficiency of different regions and set a more accurate energy-saving target. Rojas-Cardenas et al. (2017) evaluated energy efficiency in Mexico's steel sector, and discovered that the energy intensity of Mexico's steel sector is lower than that of China and the US. Makridou et al. (2016) explored energy efficiency of high energy-consuming industries in EU countries and their conclusion shows that technological progress is a major driver of energy efficiency. Camioto et al. (2016) measured energy efficiency of G7 and BRICS countries and concluded that the factors affecting the energy efficiency of the former are different from those of the latter. Some scholars studied the regional energy efficiency of some industries in China (Lin and Zhao, 2016; Lin and Zheng, 2017). Qin et al. (2017) calculated the energy efficiency of China's coastal areas. In their view, the rise in energy efficiency is mainly driven by technological progress and there is great potential for CO_2 abatement in China's coastal areas.

Table 1
The abbreviated form.

DEA	data envelopment analysis
SFEE	single factor energy efficiency
TFEE	total factor energy efficiency
DMU	decision making unit
GEE	energy efficiency under group frontier
MEE	energy efficiency under meta-frontier
TGR	technology gap ratio
TGI	technology frontier gap inefficiency
GMI	group frontier management inefficiency
CNY	Chinese Yuan
km	kilometer
mt	million ton
tce	ton coal equivalent
mtce	million ton coal equivalent
GDP	Gross Domestic Product
pcGDP	per capita GDP
IS	industrial structure
TS	transport structure
FP	fuel price
EI	energy intensity

Table 2
The basic statistics of input and output factors in the east, central and west during 2005–2015.

Region	Variable	Obs	Mean	Std. Dev.	Min	Max
All	Y	330	444.92	420.47	16.83	2045.35
	K	330	270.95	194.79	12.49	1172.00
	L	330	183.95	109.00	22.46	615.64
	E	330	9.30	5.91	0.83	31.23
East	Y	121	735.08	508.71	45.94	2045.35
	K	121	346.82	214.35	24.71	1172.00
	L	121	246.65	133.18	32.65	615.64
	E	121	12.80	7.18	1.52	31.23
Central	Y	88	393.97	284.12	76.71	1419.83
	K	88	241.70	126.63	43.65	653.27
	L	88	188.41	58.49	108.46	376.17
	E	88	8.37	3.79	2.80	16.03
West	Y	121	191.83	126.53	16.83	606.92
	K	121	216.35	192.40	12.49	1120.04
	L	121	118.00	63.18	22.46	323.66
	E	121	6.47	3.57	0.83	15.93

Based on the geographical location and economic level, we divide China into eastern, central and western regions. In order to better show Y(billion ton-km), K(billion CNY), L(thousand persons) and E(mtce) of each region, we list these data as shown in Table 2.

DEA is a nonparametric method which is based on mathematical programming, rather than econometric method. Simar and Wilson (1998) introduced the bootstrap method into the DEA model, and tried to provide a statistical basis for it. But they mentioned in the concluding part of their paper that the bootstrap method lacks a rigorous consistency argument. Moreover, they also noticed the presence of random noise in the data, and needed to find a way to solve the problem. In other words, the bootstrap method is flawed and controversial. The bootstrap method is designed to handle sampling variability, and provides an indicator of the extent to which the efficiency estimates may change when randomly selecting different samples from the population. However, this method does not attempt to explain the random noise that may be caused by measurement errors or set errors.

In addition, Coelli et al. (2005) noted that it is almost meaningless to apply the bootstrap method to efficiency analysis based on census data. For instance, when the data in the census case comes from all the cement plants in a certain country or all hospitals in a particular area, all individuals in the population are "noiseless" data and then the acquired boundary is the real frontier. It has been identified, but is not estimated. Therefore, it is unnecessary to consider repeated sampling. In view of these problems, we did not use the bootstrap method in this paper.

By reviewing the literature, we found that despite the haze and serious environmental pollution in China, no scholars had explored the provincial energy efficiency of China's transport sector from the perspective of output growth and energy conservation. However, traffic congestion and CO_2 emission have become a severe problem that cannot be ignored. Our research can attract the attention of scholars and relevant departments, and also help to recognize the