Renewable and Sustainable Energy Reviews 28 (2013) 525–530

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

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

Regional carbon emission performance in China according to a stochastic frontier model

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ARTICLE INFO

Article history:
Received 27 August 2012
Received in revised form
3 August 2013
Accepted 11 August 2013
Available online 31 August 2013

Keywords:
Carbon emission performance
Stochastic frontier model
Influential factor
Convergence

ABSTRACT

Carbon emissions, per capita carbon emissions, and carbon emissions per unit GDP are traditionally used as indicators of the real carbon emission of a region. However, input variables such as capital and labor and influential factors such as the industrial structure and regional differences are not taken into account in this approach. In this study a trans-log stochastic frontier model is used to develop an index system for measuring regional carbon emission performance that considers relevant input and output variables and influential factors. The main results are as follows: (1) carbon emission performance in China has an upward trend during this period; (2) as proved, among the nation's three major economic regions, in terms of efficiency performance they are ranked in descending order as follows: Eastern China, Central China and Western China; (3) convergence testing shows that there is a convergence trend for carbon emission performance both nationally and for the three major economic regions. Central China has the highest convergence speed and Western China has the lowest.

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1. Introduction

As concern regarding global climate change grows, international authorities have reached a consensus on the development of low-carbon economies. According to International Energy Agency (IEA) statistics, CO_2 emissions in China have exceeded those in the USA since 2007 and China now has the highest carbon emissions worldwide. At the UN 2009 Climate Conference in Copenhagen, China committed to decrease CO_2 emissions per unit GDP by 40–45% by 2020 compared to 2005 levels. The 12th 5-Year Plan for China set a rate of carbon intensity decrease that is 17% lower than that in the 11th 5-Year Plan.

Although both the Tokyo Protocol and the Copenhagen Conference clearly recommended carbon emission reduction obligations for all nations, there is ongoing discussion on how to evaluate national or regional carbon emissions and which indicator to use for scientific measurement. This issue has been explored by many researchers. Mielnik et al. proposed that CO_2 emissions per unit energy could be used as the main criterion to evaluate climate change in economic models for developing countries [1]. According to Ang, the change in energy consumption per unit GDP represents the regional CO_2 emissions [2]. Zhang et al. reported

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1364-0321/$ - see front matter
http://dx.doi.org/10.1016/j.rser.2013.08.009

that evaluation indices such as the per capita industrialized cumulative carbon emissions and carbon emissions per unit GDP are more likely to be scientific and reasonable [3]. Sun proposed the CO_2 emissions per unit GDP as a good index for measuring decarbonization among countries [4]. Besides the above indicators, per capita carbon emissions indicator is an important measure of the level of regional carbon emissions (RCE) [5,6]. The main indicators for measuring RCE are carbon emissions, per capita carbon emissions, and per unit GDP carbon emissions. However, RCE measurement using these indicators seems too simple. Any realistic emission reduction target needs a comprehensive indicator system comprising economic, social, energy, and environmental factors to measure RCE performance. Some recent studies of carbon emission performance have considered these factors and research methods for resource and environmental efficiency include the total factor approach and data envelopment analysis (DEA) [7].

One problem arises when estimating resource or environmental efficiency via the DEA method: how to deal with pollutants. Production can involve good outputs (GDP), and bad outputs (pollutants). There are two approaches for handling pollutants. In the first, pollutants are considered as undesirable outputs. For example, Chung et al. introduced the radial distance function to construct a new production index model containing desirable and undesirable outputs [8]. Zaim, Zofio, and Zhou evaluated the CO_2 emission performance of OECD countries and other regions at a macro level using different DEA models [9–11]. Wang et al. used a Malmquist index in a DEA model containing undesirable outputs to explore dynamic changes in carbon emission performance (CEP) in China. They also established several models based on environmental production technology to estimate environmental efficiency, economic efficiency, economic environmental efficiency, and two-stage efficiency for different provinces in China [12,13]. Oh and Heshmati constructed a continuous Malmquist–Luenberger productivity index to measure environmentally sensitive productivity considering variable technology and CO_2 emissions [14]. Tu calculated environmental production efficiency to measure the coordination of environmental and industrial growth according to resource inputs, industrial production and environmental pollution data for 30 provinces in China [15]. Zhou et al. built a model based on the Malmqusit index to measure the carbon emission efficiency for 18 countries with the highest global carbon emissions [16]. Lozano and Gutiérrez used a non-parametric frontier approach to model relationships among population, GDP, energy consumption, and CO_2 emissions [17]. The second approach considers pollutants as inputs. For example, Hamid added environmental factors to a production effectiveness function to construct a dynamic agency model to analyze the long-term economic growth rate for optimal policy design [18]. Lu et al. researched sustainable economic development in China under energy and environmental security constraints using energy and carbon emissions as inputs [19]. Ramanathan analyzed the energy and carbon emission efficiency of 17 countries in North Africa according to the DEA method [20]. Hu and Wang defined the total factor energy efficiency as the ratio of the target energy input to the actual energy input according to a variable DEA [21]. Mukherjee estimated the energy efficiency for the six highest energy-intensive manufacturing industries in the USA using DEA [22]. Chen constructed an input–output database for 38 industries and estimated changes in the industrial total factor productivity in China via a trans-log production function and green production accounting [23].

The second approach is used in this study and CO_2 emissions as considered as an input into the SFA model for the following reasons. Firstly, if both energy and CO_2 emissions are used as input indicators, RCE performance may be poorly defined. Secondly, the majority of production activities require an energy input, which leads to CO_2 emissions. So carbon dioxide emissions as component of energy, are introduced as input indicator of the stochastic frontier model. Thirdly, a production frontier always has an environmental effectiveness frontier, whereby environmental technology effectiveness corresponds to the minimum pollutant emissions and the most desirable output. Among environmental efficiency evaluation methods, pollutant emissions should always be minimized, which satisfies the SFA requirement for input indicators.

Methods for evaluating the technical efficiency of decision-making units (DMUs) are divided into parametric and non-parametric approaches. DEA is a parametric method, but it sets boundaries and does not consider measurement errors, which are disadvantages. The stochastic frontier analysis (SFA) method is a parametric approach proposed by Aigner, Battese, and Meeusen [24–26]. SFA considers efficiency measures and stochastic noise affecting a frontier. It estimates the frontier production function via a metering method that measures the efficiency of each DMU and considers a variety of environmental factors that influence their efficiency. Several studies have used SFA to evaluate resource and environmental efficiency. Vaninsky investigated environmental performance in the USA for 1990–2007 using SFA. The frontier comprised GDP, energy consumption, population, and CO_2 emissions indicators expressed as ratios to the total [27]. This indicators design made the Environmental performance scores of DMU be very close, the DMU discrimination was affected, so in this study GDP, CO_2 emissions and other input and output variables are directly from the original value. Du and Zou estimated the carbon emission efficiency for various regions in China from 1995 to 2009 in the SFA framework and analyzed regional differences and influential factors [28]. SFA has also been used to estimate the environmental or technical efficiency of electric utilities (Cuesta et al.; Hattori) [29,30]. From the point of view of production theory Wang et al. proposed a new total factor CO_2 emission performance index using directional distance function followed by stochastic frontier analysis techniques [31]. Reinhard et al. discussed how SFA could be incorporated into DEA. The DEA frontier should be considered as an estimate for the deterministic component of the SFA frontier [32–34]. Instead of this method, a traditional SFA model is used in the present study. In the studies discussed above, except for less literatures efficiency estimation was applied to a closed system without considering the impact of external environmental factors. According to regional systems theory, regional system efficiency is affected not only by the system itself but also by external environmental factors. Results will inevitably be inaccurate if regional system efficiency is only evaluated in terms of the input–output variables for each DMU.

The present study addresses this problem by adding environmental factors to the SFA model. It extends previous research in the following ways: (1) rather than defining CEP from a carbon emission intensity viewpoint or based on the DEA method, CEP is defined in the SFA framework; (2) instead of considering carbon emissions as an undesired output, it is used as an input to explore and improve methods for calculation regional CEP; (3) in calculating CEP, besides input and output variables, environmental factors and random factors are included in the analysis framework to yield more accurate regional CEP data; and (4) convergence testing is applied to investigate the convergence or divergence speed and identify any convergence trends for regional CEP.

The remainder of the paper is organized as follows. Section 2 describes the CEP index constructed based on the stochastic frontier model and associated variables. Section 3 presents and discusses the empirical results. Section 4 concludes this study.

2. Model structure and variable data

2.1. CEP model construction

The SFA method determines frontiers via a production function that assesses DMU efficiency and the impact of disturbances and