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Influencing factors and regional discrepancies of the efficiency of carbon dioxide emissions in Jiangsu, China

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ABSTRACT

Decreasing carbon emissions is of great significance to the development of the strategy for a low-carbon economy and for the choice of a carbon dioxide (CO_2) emission mitigation path. In order to realize the purpose of energy saving and emission reduction during the process of urbanization, both China and Jiangsu province have been urged to improve their energy efficiency and carbon dioxide efficiency. A Malmquist index based on an undesirable output data envelopment analysis (DEA) model was calculated to study the scalable industrial CO_2 emissions of 13 cities in Jiangsu province from 2000 to 2014. The impact factors on the efficiency of the CO_2 emissions are analyzed using a Tobit model, which takes the level of urbanization as the core variable and four other factors (energy consumption structure, industrialization level, foreign trade, and R&D expenditure) as the control variables. The results show that the total factor productivity (TFP) index of the low-carbon economy in Jiangsu grew by an average annual rate of 0.7%, and the total efficiency of the low-carbon economy increased by 9.3%. The main contributing factor was the average annual increase of 1.5% in technological progress during 2000–2014, but the pure technical efficiency and scale efficiency are declining. Jiangsu has not realized the full use of its resources and energy for many years. The level of industrialization and structure of energy consumption are the main impact factors on carbon emissions. In the process of urbanization, both China and Jiangsu should pay attention to optimizing the structure of energy consumption, adjusting the industrial structure, increasing the R&D, and introducing environmental protection technology. These are effective paths to achieve the goal of carbon emission reduction in China.

1. Introduction

With the rapid development of China's social economy, energy consumption and environmental problems are becoming increasingly serious. In particular, the greenhouse effect of increased carbon emissions has become the focus of international attention. The International Energy Agency announced that China became the world's largest carbon dioxide (CO_2) emitter in 2009 (China Statistical Yearbook, 2010). At the Copenhagen conference in 2009, the Chinese government committed to mitigating CO_2 emissions per unit of GDP by 40%–45% from 2005 levels by 2020, and in 2014 it also promised to stop increasing CO_2 by 2030. The realization of China's targets for carbon emission reduction requires the joint efforts of all provinces. However, as one of China's most developed provinces, the levels of energy consumption and CO_2 emissions have been increasing in line with the urbanization process in Jiangsu. Jiangsu officially announced that by 2020 the CO_2 per unit of industrial added value will decline by 19% and major industrial pollutants will reduce by 10% compared with the 2015 level (Jiangsu National Economic and Social Development segment of the 13th Five-Plan, 2016). The carbon emissions rose from 16,291.65 million tons to 81,105.98 million tons during 1990–2014, which is an increase of 4.98 times (China Energy Statistical Yearbook, 2015). This rapid growth in carbon emissions has put great pressure on the energy conservation and emission reduction obligations of Jiangsu. Accordingly, how to improve the efficiency of carbon emissions and achieve the goal of energy conservation and emission reduction are questions that are worth resolving.

The concept of carbon efficiency was first proposed to refer to the excess of the CO_2 emissions over the CO_2 emissions per unit of GDP (Kava and Yokobori, 1993). As an indicator of the carbon emission rate, it is also an important criterion for evaluating a country's energy savings and emission reduction (Sun, 2005). The differences among these studies lie in the measurement of the efficiency of the carbon emissions. Currently there are two types of ways to measure the efficiency of CO_2 emissions. One of these is by using a single factor index to study the emission efficiency. This method usually takes the ratio of total carbon

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to an element as the efficiency of the carbon emission standards, such as carbon emissions per unit of GDP (Li and Qi, 2011), but although the single factor index is straightforward, there are many deficiencies. For example, only using carbon intensity could not reflect the substitution effect of each element, because energy must be combined with other elements in the production process, and carbon intensity is also related to the economic structure, economic development level, and the endowment of regional resources. Changes in the economic structure will lead to changes in carbon intensity, while the efficiency of the carbon emissions may not have changed (Yang and Shi, 2008). Another way to measure the efficiency of CO_2 emissions is to bring the efficiency of production into the CO_2 emissions from the viewpoint of whole factors and to measure the efficiency of the actual output by identifying the frontier of production.

The undesirable output and influencing factors can be analyzed by data envelopment analysis (DEA) and Malmquist methods (Ang, 1999; Zaim and Taskin, 2000; Zofio and Prieto, 2001; Marklund and Samakovlis, 2007). China's CO_2 emission performance and its regional differences were also studied at different stages (Wang et al., 2010a,b; He and Ma, 2012; Wei et al., 2010). The results showed that R&D spending, the structure of the energy consumption, the industrial structure, and the economic level of activity were the main factors influencing carbon efficiency in China (Wang et al., 2012a,b; Wang et al., 2016a,b). The DEA-Malmquist method is applied to decompose the growth of total factor productivity (TFP) when the sample size is not big. However, the hypothesis of "facing the same technological frontier" cannot be met because of different factor endowments and economic development levels across regions. Estimating the DEA-Malmquist method and the deviation of the Solow residual value is a suitable means of estimating TFP in Jiangsu. Although the Malmquist index calculation is based on DEA, DEA analysis is a static analysis when evaluating the relative efficiency of a decision making unit (DMU), while the Malmquist index is a dynamic evaluation from which it is easy to find the dynamic change rules of the DMU.

There have been a lot of in-depth analyses of the studies of carbon efficiency and its influencing factors, but they have the following problems. First, the choice of measurement: since carbon emissions research is a complex system of multiple inputs and outputs, the dimensions of the inputs and outputs are quite different. Adopting the DEA model, which is based on the BCC model with undesirable outputs, is an approach that incorporates non-undesirable outputs into the calculation of carbon efficiency and results in more precise efficiency. Second, there is no need to make a prior assumption about the production function or to estimate the parameters based on the linear programming method; this allows the non-efficient behavior to exist, articulates the relationship between inputs and outputs, and delivers a unique advantage in the efficiency measurement of multiple inputs and outputs. Third, the previous literature shows that the energy consumption structure, industrial structure, and R&D spending are important factors influencing the efficiency of carbon emissions. As well as these factors, since 2000 the urbanization of Jiangsu has been developing rapidly, which has brought a series of problems, such as more industrial and service sector carbon emissions and non-industrialized carbon emissions. The process of foreign trade has also caused many environmental problems, so this study chooses more factors affecting carbon emissions in Jiangsu province. Finally, in contrast to the existing literature in which many provinces are considered, this study examines carbon emission efficiency and its influencing factors based on a single province. Jiangsu is an important zone in the Chang-triangle area and is one of the well-developed and rapidly growing areas in China. Jiangsu is also China's industrial heart and an important pioneer for the country in regard to technological and economic development. In 2014, Jiangsu recorded the second largest GDP in China, it accounted for 10.2% of the national GDP, and its industrial output accounted for 11.4% of the total output (China Statistical Yearbook, 2015). However, to a certain extent, this rapid growth has been based on high energy consumption at the cost of the environment. It is estimated that the process for the urbanization and industrialization of Jiangsu will be further accelerated, which will result in increased energy demands and economic development-derived carbon emissions, so taking Jiangsu province as the research object has universality. Also, it provides a good example to help popularize the significance of the need for emissions reduction in China.

The main contributions of this study can be highlighted as follows. First, this study constructed a Malmquist index using a DEA model with non-desirable outputs. On the basis of the analysis and evaluation of the change in the technological progress and efficiency of Jiangsu's industrial enterprises above a designated size, a Banker, Charnes, and Cooper (BCC)-Malmquist model based on non-desirable outputs was used to measure the efficiency of carbon emissions in Jiangsu over the years and then study the region discrepancies. Second, in order to study their influence on the efficiency of the carbon emissions in Jiangsu, a Tobit panel regression model was used. On the basis of the literature review, this study adds the factors related to urbanization and foreign trade that have influenced the efficiency of carbon emissions in Jiangsu province. Finally, the study hopes to provide some policy suggestions for the energy conservation and emission reduction initiatives of Jiangsu and the implementation of green development.

2. The calculation of CO_2 emissions efficiency

2.1. DEA model with undesirable output based on BCC-Malmquist model

The DEA basic model includes a Charnes, Cooper, and Rhodes (CCR) model for evaluating the overall efficiency and a BCC model for evaluating the technical effectiveness. The BCC model improves the CCR model since the CCR model is assumed to be an efficient measure of a fixed scale, and the technical efficiency factors are broken down into both scale efficiency and pure technical efficiency. This study is based on the BCC model and constructs the DEA model with undesirable outputs (Tobler et al., 1979; Jahanshahloo et al., 2012).

Suppose there are n decision-making units and every decision-making unit has sample units, with each sample unit having m input indicators, s expected output indicators, and k kinds of undesirable output indicators.

Setting the input index value of the jth sample unit is that $\overline{x}_j = (\overline{x}_{1j},\overline{x}_{2j},...,\overline{x}_{mj})^T$, the expected output index is that $\overline{y}_j = (\overline{y}_1 j,\overline{y}_1 j,...,\overline{y}_s j)^T$, the non-expected output index is that $\overline{z}_j = (\overline{z}_1 j,\overline{z}_2 j,...,\overline{z}_1 kj)^T$, the input indicators of the Pth decision-making unit are that: $x_p = (x_{1p},x_{2p},...x_{mp})^T$, the expected output index is that $y_p = (y_{1p},y_{2p},...y_{sp})^T$, the non-expected output index is that $z_p = (z_{1p},z_{2p},...z_{kp})^T$, and this, $T^* = \{(\overline{x}_1,\overline{y}_1,\overline{z}_1),(\overline{x}_2,\overline{y}_2,\overline{z}_2),...(\overline{x}_{\overline{n}},\overline{y}_{\overline{n}},\overline{z}_{\overline{n}})\}$, is called the sample cell set (Aparicio et al., 2007). That $T_{DMU} = \{(x_1,y_1,z_1),(x_2,y_2,z_2),(x_n,y_n,z_n)\}$ is called the decision-making unit set. The DEA model with undesirable output based on the BCC-Malmquist model is as follows (Cooper et al., 2007).

$$\begin{cases} \min\theta, \\ s.\ t.\ \theta x_p - \sum_{j=1}^{\overline{n}} \overline{x}_j\lambda_j \geqslant 0, \\ -y_p + \sum_{j=1}^{\overline{n}} d\overline{y}_j\lambda_j \geqslant 0, \\ z_p - \sum_{j=1}^{\overline{n}} \overline{z}_j\lambda_j \geqslant 0, \\ \sum_{j=1}^{\overline{n}} \lambda_j = 1, \\ \lambda_j \geqslant 0, \quad j = 1,2,...,\overline{n}+1. \end{cases} \tag{1}$$