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The shadow price of CO_2 emissions in China's iron and steel industry

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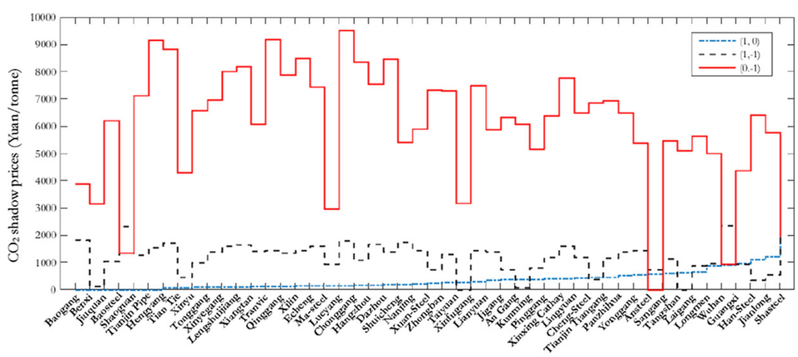
HIGHLIGHTS

- First attempt to estimate the abatement cost of CO_2 emissions in China's iron and steel industry.
- We use a unique dataset of China's iron and steel enterprises.
- The results show that the mean CO_2 shadow price is very sensitive to the choice of direction vectors.
- We find substantial heterogeneity in the shadow prices among China's iron and steel enterprises.
- We show that using an arbitrarily chosen direction vector may significantly underestimate shadow price heterogeneity.

GRAPHICAL ABSTRACT



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ABSTRACT

As China becomes the world's largest energy consumer and CO_2 emitter, there has been a rapidly emerging literature on estimating China's abatement cost for CO_2 using a distance function approach. However, the existing studies have mostly focused on the cost estimates at macro levels (provinces or industries) with few examining firm-level abatement costs. No work has attempted to estimate the abatement cost of CO_2 emissions in the iron and steel industry. Although some have argued that the directional distance function (DDF) is more appropriate in the presence of bad output under regulation, the choice of directions is largely arbitrary. This study provides the most up-to-date estimate of the shadow price of CO_2 using a unique dataset of China's major iron and steel enterprises in 2014. The paper uses output quadratic DDF and investigates the impact of using different directional vectors representing different carbon mitigation strategies. The results show that the mean CO_2 shadow price of China's iron and steel enterprises is very sensitive to the choice of direction vectors. The average shadow prices of CO_2 are 407, 1226 and 6058 Yuan/tonne respectively for the three different direction vectors. We also find substantial heterogeneity in the shadow prices of CO_2 emissions among China's major iron and steel enterprises. Larger, listed enterprises are found to be associated lower CO_2 shadow prices than smaller, unlisted enterprises.

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1. Introduction

Facing mounting pressure from increasingly environmentally conscious citizens as well as global community in climate negotiations, China has taken significant efforts in energy conservation and carbon emissions reduction in recent years. In 2009, China committed to reduce its CO_2 emissions per unit of GDP (i.e. emission intensity) by 40%–45% by 2020 from its 2005 level (Wang and Wei, 2016). China also implemented binding targets during its 12th Five-Year Plan (FYP) period (2011–2015) to reduce energy consumption per unit of GDP (i.e. energy intensity) by 16% and carbon intensity by 17% from its 2010 levels (SCC, 2011a). In the recently released 13th FYP period (2016–2010), the government pledged another 15% reduction in energy intensity and 18% reduction in CO_2 emission intensity by 2020 (SCC, 2016). China has also played an increasingly proactive role in international climate negotiations in recent years. For example, in 2015, the Chinese government made significant commitments at the Paris climate summit. China pledged to peak its CO_2 emissions no later than 2030, reduce its CO_2 emissions per unit of GDP by 60%–65% by 2030 from its 2005 level, and increase the proportion of non-fossil fuels in the total primary energy supply to 20% by 2030 (NDRC, 2015; Lomborg, 2016; Den Elzen et al., 2016). The Paris Climate Agreement was recently ratified by The Chinese government also ratified the Paris Climate Agreement at the G20 Summit in 2016. Emission reductions in energy-intensive industries are widely believed to be critical to fulfil these commitments. The focus on energy-intensive industries is also demonstrated by a series of administrative measures aiming to phase out outdated production capacity in these industries. However, given the context of a proposed national carbon trading market in an effort to improve mitigation efficiency, the extent to which energy-intensive industries should take on mitigation depends on their abatement costs of CO_2 emissions.

Iron and steel industry is one of the most energy-intensive industries in China that accounts for approximately 15% of China's total energy consumption, 12% of China's total CO_2 emissions, and 27% of the national industry emissions (Guo and Fu, 2010; Wang and Jiang, 2012; Xie et al., 2016). It is thus not surprising that energy saving and carbon emissions reduction in China's iron and steel industry has become a focal subject in recent literature. Worrell et al. (1997) compared the energy intensity of iron and steel industry in seven countries using a decomposition analysis based on physical indicators for process type and product mix. Their results show that the efficiency improvement is the main driver for energy savings in China's iron and steel industry. Wang et al. (2007) assessed the CO_2 abatement potential of China's iron and steel industry based on different CO_2 emissions scenarios from 2000 to 2030 and found that adjusting the structure of the industry and improving the technology played an important role in CO_2 emissions reduction. Zhang and Wang (2008) estimated the impact of energy saving technologies and innovation investments on the productive efficiency in China's iron and steel enterprises during the period 1990–2000 and found that the adoption and improvement of energy saving measures, such as pulverized coal injection technology, had attributed to productive efficiency growth. Guo and Fu (2010) did a survey about the development and current situations of energy consumption in China's iron and steel industry and found that its energy efficiency has significantly improved from 2000 to 2005. Tian et al. (2013) examined the trend, characteristics and driving forces of energy-related greenhouse gas (GHG) emissions in China's iron and steel industry from 2001 to 2010 and indicated that the production scale effect was the main driver for the growth of energy related GHG emissions in China's iron and steel industry. Similar to Wang et al. (2007), Wen et al. (2014) also assessed the potential for energy saving and CO_2 emissions mitigation in China's iron and steel industry but for a shorter period from 2010 to 2020. Hasanbeigi et al. (2013) constructed a bottom-up energy conservation supply curve to estimate the cost-effective and total technical potential for CO_2 emissions reduction in China's iron and steel industry during 2010–2030. Lin and Wang (2015) investigated the total factor CO_2 emissions performance and estimated the emissions mitigation potential in China's iron and steel industry during the period of 2000 to 2011. In another paper, they also analyzed the energy conservation potential of China's iron and steel sector using the co-integration method and scenario analysis (Lin and Wang, 2014). Xu and Lin (2016) also studied CO_2 emissions in China's iron and steel industry but focused on regional differences.

To sum up, most studies have shown that there is substantial potential for emissions reduction from this industry; however, the amount of actual abatement will largely depend on the marginal abatement cost (MAC). Under a carbon trading setting, firms from an industry with high MAC would rather purchase permit than actually engage abatement (even with large abatement potential). Despite the rapidly growing literature on CO_2 emissions in China's iron and steel industry, no work has attempted to estimate the abatement cost of CO_2 emissions in this industry, which seems an important gap to fill.

The estimation of the abatement cost of CO_2 emissions is fundamental to the design and implementation of carbon reduction policies. China's current emission reduction policies based on administrative targets of reduction in emission intensity is widely criticized to be lack of economic efficiency.[1] The government is taking measures to transit to market based instruments by establishing pilot carbon trading market and eventually a national trading market. However, the validity of the argument that a trading market is economically more efficient than intensity reduction targets depends very much on the heterogeneity of MAC especially at the firm level. The estimation of MAC is thus of great significance and attracts increasing attention in recent literature. Most studies have estimated China's carbon abatement cost at regional level including Wei et al. (2012), Wang et al. (2011), Choi et al. (2012), Zhang et al. (2014), Du et al. (2015), He (2015), Ma and Hailu (2016), Tang et al. (2016), Sun et al. (2015) and Wu and Ma (2017), or at industrial level such as Lee and Zhang (2012), Peng et al. (2012), Chen (2013), and Zhou et al. (2015). However, firm-level analyses are very limited due to the lack of high-quality firm-level data. The only few studies using firm-level data all focused on the electricity sector. Wei et al. (2013) evaluated the inefficiency and CO_2 shadow prices of 124 power plants located in Zhejiang Province in 2004. Du and Mao (2015) estimated CO_2 reduction potential and MAC of CO_2 for China's coal-fired power plants in 2004 and 2008. Du et al. (2016) investigated the carbon abatement cost of power plants based on a plant-level cross-sectional dataset (648 observations) for the year of 2008. To the best of our knowledge, there is no firm-level analysis on the MAC (i.e. shadow price) of CO_2 emissions in the iron-steel sector.

[1] During the 11th FYP period (2006–2010), the China's government proposed an administrative target to reduce energy intensity by 20% which was further assigned to each province. In the ending two years of this period, some industrial enterprises with high energy intensity and large difficulty in energy conservation had to switch out for power consumption limitation to reach this target, which can be extremely costly.

The CO_2 shadow price can be derived from the distance function (DF) or the directional distance function (DDF), both of which can be estimated parametrically (Lee and Zhang, 2012; Wei et al., 2013; Zhang et al., 2014; Du et al., 2015; He, 2015; Tang et al., 2016) or non-parametrically (Wei et al., 2012; Wang et al., 2011; Choi et al., 2012; Peng et al., 2012; Chen, 2013; Sun et al., 2015). The DF approach is a radial model that applies the reduction of inputs and the expansion of outputs while maintaining the inputs or/and outputs mix. The production technology specified as such may not reflect the real production process with undesirable output since the enterprise usually prefers the simultaneous reduction of undesirable outputs and the expansion of desirable outputs (Färe et al., 1993; Hailu and Veeman, 2000). Due to the limitation of the DF approach, the DDF approach was developed to suit the real product process by applying directional input or output vectors (Chung et al., 1997; Färe and Grosskopf, 2000). Although the DDF approach is more flexible, it has its own disadvantages (Chen and Delmas, 2012), such as the choice of direction is mostly arbitrary with little agreement in practice, the inefficiency scores may vary for different choices of the directional vectors (DV), or the undesirable outputs may be not monotonic which is contrary to the general beliefs in production economics.[2] Vardanyan and Noh (2006) and Molinos-Senante et al. (2015) demonstrated that the shadow prices of undesirable outputs can be extremely sensitive to the choices of DVs though the robustness of the estimates to the choice of direction vectors is subject to empirical investigation.

The DDF can also be estimated under the non-parametric Data Envelopment Analysis (DEA) approach (Boyd et al., 1996; Lee et al., 2002; Wang and Wei, 2014). The main advantage of the non-parametric DEA method is that it is not necessary to specify the functional form of the DDF (Molinos-Senante et al., 2015). However, the DEA approach is less suited to estimate the shadow price due to its non-differentiability of the frontier production function. If some efficient observations are located on the inflection, they will have different slopes and the shadow price estimated is consequentially affected by the choice of the slope (Lee and Zhang, 2012).

This paper makes a number of original contributions to the rapidly growing literature on the abatement cost of CO_2 emissions in China. Firstly, to the best of our knowledge, the estimates of the carbon mitigation cost in China's iron and steel industry, which is one of China's top energy consumers and CO_2 emitters, are very limited. We provide a most up-to-date estimate of the MAC of CO_2 emissions using a unique firm-level dataset of China's iron and steel industry in 2014. Secondly, we apply a set of different DVs in a DDF with a quadratic functional form to examine the robustness of the MAC estimates to the choice of DVs. Finally, we investigate the heterogeneity of CO_2 shadow price within the iron-steel industry by different ownership, vintage, location and size of iron and steel enterprises.

The remainder of the paper is organized as follows. Section 2 describes the model we used for CO_2 shadow price estimation. Section 3 introduces the data and the variables. Section 4 discusses the estimated results of the CO_2 shadow prices in China's iron and steel industry. Section 5 concludes with some policy implications.

2. Methodology

2.1. The output directional distance function (ODDF) and the derivation of shadow price for iron and steel enterprises

Let us consider a production process of iron and steel enterprises employing the inputs $x=(x_1, x_2, \ldots, x_N)\in R_+^N$ to produce the desirable outputs $y=(y_1, y_2, \ldots, y_M)\in R_+^M$ accompanied by the undesirable outputs $b=(b_1, b_2, \ldots, b_J)\in R_+^J$. The production feasible set $P(x)$ is defined as follows:

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

The production technology suits the standard assumptions of compact and free disposable in inputs (Färe et al., 2006). It also assumes: (1) jointness of y and b: if $(y,b)\in P(x)$ and $b=0$, then $y=0$; (2) joint weak disposability of y and b: if $(y,b)\in P(x)$ and $0\le\alpha\le 1$, then $(\alpha y,\ \alpha b)\in P(x)$; (3) free disposable of y: if $(y,b)\in P(x)$, then for $y_0\le y, (y_0,\ b)\in P(x)$. These assumptions imply that: (1) the undesirable outputs are produced jointly with the desirable outputs which means if no undesirable output is produced, then no desirable outputs is produced simultaneously; (2) any proportional reduction of the desirable and undesirable outputs together is attainable; (3) the reduction of the desirable outputs without reducing the undesirable outputs is attainable.

The output directional distance function (*ODDF*) is defined as the maximum amount by which the outputs can be adjusted along a specific DV g:

$$\overrightarrow{ODDF}\ (x,\ y,\ b;\ g)=\ \sup\left\{\ \beta : \left(y+\beta g_y,\ \ b-\beta g_b\right)\in P(x)\right\} \tag{2}$$

where $g=(g_y,-g_b)$ is an output directional vector which implies the expansion of the desirable outputs and the reduction of the undesirable outputs. The vectors g_y and g_b are always positive. The β is non-negative, scaled to reach the boundary of the output set $(y+\beta^* g_y,\ b-\beta^* g_b)\in P(x)$ where $\beta^*=\overrightarrow{ODDF}\ (x,\ y,\ b;\ g)$. A higher β means lower technical efficiency such that the iron and steel enterprise is further away from the frontier. If β equals to zero, the iron and steel enterprise is efficient and located at the production frontier.

The *ODDF* inherits its properties from the output possibility set and satisfies the following mathematical properties:

(i) $\overrightarrow{ODDF}(x,\ y,\ b;\ g)\ge 0$ if and only if $(y,b)\in P(x)$
(ii) $\overrightarrow{ODDF}(x,\ y',\ b;\ g)\ge\overrightarrow{ODDF}(x,\ y,\ b;\ g)$ for $(y',b)\in P(x)$
(iii) $\overrightarrow{ODDF}(x,\ y,\ b';\ g)\ge\overrightarrow{ODDF}(x,\ y,\ b;\ g)$ for $(y,b)\le(y,b')\in P(x)$
(iv) $\overrightarrow{ODDF}(x,\ \theta y,\ \theta b;\ g)\ge 0$ for $(y,b)\in P(x)$ and $0\le\theta\le 1$
(v) $\overrightarrow{ODDF}(x,\ y,\ b;\ g)\ge 0$ is concave in $(y,b)\in P(x)$
(vi) $\overrightarrow{ODDF}(x,\ y+\alpha g_y,\ b-\alpha g_b;\ g)=\overrightarrow{ODDF}(x,\ y,\ b;\ g)-\alpha,\ \ \alpha>0$

Property (i) ensures that the *ODDF* is non-negative for feasible output vector g. Property (ii) is a monotonicity property implying the strong disposability of the desirable outputs. Property (iii) is also a monotonicity property. If the undesirable outputs expand accompanied by the constant inputs and desirable outputs, the efficiency does not increase. Property (iv) means the weak disposability of the desirable and undesirable outputs. Property (v) defines the elasticity of substitution of the outputs. Property (vi) states the translation and homogeneity property. If the desirable outputs are expanded by αg_y and the undesirable outputs are reduced by αg_b, the value of the resulting *ODDF* will be more efficient by α where α is a positive scalar.

We use the revenue function to retrieve the output shadow prices. If p_m is the market price of the mth desirable output, the shadow price (i.e. marginal abatement cost) of the jth undesirable output q_j is (more details can be found in Färe et al., 2006):

$$q_j=-p_m\left(\frac{\partial\overrightarrow{ODDF}(x,\ y,\ b;\ g)/\partial b_j}{\partial\overrightarrow{ODDF}(x,\ y,\ b;\ g)/\partial y_m}\right) \tag{3}$$

[2] To address these limitations, we estimated the DDF using three different DVs instead of arbitrarily picking one DV, and we made an exploration about the heterogeneity in the mean value of CO_2 shadow prices to address the sensitivity of the DDF model. Moreover, in our empirical investigation, we found no negative values of shadow prices of the undesirable output.

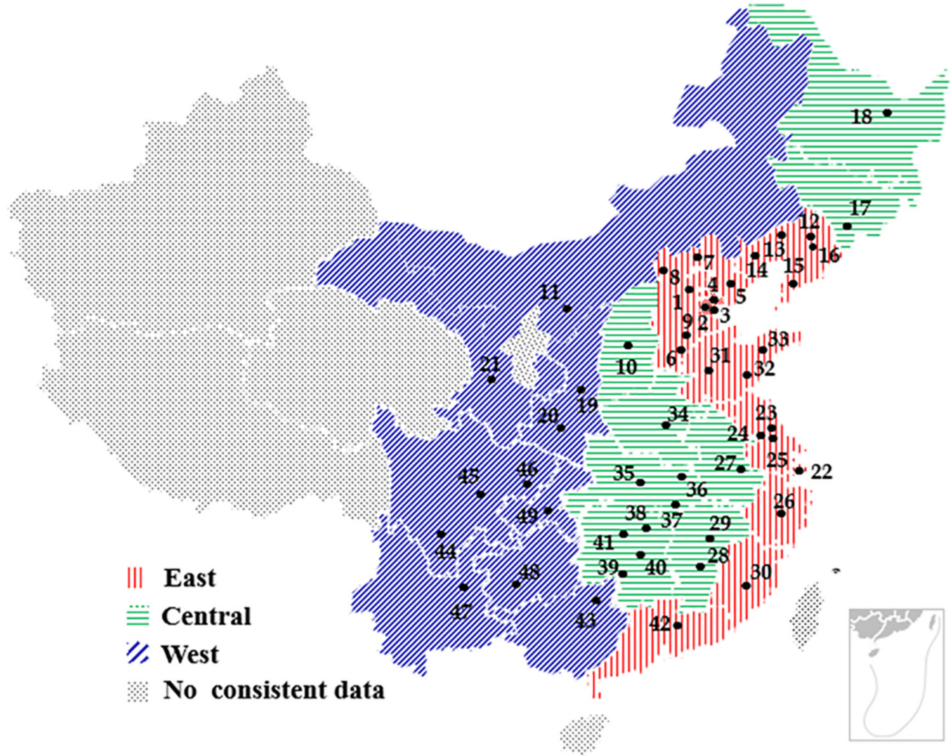

Fig. 1. Geographical locations of selected iron and steel enterprises.

2.2. The quadratic directional distance function with different DVs

We choose to parameterize the directional distance function with a quadratic form that can be easily restricted to satisfy the translation property (Chambers, 1998; Färe et al., 2005; Färe et al., 2006; Du and Mao, 2015). Rather than arbitrarily pick a DV as is done in most empirical studies, we estimate the DDF using three different DVs: $g=(1,-1)$, $g=(1,0)$ and $g=(0,-1)$. Our chosen DVs represent three different production and emissions abatement strategies. The first vector $g=(1,-1)$ captures the case of increasing the desirable output (i.e. the output value of iron and steel enterprises) and decreasing the undesirable output (i.e. the CO_2 emissions of iron and steel enterprises) simultaneously. The second vector $g=(1,0)$ describes the situation in which the desirable output can expand while the undesirable output is held constant. The third vector $g=(0,-1)$ reflects the case of reducing the undesirable output while holding the desirable output unchanged. Suppose there are $k=1,2,\ldots,K$ iron and steel enterprises, we then have the quadratic output directional distance function for iron and steel enterprise k (taking the vector $g=(1,-1)$ for an example):

$$\begin{aligned}\overrightarrow{ODDF} &= (x_k,y_k,b_k;\ 1,-1)\\ &=\alpha+\sum_{n=1}^{N}\alpha_n x_{nk}+\sum_{m=1}^{M}\beta_m y_{mk}+\sum_{j=1}^{J}\gamma_j b_{jk}\\ &\quad+\frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N}\alpha_{nn'}x_{nk}x_{n'k}+\frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M}\beta_{mm'}y_{mk}y_{m'k}\\ &\quad+\frac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J}\gamma_{jj'}b_{jk}b_{j'k}+\sum_{n=1}^{N}\sum_{m=1}^{M}\delta_{nm}x_{nk}y_{mk}\\ &\quad+\sum_{n=1}^{N}\sum_{j=1}^{J}\eta_{nj}x_{nk}b_{jk}+\sum_{m=1}^{M}\sum_{j=1}^{J}\mu_{mj}y_{mk}b_{jk}\end{aligned}\tag{4}$$

The parameters of *ODDF* can be estimated by using deterministic linear programing (LP) algorithm (Aigner and Chu, 1968) or stochastic frontier approach (SFA). The SFA has some disadvantages such as the uncertainty of the distributional assumptions for the inefficiency and error terms, and the imposing of non-linear monotonicity constraints during the estimation process (Murty et al., 2007). Hence, following Aigner and Chu (1968), we use LP algorithm to estimate the unknown parameters in Eq. (4). The parameters are derived by minimizing the sum of *ODDF* for each of iron and steel enterprise evaluated from the production frontier technology:

$$\begin{aligned}&\text{Min}\quad \sum_{k=1}^{K}\left[\overrightarrow{ODDF}(x_k,y_k,b_k;\ 1,-1)-0\right]\\ &\text{s.t.}\ \text{(i)}\ \overrightarrow{ODDF}(x_k,y_k,b_k;\ 1,-1)\geq 0,\quad k=1,\ 2,\ldots,\ K\\ &\quad\text{(ii)}\ \partial\overrightarrow{ODDF}(x_k,y_k,b_k;\ 1,-1)/\partial b_j\geq 0,\quad j=1,\ 2,\ldots,\ J;k=1,\ 2,\ldots,\ K\\ &\quad\text{(iii)}\ \partial\overrightarrow{ODDF}(x_k,y_k,b_k;\ 1,-1)/\partial y_m\leq 0,\quad m=1,\ 2,\ldots,\ M;k=1,\ 2,\ldots,\ K\\ &\quad\text{(iv)}\ \partial\overrightarrow{ODDF}(x_k,y_k,b_k;\ 1,-1)/\partial x_n\geq 0,\quad n=1,\ 2,\ldots,\ N;k=1,\ 2,\ldots,\ K\\ &\quad\text{(v)}\ \sum_{m=1}^{M}\beta_m-\sum_{j=1}^{J}\gamma_j=-1,\ \sum_{m'=1}^{M}\beta_{mm'}-\sum_{j=1}^{J}\mu_{mj}=0,\ m=1,\ 2,\ldots,\ M\\ &\qquad\sum_{j'=1}^{J}\gamma_{jj'}-\sum_{m=1}^{M}\mu_{mj}=0,\ j=1,\ 2,\ldots,\ J;\sum_{m=1}^{M}\delta_{nm}-\sum_{j=1}^{J}\eta_{nj}=0,\ n=1,\ 2,\ldots,\ N\\ &\quad\text{(vi)}\ \alpha_{nn'}=\alpha_{n'n},\ n\neq n';\ \beta_{mm'}=\beta_{m'm},\ m\neq m';\ \gamma_{jj'}=\beta_{j'j},\ j\neq j\end{aligned}\tag{5}$$

The first restriction (i) ensures that the input-output production set is feasible. Restrictions (ii), (iii) and (iv) impose the monotonicity property for all outputs and inputs. The last two restrictions are due to the translation property and the symmetry property. According to Färe et al. (2006) and Chambers (2002), for the other two DVs $g=(1,0)$ and $g=(0,-1)$, Restriction (v) needs to be changed, respectively, as:

$$\sum_{m=1}^{M}\beta_m=-1;\ \sum_{m'=1}^{M}\beta_{mm'}=0,\ m=1,\ldots,M;\ \sum_{m=1}^{M}\delta_{nm}=0;\ n=1,\ldots,N,\text{for } g=(1,\ 0)\tag{6}$$

$$\sum_{j=1}^{J}\gamma_j=1;\ \sum_{j'=1}^{J}\gamma_{jj'}=0,\ j=1,\ldots,J;\ \sum_{j=1}^{J}\eta_{nj}=0,\ n=1,\ldots,N,\text{for } g=(0,-1)\tag{7}$$

3. Data and variables

We collected a sample dataset of China's 49 major iron and steel enterprises in 2014 from the database *Mysteel Data*.[3] The iron and steel enterprises were selected to ensure consistent information of all input and

[3] Data source: *Mysteel Data*, http://data.glinfo.com/.

output variables and wide coverage of geographical locations of the iron and steel enterprises. The sample contains China's major iron and steel enterprises in 26 out of 32 provinces. Qinghai, Ningxia, Tibet, Xinjiang, Hainan and Taiwan were excluded due to lack of consistent data. Fig. 1 presents the geographical locations of these enterprises. We mark these enterprises into China's three typical geographic regions: (i) east region: Shanghai, Beijing, Tianjin, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan, Liaoning; (ii) central region: Shanxi, Henan, Hubei, Hunan and Jiangxi, Jilin and Heilongjiang; and (iii) west region: Chongqing, Sichuan, Guizhou, Yunnan, Guangxi, Shaanxi, Gansu and Inner Mongolia. Our final sample contains iron and steel enterprises of various characteristics including 55% listed and 45% unlisted enterprises, 29% large, 33% medium and 38% small enterprises, or 73% old and 27% young enterprises. Table 1 lists the full names of the selected enterprises. We also abbreviate all enterprise names to ease results illustration.

Considering the production processes of iron and steel enterprises, we employ five inputs and two outputs. The inputs include (i) total energy consumption; (ii) total water consumption; (iii) total number of employees; (iv) total volume of blast furnaces; and (v) total tonnage of converters. The blast furnaces and the converters are the core production facilities in smelting iron and steel. The outputs include (i) one desirable output - total output value of steel products, which is a combination of the output values of three major products of iron and steel enterprises (Pig iron, Crude steel and Rolled steel)[4]; and (ii) one undesirable output - CO_2 emissions. All input and output data are collected from *Mysteel Data*. Note that the CO_2 emissions of iron and steel enterprises are estimated according to the Guidelines for the Calculation and Reporting of GHG emissions from iron and steel enterprises (NDRC, 2013). Table 2 presents the descriptive statistics of the input and output data. All input and output data are normalized before estimation to overcome the convergence problem (Färe et al., 2005).

4. Results

4.1. Shadow prices of CO_2 emissions

Table 3 presents the values of the parameters of the output directional distance function (Eq. (4)) estimated with three different DVs: (1, 0), (1, −1) and (0, −1). The parameter estimates were obtained by solving the linear programming described in Eq. (5) using GAMS (General Algebraic Modeling Software).

Table 4 presents the CO_2 shadow prices of the sample iron and steel enterprises estimated using three different DVs. The average shadow prices of CO_2 are 407, 1226 and 6058 Yuan/tonne respectively for the three different directions: (1, 0), (1, −1) and (0, −1), and the mean value for all CO_2 shadow prices in three directions is 2560 Yuan/tonne. The magnitude of the shadow price for a specific enterprise is truly varied across three DVs. In addition, the correlation coefficient between the rankings under the DV (1, 0) and those under the DV (1, −1) is as low as 0.289. The correlation coefficients between the other two pairs are slightly higher at 0.305 ((1, −1) and (0, −1)) and 0.322 ((1, 0) and (0, −1)). The findings indicate that choice of direction has strong impact on the values or rankings of estimated shadow prices, implying that increasing the efficiency by expanding the steel production with/without simultaneous reduction of CO_2 emissions or reducing the CO_2 emissions while holding the steel production unchanged will result in extraordinarily different CO_2 emissions abatement cost estimations.

Fig. 2 shows the CO_2 shadow price curves of the iron and steels enterprises under three different DVs. The iron and steel enterprises are sorted in the ascending order of the shadow prices under the direction of (1, 0). As our chosen DVs cover a wide range of reasonable directions which represent the possible strategies firms may take to improve efficiency, the highest and the lowest shadow price estimated under the three different DVs can be treated as the upper and lower boundaries of the shadow prices. In most cases, the upper and lower boundaries are reached under the directions of (1, 0) and (0, −1) respectively; however, there are exceptions. In the case of Ansteel Group, reducing the CO_2 emissions alone leads to the lowest marginal abatement costs relative to the other two efficiency improvement strategies. While in the case of Taiyuan Iron and Steel Group, An Gang Group CO., LTD., Cheng-Steel Group, Tangshan Iron and Steel Group, Wuhan Iron and Steel CO., LTD., Baosteel Group, Han-Steel Group and Jianlong Group, increasing desirable output and mitigating undesirable output simultaneously results in the highest or lowest marginal abatement costs. Our results imply that even if the mean estimates of shadow prices are robust to the choice of DVs, the estimates for specific enterprises may be biased given any arbitrarily chosen DV. This suggests that using an arbitrarily chosen DV may substantially underestimate the potential for low-cost abatement opportunities. Therefore, we use the mean shadow prices of three DVs to explore the heterogeneity of MACs across the iron and steel enterprises in the next section.

Table 1
Full names and abbreviations of selected iron and steel enterprises.

No.	Full name	Abbreviation
1	Jianlong Group	Jianlong
2	Tianjin Pipe Group	Tianjin Pipe
3	Tianjin Tiangang United Special Steel CO., LTD.	Tianjin Tiangang
4	Tian Tie Group	Tian Tie
5	Tangshan Iron and Steel Group	Tangshan
6	Han-Steel Group	Han-Steel
7	Cheng-Steel Group	Cheng-Steel
8	Xuan-Steel Group	Xuan-Steel
9	Xinxing Cathay International Group	Xinxing Cathay
10	Taiyuan Iron and Steel Group	Taiyuan
11	Baogang Group	Baogang
12	Xinfugang CO., LTD.	Xinfugang
13	Ansteel Group	Ansteel
14	Lingyuan Iron and Steel Group	Lingyuan
15	Yingkou Zhongban CO., LTD.	Zhongban
16	Benxi Iron and Steel Group	Benxi
17	Shougang Tonggang Iron and Steel Group	Tonggang
18	Xilin Iron and Steel Group	Xilin
19	Lueyang Iron and Steel CO., LTD.	Lueyang
20	Shanxi Longmen Iron and Steel CO., LTD.	Longmen
21	Jiuquan Iron and Steel CO., LTD.	Jiuquan
22	Baosteel Group	Baosteel
23	Nanjing Iron and Steel CO., LTD.	Nanjing
24	Shagang Group	Shagang
25	Jiangsu Yonggang Group CO., LTD.	Yonggang
26	Hangzhou Iron and Steel CO., LTD.	Hangzhou
27	Ma-steel CO., LTD.	Ma-steel
28	Xinyu Iron and Steel Group CO., LTD.	Xinyu
29	Jiangxi Pinggang Group CO., LTD.	Pinggang
30	Sangang Group CO., LTD.	Sangang
31	Jigang Group CO., LTD.	Jigang
32	Laigang Group CO., LTD.	Laigang
33	Qinggang Group CO., LTD.	Qinggang
34	An Gang Group CO., LTD.	An Gang
35	Wuhan Iron and Steel CO., LTD.	Wuhan
36	Echeng Iron and Steel CO., LTD.	Echeng
37	Hubei Xinyegang Steel CO., LTD.	Xinyegang
38	Xiangtan Iron and Steel CO., LTD.	Xiangtan
39	Lianyuan Iron and Steel CO., LTD.	Lianyuan
40	Hengyang Iron and Steel CO.,LTD.	Hengyang
41	Lengshuijiang Iron and Steel CO., LTD.	Lengshuijiang
42	Shaoguan Iron and Steel CO., LTD.	Shaoguan
43	Guangxi Liuzhou Steel Group CO., LTD.	Guangxi
44	Panzhihua Iron and Steel (Group) CO., LTD.	Panzhihua
45	Tranvic Iron and Steel CO., LTD.	Tranvic
46	Dazhou Iron and Steel Group CO., LTD.	Dazhou
47	Kunming Iron and Steel Holding CO., LTD.	Kunming
48	Shougang Shuicheng Iron and steel (Group) CO., LTD.	Shuicheng
49	Chongqing Gangtie CO., LTD.	Chonggang

[4] Considering the various steel products of the iron and steel enterprises in the product chain, we employ the out value of the iron and steel enterprises rather than the physical output as a desirable output following He et al. (2013).

Table 2
Descriptive statistics of inputs and outputs of selected enterprises.

Variable	Measures (units)	Mean	Std. dev.	Maximum (enterprise)	Minimum (enterprise)
Inputs	Energy (million tonnes of equivalent coal)	470	356	1930 (Baosteel)	38 (Lueyang)
	Water (10^4 tonnes)	3225	3517	17,618 (Baosteel)	248 (Lueyang)
	Staff (persons)	26,636	25,933	149,673 (Ansteel)	1463 (Lueyang)
	Blast furnaces (cubic meters)	6805	6109	30,576 (Ansteel)	1000 (Tianjin Pipe)
	Converters (tonnes)	522	537	2790 (Baosteel)	45 (Lueyang)
Desirable output	Output value of major products (10^8 Yuan)	894	845	3937 (Baosteel)	62 (Lueyang)
Undesirable output	CO_2 emissions (10^4 tonnes)	1383	1371	7496 (Baosteel)	106 (Lueyang)

Table 5 summarizes recent studies on estimating the shadow prices of CO_2 emissions in China. Ma and Hailu (2016) pointed out that shadow prices estimated using DDF are more akin to long-run MACs while radial DFs are more likely to represent short-run MACs. We thus compared our results to those studies also using DDF approaches. Wei et al. (2013) found that the mean CO_2 shadow price of China's thermal power enterprises is around 2060 Yuan/tonne in 2004. Chen (2013) obtained an estimate of average CO_2 shadow price of 1689 Yuan/tonne at the industry level during the period of 2006–2010. Wang and Wei (2014) found an average shadow price of 298 Yuan/tonne in 30 cities' industrial sectors. Du et al. (2015) showed that the mean CO_2 shadow price of China's 30 provinces is 1300 Yuan/tonne. Ma and Hailu (2016) also found an average MAC of 2251 Yuan/tonne using provincial level data. Xie et al. (2016) found that the CO_2 shadow prices of China's iron and steel industry is 2507 Yuan/tonne in 2014. In this study, we found that the average shadow price of CO_2 emissions in China's major iron and steel enterprises is 407, 1226 and 6058 Yuan/tonne respectively for the three different direction vectors. This is largely consistent with the existing studies except for Peng et al. (2012) who found a much higher mean CO_2 shadow price of 17,500 Yuan/tonne in 2004 and 15,200 Yuan/tonne in 2008 in China's 24 industrial sectors. Despite the fact that many studies found large potential of CO_2 mitigation in the iron and steel sector (Wang et al., 2007; Wen et al., 2014; Lin and Wang, 2015), we find that the shadow price of CO_2 emissions in the iron and steel sector is very much comparable to those of other industries. This implies that the iron and steel industry would not have to abate more than other industries. Under a national carbon trading scheme, it is those with lower MACs that will engage in actual abatement activities (Wang et al., 2016).

4.2. Heterogeneity in the shadow price of CO_2 emissions

Both Table 4 and Fig. 2 show substantial heterogeneity in the shadow prices of CO_2 emissions across the iron and steel enterprises. Fig. 3 also compares the distribution of shadow price across different groups. It appears that enterprises of different ownership (listed vs unlisted) or different sizes tend to differ most in CO_2 shadow price, while those with different vintages or from various locations have smaller differences. These observations are also confirmed in Table 5 in which we test equality of means across groups. As our sample is relatively small, we perform the non-parametric Mann-Whitney *U* test for two-group comparisons and Kruskal-Wallis test for multi-group comparisons. The null hypothesis in both tests is that there are no differences in mean of the CO_2 shadow prices across the groups of the iron and steel enterprises. As shown in Table 5, the mean CO_2 shadow prices for listed and unlisted enterprises or enterprises of different sizes are significantly different while there seems no significant difference in the mean CO_2 shadow price across different vintage or location groups.

We find that the mean shadow price of CO_2 emissions of the listed enterprises is significantly lower than that of the unlisted. This may be because listed enterprises are typically subject to more frequent regulatory inspections and more stringent rules of environmental information disclosure, and facing higher pressure from public supervision. Listed enterprises thus need to devote more facilities and resources to environmental protection activities. As these enterprises currently do not face binding CO_2 reduction obligations, the facilities and resources devoted to environmental protection may well increase total energy consumption and associated CO_2 emissions. For instance, the operation of SO_2 and NO_X scrubbers mandated by Chinese regulatory authorities usually results in more energy consumption and CO_2 emissions. The chemical reaction of pollutant absorbing also emits additional CO_2 emissions. As a result, the reduction potentials and the marginal abatement costs of CO_2 emissions of the listed enterprises are likely to be higher and lower, respectively, than those of the unlisted iron and steel enterprises.

Next, we examine whether enterprises of various sizes exhibit differences in shadow prices. We categorize the sample enterprises into three groups based on their production capacity: (i) small enterprise:

Table 3
Estimated parameters of directional distance function with different DVs.

Parameter	Estimates by DV			Parameter	Estimates by DV		
	(1, 0)	(1, −1)	(0, −1)		(1, 0)	(1, −1)	(0, −1)
α	0.0625	−0.0120	−0.0501	η_4	0.0000	−0.0209	0.0000
α_1	0.0964	0.1617	−0.0003	η_5	−0.0170	−0.0215	0.0000
α_2	0.6730	0.2430	−0.0085	δ_1	0.5466	−0.2615	−0.0060
α_3	0.2951	0.3857	0.3842	δ_2	−0.3618	0.0618	0.1598
α_4	0.0000	−0.0004	0.0000	δ_3	−0.1371	−0.0418	−0.1705
α_5	−0.0015	−0.0023	0.0000	δ_4	0.0000	−0.0209	0.0000
β_1	−1.0000	−0.7729	−0.6563	δ_5	−0.0476	−0.0215	0.0000
e	0.0228	0.2271	1.0000	μ	0.2216	0.1052	−0.2459
α_{11}	0.0096	0.4759	0.0108	$\alpha_{12} = \alpha_{21}$	−0.4321	0.1804	0.0014
α_{22}	0.5364	−0.3343	−0.2330	$\alpha_{13} = \alpha_{31}$	−0.0497	−0.1459	0.0005
α_{33}	−0.0416	−0.0769	−0.0436	$\alpha_{14} = \alpha_{41}$	0.0000	0.0600	0.0000
α_{44}	0.0000	−0.0190	0.0000	$\alpha_{15} = \alpha_{51}$	0.0499	0.0374	0.0000
α_{55}	−0.0112	−0.0077	0.0000	$\alpha_{23} = \alpha_{32}$	0.1057	0.1267	0.1588
β_2	0.0000	0.1052	0.0623	$\alpha_{24} = \alpha_{42}$	0.0000	0.0020	0.0000
γ_2	−0.0186	0.1052	0.0000	$\alpha_{25} = \alpha_{52}$	0.0223	0.0057	0.0000
η_1	−0.0687	−0.2615	−0.0036	$\alpha_{34} = \alpha_{43}$	0.0000	0.0025	0.0000
η_2	−0.0962	0.0618	0.0838	$\alpha_{35} = \alpha_{53}$	0.0234	0.0136	0.0000
η_3	−0.0002	−0.0418	−0.0802	$\alpha_{45} = \alpha_{54}$	0.0000	0.0128	0.0000

Table 4
Estimated CO_2 shadow prices (SP) with different DVs.

Enterprise	DV: (1, 0)		DV: (1, −1)		DV: (0, −1)		Average	
	SP	Rank[a]	SP	Rank[a]	SP	Rank[a]	SP	Rank[a]
Jianlong	1223	48	564	8	5770	18	2519	20
Tianjin Pipe	5	6	1545	37	9153	47	3568	47
Tianjin Tiangang	470	37	1177	21	6958	31	2868	33
Tian Tie	84	8	459	7	4293	9	1612	7
Tangshan	637	42	0	1	5125	12	1921	9
Han-Steel	1124	47	353	5	6417	26	2632	26
Cheng-Steel	457	36	380	6	6873	30	2570	25
Xuan-Steel	245	25	749	9	7327	35	2774	29
Xinxing Cathay	419	34	1615	40	7778	39	3271	42
Taiyuan	289	27	0	1	3174	7	1154	3
Baogang	0	1	1836	46	3882	8	1906	8
Xinfugang	298	28	1454	34	7497	37	3083	36
Ansteel	594	40	749	10	0	1	448	1
Lingyuan	442	35	1184	22	6501	28	2709	28
Zhongban	286	26	1288	25	7291	34	2955	34
Benxi	0	1	126	4	3167	6	1098	2
Tonggang	98	10	1407	30	6964	32	2823	32
Xilin	142	16	1457	35	8491	45	3363	45
Lueyang	148	19	1807	45	9517	49	3824	49
Longmen	887	44	955	16	5002	11	2282	13
Jiuquan	0	1	1040	18	6210	23	2417	16
Baosteel	0	1	2331	47	1336	3	1222	4
Nanjing	236	24	1439	32	5899	20	2525	21
Shasteel	3899	49	3794	49	1940	4	3211	40
Yonggang	549	39	1453	33	5396	14	2466	18
Hangzhou	181	21	1673	42	7546	38	3133	38
Ma-steel	147	18	946	14	2973	5	1355	5
Xinyu	96	9	1001	17	6587	29	2561	24
Pinggang	403	33	1204	23	6375	25	2661	27
Sangang	604	41	1153	20	5472	16	2410	15
Jigang	373	30	750	11	6338	24	2487	19
Laigang	668	43	880	13	5645	17	2397	14
Qinggang	135	15	1349	26	7891	40	3125	37
An Gang	383	31	67	3	6084	21	2178	12
Wuhan	924	45	2363	48	947	2	1411	6
Echeng	144	17	1591	38	7445	36	3060	35
Xinyegang	104	11	1594	39	8024	41	3241	41
Xiangtan	128	13	1421	31	6086	22	2545	22
Lianyuan	357	29	1402	29	5888	19	2549	23
Hengyang	84	7	1719	43	8841	46	3548	46
Lengshuijiang	112	12	1659	41	8187	42	3319	43
Shaoguan	0	1	1265	24	7126	33	2797	31
Guangxi	978	46	950	15	4370	10	2099	10
Panzhihua	524	38	1387	27	6480	27	2797	30
Tranvic	128	14	1459	36	9186	48	3591	48
Dazhou	194	22	1402	28	8466	44	3354	44
Kunming	392	32	820	12	5160	13	2124	11
ee	199	23	1750	44	5413	15	2454	17
Chonggang	170	20	1096	19	8366	43	3211	39
East	414	–	1219	–	5939	–	2524	–
Central	397	–	1347	–	5706	–	2483	–
West	385	–	1365	–	6000	–	2583	–
Mean	407	–	1226	–	6058	–	2564	–
Std. Dev.	586	–	655	–	2156	–	723	–

[a] The enterprises are ranked in the ascending order of shadow prices by each direction vector.

with total annual steel production of <5 million tonnes; (ii) medium-sized enterprise with total annual steel production of between 5 million and 10 million tonnes, and (iii) large enterprise with total annual steel production of >10 million tonnes. Fig. 3 and Table 6 show that there appear to be economies of scale in the cost of CO_2 mitigation: larger enterprises tend to exhibit significantly lower marginal abatement cost.

Iron and steel enterprises of different vintages may use very different technologies that are expected have bearings on the cost of CO_2 mitigation. We divide the sample iron and steel enterprises into two groups: (i) young enterprises that have operated for <50 years, and (ii) old enterprises that have operated for >50 years. Despite our expectations to the contrary, the results in Table 6 show no significant differences in mean shadow price across vintage groups.

Wu and Ma (2017) found strong city-level evidence of substantial heterogeneity in the mean shadow prices of CO_2 emissions across Chinese geographical regions; however, in the iron and steel industry, we find no significance difference across regions. We divide the iron and steel enterprises into three geographical groups: (i) east region: Shanghai, Beijing, Tianjin, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan, Liaoning; (ii) central region: Shanxi, Henan, Hubei, Hunan and Jiangxi, Jilin and Heilongjiang; and (iii) west region: Chongqing, Sichuan, Guizhou, Yunnan, Guangxi, Shaanxi, Gansu and Inner Mongolia. As environmental regulation in the east region is typically more stringent than that in the central and west regions (SCC, 2011b), we thus expect differences in the shadow prices of CO_2 emissions across regions. However, our results show that the differences in the mean shadow prices are insignificant. Nevertheless, we find that enterprises in the east and central regions have higher degree of dispersion in the shadow prices of CO_2 emissions than those in the west regions. This implies higher potential for the iron and steel enterprises in the east or central regions to benefit from emission trading in the coming national carbon trading market in China.

5. Conclusions and policy implications

The iron and steel industry is one of the most energy-intensive industries contributing substantial amount of China's energy consumption and CO_2 emissions. It has been widely believed that the industry has taken on significant carbon mitigation to help fulfil the energy and emission intensity targets set by the Chinese government. However, whether this remains the case under China's proposed national carbon trading market will largely depends on the MAC of carbon mitigation.

In this paper, we estimated the CO_2 shadow prices of China's 49 major iron and steel enterprises in 2014 based on DDF approach using three different DVs: $g = (1, -1)$, $g = (1, 0)$ and $g = (0, -1)$ representing three different production and emissions abatement strategies. The results show that the mean CO_2 shadow price of China's iron and steel enterprises is very sensitive to the choice of direction vectors. The average shadow prices of CO_2 are 407, 1226 and 6058 Yuan/tonne respectively for the three different direction vectors. In addition, we found that the choice of directions also has an impact on the order of the sequence of the MAC estimates. One might get robust estimates of mean shadow prices but results are much less robust in terms of the order when using different directions.

Our estimate of the mean MAC level in the iron and steel industry is very much comparable to those in other industries found in recent literature. However, we show that arbitrarily chosen direction vectors as is common practice in this literature may substantially underestimate the potential of low-cost abatement opportunities and the benefit of carbon trading. We also find significant difference in the mean and dispersion of MAC across groups of iron and steel enterprises with different characteristics, suggesting both intra-group and inter-group heterogeneity in MAC. Larger, listed enterprises are found to be associated lower CO_2 shadow prices than smaller, unlisted enterprises. Our findings provide useful information for better-informed carbon mitigation policy making and strong support for China's proposed national carbon trading market.

Although this study provides useful information for policy makers and enterprises about the abatement cost of carbon reduction, it has some limitations. Caution needs to be taken when making use of the results due to the limited number of iron and steel enterprises. The second limitation relates to the limited consideration of the complex production process for integrated steelmaking. Unlike the construction of energy conservation supply curve in iron and steel industry (Worrell et al., 2001), the DDF model simply consider the final output of production process which may cause biased estimation. Further research is warranted to better address these issues.

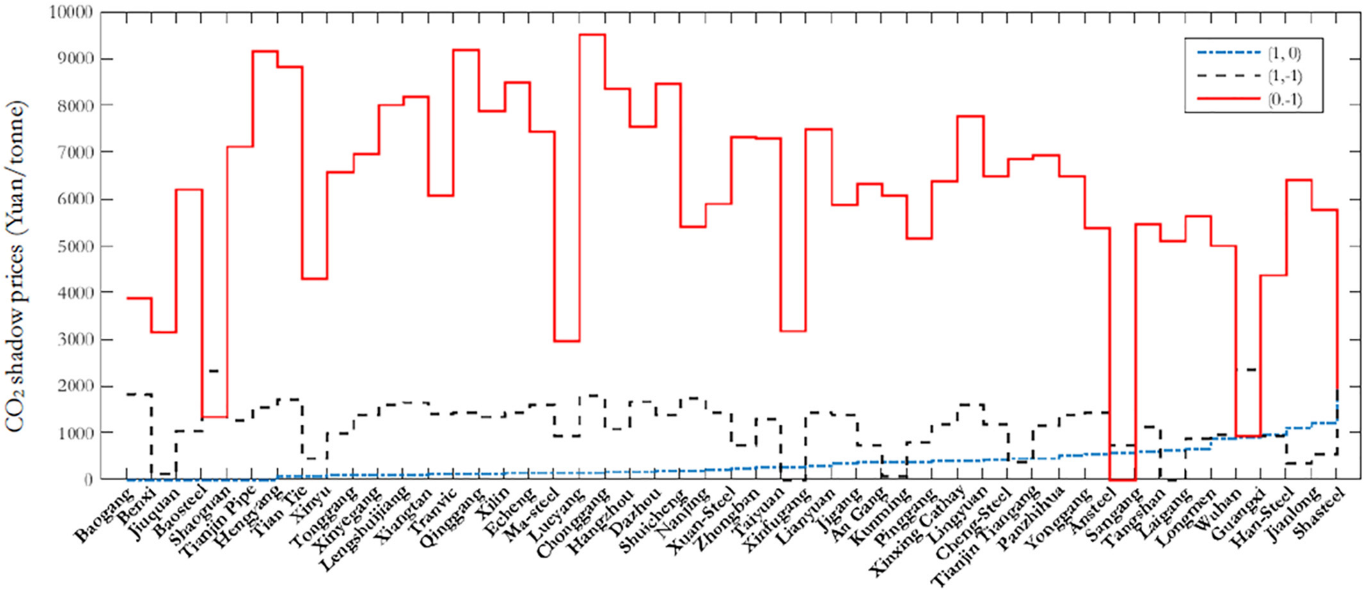

Fig. 2. CO_2 shadow price curves of China's iron and steel enterprises.

Table 5
Summary of studies on estimating CO_2 shadow prices in China.

Study	Sample	Period	Method[a]	Average shadow price
Wang et al. (2011)	28 provinces	2007	DDF	475 Yuan/tonne
Wei et al. (2012)	29 provinces	1995–2007	SBM	114 Yuan/tonne
Choi et al. (2012)	30 provinces	2001–2010	SBM	46 Yuan/tonne
Peng et al. (2012)	24 industrial sectors	2004 & 2008	DDF	17,500 & 15,200 Yuan/tonne
Lee and Zhang (2012)	30 manufacturing industries	2009	DF	20 Yuan/tonne
Wei et al. (2013)	124 thermal power plants	2004	DDF	2060 Yuan/tonne
Chen (2013)	38 industrial sectors	1981–2010	DDF	1689 Yuan/tonne
Wang and Wei (2014)	30 cities' industrial sectors	2006–2010	DDF	298 Yuan/tonne
Du et al. (2015)	30 provinces	2001–2010	DDF	1300 Yuan/tonne
Ma and Hailu (2016)	30 provinces	2001–2010	DF/DDF	132/2251 Yuan/tonne
Xie et al. (2016)	9 key industrial sectors	2005–2014	DDF	721 Yuan/tonne
This study	49 iron and steel enterprises	2014	DDF	2564 Yuan/tonne

[a] SBM, DF and DDF denote slacks-based measure, distance function and directional distance function, respectively.

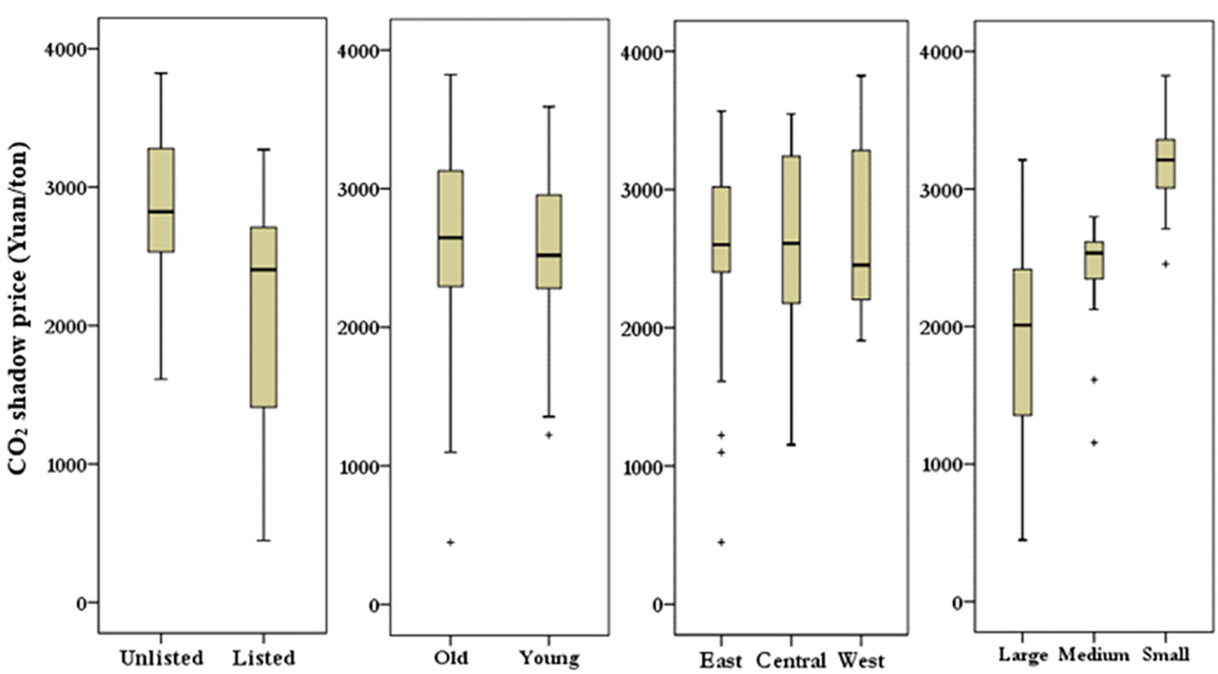

Fig. 3. Distribution of CO_2 shadow prices by group.

Table 6
Heterogeneity in CO_2 shadow prices by group.

Characteristics	Groups	No. of enterprises	Average SP (Yuan/tonne)	Coefficient of variation	P-value
Ownership	Unlisted enterprises	27	2865	0.18	0.002[†]
	Listed enterprises	22	2195	0.36	
Vintage (years old)	Old (≥50)	36	2585	0.28	0.684[†]
	Young (<50)	13	2505	0.30	
Location	East	24	2492	0.30	0.882[††]
	Central	14	2555	0.30	
	West	11	2732	0.23	
Size (million tonnes of steel products)	Large (>10)	14	1915	0.38	0.000[††]
	Medium (5–10)	16	2395	0.18	
	Small (<5)	19	3184	0.11	

† Mann-Whitney *U* test.
†† Kruskal-Wallis test.

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