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Original Research

An Empirical Study on the Shadow Price of Carbon Dioxide Emissions in China's Industry

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Abstract

The shadow price of CO_2 emissions plays a fundamental role in evaluating CO_2 abatement costs. In this paper, a directional environment production frontier function model based on the non-parametric method is established to measure the distance between actual production points and the effective production frontier surface, with which CO_2 shadow prices of 36 industrial sectors in China are estimated during 2006-2015. The empirical studies show that: (1) there is a negative relationship between shadow price and carbon intensity. The average shadow price of the top five sectors with the highest carbon intensity is 373.92 Yuan/t, while the top five sectors with the lowest carbon intensity are 50254.54 Yuan/t. CO_2 abatement potential differs significantly across sectors, so the sector-specific environmental policies should be concerned; (2) shadow prices of CO_2 have an upward tendency with time in all sectors, and they rise with a greater speed in the low carbon intensity sectors than in the high ones, which implies that emissions reduction is accompanied by increasing economic sacrifices; (3) there is an additional 3.07% growth of industrial value owing to the CO_2 emissions increasing by 6.39% every year; and (4) two typical sectors are selected to further analyze their CO_2 abatement characteristics, respectively.

Keywords: shadow price, carbon dioxide emissions, industrial sectors, directional environment production frontier function

Introduction

The Paris Conference holds great significance in terms of establishing a legally binding and global agreement on climate change with the aim of keeping global warming below 2ºC above preindustrial levels [1]. However, as one of the largest economies in the world, China is the biggest emitter worthy of the name and its annual growth of emissions has been more than the sum of North America and Europe [2]. As a responsible country, China has committed to reducing CO_2 emissions per unit of GDP (i.e., carbon intensity) by 40-45% by 2020 compared to 2005 [3]. Furthermore, in the Paris Climate Conference, China's government pledged to peak its CO_2 emissions no later than 2030 [4] and further reduce carbon intensity by 60-65% of the 2005 level [5, 6]. Determining how large the economic sacrifice will be for achieving the upper goals has attracted increasing attention in recent literature [7,

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8]. The estimation of marginal abatement cost (MAC) is thus of great significance. In earlier studies, due to the lack of applicable tools, the cost of pollutants is generally measured with the physical quantity or the treatment cost of pollutants, which cannot reflect its real cost. Afterward, people gradually turned to simulate the shadow price of pollutants, which is the opportunity cost in terms of less output or more inputs when reducing the pollutant with one unit [9-11]. In recent years, the distance function has been widely used to estimate the shadow price of pollutants. It was first proposed by Shephard [12]. Afterward, Färe et al. [13] incorporated undesirable outputs into the Shephard distance function and constructed a Shephard output distance frontier function to estimate the shadow price of undesirable outputs. Hailu and Veeman [14] employed a translog Shephard input distance function to compute the shadow price. In this context, the Shephard distance function was creatively employed to derive the shadow price of pollutants and then there emerged massive literature for estimating the shadow price of pollutants based on it [15-20].

However, the Shephard distance function has the drawback of assuming the same proportional adjustment for all outputs (desirable and undesirable), which is not in accordance with the expectations of policymakers [21]. Comparatively, a directional distance function is able to distinguish the discrepancy between good outputs and bad ones with negative externality, and allows for the simultaneous expansion and contraction in desirable and undesirable outputs, respectively. Therefore, it can construct a model covering joint productions of good and bad outputs more objectively. So, in the presence of environmental regulation, the directional distance function is more suitable for estimating the shadow price of pollutants [22, 23]. Matsushita and Yamane [24] employed a directional distance function to derive shadow prices of CO_2 in the electric power sector of Japan. Xie et al. [25] investigated the inefficiency level, shadow price and substitution elasticity of industrial SO_2 emissions in China from 1998 to 2011 based on a directional distance function. Lee et al. [26] conducted an empirical study with a directional distance function on Korea's electric power industry during the period of 1990-1995.

Generally, there are still two ways to describe a distance function, i.e., parametric or non-parametric [27]. Zeng et al. [28] used parametric directional distance function to estimate the shadow prices of China's provincial SO_2 emissions for 2001-2013. Molinos-Senante et al. [29] employed a parametric model to estimate the shadow price of CO_2 in 25 Spanish wastewater treatment plants in 2010. Molinos-Senante and Guzman [30] computed the shadow price of CO_2 for the case of Chilean drinking water treatment plants using parametric directional distance function estimation. Generally speaking, the parametric method has specific economic meaning, while some defects still exist in this method. First, it needs to presuppose the function form of the production frontier, which is a great challenge for empirical research. Second, the parametric model confines the shadow price as an average result and the value of each individual cannot be obtained. Compared with the parametric method, the non-parametric method avoids the possible mistakes of falsely assuming the function form, and then becomes more flexible for the application. Second, it is insensitive to the measurement units of variables

Table 1. Summary of studies on estimating CO_2 shadow prices of China's industrial sectors.

Study	Sample	Period	Methodology	Shadow price	Unit
Xie et al. [34]	9 key industrial sectors	2005-2014	P/NP-DDF	731.75	Yuan/t
Du et al. [35]	648 coal-fuelled power plants	2008	P-DDF	235	$/t
Du and Mao [36]	518/640 power plants	2004/2008	P-DDF	955/1142	Yuan/t
Liu et al. [37]	Electric power generation sector	2000-2012	P-DDF	116.7	Yuan/t
Peng et al. [38]	Thermal power sector	2004-2013	P-DDF	316.21	Yuan/t
Xian et al. [39]	Power sector	2011-2015	P-DDF	294.5	Yuan/t
Liu and Lin [8]	Construction sector	2003-2012	P-DDF	567.1	Yuan/t
Wang et al. [40]	Construction sector	2004-2014	P-DDF	1698.04	Yuan/t
Lee and Zhang [41]	30 manufacturing sectors	2009	P-SIDF	3.13	$/t
Yuan et al. [42]	24 sectors	2004 /2008	NP-DDF	15537/17258	Yuan/t
Chen [43]	38 industrial sectors	1980-2008	P/NP-DDF	26800/32700	Yuan/t
Wang et al. [52]	Iron and steel sector	2014	P-DDF	2563.67	Yuan/t
Wang and He [53]	Regional transportation sectors	2007-2012	NP-DDF	5410	Yuan/t

Notes: SODF, SIDF and DDF denote Shephard output distance function, Shephard input distance function and directional distance function. P and NP denote parametric method and non-parametric method respectively.

and need not transform the data into dimensionless form. Finally, the weights of inputs and outputs are decided through optimization solution, which improves the objectivity standard of the estimation. Although the non-parametric method ignores the impact of random shocks on the frontier output and its results cannot be statistically tested, the random impact is averaged and greatly weakened when the samples are most abundant, and it distorts little on the overall characteristics of the examined objects. Mekaroonreung and Johnson [31], Lee and Zhou [32], Kaneko et al. [33] and Xie et al. [34] all used the non-parametric method to describe the distance function and thereby estimate shadow prices of pollutants. Therefore, the non-parametric method is more practical for calculating the CO_2 shadow price and is used in this study.

In China, industrial value-added accounted for over 30% of GDP, while its CO_2 emissions account approximately for 88% of total emissions. More and more strict regulations on CO_2 emissions undoubtedly hamper industrial production. So, CO_2 shadow price in industry is well worth studying. Table 1 lists some previous studies on the CO_2 shadow price of industrial sectors. Most of them focus on the CO_2 shadow price in a single sector, such as power plants [35-39] or construction sector [8, 40]. Some others focus on several sectors [41, 42]. Only a very few studies have covered all industrial sectors [43]. Therefore, shadow prices of CO_2 emissions in all industrial sectors deserve further study.

There are four attributions of this paper: (1) construct a directional environment production frontier function model based on the non-parametric method, with which the CO_2 shadow prices of 36 industrial sectors of China are estimated from 2006 to 2015; (2) divide all the industrial sectors into two groups of high-carbon and low-carbon intensity sectors. Then make a deep study of the characteristics and variation trends of CO_2 shadow prices in each group, thereby putting forward sector-specific environmental policies and targets; (3) study the marginal effect and absolute effect of CO_2 emissions on the industrial value-added and investigate the environmental cost of economic growth; (4) select the typical sector of Manufacture of Computers, Communication and other Electronic Equipment from the low-carbon intensity group and the sector of Production and Supply of Electric Power and Heat Power from the high-carbon intensity group respectively, for further analyzing their CO_2 shadow prices and abatement potential.

The remainder of this paper is organized as follows. Section 2 constructs the directional environment production frontier function model that is applied to estimate the shadow price. Section 3 discusses data sources and statistical characteristics of variables. Section 4 denotes empirical results and discussions, and Section 5 denotes the main conclusions and policy implications.

Methodology

Output Possibility Boundary

In this paper, bad outputs are integrated into multi-output productivity measurement framework and then output possibility boundary is constructed [44].

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

$P(x)$ includes all optimal combinations of good outputs (y) and bad outputs (b). Here, inputs are expressed as $x_k(k = 1, ..., K)$, while $y_k(u = 1, ..., U)$ and $b_v(v = 1, ..., V)$ respectively represent good outputs and bad outputs. There are four following assumptions about output possibility boundary $P(x)$.

(1) Free disposability or strong disposability of inputs means that good outputs would not be reduced as inputs increase, i.e., if $x_1 \leq x_2$, then $P(x_1) \subseteq P(x_2)$
(2) Free disposability of good outputs denotes that a reduction in good outputs can be achieved at no cost, i.e., if $(y, b) \in P(x)$ and $y_1 \leq y$, then $(y_1, b) \in P(x)$.
(3) Weak disposability means the abatement of bad outputs would not be free and usually at the expense of the reduction in good outputs, namely, if $(y, b) \in P(x)$, and $0 \leq \alpha \leq 1$, then $(\alpha y, \alpha b) \in P(x)$.
(4) Null-jointness indicates that good outputs and bad outputs belong to joint production, formally, if $(y, b) \in P(x)$ and $b = 0$ then $y = 0$.

According to Färe et al. [13], a mathematical model is constructed to express output possibility boundary that satisfies the above hypotheses. Correspondingly, environmental technology is defined as:

$$P(x) = \begin{cases} \lambda Y \geq y_{i,u}, & u = 1, \dots, U \\ \lambda X \leq x_{i,k}, & k = 1, \dots, K \\ \lambda B = b_{i,v}, & v = 1, \dots, V \\ \lambda_i \geq 0, & i = 1, \dots, I \end{cases} \tag{2}$$

…where $i = 1, ..., I$ represent decision-making units and $(X_{(I \times K)}, Y_{(I \times U)}, B_{(I \times V)})$, represent input-output matrix. Meanwhile, λ signifies the proportion that per unit of resource is used to put into production.

Directional Environment Distance Function

Directional environment distance function gives the possibility that good outputs increase while bad outputs decrease simultaneously. It fully describes the characteristics of the production process and inherits all properties of output possibility boundary. This paper assumes that good outputs and bad outputs satisfy the requirement for the above environmental technology and pollutant emissions have no constraint of environmental regulation.

According to Färe et al. [45], we specify the production technology by constructing directional environment output distance function with direction vector g = (g_y, $-g_b$) and $g \neq 0$. Here, directional environment output distance function can be expressed as:

$$\vec{D}_0(y,x,b;g_y,-g_b) = \sup[\delta:(y+\delta g_y, b-\delta g_b) \in P(x)] \quad (3)$$

…where δ denotes the possible maximum reduction of bad outputs and expansion of good outputs under given production technology and inputs.

Directional Environment Production Frontier Function

Static Directional Environment Production Frontier Function

The relationship between directional environment production frontier function and directional environment distance function is:

$$R(y,x,b;g_y - g_b) = (1+\vec{D}_0(y,x,b;g_y,-g_b))y \quad (4)$$

This paper chooses $g = (y, -b)$ as the directional vector, which economically means the proportional expansion of good outputs and constriction of bad outputs is based on the existing scale. Fig. 1 gives the explanation of the directional environment production frontier function. According to whether or not to consider the period change, the function is divided into two types, namely static or dynamic directional environment production frontier function. In this sense, static directional environment production frontier function of t period is constructed as follows:

$$\begin{aligned} & R^t(y_i^t, x_i^t, b_i^t; y_i^t, -b_i^t) = \max_{\lambda,\delta}(1+\delta)y_i^t \\ s.t\quad & \lambda_i^t Y_{I\times U}^t \geq (1+\delta)y_{i,u}^t, \quad u=1,\cdots,U \\ & \lambda_i^t X_{I\times K}^t \leq x_{i,k}^t, \quad k=1,\cdots,K \\ & \lambda_i^t B_{I\times V}^t = (1-\delta)b_{i,v}^t, \quad v=1,\cdots,V \\ & \lambda_i^t \geq 0, \quad i=1,\cdots,I \end{aligned} \quad (5)$$

Similarly, constructing static directional environment production frontier function in (t + 1) period only needs to replace the superscript t of Equation (5) with (t + 1).

Dynamic Directional Environment Production Frontier Function

Dynamic directional environment production frontier function takes the period factor into account, which is utilized to analyze the relationship between pollutant changes and outputs in different periods. Here, first we construct a dynamic environment production frontier function with outputs and inputs of t period:

$$\begin{aligned} & R^t(y_i^t, x_i^t, b_i^{t+1}; y_i^t, -b_i^t) = \max_{\lambda,\delta}(1+\delta)y_i^t \\ s.t\quad & \lambda_i^t Y_{I\times U}^t \geq (1+\delta)y_{i,u}^t, \quad u=1,\ldots,U \\ & \lambda_i^t X_{I\times K}^t \leq x_{i,k}^t, \quad k=1,\ldots,K \\ & \lambda_i^t B_{I\times V}^t = b_{i,v}^{t+1} - \delta b_{i,v}^t \quad v=1,\ldots,V \\ & \lambda_i^t \geq 0, \quad i=1,\ldots,I \end{aligned} \quad (6)$$

Secondly, a dynamic environmental production frontier function based on outputs and inputs of (t + 1) period is constructed.

$$\begin{aligned} & R^{t+1}(y_i^{t+1}, x_i^{t+1}, b_i^t; y_i^{t+1}, -b_i^{t+1}) = \max_{\lambda,\delta}(1+\delta)y_i^{t+1} \\ s.t\quad & \lambda_i^{t+1} Y_{I\times U}^{t+1} \geq (1+\delta)y_{i,u}^{t+1}, \quad u=1,\ldots,U \\ & \lambda_i^{t+1} X_{I\times K}^{t+1} \leq x_{i,k}^{t+1}, \quad k=1,\ldots,K \\ & \lambda_i^{t+1} B_{I\times V}^{t+1} = b_{i,v}^t - \delta b_{i,v}^{t+1} \quad v=1,\ldots,V \\ & \lambda_i^{t+1} \geq 0. \quad i=1,\ldots,I \end{aligned} \quad (7)$$

$X^t_{I\times K}$ and $Y^t_{I\times U}$ are input matrix and output matrix with all decision-making units of t period. Correspondingly, $X^{t+1}_{I\ K}$ and $Y^{t+1}_{I\ U}$ are respectively the input matrix and output matrix of (t + 1) period.

Estimation of Shadow Price of CO_2 Emissions

Following Caves et al. [9] and Färe et al. [46], this paper exploits the geometric mean of environmental production frontier functions in two periods. Constructing marginal output effect (*ME*) with the relationship between environment production frontier function and pollutants emissions is as follows:

$$ME = \left[\frac{R^t(y^t, x^t, b^{t+1}; y^t, -b^t)}{R^t(y^t, x^t, b^t; y^t, -b^t)} \times \frac{R^{t+1}(y^{t+1}, x^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})}{R^{t+1}(y^{t+1}, x^{t+1}, b^t; y^{t+1}, -b^{t+1})}\right]^{\frac{1}{2}} - 1 \quad (8)$$

This paper takes CO_2 as bad outputs. From the perspective of the relationship between CO_2 emissions and outputs, the shadow price of CO_2 emissions can be expressed as:

$$CSP = \frac{y_{i,t-1} \text{ X } ME_{i,t}}{CO_{2i,t} - CO_{2i,t-1}} \quad (9)$$

Data Source and Statistical Characteristics of Variables

This paper takes China's 36 industrial sectors as basic research units, where industrial value-added represents desirable outputs and CO_2 emissions represent undesirable outputs. Capital stock, employees and energy consumption make up the inputs. All data are collected from [47-49]. Statistical descriptions of variables are listed in Table 2.

(1) Capital stock. Generally, annual real capital stock is estimated by the perpetual inventory method.

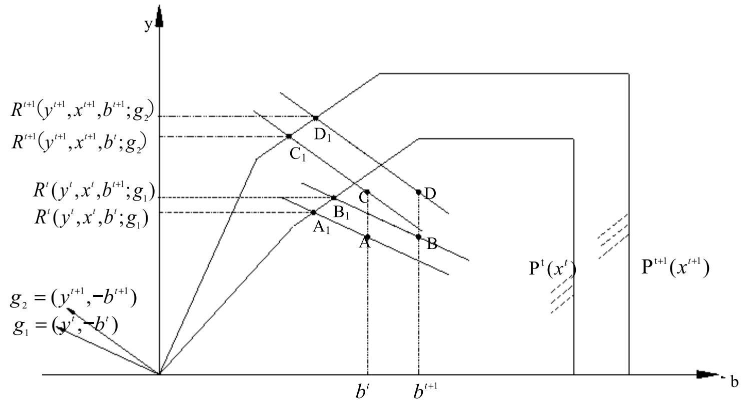

Fig.1. The illustration of Directional Environmental Production Frontier Function.

According to existing research results and the proposed method by Chen Shiyi [50], this paper extends current capital stock sequence to 2015.

(2) Carbon dioxide emissions. Based on the method given by IPCC.2006 [51] and eight main energy sources (i.e. coal, coke, crude oil, gasoline, diesel oil, kerosene, natural gas and fuel oil), CO_2 emissions can be estimated.

Results and Discussion

Overall Analysis of the Industry

Sector Heterogeneity of the Shadow Price of CO_2 Emissions

In this section, 36 sectors are ranked in ascending order based on carbon intensity, and then the former half is defined as the low-carbon intensity sector (LCIS) while the latter half is the high-carbon intensity sector (HCIS). Then we analyze the characteristics of the shadow price and further discuss its sector heterogeneity.

Table 3 illustrates average shadow prices of CO_2 emissions of 36 industrial sectors during 2005-2015. From it, we can see that the top five sectors with the highest carbon intensities are heavy chemical industrial sectors, whose average shadow price is 373.92 yuan/t – far below the average value of the whole industry. On the contrary, the top five sectors with the lowest carbon intensity are equipment manufacturing sectors, in which the average shadow price is 50254.54 yuan/t – far above the average value of the whole industry. Thus it can be seen that shadow price has strong sector heterogeneity. The essence of emissions abatement lies in energy efficiency. On grounds of diverse CO_2 emissions and energy efficiency across sectors, the difficulties and costs of further emissions abatement are quite different. Considering massive CO_2 emissions and considerable room for improvement in energy efficiency in HCIS, it is relatively easy to reduce CO_2 emissions, and as a result we do not need to pay much for it. On the contrary, LCIS possesses smaller emissions and higher energy efficiency, and further emissions abatement on this basis is more difficult and costly. Sequence the numbers in the second and fifth columns in ascending order and the order is indicated by the corresponding superscript. Then we can find that there is a negative relationship between carbon intensity and shadow price. As shown in Table 3, the sectors included in LCIS simultaneously embody the characteristics of low-carbon intensity and high shadow price, while the situation of sectors belonging to HCIS are completely opposite. For example, the carbon intensity of Manufacture of Computers,

Table 2. Statistical descriptions of variables.

Variable	Number	Mean	Standard deviation	Minimum	Maximum
Industrial value-added (10^8 Yuan)	396	4332.89	4006.46	3.7	21217
Producer price index of industrial products (2005 = 100)	396	113.58	18.40	78.80	186.75
Capital stock (10^8 Yuan)	396	12283.90	15305.34	218.2	109125.36
Price index of investment on fixed assets (2005 = 100)	11	115.93	10.00	100	126.24
Annual average number of employees (10^4 persons)	396	341.71	278.55	0.3	1479.57
Energy consumption (10^4 t of tce)	396	6499.75	11903.2	101.68	69342.42
CO_2 emissions (10^4 t)	396	24112.25	63265.34	0.76	381628.06

Note: tce refers to “standard” tons coal equivalent.

Table 3. Shadow prices of CO_2 emissions and output effects by sectors (averages during 2006-2015).

Project	Carbon intensity (t/ 10^4 Yuan)	Marginal effect (%)	Absolute effect (10^8 Yuan)	Shadow price (Yuan/t)
Low Carbon Intensity Sector (LCIS)				
Manufacture of Tobacco	0.05 [1]	-1.57	-71.10	40897.95 [34]
Manufacture of Computers, Communication and other Electronic Equipment	0.06 [2]	-0.18	-88.70	83891.78 [36]
Manufacture of Measuring Instrument and Machinery	0.07 [3]	0.77	-6.26	62618.54 [35]
Manufacture of Electrical Machinery and Apparatus	0.14 [4]	5.71	425.19	34179.63 [33]
Manufacture of Leather, Fur, Feather and Related Products and Footwear	0.15 [5]	1.90	49.22	29684.80 [32]
Manufacture of Furniture	0.16 [6]	4.13	34.36	29449.05 [31]
Printing and Reproduction of Recording Media	0.17 [7]	4.06	44.16	28107.05 [30]
Manufacture of Textile, Wearing Apparel and Accessories	0.21 [8]	0.83	14.99	21360.56 [28]
Articles for Culture, Education, Arts and Crafts, Sport and Entertainment	0.23 [9]	7.83	71.72	23839.87 [29]
Manufacture of Transportation Equipment	0.27 [10]	0.93	-0.26	16727.58 [26]
Production and Supply of Water	0.28 [11]	3.29	11.66	17583.98 [27]
Manufacture of Metal Products	0.33 [12]	2.88	118.95	13991.53 [25]
Manufacture of Special Purpose Machinery	0.34 [13]	-0.43	-74.88	13776.49 [23]
Mining and Processing of Non-ferrous Metal Ores	0.38 [14]	3.65	40.50	12352.63 [22]
Manufacture of General Purpose Machinery	0.42 [15]	2.41	58.69	10831.94 [21]
Manufacture of Rubber and Plastic Products	0.46 [16]	1.95	64.34	9903.63 [20]
Manufacture of Medicines	0.51 [17]	5.19	208.87	9251.71 [19]
Timber, Manufacture of Wood, Bamboo, Rattan, Palm and Straw	0.55 [18]	22.14	195.97	13940.23 [24]
Average	0.27	3.64	60.97	26243.83
High Carbon Intensity Sector (HCIS)				
Processing of Food from Agricultural Products	0.65 [19]	4.69	291.10	7346.11 [18]
Manufacture of Liquor, Beverages and Refined Tea	0.67 [20]	3.53	115.54	7074.70 [17]
Mining and Processing of Ferrous Metal Ores	0.75 [21]	5.33	61.01	5918.10 [16]
Manufacture of Textile	0.88 [22]	4.48	358.12	5710.29 [15]
Manufacture of Foods	0.97 [23]	3.62	89.68	4758.18 [14]
Extraction of Petroleum and Natural Gas	1.21 [24]	-0.49	-33.30	4044.59 [13]
Mining of Other Ores	1.69 [25]	-9.28	-0.06	2575.20 [11]
Mining and Processing of Non-metal Ores	1.86 [26]	1.90	16.65	2417.16 [10]
Manufacture of Chemical Fibers	1.90 [27]	1.42	19.92	2591.47 [12]
Smelting and Pressing of Non-ferrous Metals	3.21 [28]	8.84	402.47	1654.08 [9]
Manufacture of Paper and Paper Products	3.45 [29]	2.23	40.72	1345.90 [8]
Manufacture of Raw Chemical Materials and Chemical Products	5.72 [30]	4.33	452.85	822.86 [7]
Production and Supply of Gas	6.95 [31]	-4.03	-19.08	733.67 [6]
Manufacture of Non-metallic Mineral Products	7.00 [32]	3.23	211.43	649.43 [5]
Mining and Washing of Coal	7.88 [33]	4.17	200.75	608.39 [4]

Table 3. Continued.

Smelting and Pressing of Ferrous Metals	12.69 [34]	3.22	299.72	371.55 [3]
Production and Supply of Electric Power and Heat Power	30.52 [35]	2.32	177.20	157.59 [2]
Processing of Petroleum, Coking and Processing of Nuclear Fuel	59.96 [36]	3.88	112.00	82.62 [1]
Average	8.22	2.41	155.37	2714.55

Note: Superscripts in the second and fifth columns are the sequence numbers of each sector arranged with carbon intensity and shadow price in ascending order.

Communication and other Electronic Equipment is quite low at only 0.06 t/10^4 yuan. However, its shadow price is the highest of 83891.78 yuan/t among sectors. Instead, processing of petroleum, coking and processing of nuclear fuel simultaneously possesses the highest carbon intensity of 59.96 t/10^4 yuan and lowest shadow price of 82.62 yuan/t.

Time Trend of the Shadow Price of CO_2 Emissions

Fig. 2 depicts the time trend of shadow price in the whole industry, with HCIS and LCIS during 2005-2015 separately. It shows that the average shadow prices of CO_2 emissions in the whole industry has an obvious upward trend. With the exception of 2014, the shadow prices in other years are on the rise. To be specific, shadow prices increase from 7644.92 yuan/t in 2006 to 20765.58 yuan/t in 2015. The shadow prices in LCIS are at a high level, with an average of 26243.83 Yuan/t and increase over time. Conversely, the shadow prices of HCIS remain low with an average of 2714.55 Yuan/t, which are far below the average value of the whole industry and increase slowly. Based on this, the upward trend of the shadow price in the whole industry is mainly driven by LCIS, while HCIS has a finite contribution to it. An increase in the shadow price

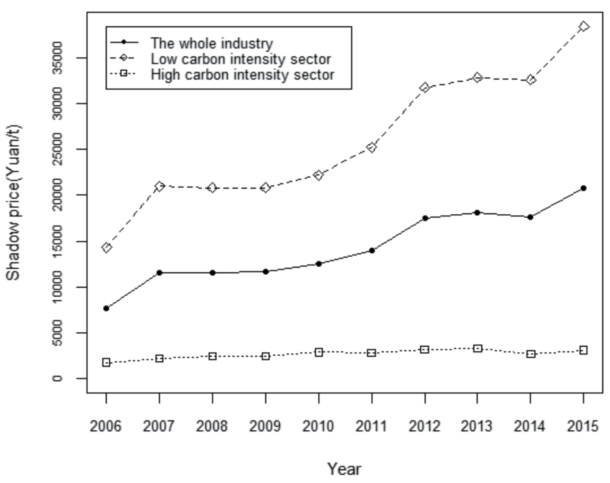

Fig. 2. Trends of average shadow price of CO_2 emissions across sectors during 2006-2015.

indicates that increasing a unit of CO_2 can bring more industrial value-added and vice versa. On the one hand, shadow prices rise over time, which may be because it is calculated at a constant 2005 price in this paper, which implies a rising price trend. On the other hand, with the improvement of energy efficiency and the decline of carbon intensity, for a decision-making unit there is less space for emissions abatement. Consequently, further emissions abatement is costly as well as shadow price being on the rise similarly.

Output Effects of CO_2 Emissions

Output effects of CO_2 emissions can be observed in perspectives of marginal effect and absolute effect. Marginal effect is the index of output growth resulting from the increase or decrease of CO_2 emissions with the given technical efficiency and inputs, and is expressed by the aforementioned *ME.* Absolute effect is used to measure the variation quantity of outputs caused by CO_2 emissions change. Considering the weak disposability of Directional Environment Production Frontier Function, some costs have to be paid for reducing CO_2 emissions. Therefore, output effects are always the same change direction as CO_2 emissions. Fig. 3 portrays the marginal effect and absolute effect of CO_2 emissions on outputs. From it, we can see that CO_2 emissions have increased from 5.84 billion tons to 10.85 billion tons during 2005-2015, with a cumulative increase of 85.79%, while the cumulative marginal effect of additional CO_2 emissions on industrial value-added is only 30.69%, that is, the absolute effect is 3894.14 billion yuan. In order to study the environmental costs of economic growth more specifically, a virtual growth rate is proposed, which is equal to the actual growth rate minus *ME* (i.e., marginal effect). Fig. 3 shows that the virtual growth rates for 2006-2016 are 15.04%, 15.04%, 6.18%, 9.03%, 8.17%, 12.53%, 5.74%, -0.68%, 11.92%, and 9.13% respectively, with an average of 9.21%. Compared with the actual growth rates of 12.28%, the difference is *ME*, whose value is 3.07%. That is to say, for catching the annual 3.07% growth of industrial value-added, we must endure more CO_2 emissions that are increased by 6.39% a year.

In this section, only the overall characteristics of CO_2 shadow price and the environmental costs of economic growth in the whole industry can be seen while the specific situation of a sector cannot

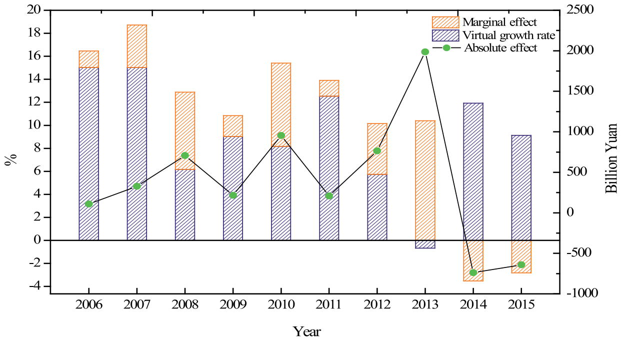

Fig. 3. Marginal effect and absolute effect of CO_2 emissions on outputs.

be observed. Therefore, in the next section, we will explore the characteristics of CO_2 shadow price and the environmental costs of economic growth in some specific sectors. On this basis, two representative sectors will be taken into account.

Representative Cases Analysis

Low-Carbon Intensity Sector: Manufacture of Computers, Communications and Other Electronic Equipment

Manufacture of computers, communication and other electronic equipment, a high-tech sector supported by China's government, is a kind of typical sector with low carbon intensity and high shadow price. Its overall carbon intensity is far below the whole industry, and decreasing with time, which indicates that its technical efficiency is at a high level and has an upward trend. Table 4 denotes that the CO_2 emissions of this sector decreased from 6692.78 thousand tons in 2005 to 6030.25 thousand tons in 2015, i.e., CO_2 emissions were reduced by 9.9%. Due to emission abatement, industrial value-added is reduced by 88.7 billion yuan totally. Given that there are not only increases but also decreases in CO_2 emissions during 2005-2015, the increase effect and reduction effect of CO_2 emissions on outputs generally counteract each other. A simple addition of them would normally weaken the impact of CO_2 emissions on outputs. Therefore, we separately calculate the contribution of increase and reduction in CO_2 emissions to outputs. CO_2 emissions increased by 3661.3 thousand tons in 2006-2008, 2012 and 2015. Accordingly, the industrial value-added is increased by 262.78 billion yuan, accounting for 4.23% of the total industrial value-added in the corresponding years. In other years, CO_2 emissions are reduced by 4323.7 thousand tons, and the industrial value-added consequently is reduced by 351.48 billion yuan, constituting 4.88% of the total industrial value-added in the corresponding years. From this perspective, the losses caused by emissions abatement are greater than the gains arising from an increase in CO_2 emissions.

In this sector, virtual increase rates in this sector are 19.23%, 17.20%, -1.91%, 8.25%, 17.02%, 28.82%, 2.70%, 21.82%, 12.62%, 10.32% respectively, of which the mean is 13.61% rather than the actual 13.43%. Industrial growth rate is decreased by 0.18% annually, which is the cost of emissions abatement in this sector.

As illustrated in Table 4, shadow prices of CO_2 emissions in this sector increased significantly from 45055.22 yuan/t in 2006 to 159635.88 yuan/t in 2015. Average shadow price is 83891.78 yuan/t, the highest level among all sectors, which denotes that energy efficiency is at a high level. In other words, increasing a unit of CO_2 emissions would bring about more outputs

Table 4. Shadow prices and output effects of CO_2 emissions in the manufacture of computers, communications and other electronic equipment (2005-2015).

Item	CO_2 emissions (10^4t)	CO_2 emissions growth rate (%)	Industrial value-added (10^8 Yuan)	Real industrial growth (%)	Carbon intensity (t/10^4Yuan)	Marginal effect (%)	Absolute effect (10^8 Yuan)	Shadow price (Yuan/t)
2005	669.28		6057.02		0.110			
2006	680.92	1.74	7274.48	20.10	0.094	0.86	52.44	45055.22
2007	692.16	1.65	8583.88	18.00	0.081	0.79	57.89	51497.32
2008	898.05	29.75	9613.95	12.00	0.093	13.90	1193.66	57976.80
2009	845.78	-5.82	10123.49	5.30	0.084	-2.95	-283.97	54329.36
2010	843.68	-0.25	11834.36	16.90	0.071	-0.13	-12.57	59884.36
2011	623.63	-26.08	13716.02	15.90	0.045	-12.92	-1529.34	69501.00
2012	758.81	21.68	15375.66	12.10	0.049	9.40	1289.19	95369.34
2013	605.97	-20.14	17113.11	11.30	0.035	-10.52	-1617.35	105821.78
2014	600.85	-0.84	19200.91	12.20	0.031	-0.42	-71.60	139846.76
2015	603.03	0.36	21217.00	10.50	0.028	0.18	34.65	159635.88

Table 5. Shadow prices and output effects of CO_2 emissions in the production and supply of electric power and heat power (2005-2015).

Item	CO_2 emissions (10^4 t)	CO_2 emissions growth rate (%)	Industrial value-added (10^8 Yuan)	Industrial real growth (%)	Carbon intensity (t/10^4Yuan)	Marginal effect (%)	Absolute effect (10^8 Yuan)	Shadow price (Yuan/t)
2005	214232.92		6173.84		34.70			
2006	243041.89	13.45	6988.79	13.20	34.78	6.51	402.02	139.55
2007	265638.35	9.30	7953.24	13.80	33.40	4.55	317.66	140.58
2008	274559.32	3.36	8637.22	8.60	31.79	1.67	132.44	148.46
2009	291196.08	6.06	9155.45	6.00	31.81	2.99	257.84	154.98
2010	304195.87	4.46	10162.55	11.00	29.93	2.21	202.13	155.49
2011	343269.78	12.84	11188.97	10.10	30.68	6.23	632.94	161.99
2012	350341.48	2.06	11748.42	5.00	29.82	1.02	114.66	162.14
2013	381628.06	8.93	12476.82	6.20	30.59	4.37	513.35	164.08
2014	354847.46	-7.02	12751.31	2.20	27.83	-3.57	-445.72	166.43
2015	335349.40	-5.49	12815.07	0.50	26.17	-2.79	-355.28	182.21

and vice versa. There exists high energy efficiency and less energy consumption, which means that further emissions abatement on the basis of its small scale of CO_2 emissions is more difficult and costly.

High Carbon Intensity Sector: Production and Supply of Electric Power and Heat Power

The production and supply of electric power and heat power is a typical sector with high carbon intensity and low shadow price. It accounts for the largest proportion of the total CO_2 emissions in the whole industry, approximately 35%, while the industrial value-added constitutes only 6.42%, between which there exists a significant discrepancy. Here, the serious mismatch between energy consumption and economic growth can be observed.

4.58% annual average growth rate of CO_2 emissions contributes to 7.66% expansion of outputs in this sector. Although there are not only increases but also decreases in carbon intensity, on the whole, it declines from 34.70 t/10^4 yuan in 2005 to 26.17 t/10^4 yuan in 2015, which indicates that energy efficiency slightly improves during this period. This paper aims to know the effects of CO_2 emissions on outputs when maintaining technical efficiency and inputs constant. CO_2 emissions in this sector increased from 2142.33 million tons in 2005 to 3353.49 million tons in 2015, increasing by 56.53% during this period. Industrial value-added measured in constant 2005 price increases from 617.38 billion yuan in 2005 to 1281.51 billion yuan, increasing by approximately one-fold. Among them, the increase in CO_2 emissions led to an increase of 177.2 billion yuan in outputs. However, CO_2 emissions are decreased by 267.81 million tons and 194.98 million tons respectively in 2014 and 2015, in this sense, the increase effect and reduction effect of CO_2 emissions on outputs would offset each other so that the actual effect of CO_2 emissions on outputs cannot observed. Supposing that only the years with an increase in CO_2 emissions are taken into account, the contribution of CO_2 emissions to annual average industrial growth accounts for 2.32%. When all years are considered, the virtual annual growth rate of this industry was 5.34% during 2006-2015, while the actual growth rate is 7.66%. The extra 2.32% is at the environmental cost of CO_2 increasing by 4.58% annually. Table 5 shows us that the shadow price of CO_2 emissions has no obvious change over 2006-2015. For instance, shadow price was 139.55 Yuan/t in 2006, but in 2015 it is still only 182.21 yuan/t – far lower than the average shadow price in the whole industry. In view of this, an increase in outputs resulting from adding one unit of CO_2 emissions is very limited. Similarly, reducing a unit of CO_2 emissions is not costly. CO_2 emissions in this sector are large, which constitute nearly 35% of the whole industry, while the shadow price is quite low. Therefore, emissions abatement is relatively easy. However, considering that the industry is closely related to basic people's livelihoods (although there exist low shadow price and high potential to reduce emissions), measures for reducing CO_2 emissions have not yet been taken, as well as CO_2 emissions have been increasing except for individual years.

Conclusion and Policy Implications

This paper employs a non-parametric model of the directional environment production frontier function model to estimate CO_2 shadow price in 36 industrial sectors of China during 2006-2015, and achieves the main results of:

(1) There is a negative relationship between CO_2 shadow price and carbon intensity across sectors. The average shadow price of the top five sectors with the highest carbon intensity is 373.92 yuan/t, while that of the top five sectors with the lowest carbon intensities are 50254.54 yuan/t. CO_2 abatement potential differs significantly across sectors, so the sector-specific environmental policies or targets should be concerned.
(2) Shadow prices of CO_2 emissions have an upward tendency with time in all sectors, and they rise with a greater speed in the low carbon intensity sectors than in the high ones, which implies that in China, economic sacrifices are increasing with carbon emissions reductions.
(3) CO_2 emissions have increased from 5.84 billion tons to 10.85 billion tons during 2005-2015 in China's industrial sectors, with a cumulative increase of 85.79%. While the cumulative marginal effect of CO_2 emissions on industrial value–added is only 30.69%, the absolute effect is 3894.14 billion yuan. With the technical efficiency and other inputs unchanged, there is an average 3.07% growth of industrial value-add of China owing to the increase in CO_2 emissions every year, minus which the growth rate is only 9.21% rather than the official number of 12.28%.
(4) The average shadow price of CO_2 emissions in communication and other electronic equipment is 83891.78 yuan/t, which is the highest in all sectors. Additionally, its average actual and virtual growth rates of output are 13.43% and 13.61%, respectively. Thus, energy efficiency is at a high level in this sector and further emissions abatement is more difficult and costly.
(5) CO_2 emissions in the production and supply of electric power and heat power ranks No. 1 in all sectors while the shadow price is the lowest, which suggests there is a relatively huge potential in emissions abatement. Furthermore, an average 2.32% growth of the value-added in this sector is owed to the growth of CO_2 emissions by 4.58% annually. From the overall point of view, this sector should strengthen environmental regulations to control its emissions.

Our empirical results have several important implications. First, when government assigns the industrial sectors emission reduction targets, their sector heterogeneity pertaining to the shadow price should be considered. When the target exceeds their present ability, the sectors will pay a lot and be under considerable pressure. This paper finds that there is a negative relationship between shadow price and carbon intensity. That is, compared to the low carbon intensity sector, the high carbon intensity sector has the lower marginal abatement cost, thereby possessing a relatively huge potential for carbon emissions reduction. Hence, when the Chinese government places the burden of reducing carbon emissions on the industrial sectors, the high carbon intensity sectors should be assigned to more tasks while the low carbon intensity sectors are the opposite. Second, the Chinese government is constructing the emission trading scheme (ETS) and until now only the power generation sector is included in the national ETS. More sectors taking part in this scheme will undoubtedly improve market efficiency. Emission quotas flowing from sectors with low shadow price to the ones with high prices will have a win-win result, which can form a more instructive equilibrium price of emission quota and contribute to achieving the overall cost-effectiveness in reducing CO_2 emissions. Third, with CO_2 emissions, reducing the marginal abatement costs of sectors may increase with time. The government must take these changes into account when formulating emission reduction policies for preventing the emission reduction target assigned to the sectors beyond their ability to withstand. Fourth is that in recent years, many heavy industrial sectors of China encounter the problem of overcapacity. This study shows that the shadow prices of most heavy industrial sectors are relatively low, thereby having a large potential and space for emissions reduction. So, increasing the discharge standard of pollutants or eliminating enterprises that fail to meet the standard may be an effective way for urging these sectors to mitigate their carbon emissions. Finally, China's previous economic development model was extensive, which has brought severe environmental problems. It is predictable that with the price of carbon emission increasing, industrial sectors will have no choice but to apply cleaner energy or more effective production ways. So, with the reduction of carbon emissions, China will inevitably experience a deep revolution in the structures of economy and energy consumption.

Author Contributions

Qunli Wu designed this paper and made overall guidance, Hongjie Zhang wrote the manuscript, Ruke Zhang analyzed the data and Chunxiang Li contributed materials.

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Conflicts of Interest

The authors declare no conflicts of interest.

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