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Original Articles

Driving factors of China's energy productivity and its spatial character: Evidence from 248 cities

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ABSTRACT

Energy productivity is a key indicator to evaluate energy efficiency. However, few researchers focus on China's energy productivity at the city level or its spatial patterns. The aim of this paper is to investigate the determinants and spatial character of changes to China's energy productivity at the city level. The change in energy productivity is decomposed using a distance function approach, and its spatial character is identified through exploratory spatial data analysis, based on data from 248 cities between 2010 and 2014. The study revealed that China's overall energy productivity exhibited a downward trend caused primarily by the effects of technological and technical efficiency changes at the city level. Additionally, significant spatial autocorrelation existed in energy productivity, although most cities did not show significant spatial clustering. Based on the above results, we provide relevant suggestions for policymakers.

1. Introduction

Climate change is a subject of growing concern for many scholars and governments. One of the most effective methods to tackle this problem is to improve the efficiency of energy use (Ang et al., 2010). According to recent research by Du and Lin (2017), the world's energy use efficiency has significantly improved over the past decades. Furthermore, they found that developing countries lagged behind in terms of technological progress, compared to developed countries, although developing countries outperformed the latter in terms of efficiency improvement. Indeed, improving energy use efficiency is important both theoretically and practically, especially for developing countries. Following substantive economic reforms, China, the largest developing country, ranks as the second largest economy in terms of its GDP, with an average annual growth rate of over 9%, according to the China Statistical Yearbook (1981–2016). Because energy plays an indispensable role in this process (Hu et al., 2018), rapid economic growth has led to an increasing demand for energy. In 1978, China's total energy consumption of standard coal was 571 Mt, but increased to 4300 Mt by 2014 (China Statistical Yearbook, 1981–2016). Moreover, with continued urbanization, China's energy demand will continue to grow in the future and exert pressure on economic development and environmental protection. Hence, improving energy efficiency in the country has become an important issue.

To address this problem, it is important to accurately measure energy efficiency. Energy productivity, which is defined as the ratio of output divided by energy consumption (Patterson, 1996; Dimitropoulos, 2007), is a key indicator to evaluate the energy efficiency of industries and economies. Thus, extensive research has been conducted on issues related to energy productivity. Two strands can be identified in the research. The first focuses on energy productivity change in terms of its tendencies. For instance, Uhlin (1998) analyzed energy productivity in Swedish agriculture using I-O analysis, and found that energy productivity had changed dramatically. Miketa and Mulder (2005) examined ten manufacturing sectors' energy-productivity convergence across 56 developed and developing countries. Recently, Parker and Liddle (2017) explored economy-wide manufacturing energy productivity club convergence for OECD and non-OECD countries. The second strand investigates energy productivity problems from the perspective of its sources. Honma and Hu (2009) computed energy productivity changes of regions in Japan using total-factor frameworks based on data envelopment analysis. Hargroves et al. (2016) researched energy productivity and de-carbonization of the global economy by analyzing five-factor resource productivity. Atalla and Bean (2017) used different types of analysis to investigate drivers of energy productivity changes in 39 countries.

China's energy productivity and its driving forces have been studied extensively, in part because China's energy productivity, though

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relatively low, has risen considerably since 1978 (Wang, 2011). For example, Fisher-Vanden et al. (2006) identified the key determinants of rising energy productivity within the industrial sector and found that rising energy prices, research and development expenditures, ownership reforms in the enterprise sector, and shifts in the industrial structure were principal drivers of China's declining energy intensity and use over time. Uwasu et al. (2012) explored the provincial structure of energy productivity and determining factors, and found disparity in energy technology levels across the provinces. Wang and Wei (2016) employed an aggregated specific energy productivity indicator to investigate the sources of energy productivity change in the country, and found that energy-specific productivity changes were mainly caused by technical changes rather than efficiency changes during the time period.

Such research offers insights regarding the determinants and trends affecting energy productivity. Indeed, their empirical results enrich our knowledge of China's energy productivity, but they are far from conclusive. Moreover, there are shortcomings in the existing literature. First, most studies analyze energy productivity at a macro-level, such as the national or provincial levels. Macro-level assessments can provide inadequate information for policymaking by smaller administration units such as municipalities, since policy implementation in China follows a hierarchical diffusion process (Schreifels et al., 2012). Consequently, it is difficult to allocate energy conservation targets. Second, the focus on the spatial character of China's energy productivity is insufficient, especially at the city level. Geography is a significant factor in environmental and resource economics (Anselin, 1995), insofar as adjacent cities and regions inevitably exert mutual influence (Maddison, 2007). It is thus useful to identify spatial patterns in energy productivity for the sake of policymaking.

Therefore, given the insufficient attention to China's energy productivity from the perspective of smaller administration units, this paper focuses on the driving factors of energy productivity change and its spatial character at the city level. Specifically, we analyzed the determinants of energy productivity change in terms of the factor substation effect at the city level, based on data from 248 cities between 2010 and 2014, using a distance function approach proposed by Wang (2007). It should be noted that the influence of factor substitution on energy productivity can be analyzed from two perspectives: viz., elasticity and effect (Wang et al., 2017). However, considering that one of the aims of this paper is to determine the effect of factor substitution on energy productivity, the method proposed by Wang (2007) is more suitable. Furthermore, Wang et al. (2017) recently proposed a new approach to decompose the change of energy productivity. Their proposal was to uncover sources of energy productivity change by combining production-theoretical decomposition analysis with stochastic frontier analysis, especially for the periodic fluctuations of energy productivity change. However, stochastic frontier analysis requires setting the distribution form of invalid items, and setting the function form to a production function (or a cost function) (Coelli et al., 2005). This risks a misinterpretation of its economic meaning. The distance function frame, by contrast, is a non-parametric method that is relatively more objective. Another concern is that the fluctuation of energy productivity change is not significant beyond five years. Thus, we utilized the distance function approach (Wang, 2007; Shepherd, 2015). Moreover, we evaluated the spatial character of energy productivity at the city level through spatial exploratory analysis.

The study contributes to current literature in the following three ways. First, key factors to China's energy productivity change were identified at the city level. Second, the spatial pattern of China's energy productivity was explored at the city level. Third, a distributional evaluation of energy productivity was conducted at the city level. This study drew some interesting conclusions, which will be of valuable use in policymaking and implementations of energy conservation targets at smaller administration levels.

The rest of the paper is arranged as follows: Section 2 discusses the methodology used, including a decomposition framework based on the distance function, spatial correlation analysis, and data sources; Section 3 analyzes the empirical results, using distributional evaluation analysis, decomposition analysis of energy productivity, and exploratory spatial data analysis of 248 cities; and the final section summarizes the main conclusions of this research.

2. Methodology and data sources

2.1. Decomposition framework

We decomposed energy productivity change into multiple components using Shephard distance functions, as described in Wang (2007). In a simplified productive process, if total energy consumption (E), capital (K), and labor force (L) are the input factors, the gross regional product (Y) represents the output factor. Thus, such output technology can be expressed as follows:

$$T = \{(K,L,E,Y){:}\ \ (K,L,E)\ \text{ can produce Y}\} \tag{1}$$

In Eq. (1), the output technology set is presumed to be a closed and bounded set, which means that a limited input can produce only a finite output (Färe and Primont, 1995). In set T, the input and output can be hypothesized to meet free disposability. Thus, the output-oriented Shephard distance function can be defined as follows:

$$D_y^t(K^t,L^t,E^t,Y^t) = \inf\{\theta{:}\ (K^t,L^t,E^t,Y^t/\theta) \in T\} \tag{2}$$

From Eq. (2), we can verify that $1/\theta$ measures the maximum feasible expansion of the observed output, when the energy consumption, capital, labor force, and output technology are known. Wang (2007) demonstrated that $D_y^t(K^t,L^t,E^t,Y^t) \leqslant 1$ always holds and $D_y^t(K^t,L^t,E^t,Y^t) = 1$ if and only if (K^t,L^t,E^t,Y^t) is on the boundary or frontier of technology T.According to the definition of the output-oriented Shephard distance function, output distance functions are homogeneous functions of degree $+1$ in outputs, namely, $D_y^t(K^t,L^t,E^t,\alpha Y^t) = \alpha D_y^t(K^t,L^t,E^t,Y^t)$, where α is a positive scalar. Therefore, based on the technology in time period t as a reference, the energy productivity changes between time periods t and τ can be written as follows:

$$\begin{aligned} EP_i &= \frac{Y_i^\tau/E_i^\tau}{Y_i^t/E_i^t} = \left\{\frac{[Y_i^\tau/D_y^t(K_i^\tau,L_i^\tau,E_i^\tau,Y_i^\tau)]\cdot(1/E_i^\tau)}{[Y_i^t/D_y^t(K_i^t,L_i^t,E_i^t,Y_i^t)]\cdot(1/E_i^t)}\right\} \times \frac{D_y^\tau(K_i^\tau,L_i^\tau,E_i^\tau,Y_i^\tau)}{D_y^t(K_i^t,L_i^t,E_i^t,Y_i^t)} \\ &\times \frac{D_y^t(K_i^\tau,L_i^\tau,E_i^\tau,Y_i^\tau)}{D_y^\tau(K_i^\tau,L_i^\tau,E_i^\tau,Y_i^\tau)} = \frac{D_y^t(K_i^t,L_i^t,E_i^t,1)\cdot E_i^t}{D_y^t(K_i^\tau,L_i^\tau,E_i^\tau,1)\cdot E_i^\tau} \times \frac{D_y^\tau(K_i^\tau,L_i^\tau,E_i^\tau,Y_i^\tau)}{D_y^t(K_i^t,L_i^t,E_i^t,Y_i^t)} \\ &\times \frac{D_y^t(K_i^\tau,L_i^\tau,E_i^\tau,Y_i^\tau)}{D_y^\tau(K_i^\tau,L_i^\tau,E_i^\tau,Y_i^\tau)} = \frac{D_y^t(k_i^t,l_i^t,e_i^t,1)}{D_y^t(k_i^\tau,l_i^\tau,e_i^\tau,1)} \times \frac{D_y^\tau(K_i^\tau,L_i^\tau,E_i^\tau,Y_i^\tau)}{D_y^t(K_i^t,L_i^t,E_i^t,Y_i^t)} \\ &\times \frac{D_y^t(K_i^\tau,L_i^\tau,E_i^\tau,Y_i^\tau)}{D_y^\tau(K_i^\tau,L_i^\tau,E_i^\tau,Y_i^\tau)} = PEPCH_i^t \times EFFCH_i \times TECH_i^\tau \end{aligned} \tag{3}$$

In Eq. (3), $k_i^t = K_i^t/(E_{1i}^t + \ldots + E_{ni}^t)$, $l_i^t = L_i^t/(E_{1i}^t + \ldots + E_{ni}^t)$, $e_i^t = E_i^t/(E_{1i}^t + \ldots + E_{ni}^t)$ denote capital-energy ratio, labor-energy ratio, and energy supply composition in time period t , respectively. On the right side of Eq. (3), the first component ($PEPCH_i^t$) measures the maximum potential energy productivity change of the *ith* city using time period t and technology T as reference, which depends on the changes in capital-energy ratio, labor-energy ratio, and energy supply composition. The second component ($EFFCH_i$) represents the technical efficiency change of the *ith* city that measures the change between observed production and maximum potential production between time periods t and τ. The third component ($TECH_i^\tau$) represents the technological change of the *ith* city by capturing the shift in technology or production frontier between time periods t and τ.In order to isolate the effects of changes in k, l, and e between time periods t and τ, on $PEPCH_i^t$, following Wang (2007), we decomposed it in six ways with three factors in each of them. Subsequently, we calculated the geometric mean of the decompositions and rearranged them into three