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Factor substitution and energy productivity fluctuation in China: A parametric decomposition analysis

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ABSTRACT

Technical research on energy productivity can support government officials as they evaluate practical energy policies for the future. This study proposed a parametric method to decompose China's energy productivity rate of change into six factors based on a theoretical stochastic frontier analysis. The method was applied to conduct an empirical study using inter-provincial panel data in China from 1995 to 2012. The results highlighted three key points. First, the general rate of change in energy productivity was mainly influenced by a steady positive rate of change in technical progress, combined with a steady negative rate of change in technical efficiency. The core factors causing fluctuations in energy productivity included: a positive rate of change in the substitution of capital and energy, and a negative rate of change in the substitution of labor and energy. Second, from a geographic perspective, provinces with a high rate of change in technical progress experienced a weaker deterioration in technical efficiency. However, the rate of change in technical efficiency tends to decline as the rate of change in technical progress increases. Third, there is a similar changing trend between the substitution of capital and energy and the substitution of labor and energy.

1. Introduction

Energy is required for production, and significantly influences the economy. However, economic growth that depends on energy, especially fossil fuels, can impede sustainable economic development and harm the ecological environment. There are many signals that China must resolve problems with the relationship between energy and economy. These signals include: the tension between energy supply and demand; an annual average $100 billion economic loss (approximately 5.8% of gross domestic product (GDP)) caused by environmental pollution (World Bank, 2007); China's 2014 worldwide ranking at 118th for environmental-protection performance; and China's carbon reduction commitment at the *Copenhagen Conference*. Given this background, improving energy efficiency is a significant way to solve the energy problem.

Researchers have defined energy efficiency differently, using terms such as energy physical efficiency (Sakamoto et al., 1999), energy thermodynamics efficiency (Lister and Buffett, 1995), energy allocative efficiency (Khiabani and Hasani, 2010), energy productivity (the inverse of energy intensity, defined as the ratio between economic output and energy input) (Panesar and Fluck, 1993; Dimitropoulos, 2007), and total factor energy efficiency (Hu and Wang, 2006; Wang et al., 2013; Özkara and Atak, 2016).

Energy productivity is easier to understand than these terms, and is more easily compared across time and space. Energy productivity can constrain social and economic development from the perspective of input factors, and can be decomposed into useful effects, including substitutions between energy and other input factors. Therefore, energy productivity is a widely used metric in China (Wang, 2007; Wang and Wei, 2016).

China's overall energy productivity rose from 2886.70 to 5160.78 thousand Renminbi (RMB) per thousand tons of standard coal between 1995 and 2012, representing an average annual growth rate of 3.99% (National Bureau of Statistics of China (NBSC), 2013). The following discussion reviews the factors impacting the rapid growth in energy productivity.

First, China's rate of change in overall energy productivity has fluctuated significantly. Energy productivity experienced a variable increase from 1995 to 2001 and 2006–2012, with a positive overall rate of change. From 2002–2005, energy productivity experienced a downward trend, with a negative rate of change. The rate peaked at 8.75% in 1998, and then dropped to −1.98% in 2003 (NBSC, 2013).

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Second, different provinces have experienced significant differences in energy productivity. For example, while Shanghai and Hainan provinces experienced high energy productivity (1995–2012), Shanghai's annual rate of change was 4.99% and Hainan's annual rate of change was −0.32%. In contrast, while Shanxi and Xinjiang provinces have low energy productivity, Shanxi's annual rate of change was 5.64%, and Xinjiang's annual rate of change was 0.95% (NBSC, 2013). Therefore, regional heterogeneity is an important issue when energy efficiency is studied.[1]

Many researchers have studied the evolution of energy productivity in China over both time and geographies, using many perspectives to study the factors influencing energy productivity (Dimitropoulos, 2007; Wan et al., 2015; Wang and Wei, 2016). Energy productivity is the ratio between economic output and energy input; however, energy input is not the only driver of economic output. Changes in energy productivity depend on the change in total factor productivity (TFP) and factor substitution effects, i.e. the substitution effect between energy and other factors and the substitution effect among different energies (Boyd and Pang, 2000; Smyth et al., 2012).

Past studies have applied two approaches to study the effect of TFP in promoting energy productivity. The first approach estimates the optimal energy input to achieve a certain output under the total factor framework. This allows researchers to study the improvement potential associated with energy productivity (Lansink and Ondersteijn, 2006; Honma and Hu, 2008; Chang and Hu, 2010). The second approach introduces TFP information into the decomposition factors of energy productivity (Wang, 2007; Wang and Wei, 2016), or constructs an econometric model to analyze the promoting effect of TFP (Boyd and Pang, 2000).

Two other types of studies have examined the influence of factor substitution on energy productivity. The first type of study estimates inter-factor substitution elasticity (Roy et al., 2006; Koetse et al., 2008; Smyth et al., 2011; Wesseh et al., 2013; Kim and Heo, 2013; Adetutu, 2014; Haller and Hyland, 2014) and inter-fuel substitution elasticity (Jones, 1996, 2014; Serletis et al., 2010, 2011; Smyth et al., 2012; Gao et al., 2013; Steinbuks and Narayanan, 2015). This involves analyzing how and how much the two forms of substitution elasticity promote energy productivity. The second type of study directly studies the influence of the inter-factor substitution effect and inter-fuel substitution effect on energy productivity (Wang, 2007).

To use both productivity information and factor substitution information in a total factor framework, some scholars have organically combined TFP and factor substitution to study the factors driving energy productivity. For example, Wang (2007, 2011) decomposed changes in China's energy productivity into several components, including changes in capital-energy ratio, labor-energy ratio, output structure, technical efficiency change, and technical progress change. These studies assumed constant returns to scale of production technology. Lin and Du (2014) accounted for variable returns to scale, and productivity information such as technical progress and factor substitution information. They decomposed the factors influencing energy intensity in China using data envelopment analysis (DEA).

This paper expands the existing literature, while acknowledging the reality of China's fluctuating energy productivity rate. This study accounts for both TFP and random factors, and emphasizes the driving factors using the concept of factor substitution. The paper contributes to the field in the following ways. First, the study decomposes the driving factors of energy productivity from the perspective of the rate of change, instead of the absolute level. This facilitates a dynamic analysis of energy productivity changes. Second, the study theoretically decomposes the rates of change in energy productivity into six different driving factors. This allows for the consideration of random factors and the combination of both TFP information and substitution effects. The study also empirically analyzed real-world data from China, using stochastic frontier analysis (SFA). This study helps explain the periodic fluctuation of China's energy productivity rate, and the significant regional differences.

2. Methodology

There are few studies on the decomposition of energy productivity; however, there is extensive literature on CO_2 emissions, CO_2 intensity, and energy intensity changes. Index Decomposition Analysis (IDA), Structural Decomposition Analysis (SDA), and Production-theoretical Decomposition Analysis (PDA) (Zhou and Ang, 2008; Wang et al., 2015, 2017a, 2017c; Ang et al., 2016) are commonly used decomposition techniques. Wang et al. (In press) thoroughly compared IDA, SDA and PDA. PDA generally provides a better economic explanation for the decomposition of variables; however, PDA is deployed using DEA, making it impossible to differentiate random factors. Thus, this study drew on the idea of PDA, but also applied SFA and insights from studies by Henderson and Russell (2005), Wang (2011), Kuang and Peng (2012), and Lin and Du (2014) to conduct the factorization, with some modifications.

Using the traditional calculation method, energy productivity is defined as[2]:

$$EP_{ij} = Y_{ij}/E_{ij} \tag{1}$$

In Eq. (1), i and j represent year and regions, respectively; EP refers to energy productivity; Y and E stand for GDP and energy consumption. The expression $X \in R_+^n$ is introduced as the vector of multi-factor inputs, and $x = X/E$ refers to the factor inputs per unit of energy. This results in the following stochastic frontier production function model:

$$EP_{ij} = f(x_{ij}, t)e^{v_{ij}-u_{ij}} \tag{2}$$

In Eq. (2), $f(.)$ represents the deterministic frontier output of each decision-making unit of production. This indicates the deterministic maximum output of factor inputs per unit of energy under current technical conditions. The factor t refers to time, representing the technical standard; v stands for random difference item, meeting *iid* $N(0, \sigma_v^2)$; and u represents technical inefficiency, complying with *iid* $|N(0, \sigma_u^2)|$.

Calculating the logarithm of the left and right side of Eq. (2), taking the derivative of time t, and omitting the subscript ij for simplicity leads to the following result:

$$\frac{dLnEP}{dt} = \sum_n \frac{\partial Lnf(x,t)}{\partial Lnx_n}\frac{\partial Lnx_n}{\partial t} + \frac{dLnf(x,t)}{dt} + \frac{dLne^{-u}}{dt} + \frac{dLne^{v}}{dt} \tag{3}$$

The left side of Eq. (3) is the growth rate of output per unit of energy ($\dot{EP}$). The first term on the right side of the equation

[1] Recently, Wang et al. (2017b) proposed an extended non-parametric frontier approach to study economy-wide energy efficiency and productivity performances accounting for sectoral heterogeneity. This provides a more global perspective to analyze energy efficiency.

[2] This study measures energy efficiency using energy productivity, rather than energy intensity, for the following reasons. First, given a certain technology, using energy productivity allows us to minimize energy input while maximizing outcomes. Some literature has highlighted the exclusive meaning of the energy productivity index. For example, Bean (2014) suggested that energy productivity "has a more positive connotation [than energy intensity], and is more intuitive, is aligned with efficiency, and portrays grander ambition." Second, Energy productivity is similar to the often-used concepts of labor productivity and capital productivity. When evaluating efficiency using a production function, energy productivity is more accurate and closer to the category of outcomes in economic terms. That is, the ratio of GDP to energy aligns with realistic processes associated with inputs and outcomes (Wang, 2011; Atalla and Bean, 2016). Third, energy productivity is the reciprocal of energy intensity; analyzing changes in energy productivity aligns with changes in energy intensity, allowing the transformation of analytical results.