Energy Policy 58 (2013) 329–336

Contents lists available at SciVerse ScienceDirect

Energy Policy

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

Decomposing the change of CO_2 emissions: A joint production theoretical approach

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HIGHLIGHTS

- Decomposing the change of CO_2 emissions by a joint production theoretical method.
- Isolating both the GDP composition and energy supply composition change effects.
- Identifying the different input ratio changes effect on change of CO_2 emissions.
- Finding the economic growth is the crucial driver to the CO_2 emissions increase.
- GDP composition and capital–energy ratio have great effect on emissions reduction.
- Proposing some policy implications for China from an international perspective.

ARTICLE INFO

Article history:
Received 27 November 2012
Accepted 14 March 2013
Available online 15 April 2013

Keywords:
Decomposition analysis
CO_2 emissions
Data envelopment analysis

ABSTRACT

This paper presents an alternative decomposition method to explore the driving forces of change in carbon emissions by using distance functions estimated by data envelopment analysis. The proposed approach can isolate the effects of changes in GDP composition and energy supply composition on the change of carbon emissions. In addition, it is capable of identifying the effects of changes in different input ratios, which may be very important if there are substitution effects among different inputs. Moreover, the proposed model can measure the effects of changes in good and bad output technical efficiencies. Consequently, this decomposition technique allows a change of carbon emissions to be decomposed into contributions from ten factors, which provides more insights for policy makers. We apply this model to decompose carbon emissions in 25 OECD counties and China. For the sample countries as a whole, the empirical results indicate that the economic growth is the crucial driver to carbon emissions increase, while the changes in GDP composition and capital–energy ratio are two main drivers to carbon emissions reduction. In particular, we discuss in detail the driving forces of China's carbon emissions change in order to propose some valuable policy implications for China from an international perspective.

1. Introduction

Global warming, which is mainly contributed to by carbon emissions, has gained increasing attention in recent years. Many researchers devote themselves to studying the driving factors that affect change of aggregate carbon emissions based on a variety of decomposition methods. There are two widely used decomposition approaches, namely the structural decomposition analysis (SDA) and index decomposition analysis (IDA).

SDA is based on the input–output model in quantitative economics, and usually requires input/output (I/O) tables from more than one year. However, I/O tables are not constructed annually in many countries. Rose and Casler (1996) review previous SDA literature and summarize the SDA's features. Peng and Shi (2011) and Chang Yih et al. (2008) use SDA to analyze CO_2 emissions in China. IDA uses an index number framework and requires only sector level data. In addition, both multiplicative and additive decompositions are adopted in IDA, while only the additive decomposition can be applied in SDA. Therefore, IDA is a widely accepted decomposition technique to decompose carbon emissions, such as Ang et al. (1998), Ang and Liu (2001), Wang et al. (2005), Lee and Oh (2006), Liu et al. (2007), Hatzigeorgiou et al. (2008), Tunç et al. (2009), Zhang et al. (2009), and Zha et al. (2010). Ang and Zhang (2000) survey the IDA literature and provide the methodology, and Hoekstra and van den Bergh (2003) compare SDA with IDA in detail.

Several researchers have recently developed methodologies to decompose the change of undesirable outputs by combining

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0301-4215/$ - see front matter
http://dx.doi.org/10.1016/j.enpol.2013.03.034

decomposition analysis with distance functions estimated by data envelopment analysis (DEA). Zhou and Ang (2008) call this decomposition technique the production theoretical decomposition analysis (PDA) since it is conducted in production theory framework. Compared with IDA/SDA, PDA allows separate assessment of technical efficiency change effect and technological change effect based on the measure of production technology. PDA therefore is a significant decomposition technique since it yields more insights into the influence of production technologies which implies more explicit policy suggestions. In addition, PDA uses panel data which are easy to collect. Those applications of PDA differ mainly in the way that technology scales on outputs and inputs. Assuming an output based on radial measure which scales on good and bad outputs symmetrically, Pasurka (2006) applies Shephard output distance functions to decompose the change of NO_x and SO_2 emissions from U.S. coal-fired power plants into technical efficiency change, technical change, growth of fuel and non-fuel inputs, and changes in the mix of good and bad outputs. Zhou and Ang (2008) distinguish the category of technology into carbon emissions technology and the energy-usage technology, and apply two Shephard input distance functions for input and undesirable output respectively. Consequently, the components driving the change in CO_2 emissions are decomposed into contributions from seven factors: carbon factor change, energy intensity change, GDP change, CO_2 emissions technical efficiency change, carbon abatement technology change, energy usage technical efficiency change, and energy savings technology change. Zhang et al. (2012) extend Zhou and Ang (2008) by introducing Shephard output distance functions for good output. Thus, two additional contributors to the change of carbon emissions, the good output technical efficiency change and good output technical change, are taken into account. However, those decomposition models do not measure the structure effects, which have been regarded as important factors in explaining changes in carbon emissions.

Kim and Kim (2012) assess productive efficiency through a Shephard input distance function for the single input of energy consumption, and impose the logarithmic mean Divisia index method (LMDI) to measure the changes in energy mix and industrial structure as well as the change in production technology. Consequently, Kim and Kim (2012) decompose the change of CO_2 emissions into seven components: CO_2 emission factor effect, energy mix effect, potential energy intensity effect, structural effect, economic activity effect, energy usage efficiency effect, energy saving technical change effect. Based on the homogenous properties of output distance function when the production technology is constant-returns-to-scale (CRS), Wang (2007) and Li (2010) introduce the effects of industrial structure and energy mix into the proposal decomposition model by using the generalized Fisher index approach proposed by Ang et al (2004). By using Shephard output distance functions, Wang (2007) proposes a model to decompose the energy productivity changes into six components: output technical efficiency change, output technical change, change in capital–energy ratio, change in labor–energy ratio, change in energy supply composition, and change in output composition. Therefore, the model proposed by Wang (2007) takes into account the changes in industrial and energy supply structure effects and the ratios of different inputs. However, because of unavailability of the data, Wang (2007) cannot quantify the effects of the change in the composition of national output in the empirical analysis. Li (2010) decomposes the change of carbon emissions into seven contributors: economic growth, good output technical efficiency change, good output technical change effect, change in capital–carbon ratio, change in labor–carbon ratio, change in energy–carbon ratio, and the GDP composition effect. Li (2010) introduces the effect of change in industrial structure as that of Wang (2007). Li (2010) introduces the changes in different input-carbon ratios (changes in the capital–carbon ratio, labor–carbon ratio, and energy–carbon ratio) instead of different inputs ratios (changes in the capital–energy ratio, and labor–energy ratio), which are introduced in Wang (2007). The common characteristic in these two papers is that they assess productive efficiency through output distance function for desirable output subvector.

Based on Wang (2007) and Li (2010), we distinguish the category of technology into good output technology and bad output technology, and present an alternative PDA approach in this paper. The proposed decomposition technique allows a change of CO_2 emissions to be decomposed into contributions from ten factors, which can be classified into five categories: (1) changes in structure, including industrial structure change and energy supply structure change; (2) changes in different input ratios, including the changes in capital–energy ratio and labor–energy ratio, which may be very important if there are substitution effects among different inputs; (3) changes in technical efficiency, including carbon emissions technical efficiency change and desirable output technical efficiency change; (4) technical change, including carbon emissions technical change and desirable output technical change; and (5) the effect of economic growth.

We focus on an application using data from 25 OECD countries and China. In the past three decades, China has witnessed a significant rise in economic growth, and it has made great progress in the productivity and technical levels. Moreover, China has been the largest energy-related CO_2 emitter in the world, although the carbon emission per capita is very low. Therefore, another highlight of this paper is to investigate the driving forces affecting China's carbon emissions change in an international perspective, and the empirical results may imply some valuable policy implications for China to reduce its carbon emissions.

The remainder of this paper is organized as follows. Section 2 proposes a decomposition approach for carbon emissions. In Section 3, we apply this approach to decompose the change of carbon emissions in 26 countries. Section 4 presents policy recommendations for China. Section 5 concludes this study.

2. Methodology

2.1. Decomposition model

We consider a production process including two outputs and three inputs. The two outputs are a desirable output of gross domestic product (Y) and an undesirable one of CO_2 emissions (C), and capital stock (K), labor force (L) and energy (E) are the three inputs. The production technology at any time t is described by the following set:

$$S^t = \{(K^t, L^t, E^t, C^t, Y^t)\ (K^t, L^t, E^t) \text{ can produce } (C^t, Y^t)\} \tag{1}$$

S^t satisfies the standard properties of the production set. S^t is a closed set, which implies that finite amounts of inputs can only produce finite amounts of outputs. Inputs and desirable outputs are strong disposability, that is, if $(K^t, L^t, E^t, C^t, Y^t) \in S^t$ and $(K'^t, L'^t, E'^t) > (K^t, L^t, E^t)$ (or $Y'^t < Y^t$), then $(K'^t, L'^t, E'^t, C^t, Y^t) \in S^t$ (or $(K^t, L^t, E^t, C^t, Y'^t) \in S^t$) (see Färe and Primont (1995)). Joint outputs (good and bad outputs) are weakly disposable, which means that it is feasible to reduce good and bad outputs proportionally. That is, if $(K^t, L^t, E^t, C^t, Y^t) \in S^t$ and $0 \le \beta \le 1$, then $(K^t, L^t, E^t, \beta C^t, \beta Y^t) \in S^t$. Joint outputs (good and bad outputs) are nulljoint, i.e., if $(K^t, L^t, E^t, C^t, Y^t) \in S^t$ and $C^t = 0$, then $Y^t = 0$. It is technically (or economically) impossible to produce the good outputs without simultaneously producing some bad outputs (for more, see Färe et al. (2004)).