Renewable and Sustainable Energy Reviews 73 (2017) 19–25

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

A comparison of carbon dioxide (CO_2) emission trends among provinces in China

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ARTICLE INFO

Keywords:
Decomposition
Shephard distance function
Production-theory decomposition analysis
Data envelopment analysis

ABSTRACT

As the world leader in CO_2 emissions, China is a key focus for climate change mitigation. In this paper, we conducted a cross-province comparison of CO_2 emission trends in China from 2006 to 2012. We determined effects of CO_2 emission factor (EMF), energy mix change (EMX), potential energy intensity change (PEI), industrial structure (STR), economic activity (EAT), technological change (BPC) and energy efficiency change (EC) as underlying forces of CO_2 emission changes with production-based decomposition. Compared to other production-theory decomposition analyses (PDA), the method used in this paper can overcome the weakness of PDA on the measurement of structural changes and energy mix effect. The results provided strong evidence that EAT is the main driver behind rising emissions, while changes in PEI, EMX and EC have led to CO_2 emission reductions in most provinces/municipalities in China. In particular, we introduced the global benchmark technology to establish the relationship between CO_2 emissions and energy use technology. The potential CO_2 reductions in China were further measured under the scenarios of contemporaneous technology and global technology. The principal empirical implication is that the promotion of energy conservation technology and reductions in inter-regional technological disparity would be effective in reducing CO_2 emissions in technically inefficient regions.

1. Introduction

As the world leader in CO_2 emissions from fossil fuel combustion, China has attracted worldwide attention with its accelerating CO_2 emissions over the past three decades. Considering its critical role in global CO_2 emissions, China becomes a key focus for effects in emission mitigations. In this context, a lot of efforts have been made to identify and quantify the underlying driving forces that affect CO_2 emission changes in China. In literature, factors that influence changes of China's CO_2 emissions have been widely discussed in previous studies [1–5]. However, CO_2 emission trends among different provinces in China have been less systematically investigated [6].

It should be noted that significant diversity exists among eastern, central and western areas in China [7]. For example, indicators such as per capita GDP, carbon emission intensity and energy efficiency differ greatly across regions in China [8], and the differences are most prominent between the developed regions in eastern area and the less developed regions in western area of China. In order to control greenhouse gas emissions, the Chinese government established a set of carbon emission reduction targets for different regions in the 11th and 12th Five-Year Plans (FYP) for national economic and social development. However, how to reasonably allocate regional CO_2 reduction targets based on the actual situations and reduction potential of various regions is still worthy of discussion [9]. Therefore, understanding the key drivers behind China's growing CO_2 emissions and developing regional emission reduction policies in China have theoretical and practical values for decision makers.

CO_2 emissions in China have attracted increasing attentions in light of China's decisive role in the global carbon emission mitigation. Technically, CO_2 emission changes can be analyzed by attributing the changes in CO_2 emissions into several pre-defined factors by adopting decomposition analysis [10]. In literature, the structural decomposition analysis (SDA) and the index decomposition analysis (IDA) are the most commonly used decomposition techniques [11–20].[1] In terms of data and methodologies, the SDA uses the input–output framework and data, while the IDA uses only sector level data to decompose

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[1] A useful summary of the various methods of IDA can be found in [14]. In addition, Ang et al. [46] also provides a systematic review on the existing IDA-based energy efficiency accounting systems. Additionally, [17] provided a comparison between SDA and IDA.

http://dx.doi.org/10.1016/j.rser.2017.01.102
Received 6 January 2016; Received in revised form 24 November 2016; Accepted 15 January 2017
1364-0321/

changes in indicators. Therefore, compared to SDA, the method of IDA is more flexible, easy to use, and has relatively lower data requirements for empirical models. As a result, IDA has been widely used to decompose CO_2 emissions in different countries and various time periods [21–25]. Under the framework of IDA, factors such as the carbon intensity of energy use, energy intensity, structural change and economic activity were identified as the major factors affecting CO_2 emissions, and the decline in energy intensity was identified as the driving force for the considerable decrease in China's CO_2 emissions [26–28]. However, IDA could not provide a quantitative analysis for the impacts of technological change effect, substitutions between energy and other inputs (i.e., capital and labor), and the effect of technical efficiency change on sectoral intensity change, because it simply regards the energy/emission intensity change as the effect of production technology [29,30]. Therefore, the method of IDA is difficult to provide reasonable explanations on the mechanism of sectoral energy/emission intensity changes based on economic theories [31,32].

More recently, in order to analyze the impact of production technology, decomposition analysis was improved and conducted within the production theory framework. [33] proposed production-theoretical decomposition analysis (PDA) based on Shephard output distance functions, which can be computed using data envelopment analysis (DEA) techniques. Empirical analyses of CO_2 emission changes based on the method of PDA include [34–38], etc. The proposed methodologies can assess the effects of “technological change” and “technical efficiency change”. The former measures the effect of best practice technology, and the latter measures the effect of changes in production efficiency. PDA provides detailed information about the influence of production technologies, which could be used to evaluate the degree of “energy efficiency paradox” [36]. However, its measurement on energy mix effect and the industrial structure effect, which are regarded as important factors of emission change, is possibly inconsistent with reality. For example, when industrial structure transforms from energy intensive industries to less energy intensive industries, it is expected that the industrial structure change would reduce an economy's overall energy intensity. However, results from PDA indicates that such an industrial structure transformation has a negative effect on energy intensity reduction [39]. PDA has a similar problem for the measurement of energy mix effect. When energy consumption structure has been improved, it is expected that such improvement would promote energy intensity reduction or at least would not has a negative impact on energy intensity reduction. However, results from PDA demonstrate the inconsistency.

The main reason for the above problems of PDA is that the structural components in output distance function are symmetrical. In other words, different properties of industries and energies cannot be reflected in the PDA model. Specifically, the lower energy consumption feature of the tertiary industry sector compared to the second industry sector is not reflected in the distance function. Therefore, the PDA model cannot provide information on the real effect of industrial structure transformation. In the PDA model, the output proportions of three sectors (primary, secondary, and tertiary) are all included in the output distance functions. The industrial structure was assumed to change as follows: the share of primary industry remained constant, the share of secondary industry declined, while the share of tertiary increased correspondingly. On one hand, the declined proportion of secondary industry in output would make the value of output distance function smaller; on the other hand, the increased proportion of tertiary industry in output would make the value of output distance function bigger. If the effect of the latter were bigger than the former, the industrial structure transformation would have a negative impact on energy intensity reduction, which is contrary to fact.

Based on the above analysis, we combined the advantages of IDA and PDA to examine the influencing factors of China's CO_2 emission changes and compare CO_2 emissions among provinces in China. Specifically, we establish the decomposition model based on the Shephard energy distance function to disaggregate the provincial level changes of CO_2 emissions in China during 2006–2012, and then introduce the global benchmark technology to establish the relationship between CO_2 emissions and energy use technologies. The central idea of the combination is introducing Shephard energy distance functions which captures the impacts from production technology in the expression of the aggregate CO_2 emissions, and then conducting IDA (e.g., LMDI) for this equation to identify the influencing factors driving change in the aggregate CO_2 emissions. In this sense, PDA and IDA are embodied together to provide the mechanism of CO_2 emission change. **The contributions of this paper lie in the following aspects:** First, the decomposition method used in this paper can overcome the weakness of PDA on the measurement of structural changes, and thus can produce more reasonable results; Second, the proposed approach has been applied in the field of investigating CO_2 emission trends among provinces in China; Third, from the methodological perspective, this paper specifies a different production technology setting which could be extended to other application areas.

The remainder of this article is organized as follows: Section 2 describes methodology and data; Section 3 presents and discusses the empirical results; Section 4 is conclusions and implications.

2. Methodology and data

2.1. The decomposition model

The CO_2 emissions of country $n = 1, \ldots, N$ can be expressed as:

$$C_{\mathrm{t}}^{n} = \sum_{ij} C_{\mathrm{ij},t}^{n} = \sum_{ij} \frac{C_{\mathrm{ij},t}^{n}}{E_{\mathrm{ij},t}^{n}} \frac{E_{\mathrm{ij},t}^{n}}{E_{i,t}^{n}} \frac{E_{i,t}^{n}/Y_{i,t}^{n}}{D_{i}^{g}(E_{i,t}^{n}, Y_{i,t}^{n}, C_{i,t}^{n})} \frac{Y_{i,t}^{n}}{Y_{\mathrm{t}}^{n}} Y_{\mathrm{t}}^{n} \frac{D_{i}^{g}(E_{i,t}^{n}, Y_{i,t}^{n}, C_{i,t}^{n})}{D_{i,t}^{c}(E_{i,t}^{n}, Y_{i,t}^{n}, C_{i,t}^{n})} D_{i,t}^{c}(E_{i,t}^{n}, Y_{i,t}^{n}, C_{i,t}^{n}) \tag{1}$$

where $E_{ij,t}^{n}$ denotes the consumption of the type-j energy in the sub-sector i of country n at the period t, and $C_{ij,t}^{n}$ represents the CO_2 emissions from $E_{ij,t}^{n}$; $D_{\mathrm{i}}^{g}(\cdot)$ and $D_{\mathrm{i}}^{\mathrm{c}}(\cdot)$ are the Shepard energy distance functions defined on the contemporaneous benchmark technology and the global benchmark technology, respectively. Specifically, the contemporaneous production technology for the industrial sub-sector $i = 1, \ldots, I$ at time period $t = 1, \ldots, T$ can be expressed as:

$$T_{i,t}^{\mathrm{c}} = \{(E_{i,t}, Y_{i,t}, C_{i,t}): E_{i,t} \text{ can produce} (Y_{i,t}, C_{i,t})\} \tag{2}$$

The global benchmark technology for the industrial sub-sector i is defined as ([40] and [41]):

$$T_{i}^{\mathrm{g}} = \{T_{i,1}^{\mathrm{c}} \cup T_{i,2}^{\mathrm{c}} \cup \ldots \cup T_{i,T}^{\mathrm{c}}\} \tag{3}$$

According to [42], the Shepard energy distance function relative to the contemporaneous benchmark technology and the global benchmark technology can be described as Eq. (4) and Eq. (5), respectively.

$$D_{i,t}^{c}(E_{i,t}, Y_{i,t}, C_{i,t}) = \sup\{\theta: (E_{i,t}/\theta, Y_{i,t}, C_{i,t}) \in T_{i,t}^{c}\} \tag{4}$$

$$D_{i}^{g}(E_{i,t}, Y_{i,t}, C_{i,t}) = \sup\{\theta: (E_{i,t}/\theta, Y_{i,t}, C_{i,t}) \in T_{i}^{g}\} \tag{5}$$

Using DEA-type linear programming technique, the Shepard energy distance function can be estimated through the following optimization problems.

$$[D_{i,t}^{c}(E_{i,t}, Y_{i,t}, C_{i,t})]^{-1} = \min \theta s.\ t. \quad \sum_{n=1}^{N} \lambda_n E_{i,t}^{n} \le \theta E_{i,t} \sum_{n=1}^{N} \lambda_n Y_{i,t}^{n} \ge \theta Y_{i,t} \sum_{n=1}^{N} \lambda_n C_{i,t}^{n} = \theta C_{i,t} \lambda_n \ge 0, n = 1, \ldots, N, \quad t = 1, \ldots, T \tag{6}$$