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ORIGINAL PAPER

The carbon dioxide marginal abatement cost calculation of Chinese provinces based on stochastic frontier analysis

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Abstract The Chinese government made a commitment to achieve a 40–45 % reduction in carbon emissions per unit of gross domestic product (GDP) by 2020 compared with 2005. Most provinces followed the national commitment due to unified task of 40–45 % reduction in carbon emissions. However, different industrial structures, energy consumption structures and natural resources endowment of each province vary the emission abatement costs. Each province should take the carbon dioxide abatement cost into consideration for the carbon dioxide reduction target. Data envelopment analysis (DEA) and linear programming (LP) methods were used to measure the marginal abatement cost in previous studies. In this paper, we built a quadratic parametric directional distance function (DDF) to measure the carbon dioxide marginal abatement cost of Chinese provinces. To overcome the flaw of ignoring random errors in previous research, this paper compared results of stochastic frontier analysis (SFA) method and DEA method. Because DEA method only considers the inefficiency and SFA method can distinguish the random error from inefficiency, the result of the average carbon dioxide marginal abatement cost of each province calculated by SFA was 55 % lower than DEA method. As the random error may be introduced by chosen function form, Spearman test and paired sample T test were used to test the correlation of two methods' MAC results. The results show that the ranking order MAC results sequence of SFA method and DEA method is highly correlated. But the MAC value of SFA and DEA methods has significant difference. As half of the error comes from the random error, the MAC results calculated by SFA method are more precise than DEA method. So SFA method is more appropriate than DEA in this paper. This result reinforces the feasibility of the Chinese government carbon dioxide emission reduction target. However, this study proved that the carbon dioxide emissions and marginal

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abatement cost varied from province to province. Furthermore, there was no distinct correlation between carbon dioxide emissions and the marginal abatement cost. On the contrary, the marginal abatement cost was related to the industrial structures, energy consumption structures and natural resources endowment of each province. Therefore, two policy suggestions are proposed as CO_2 emission reduction principle: First, central government should establish CO_2 emission reduction targets based on MAC and local economic affordability. Second, resource endowments and embodied carbon transfer should be considered.

1 Introduction

The rapid development of the Chinese economy caused a large amount of carbon dioxide (CO_2) emissions. The CO_2 emissions of China increased quickly since 2000 (Song 2010; Guo et al. 2010), as the proportion of Chinese CO_2 emissions in the global emissions increased from 12.9 % in 2000 to approximately 23 % in 2010 (China Electricity Council 2011; Qi et al. 2014). According to a scientific forecast, the proportion will drastically increase to one-third of the global emissions if no effective CO_2 emission restriction is imposed in China (Liao and Wei 2011). Facing both the awareness of environmental protection and the international pressure on CO_2 emission reduction, the Chinese government made a commitment to achieve a 40–45 % reduction in carbon emissions per unit of GDP by 2020 compared with 2005 in the Climate Conference in Copenhagen in 2009 (China.com 2009). Lacking the central government's differentiation carbon dioxide reduction allocation, most provinces follow the national commitment. However, the industrial structure, energy consumption structure and natural resources of each province vary. Hence, it is not appropriate for all provinces[1] to impose identical CO_2 emission reduction criterion. To address this issue, previous studies researched the CO_2 emission abatement costs of China as a whole, as well as in individual Chinese provinces. Policy suggestions were also proposed by these studies.

The related studies about Chinese CO_2 abatement cost can be divided into two aspects: the marginal abatement cost (MAC) and macro-abatement cost (Wang et al. 2007; Fan et al. 2010; Xu and Dong 2011; Chang 2014). The CO_2 MAC, also called the CO_2 shadow price, is defined as the decrement amount of GDP when reduced to the last unit of CO_2 emissions in a certain abatement technology status (Fan 2011; Chen 2010; Matsushita and Yamane 2012). The CO_2 macro-abatement costs are defined as the decrement of GDP when imposing CO_2 emission reduction measures in a certain period (Wang et al. 2007, Fan et al. 2010, Xu and Dong 2011). The MAC can express the difficulty of CO_2 reduction more directly than the macro-abatement cost.

The directional distance function (DDF) was widely used in previous studies to calculate the CO_2 MAC. However, the different forms of the DDF model will lead to different calculation results. In addition, the two methods commonly used by previous studies to solve DDF, data envelopment analysis (DEA) and linear programming (LP), have flaws.

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[1] Beijing, Tianjin, Shanghai and Chongqing are municipalities.

The DEA method cannot deal with random errors and wrap them into inefficiency terms. Besides, the DEA method can only be applied when the distance function is differentiate everywhere. Moreover, the different frontier of production function and direction vector of the DEA method will lead to different CO_2 MAC results. The LP method does not take the measuring errors and approximation errors into consideration. Therefore, the calculated results of the CO_2 reduction cost varied in previous studies.

The DDF, followed by the stochastic frontier analysis (SFA) method, is able to differentiate between random noise and inefficiency; therefore, it was used to accurately measure the CO_2 MAC of Chinese provinces in this paper. In this paper, we used DDF and SFA method to overcome the flaw of ignoring random errors and approximation errors. And the calculation of marginal abatement cost of Chinese provinces in this paper contributed to proposing the policy suggestions.

This paper is organized as follows. Section 2 introduces the literature review of carbon dioxide abatement costs. Section 3 describes the model and method. Section 4 constructs the direction distance model and stochastic frontier analysis. The conclusion and policy suggestions are given in Sect. 5.

2 Literature review

The existing studies showed that a multitude of quantitative models were used to measure the CO_2 MAC.

2.1 Distance function

The existing studies showed that distance function model, especially parametric DDF model, was the most widely used model in CO_2 MAC. The Shephard output distance function was used by Lee (2005) and Rezek and Campbell (2007) to measure the American power station's MAC of sulfur dioxide, nitrogen dioxide, carbon dioxide and mercury. Hailu and Veeman (2000) then used Shephard output distance function to measure the Canadian paper industry's sulfur dioxide MAC. Lee and Zhang (2012) used input distance function to measure Chinese manufacturing industries' MAC. Wang and Wei (2014) used output distance function to measure CO_2 MAC of energy sectors of 30 Chinese provinces.

The DDF was applied in many fields of MAC. (Färe et al. 2005) measured the MACs of sulfur dioxide and carbon dioxide of 209 American power facilities. Matsushita and Yamane (2012) measured the CO_2 and low-level radioactive waste MACs of the Japanese electric power sector. Gómez-Calvet et al. (2014) measured the MAC of undesirable output in 25 European countries. Molinos-Senante et al. (2015) measured the MAC of Spanish wastewater treatment plants. Wang et al. (2014a) measured the MACs of total nitrogen, total phosphorus and chemical oxygen demand in the Chinese agriculture industry. In addition, previous studies measured the CO_2 MACs of the industrial sectors of China and Chinese provinces using the DDF (e.g., Chen 2010; Qin et al. 2011; Wen and Wu 2011; Wang et al. 2011a; Yuan et al. 2012; Chen 2013; Zhou et al. 2015).

Specifically, the CO_2 MACs of Chinese provinces were calculated by previous studies. Wang et al. (2011b) measured the CO_2 MACs of 28 provinces in 2007 by nonparametric DDF and DEA methods. Liu et al. (2011) measured the CO_2 MACs of 30 provinces from 2005 to 2007 by nonparametric DF and DEA methods. Huang and Wei (2012) measured the CO_2 MACs of 29 provinces from 1995 to 2007 by DDF and LP methods. Zhang et al.

Table 1 Comparison of the estimated CO_2 MACs of Chinese provinces

Studies	Method	Sample	MAC (yuan/ton)
(Wang et al. 2011a, b)	DDF/DEA	28 provinces, 2007	475
Liu et al. (2011)	DF/DEA	30 provinces, 2005–2007	1739
Huang and Wei (2012)	DDF/LP	29 provinces, 1995–2007	1128
Zhang et al. (2014)	DDF/LP	29 provinces, 2006–2010	80.19
He (2015)	DF/LP	29 provinces, 2000–2009	104

(2014) measured the CO_2 MACs of 30 provinces from 2006 to 2010 using DDF and LP methods. He (2015) measured the CO_2 MACs of 29 provinces from 2000 to 2009 using DF and LP methods. Due to the different methods and samples, the CO_2 MAC results varied (see Table 1).

2.2 Other models

The marginal cost curve model, vector autoregression (VAR) model and MARKAL model are commonly used in CO_2 MAC calculation. The marginal cost curve model was used by Li et al. (2010), Garg et al. (2014) and Wang et al. (2014b) to measure the CO_2 MACs of China, India and the Chinese energy sector, respectively. Ba and Wu (2010) and Xu and Lin (2015) used the VAR model to measure the CO_2 MACs of China and the Chinese transportation sector, respectively. The MARKAL model and the MARKAL-MACRO model were used to measure the CO_2 MACs of China and Taiwan's energy sectors(Chen 2005; Chen et al. 2007; Ko et al. 2010).

2.3 Comments on the literature

All of the above-mentioned models have room for improvement. Although the marginal cost curve model is simple in computation, the form of the cost curve will lead to a fitting error. The GDP was treated as the input in the VAR model and MARKAL model, while the distance function model considered the GDP as the output. Therefore, the GDP and CO_2 emission could be treated equally in the distance function model. Hence, the distance function model was more suitable, as the MAC had close relationship with economic loss.

The parametric distance function and nonparametric distance function were two popular methods used to measure CO_2 MACs (Liu et al. 2011). The parametric distance function needs to pre-establish a function which is different everywhere, while a specific function is not needed in the nonparametric distance function. The parametric distance function can be manipulated algebraically (Choi et al. 2012). In the 1970s, the Shephard output distance function was first used to measure the MACs of pollutants (Shephard 1970). The desirable and undesirable outputs were changed in the same ratio in the Shephard output distance function (Tu 2009; Dou and Li 2012; Chen 2011). However, in the reality, we want to increase the desirable output while decreasing undesirable output. The DDF which was proposed by Chambers et al. (1996) and (Färe et al. 1993) can achieve what reality requires. Besides, the directional distance function is invariant to affine data transformation under variable returns to scale (Aparicio et al. 2016).

The DEA and LP methods are usually used to solve the distance function. However, the DEA method can only be applied when the function is differentiable everywhere. Moreover, DEA method cannot deal with random errors and wrap it into inefficiency term (Lee

et al. 2002; Vardanyan and Noh 2006). Although the LP method can guarantee that the function is differentiable everywhere, the statistic noise will affect the results prominently, when particular points are ignored in the LP method (Zhang and Choi 2014; Zhou et al. 2010). Hence, both the DEA and LP methods have flaws.

To measure the MAC more precisely, the DDF and SFA were used in this paper to overcome DEA and LP defects. SFA method is included to overcome the flaw of ignoring random errors. Moreover, the SFA has a translation property, which can consider the influence of statistical noise on the model (Du and Mao 2015).

3 Model and Method

The DDF model measuring the MAC of undesirable output was proposed by Chambers et al. (1996) and (Färe et al. 1993) separately. The DDF depicts an input–output process with multiple inputs and outputs based on production function. Then, a production possibility curve (PPC) in the two-dimensional space was built. However, the PPC boundary optimal cannot be touched as the restriction of technology. Hence, the MAC can be measured by the distance between the output set and PPC boundary.

3.1 Establishment of DDF

In a certain Chinese province, we considered a production process that employs three inputs: capital (X_k), labor (X_L) and energy (X_E), one desirable output GDP (y) and one undesirable output CO_2 emission (b). The production technology set P can be defined as:

$$P = \{(y, b) : X \text{ can produce } (y, b)\} \tag{1}$$

The set has the following properties:

(1) Inputs are free disposability: The increase in inputs will lead to increased output, that is to say, if $x' \geq x$, then $P(x') \supseteq P(x)$.
(2) Weak disposability of undesirable outputs: The proportionate reduction of desirable and undesirable outputs simultaneously is possible with the given inputs; in other words, $(y, b) \in P$, $0 \leq \theta \leq 1$, then $(\theta y, \theta b) \in P$.
(3) Free disposability of desirable: The desirable output reduction is possible with the given inputs and undesirable output, so, $(y, b) \in P$, $y' \leq y$, then $(y', b) \in P$.
(4) Null-jointness: The desirable output must be accompanied by the generation of undesirable, and the only way to avoid desirable and undesirable outputs is to stop all production activities, which means $(y, b) \in P$, and $b = 0$, then $y = 0$.

Let $g = (g_y, g_b)$ as the directional vector which indicates the expansion of GDP in the direction of g_y and the reduction of CO_2 in the direction of g_b, then the DDF can be defined as:

$$\vec{D}(X, y, b; g) = \sup\{\beta : (y + \beta g_y, b - \beta g_c) \in P \tag{2}$$

where β represents the maximum proportion of expansion or reduction. $\beta = 0$ when the decision-making unit lies on the production frontier.

Figure 1 shows the schematic diagram of the DDF and the MAC of CO_2 emission.

Point A stands for a certain region in the production technology set P, while coordinate axis y and axis b represent the GDP and CO_2 emission in this region, respectively. A moves

Fig. 1 Directional distance function
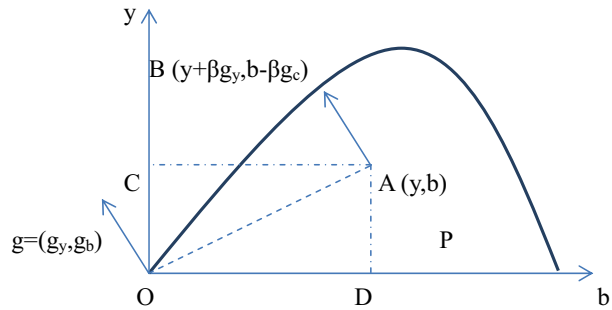
toward point B, which not only reduces the undesirable output (CO_2 emission), but also increases the desirable output (GDP). Hence, the DDF is measured by $\beta = AB/Og$.

3.2 Calculation of DDF

Translog and the quadratic form of function are used to calculate the DDF. The translog form of function depicts a simultaneously proportionate transformation of desirable and undesirable output. The quadratic form of function depicts a transformation of the increase in the desirable output, while decreasing the undesirable output at the same time (Wei et al. 2013). Hence, the quadratic form is suitable for reality.

$$\vec{D}(x, y, b; g_y, g_b) = \alpha_0 + \sum_{i=K,L,E} \alpha_i x_i + \alpha_y y + \alpha_b b + \frac{1}{2} \sum_{i=K,L,E} \sum_{j=K,L,E} \alpha_{ij} x_i x_j + \frac{1}{2} \alpha_{yy} y^2 + \frac{1}{2} \alpha_{bb} b^2$$
$$+ \sum_{i=K,L,E} \alpha_{iy} x_i y + \sum_{i=K,L,E} \alpha_{ib} x_i b + \sum_{i=K,L,E} \alpha_{ib} x_i b + \alpha_{yb} y b \qquad (3)$$

subject to:

$$\begin{aligned} g_y \beta_y - g_b \gamma_b &= -1; \\ g_y \beta_{yy} - g_b \mu_{yb} &= 0; \\ g_y \mu_{yb} - g_b \gamma_{bb} &= 0; \\ g_y \sum_{i=K,L,E} \delta_i - g_b \sum_{i=K,L,E} \eta_i &= 0; \\ g_y^2 \beta_{yy} + g_b^2 \gamma_{bb} - g_y g_b \mu_{yb} &= 0; \end{aligned} \qquad (4)$$

where α_0, α_i, α_b, α_{ij}, α_{yy}, α_{bb}, α_{iy}, α_{ib} and α_{yb} are the coefficients of the DDF function. β_y, β_{yy}, γ_b, γ_{bb}, μ_{yb}, δ_i and η_i are the coefficients of the constrains of DDF function.

The DEA and LP methods are usually used to solve DDF. However, the production function form will distinctly affect the results (Zhou et al. 2015). Hence, the SFA method, which can manage random errors, was used to solve DDF in this paper.

The SFA method was proposed by Aigner et al. (1977). Färe et al. (2005) applied the SFA to DDF.

$$\vec{D}_0(x_n, y_n, b_n; g_y, -g_b) + v^n - u^n = 0 \qquad (5)$$

where v represents random noise (random error) and satisfies a normal distribution (i.e., $v^n \sim N(0, \sigma_v^2)$, and u represents the inefficiency and satisfies a half-normal distribution (i.e., $u^n \sim N^+(0, \sigma_n^2)$.

The revenue of a certain region can be defined as:

$$R = p[y + (1 - \vec{D}_0)g_y] - p_b[b + (1 - \vec{D}_0)g_b] \tag{6}$$

where p represents the price of GDP ($p = 1$). p_b represents the price of CO_2 and indicates the MAC in this paper.

The MAC expressed by Eq. 7 after taking the partial derivation of b and y on Eq. 6 is:

$$p_b = \frac{\partial \vec{D}_0}{\partial b} \times \frac{\partial y}{\partial \vec{D}_0} \tag{7}$$

Equation 3 is the first-order homogeneous equation, which contains desirable and undesirable outputs. To measure the MAC, the natural logarithm was taken as the normalization process on Eq. 3.

$$\ln D_0 = \ln(D_0/y) = \ln D_0 - \ln y \tag{8}$$

Hence,

$$-\ln y = \alpha_0 + \alpha_k \ln x_k + \alpha_l \ln x_l + \alpha_e \ln x_e + \gamma_b \ln b + \frac{1}{2}\alpha_{kl} \ln x_k \ln x_l + \frac{1}{2}\alpha_{le} \ln x_l \ln x_e$$
$$+ \frac{1}{2}\alpha_{ke} \ln x_k \ln x_e + \frac{1}{2}\gamma_{bb}(\ln b)^2 + \eta_k \ln x_k \ln b + \eta_l \ln x_l \ln b + \eta_e \ln x_e \ln b - \ln D_0 \tag{9}$$

Therefore, if $0 < D_0 < 1$, then $\ln D_0 < 0$.

According to Eq. 4 and the numerical values of the inputs and outputs, the MAC can be expressed as:

$$p_b = -\frac{y}{b}\left(\frac{\partial \ln D_0}{\partial \ln b} \Big/ \frac{\partial \ln D_0}{\partial \ln y}\right)$$

$$= -\frac{y}{b}(\gamma_b + \gamma_{bb} \ln b + \eta_k \ln x_k + \eta_l \ln x_l + \eta_e \ln x_e) \tag{10}$$

3.3 Data

3.3.1 Data resources

The inputs in this study included capital, labor and energy. The perpetual inventory method, which is proposed by Goldsmith in 1951, is generally accepted by previous studies to measure capital stoke. The perpetual inventory method was widely used in the measurement of Chinese capital stoke (e.g., Zhang et al. 2004; Shan 2008; Xiang and Ye 2011; Fan 2012). The labor and GDP were derived from the *2014 China Statistic Yearbook* (CSY 2014), and the energy consumption was derived from the *2014 China Energy Statistic Yearbook* (CESY 2014). Moreover, the energy consumption was estimated as standard coal by considering the standard coal coefficient. The CO_2 emission was measured by the IPCC method.

3.3.2 Measurement of CO_2 emission

The CO_2 emission coefficient method is the most commonly used method to measure CO_2 emissions. According to the IPCC 4th Climate Change Assessment Report, 90 % of CO_2

emissions came from the combustion of fossil fuels in developed countries. Fossil fuels are the main energy resource in undeveloped countries, like China. Therefore, the CO_2 emissions from fossil fuels account for more than 90 % in China (Diakoulaki and Mandaraka 2007).

Due to the specific application of energy resources from the *2014 China Energy Statistic Yearbook*, seven energy resources were chosen to measure CO_2 emissions: coal, coke, kerosene, gasoline, fuel oil, diesel and natural gas. Most crude oil is used to produce fuel oil and gasoline. Hence, crude oil was not taken into account in this study.

According to the *2006 IPCC Guidelines for National Greenhouse Gas Inventories* (IPCC 2006), the CO_2 emissions can be calculated by Eq. 11:

$$C_i = E_{ij} \times \delta_j \qquad (11)$$

where C_i represents the CO_2 emissions of province i, E_{ij} represents the consumption of energy j in province I, and δ_j represents the coefficient of CO_2 emissions of energy j.

The emission factors of energy resources were discussed in previous studies (e.g., Xu et al. 2006; Wang and Zhu 2008). The U.S. Department of Energy Information Administration, the Chinese Academy of Engineering, the Sustainable Development Strategy Research Group of the Chinese Academy of Sciences, the Energy Research Institute of the National Development and Reform Commission and the Institute of Policy and Management of the Chinese Academy of Sciences all measure the emission factors of energy. However, the different varieties of energy and carbon contents of energy caused mixed results.

The measurement of the CO_2 emission factor proposed by the IPCC is shown by Eq. 12.

$$\delta_j = M_j \times \beta_j \times \varepsilon_j \times \omega \qquad (12)$$

where M_j represents the net calorific value of energy j, β_j represents carbon content of the unit heat value of energy j, and ε_j represents the carbohydrate oxidation of energy j. ω represents the gasification coefficient of CO_2 and has a constant value of 44/12. According to the standard coal coefficient, net calorific power, carbon content and oxygenation efficiency in the *2014 China Energy Statistic Yearbook* and Eq. 11, the CO_2 emission factors were measured (see Table 2).

By placing the energy consumption data and CO_2 emission factors of each energy in Eq. 10, the CO_2 emissions of Chinese provinces could be calculated.

3.4 Measurement of CO_2 MAC

Table 3 shows the descriptive statistics of five variables.

Take the logarithm of variables to unify the dimension.

Table 2 CO_2 emission factors of energy unit: kg-CO_2/kg

Energy	CO_2 emission factor	Energy	CO_2 emission factor
Coal	2.3816	Fuel oil	3.1704
Coke	2.8526	Diesel oil	3.0959
Kerosene	3.0333	Natural gas	2.1650
Gasoline	2.9250		

Table 3 Descriptive statistics of input and output variables

	Capital (10^9 yuan)	Labor (10^5 persons)	Energy (10^5 TCE)	GDP (10^9 yuan)	CO_2 (10^5 ton)
Mean	23898.26	4506.8	86358.48	20973.39	1610511
Maximum	58895.16	10644	210072.1	62163.97	4295983
Minimum	4443.382	578	13300.89	2101.05	143943.6

Table 4 DDF's coefficient

Coefficient	Value	Coefficient	Value
r_b	−0.038	η_l	−0.019
r_{bb}	0.068	η_e	0.008
η_k	−0.031		

The DDF's coefficient was calculated by using the CO_2 emission values in Eq. 10 and the Fronter4.1 software (see Table 4).

The CO_2 MACs of Chinese provinces can be measured by Eq. 10.

4 Results and discussion

4.1 Results
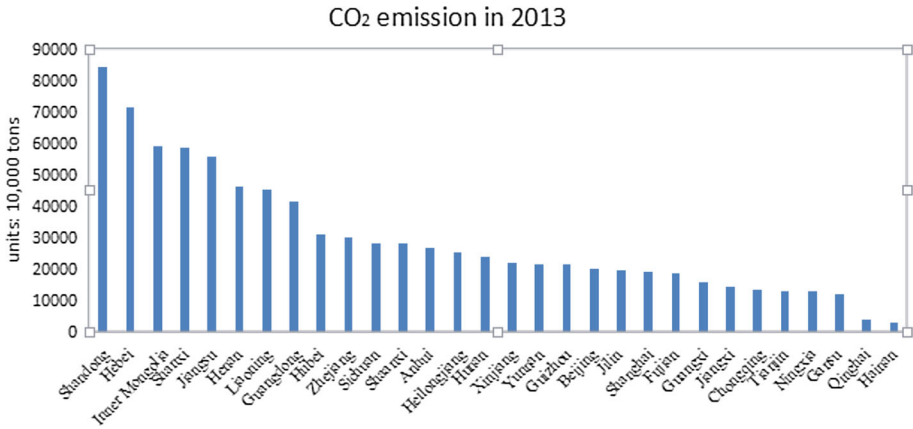
4.1.1 CO_2 emissions

According to Fig. 2, the CO_2 emissions of Chinese provinces differed drastically. The large CO_2 emitters, like Shandong Province, Hebei Province and Inner Mongolia, were provinces with flourishing industries. The small CO_2 emitters were classified into two groups. Beijing City and Tianjin City had small territories and well-developed tertiary industries. Provinces which are less developed like Ningxia Province, Gansu province and Qinghai Province were also small emitters.

4.1.2 MAC

In this paper, we used DEA and SFA methods to calculate the 30 provinces' carbon dioxide MAC in 2013. Fronter4.1 and Deap2.1 softwares are used.

According to Fig. 3, the MACs of Chinese provinces differed exceedingly. The calculation results of the SFA method were as follows. The eastern provinces, like Beijing and Shanghai, had high MACs, while the western and southern provinces, like Guizhou and Gansu, had low MACs. Provinces with affluent industries, like Shanxi and Inner Mongolia, also had low MACs. The results of the DEA method shows that Beijing, Shanghai, Guangdong and Tianjin have over 200 yuan/ton MACs and the MAC value of Inner Mongolia and Ningxia is 0.

The average result of the MAC calculated by the SFA method was 55 % lower than the DEA method.

Fig. 2 CO_2 emission of Chinese provinces in 2013 (units: 10 thousand tons)
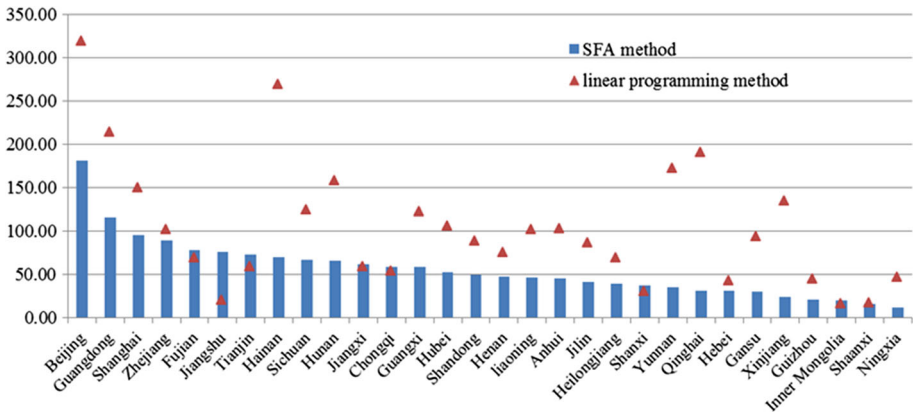
Fig. 3 CO_2 MAC of Chinese provinces in 2013 using the SFA and DEA methods (units: yuan/ton)

4.2 Discussion

4.2.1 Comparison between SFA and DEA methods

SPSS 21.0 software was used to conduct Spearman test and paired sample T test. Figure 4 shows the correlation coefficient in Spearman test is 0.818 which means the ranking order of MAC results of SFA and DEA methods is highly related. The MAC ranking order of most of the provinces is stable except Heilongjiang, Shandong, Henan and Sichuan. Heilongjiang and Shandong have huge CO_2 output. Henan and Sichuan have large energy input. Besides, the capital input in Sichuan is also high. The large difference between inputs and outputs will lead to different production frontier, and the MAC ranking order will be different.

Correlations

			SFA	DEA
Spearman's rho	SFA	Correlation Coefficient	1.000	.818**
		Sig. (2-tailed)	.	.000
		N	30	30
	DEA	Correlation Coefficient	.818**	1.000
		Sig. (2-tailed)	.000	.
		N	30	30

**. Correlation is significant at the 0.01 level (2-tailed).

Fig. 4 Spearman test correlations

Figure 5 shows the basic information of MAC sequence calculated by SFA and DEA. The mean value, standard deviation and the standard error mean of SFA sequence were lower than those of DEA sequence. So the SFA sequence is more stable than DEA sequence.

Figure 6 shows the absolute value of paired sample T test is 7.182 and it is higher than the critical value when the degree of freedom is 29. Hence, the value of SFA and DEA sequence has significant difference.

4.2.2 Reliability test of the SFA result

Fronter4.1 software was used to measure the coefficient of DDF. The result showed that $\gamma^2 = \sigma_u^2/\sigma^2 = 0.5$. The result of r represents that half of the error was caused by random errors. Hence, the SFA method is appropriate in this paper.

Meanwhile, the coefficient of Eq. 10, standard deviation and statistical tests at 1 % significance are shown in Table 5.

The critical value of 19° of freedom was 1.729, as determined from the critical value table of the t test. The absolute value of the t ratio value in Table 4 was greater than the critical value, which meant that the t test of coefficient was significant and the coefficient result was reliable.

Our calculation results of the average carbon dioxide MAC of those provinces are 55 % less than the previous calculations, so from the economic point of view, the national CO_2 emission reduction target of 40–45 % is feasible.

4.2.3 Influence factor analysis of MAC

The composition of CO_2 emissions and the comparison between CO_2 emission and MACs are shown in Figs. 7 and 8, respectively.

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	SFA	56.0246	30	34.28932	6.26034
	DEA	125.5333	30	77.24155	14.10231

Fig. 5 Basic information of MAC sequence calculated by SFA and DEA

Paired Samples Test

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	SFA - DEA	-69.50872	53.01005	9.67827	-89.30300	-49.71444	-7.182	29	.000

Fig. 6 Paired sample test value

Table 5 Coefficient of DDF, standard deviation and t ratio

| Coefficient	Coefficient value	Standard deviation	T ratio
r_b	−0.038	2.682	−1.825
r_{bb}	0.068	2.041	3.376
η_k	−0.031	1.374	−2.319
η_l	−0.019	1.298	−1.923
η_e	0.008	1.147	−7.082
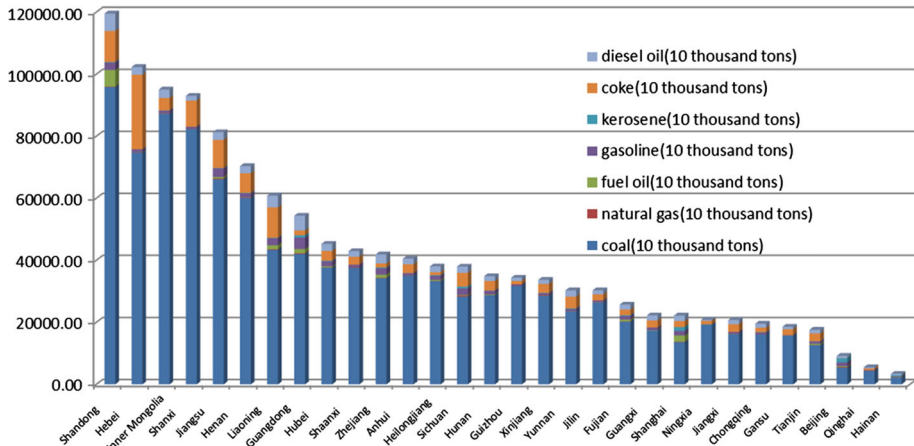
Fig. 7 CO_2 emissions of Chinese provinces in 2012

In general, there were no distinct correlations between the CO_2 emissions and MACs of the Chinese provinces. Industrial structures, energy consumption structures and natural resources were the factors that influenced the CO_2 emissions and MACs of Chinese provinces.

(1) Industrial structures

Figure 7 shows that large CO_2 emitters like Shandong, Hebei, Shanxi and Inner Mongolia were highly developed industry provinces. According to the 2013 *China Statistic Yearbook* (CSY 2014), the ratios of the secondary industries of large emitters were more than 50 %. High-carbon secondary industries, such as the steel industry and mining industry, were the leading industries in those large emitters. Hence, the MACs of large emitters were low. Small emitters were divided into two groups. The first group consisted of provinces with highly developed, but low-carbon tertiary industries, such as the financial industry, wholesale and retail trade industry and catering accommodation industry. Beijing,
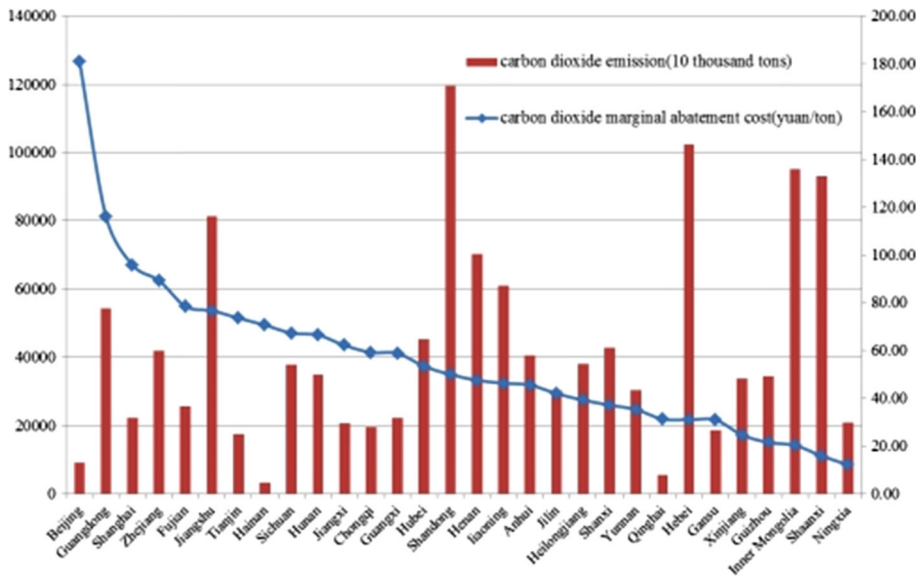
Fig. 8 Comparison between CO_2 emission and MAC of Chinese provinces

Tianjin, Shanghai and Hainan were in the first group. The ratios of the low-carbon industries in those provinces were more than half of the total ratio of the tertiary industries. Low-carbon industries emit little CO_2, and it would be a large economic loss to reduce CO_2 emission. Therefore, the MACs of the first group of small emitters were low. The other group of small emitters included western provinces, like Ningxia, Gansu and Qinghai, with rising new energy industries. However, there were still metallurgy industries with large CO_2 emissions in those provinces. Hence, with relatively small CO_2 emissions, the MACs of the second group of provinces were low.

(2) Energy consumption structures

Coal was the main emitter of CO_2 emissions in the whole country (see Fig. 7). The average ratio of the CO_2 emissions from the coal combustion of 30 Chinese provinces was 80 %. Coal was mainly used for power generation, the production of building materials and domestic use. Moreover, coke, mainly used in metal smelting, had the second large CO_2 emission. Hebei Province, one of the largest steel provinces in China, consumed a large amount of coke for metal smelting, with 23 % of the CO_2 emissions coming from coke. Diesel oil was mainly used as fuel for large vehicles and vessels. Gasoline was the fuel for compact cars. The blossoming trade and large demand for transportation in Shanghai, Guangdong and Zhejiang consumed large amounts of diesel oil and gasoline. Small amounts of kerosene and fuel oil were consumed, and natural gas is a relatively clean energy. The CO_2 emissions from these three energies were low. It is easier to reduce high-carbon energy's CO_2 emission. Therefore, the MACs of Hebei Province and Shandong Province were low, while Beijing and Shanghai were high.

(3) Natural resources

Southern provinces, such as Hubei, Sichuan and Yunnan provinces, had abundant hydropower. The ratios of hydropower in Hubei, Sichuan and Yunnan provinces among all provinces were 16, 17 and 14 % in 2013, respectively. Inner Mongolia, Hebei and Liaoning provinces had affluent wind power resources, and the ratios of installed capacity

of wind-driven power among all provinces were 35, 10 and 9 %, respectively (2014 China Energy Statistic Yearbook). Hydropower and wind power are clean energy and will not produce CO_2 emissions. Hence, the MACs of the above-mentioned provinces were high.

5 Conclusion and the policy suggestions

5.1 Conclusion

(1) As SFA method can distinguish the random error from inefficiency, the MAC results were more precise than DEA method. But SFA MAC average results were 55 % less than the DEA method's results in this study as random errors were taken into account. So from the economic point of view, the national CO_2 emission reduction of 40–45 % is feasible.

(2) The ranking order MAC results sequence of SFA method and DEA method is highly correlated. But the MAC value of SFA and DEA methods has significant difference.

(3) There were no distinct correlations between CO_2 emissions and MACs.

(4) The CO_2 emissions and MACs of each province varied, due to the different industrial structures, energy consumption structures and natural resources among Chinese provinces.

5.2 Policy suggestions

According to the results of this study, MAC of each province is substantially different. Hence, the central government should formulate a fair CO_2 emission reduction principle considering the MAC, the different industrial structure and the level of economic of each province. Two suggestions are made as follows:

5.2.1 Formulate CO_2 emission reduction targets principle based on MAC and affordability of the local economy

The MAC and the affordability of the local economy should be considered when allocating the annual CO_2 emission reduction target of each province. On the other hand, the central government should highlight the leading role of the developed provinces. Each province has different MAC due to the different industry structure and leading industry in the province. The major industries of less developed provinces are mostly high CO_2 emission and low value-added secondary industries such as thermal power, steel and chemical industries. The MAC of those provinces is relatively lower, and their CO_2 emission reduction is easier. The developed provinces, on the contrary, have high economic development level and high value-added tertiary industries. The MAC of developed provinces is high, and their CO2 emission reduction is more challenging.

Therefore, the central government should first ensure the accomplishment of the total CO_2 emission reduction task and demonstrate the CO_2 emission reduction determination. Based on the principle that lower MAC reduces more CO_2 emissions and higher MAC reduces less, the annual CO_2 emission reduction targets of each provinces can then be determined by reasonably increasing the targets in lower MAC provinces and appropriately decreasing the targets in higher MAC ones. Furthermore, as the developed provinces with high MAC reduce less CO2 emissions, a feedback mechanism in which developed

provinces compensate developing provinces should be established. Finally, the leading role of developed provinces in CO_2 emission reduction should be established, while industrial structure transformation and tertiary industry developing should be encouraged in developing provinces.

5.2.2 CO_2 emission reduction targets should consider natural resource endowments and embodied carbon transfer

When determining the annual emission reduction targets, the central government should establish a corresponding subsidy mechanism in accordance with the supply and demand of raw material and energy between the provinces. The transportation of raw material and energy between provinces will result in embodied carbon transfer. CO_2 emission reduction target should consider the natural resource endowment and raw material and energy import/export situation. A subsidy mechanism should be established to compensate raw material and energy output provinces to ensure that the emission reduction targets of the provinces are fair and reasonable.

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