Investigation on carbon shadow prices based on data envelopment analysis: evidence from China

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Abstract. The shadow price of undesirable outputs is a useful measurement to assess the performance of environmental regulations. This paper makes a non-parametric estimation of the carbon shadow price (CSP) in China at the regional level during 2007-2020. By applying the non-oriented slack-based measurement data envelopment analysis (SBM-DEA) model, as well as Bootstrap-DEA methods, this paper presents that there was a stable increasing trend of CSP since the establishment of pilot carbon emissions trading markets after 2011. This paper also reveals that the carbon emissions trading market in China is not yet fully efficient, and the operation modes of the carbon emissions trading market in China could be further improved. Policy implications are also needed for the improvement of the carbon emissions trading market.

Keywords: Carbon shadow price, Data envelopment analysis, Bootstrap-DEA method

1 Introduction

Carbon trading is thought to be one of the most cost-effective ways to mitigate carbon emissions issues[1]. The carbon emissions trading market provides marketization means for green environmental projects and opens up a new channel for financing these projects[2]. In October 2011, the National Development and Reform Commission (NDRC) announced to establish seven administrative areas to build up pilot carbon shadow price carbon emissions trading markets including Beijing, Shanghai, Hubei, Guangdong, Shenzhen, Tianjin, Chongqing and Fujian. The establishment of carbon emissions trading markets witnesses the practice of using market mechanisms to help control carbon emissions reduction.

The shadow price reflects the price at which resources are optimally utilized, also known as the optimal plan price[3]. [4] also defines the shadow price as the increase in social welfare caused by the marginal increment of goods or production factors. The carbon shadow price (CSP) is also regarded as the opportunity cost of emissions reduction in terms of economic output loss, which is regarded as a comprehensive measuring

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indicator for making sound decisions related to carbon trading[5]. When considering the carbon emissions trading markets, participants with lower CSP will have the advantage of obtaining additional net income to meet the certain carbon allowance [6]. So, it is important to investigate the relationship between the real CSP and the carbon trading price of carbon emission trading markets in different regions.

By incorporating the slack of input excesses and output deficits as the slack variables, and estimating the dual linear program of the SBM model, we can get the shadow price of carbon emissions, which solves the clack problem and improve the accuracy of results compared with traditional models [7]. After that, scholars have extended it to evaluate the environmental efficiency and shadow price of pollution at different levels. For example, [8] studied the CSP of 285 cities in China using the dual model of SBM-DEA. [9] adopt the modified dynamic SBM model to evaluate China's carbon emissions efficiency from 2007 to 2017.

However, according to [10], the traditional DEA model like the SBM model is vulnerable to extreme values and may face a deviation problem, especially in the case of small samples. The Bootstrap-DEA method is essentially a nonparametric Monte Carlo simulation method that takes a numerical simulation of the original sample data and conducts DEA calculation with data uncertainty eliminated[11]. Utilizing the bootstrap method could provide large-sample of evaluation results and correct the biased estimates[12]. On this basis, this paper will further calculate the CSP based on the Bootstrap-DEA method to modify the CSP gained from the statistical results. We also compare the estimated CSP with carbon trading prices in seven pilot carbon emissions trading markets obtained from the Reset database in China for the years 2013-2020, in order to find the difference between the theoretical carbon price and realistic carbon price trading in the market. Results reveal that the carbon emissions trading market in China could be further improved, and government intervention and governance should be strengthened to stimulate the vitality of carbon emissions trading activities to help realize the theoretical equilibrium price.

2 Methods

2.1 SBM model

Based on[13], we adopt a dual model of non-parametric linear programming form based on a non-oriented slack-based measurement data envelopment analysis (SBM-DEA) model in the estimating of the carbon shadow price (CSP).

Suppose there are J decision-making units (DMUs). Let n, m, and r denote the input factor, desirable and undesirable output, with each having N inputs, M desirable outputs, and R undesirable output, respectively. The non-parametric linear programming is defined as follows:

$$\rho_0{}^* = min \frac{1 - \frac{1}{N}\sum_{n=1}^{N}\frac{s_n^x}{x_{nk}}}{1 + \frac{1}{M+R}\left(\sum_{m=1}^{M}\frac{s_m^y}{y_{mk}} + \sum_{r=1}^{R}\frac{s_r^c}{ca_{rk}}\right)}$$

$$\text{s.t.}\begin{cases} \sum_{j=1}^{J}\lambda_j x_{nj} + s_n^x = x_{nk}, n = 1,2,\cdots N; \\ \sum_{j=1}^{J}\lambda_j x_{mj} + s_m^x = x_{mk}, m = 1,2,\cdots M; \\ \sum_{j=1}^{J}\lambda_j ca_{rj} + s_r^c = ca_{nk}, r = 1,2,\cdots R; \\ \sum_{j=1}^{J}\lambda_j = 1\,, s_n^x, s_m^y, s_r^c, \lambda_j \geq 0, j = 1,2,\cdots J, \end{cases} \tag{1}$$

where $\rho_0{}^*$ denotes the efficiency score of DMU_0, and $\rho \in (0,1]$. s_n^x, s_m^y, and s_r^c represent the slacks of potential in input, desirable outputs, and undesirable outputs; x_{nk}, y_{mk}, and ca_{rk} are the actual inputs, desirable and undesirable outputs for the DMU_k, respectively. The CO_2 emissions inefficient DMU_k has the full efficiency of CO_2 emissions under the condition that s_n^x, s_m^y, $s_r^c = 0$, and $\rho_0{}^* = 1$, which can be improved by reducing undesirable outputs s_r^c. λ_j are the intensive vectors, where $\lambda_j \geq 0$ indicates a constant return to scale production.

By adopting the Charnes-Cooper transformation, we can obtain the dual liner programming as follows:

$$\max Z = u^m y_{mk} - u^n x_{nk} - u^r ca_{rk}$$

$$\text{s.t.}\begin{cases} Z \leq 0; \\ u^m \geq \frac{1+Z}{M+R}\left(\frac{1}{y_{mk}}\right); \\ u^r \geq \frac{1+Z}{M+R}\left(\frac{1}{ca_{rk}}\right); \\ u^n \geq \frac{1}{N}\left(\frac{1}{x_{nk}}\right), \end{cases} \tag{2}$$

where Z is the virtual profit. u^m, u^r, and u^n are the dual variables of desirable output, inputs, and undesirable output. Assume that the market price of desirable output to 1, and then the shadow price of CO_2 emissions p^b is:

$$p^b = p^y \frac{u^n}{u^m}. \tag{3}$$

2.2 Bootstrap-DEA model

The Bootstrap-DEA method could obtain the bias-corrected results of carbon shadow price through repeated sampling. Following [12, 14], the calculation process of the Bootstrap-DEA method based on the SBM model is as follows:

1. Adapting the SBM model with the original data set $R_j = (x_j, y_j, ca_j)$ to calculate the initial value of CSP $\widehat{p_j^b}$, where
2. Conducting bootstrap method to obtain repeated samples$\widehat{\beta_j}$.
3. Obtain the adjusted new data set $R^*{}_j = (x^*{}_j, y^*{}_j, ca^*{}_j)$:

$$R^*{}_j = R_j\left(\frac{\widehat{p_J^b}}{\beta_j}\right). \tag{4}$$

4. Repeat the above process N times to get the bias-corrected value of CSP ${p^b}^*_j$.
5. Finally, we could get the estimated value of CSP by the equation:

$$\widetilde{p_j^b} = 2\widehat{p_j^b} - \frac{1}{N}\sum_{n=1}^{N} \widehat{p^b}^*_{jn}, \tag{5}$$

where $n = 1,2,\cdots N$ represents the n times random sampling of the bootstrap method, and we set N as 1000 in this study.

3 Data and Results

3.1 Data collection

The panel data set includes 30 provinces and municipalities in China from 2007 to 2020, which excludes Hong Kong, Macau, Taiwan and Tibet for data availability and comparability. According to[15], we collect 5 types of data in China at the regional level, including labour force (L), capital stock (K), and energy consumption (E) as inputs, and regard real gross domestic product (GDP) as desirable output. CO_2 emissions (C) are selected as undesirable output to calculate the shadow price. To be specific, the number of industrial employees is adopted to illustrate the labour force (L), which is obtained from the China Statistical Yearbook and statistical yearbooks of each region. Referring to [16], we adopt the perpetual inventory method to calculate the capital stock. Data on energy consumption are collected from the China Energy Statistical Yearbook and are converted into tons of standard coal equivalent (TCE). Real GDP data are also acquired from China Statistical Yearbook and are deflated by price indices to constant 2000 prices. Data on CO_2 emissions (C) are calculated by the formula provided by the 2006 Intergovernmental Panel on Climate Change (IPCC) guidelines[17].

The total number of observations is 420, and all monetary variables are transformed into actual variables based on the year 2000 considering purchasing power parity of RMB. The summary statistics of indices are shown in Table 1.

Table 1. describes the statistics of all the raw data mentioned above. (Source: Processed Data)

Indices	Unit	Mean	St.dev.	Min.	Max.
Labour force	10^4 persons	2552.74	1635.70	279	7039.00
Capital stock	10^8 RMB	52811.05	44897.85	2323.61	239587
Energy consumption	10^4 TCE	14060.09	8706.17	1057	41826.80
GDP	10^8 RMB	4683.44	3491.48	358.04	16536.89
CO_2 emissions	10^4 tons	40478.09	29245.94	3713.587	155811.90

3.2 Carbon shadow price results

The average value of CSP obtained from actual data in China by adopting the SBM model and the Bootstrap-DEA model is illustrated in Figure 1 for comparison. It can be seen that both of the two methods follow a fluctuating upward trend for the study period, indicating that the environmental performance of China is improving. To be specific, the initial CSPs without bias correction tends to be overestimated, and the result obtained through the Bootstrap-DEA model are more dispersed. Similar findings were in agreement with those of [18] and [6].

We could also notice there exist three turning points in the results for both two different methods during the whole period. The first turning point is in 2009. The 2008 financial crisis might have caused the decline of CSP. The second turning point is in 2012, and CSP had been on a stable increasing trend after this year. This can be attributed to the establishment of pilot carbon emissions trading markets in seven regions of China since 2011. The third obvious turning point is in 2019 when the COVID-19 pandemic could be responsible for the slight decrease of the CSP after this point, but the overall trend is still increasing.

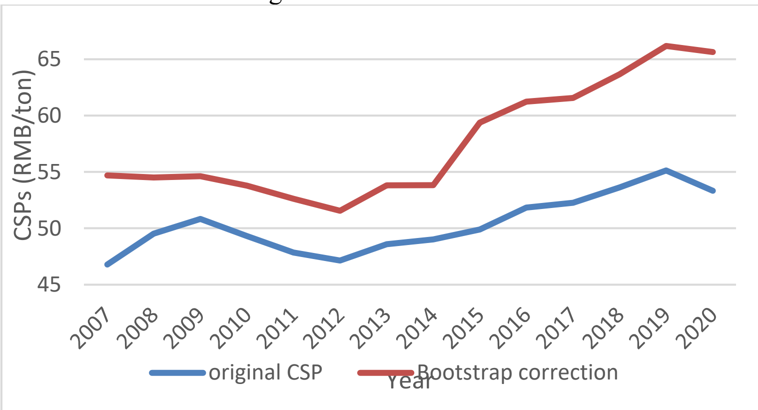

Fig. 1. Dynamics of average CSP at the regional level in China (RMB/ton). (Source: Processed Data)

To further identify the characteristics of regional-level disparities, we separate 30 provinces into eastern, western, northeastern, and central regions (displayed in Figure 2). It can be seen that the average CSPs for all four regions follow a slightly upward trend during 2007-2020, although the absolute values of the CSPs differ. In general, the relative variation of CSP via the two methods is the same, and bias-corrected results gained from the Bootstrap-DEA method still show an enhanced dispersion compared with the original results. However, differences between the four regions still exist. The eastern region exhibits the highest CSP in China during the study period than those of other regions, as most economically developed provinces are located in this region (i.e., Beijing, Shanghai, Guangdong, and Hainan). In comparison, the west and central regions exhibit lower levels and a slow but fluctuant rise of CSP. The northeast region has relatively the lowest level of CSP but a significantly faster growth rate. As for the bias-corrected CSP by the Bootrap-DEA method, the results of eastern and western regions were higher than the original CSP but declined to a certain level for northeastern and central regions.

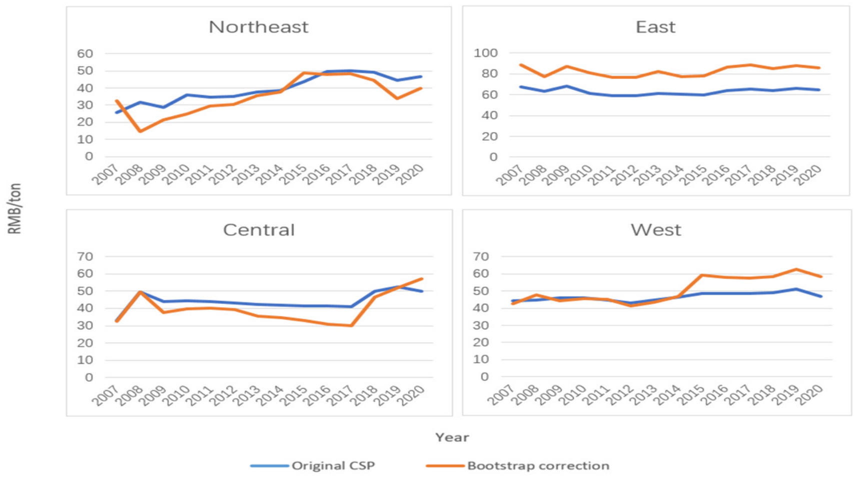

Fig. 2. Regional CSPs in China over time (RMB/ton). (Source: Processed Data)

In view of data availability, we simultaneously compare the results of the dynamic average value of CSP, as well as carbon trading prices of the above seven pilot carbon emissions trading markets obtained from the Reset database in China for the years 2013-2020. As can be seen from Figure 3, Beijing, the capital of China, a developed city, where its pilot carbon trading price ranked first over other pilot areas. One could also notice that the carbon emissions trading price in the Beijing pilot is also the only one that exceeds the estimated CSP from 2015 and shows the best development over time compared with other pilots. The Shanghai carbon trading pilot also showed a conspicuous performance since 2016, as Shanghai is also a developed city and is the financial centre of China. As the Fujian carbon emissions trading market was established in late 2016, its carbon trading price was still at the lowest level compared with other pilots. However, the carbon trading price in other pilots is at a relatively low level compared with the estimated CSP., indicating that it is difficult to realize the theoretical carbon trading price in the short run.

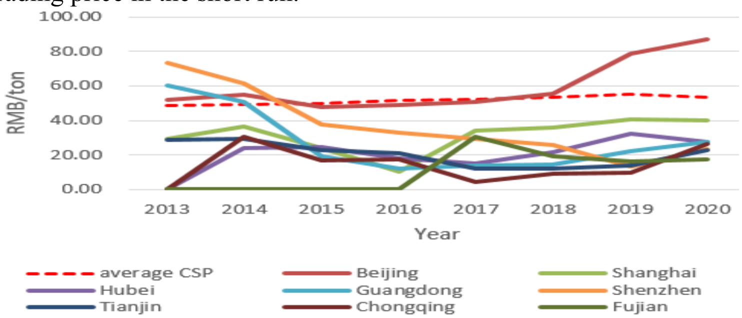

Fig. 3. Average CSP and carbon emission allowance trading price of experimental regions over time (RMB/ton). (Source: Processed Data)

4 Conclusions

This research illustrates the data envelopment analysis (DEA) of the SBM model to calculate the carbon shadow price (CSP) in China at the regional level. The Bootstrap-DEA model is also considered to obtain the bias-corrected results. The findings demonstrate that China possesses the immense capability for emission reduction, but the carbon emissions trading market in China is not yet fully efficient, and the operation modes of the carbon emissions trading market in China could be further improved. The environmental decision-makers should make some targeted policies based on the characteristic of companies supporting cleaner production projects in different regions.

In future research, we will consider more factors influencing the CSP like policy systems to get more comprehensive results. More models could also be considered to obtain more precise results.

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