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Evaluation of marginal abatement cost and potential reduction in China's industrial carbon emissions: A quadratic directional output distance function approach

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A B S T R A C T

As a relevant indicator for quantifying the value of carbon emissions, the marginal abatement cost (MAC) of carbon emissions has received increasing attention from academics and policymakers. This study uses a quadratic directional output distance function to analyse the technical efficiency, potential emission reduction and shadow prices of China's industrial carbon emissions. The results show that the technical efficiency of China's industry gradually decreased during the sample period. From the perspective of regions with different carbon intensity and industrial output, regions with lower carbon intensity and higher industrial output gradually closed to the optimal frontier for the technology use level and had relatively high technical efficiency. Rising technical inefficiency and carbon emissions led to a potential emission reduction that also exhibits an upwards trend. In addition, the MAC of industrial carbon emissions exhibits a U-shaped trajectory, with 2011 as the turning point. Generally, in recent years, regions with lower carbon intensity and those with higher industrial output have a relatively high MAC for industrial carbon emissions. The empirical findings reveal that a carbon emission reduction policy should be formulated and targeted to each province, and the principle of 'easy before difficult' can be followed to promote emission reduction.

Introduction

As the largest emitter of carbon dioxide (CO_2) emissions in the world, China is under enormous pressure to reduce its emissions. China is now in the intermediate and late stages of industrial development, and the Chinese industry has been labelled 'high consumption and high emissions'. China's industrial fossil energy use and CO_2 emissions account for 70 % of China's total energy consumption and CO_2 emissions (Wang & Feng, 2018a,b). To promote low-carbon development, the Chinese government set several emissions mitigation targets. The 13th Five-Year Plan set a target to achieve carbon abatement per unit of GDP by 40 %–45 % by 2020 compared to the 2005 level, working towards achieving the goal of peak carbon emissions by 2030 and aiming for carbon neutrality by 2060. To reach these targets, the Chinese government took several emission reduction measures, such as compelling the elimination of outdated production facilities and technologies in high-energy consumption industries via administrative and legislative means and promoting new energy technologies.

The Chinese government has also started to emphasise and strengthen its market position to deploy environmental resources, gradually strengthening the crucial role of market mechanisms in the allocation of environmental resources (Guo & Feng, 2021). In 2011, pilot carbon trading projects led by the National Development and Reform Commission were launched in Beijing, Tianjin, Shanghai, Chongqing, Guangdong, Hubei and Shenzhen. On 19 December 2017, the National Carbon Emission Trading Market Construction Plan (Power Generation Industry) was issued, and the framework of China's carbon emissions trading system was completed, establishing a national carbon emissions trading market for the first time.

Assessing the value of carbon emissions has emerged as a significant area of research and policy focus following the inception of the Kyoto Protocol (Jin & Chen, 2022). In recent years, the Chinese government has implemented a range of measures to facilitate carbon reduction. What is the opportunity cost of continuing measures such as the above emission reduction policies? What are the influencing factors of opportunity cost for carbon emission reduction? How can mitigation measures for achieving carbon emission reduction be

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achieved at a lower cost? Determining the answers to these questions could advance carbon emission reduction and the efficient operation of carbon trading markets. The shadow price of carbon emissions, namely the theoretical equilibrium price of carbon emission trading, is the marginal emission reduction cost (marginal abatement cost, MAC) of CO_2 emissions.[1] The study's findings provide a significant reference for the government to conduct rational allocations of carbon emissions, compensate for enterprises' emission reduction and offer relevant insights for carbon emissions trading prices in the primary market and guiding the market trading price.

As a 'bad' output, carbon emissions lack actual trading value; thus, no clear market price is evident. As the embodiment of social cost, the shadow price (MAC) can effectively reflect the trading price of such bad output. Therefore, accurately measuring the carbon emission shadow price is crucial to determining rational carbon emission prices. Among all related estimation approaches, the directional distance function (DDF) is more relevant to practical needs due to its characteristic of allowing non-desired and desired outputs to vary in different proportions. In addition, with the innovation of production technology and the increase in green growth requirements, the DDF provides an effective way to expand desired outputs while cutting non-desired outputs. Considering this, DDF is increasingly favoured by more researchers. Additionally, different Chinese regions exhibit various features. To examine regional discrepancies and provide an evidence-based reference for the government to assign carbon emission reduction tasks, this study measures the shadow price of industrial CO_2 emissions (ICE) at different group levels. For the above two issues, we use provincial panel data from China's industrial sector and develop a quadratic directional output distance function approach for measuring the shadow price of industrial CO_2 emissions. This study also calculates different regions' potential industrial carbon reductions, which may offer a valuable reference for the government to assign carbon emission reduction tasks. In brief, analysing the shadow price of ICE can provide a relevant reference for the government to accurately implement ICE allocations and compensate enterprises' emission reduction, and it is also relevant for the pricing of carbon emissions trading in the primary market and guiding the market trading prices.

The remainder of this study is structured as follows. Section "Literature review" reviews the previous related studies. Section "Models and data" details the model construction and introduces the data used for processing. Section "Empirical results and discussion" discusses the shadow price and potential carbon emission reduction at the national, group and provincial levels. Section "Conclusions and policy implications" summarises the full text and offers some relevant policy proposals.

Literature review

Previous research has primarily used two different methods for measuring shadow price: computable general equilibrium and the distance function. The distance function method only requires historical input–output data to estimate the shadow price and does not require an abundance of assumptions regarding future forms of economic development and technological progress (Wang et al., 2018). In addition, the estimated results can effectively measure the MAC and potential emission reductions; thus, the distance function has been extensively used for quantifying pollutant shadow prices (Zhang et al., 2019).

The Shephard distance function and DDF are the two most commonly employed distance functions (Murty & Kumar, 2002). The Shephard distance function approach only requires the actual pollution emissions and does not require input–output price information. By using the dual relationship between output distance and income functions, we can obtain the pollutant shadow price, which provides a clearer economic meaning. Given the advantages of the distance function, this method has been widely used for pollutant shadow price measurement. For instance, Reig-Martínez et al. (2001) estimated the shadow price of two industrial wastes in the ceramic pavement industry in Spain using the Shephard output distance function. Park and Lim (2009) also applied the output distance function to calculate the shadow price of CO_2 emissions from electric power plants in Korea.

However, the Shephard distance function only allows for the change rate of good output to be the same as that of bad output, and that does not suit the needs of policymakers, for whom good output should increase while bad output decreases (Cheng & Kong, 2022; Li et al., 2023; Wu et al., 2023). Under this circumstance, Chambers et al. (1996) proposed the DDF, which eliminates the angular constraint by simultaneously adjusting the input and output in different directions. Chung et al. (1997) first applied the DDF to a study containing bad outputs. The basic idea of DDF is to incorporate good and bad outputs that occur in the production course into the model, enabling disproportionate scale changes in both forms of output; that is, as good output increases, bad output can decrease. This model also means that the observation point meets the frontier of efficiency only when good output is unable to continue to expand and bad output is unable to continue to shrink. DDF conforms to the actual circumstances and has considerable flexibility and low data requirements (i.e. DDF only requires the corresponding input and output data, which are extremely easy to obtain); thus, the technique is more attractive to scholars for measuring shadow price (or MAC).

Examples of relevant DDF–shadow price studies include Du and Mao (2015), who examined the CO_2 MAC of Chinese coal-fired power plants, combining production theory with output DDF. Molinos-Senante et al. (2015) used parametric quadratic DDF to calculate the CO_2 shadow price of wastewater treatment plants. Kaneko et al. (2010) used non-parametric DDF to evaluate the sulfur dioxide (SO_2) emissions MAC of China's thermal power sector. Liu and Feng (2018) estimated the CO_2 emissions shadow prices of 165 countries using a quadratic output DDF and examined its influencing factors. He et al. (2018) estimated the provincial CO_2 MAC for China employing parametric DDF. Wang et al. (2020) also used DDF to measure the MAC of China's regional CO_2 emissions. Ji and Zhou (2020) employed a multi-pollutant parametric output DDF to evaluate the MACs of CO_2, SO_2 and nitrogen oxide (NOx) emissions in 105 cities across China from 2006 to 2014. Wu et al. (2020) adopted the quadratic DDF model to calculate the CO_2 emissions MAC of the Chinese 30 provinces and determined quotas for CO_2 emissions among provinces based on the results. Wu et al. (2021) used DDF and slacks-based measure (SBM) techniques to measure the shadow prices of SO_2 and CO_2 in China. Wang et al. (2022) used non-parametric DDF to calculate carbon shadow prices in 152 countries worldwide. Thuy et al. (2023) applied DDF to estimate the MAC of three water contaminants in the seafood processing industry in Vietnam.

Parametric and non-parametric approaches have primarily been used to calculate the distance function (Ma et al., 2019; Oh et al., 2020; Xian et al., 2020). The non-parametric method predominantly employs data envelopment analysis (DEA). Examples of researchers who have used non-parametric approaches include Choi et al. (2012), Wang and He (2017), Wu et al. (2019), Chen et al. (2021), Kumar and Jain (2021)), Shen et al. (2021), Baležentis et al. (2022), Yue et al. (2023) and Silva and Magalhães (2023). In parametric methods, the distance function is approximately expressed using a translog or quadratic function, and the corresponding parameters are estimated using linear programming or stochastic frontier analysis (SFA). As one of the non-parametric methods, DEA may have the defect of the estimation result not being unique when estimating the shadow

[1] The meaning of MAC is equal to the shadow price in this manuscript.

price. Additionally, by parameterising the DDF, the boundary of production is represented in the form of a specific production function, and the shadow price of bad output can be obtained through differentiation, but using the non-parametric method to calculate the shadow price of bad output through differentiation is difficult.

Many scholars have adopted parametric approaches to estimate DDF when investigating shadow prices. For example, Tang et al. (2016) employed a parametric DDF approach to estimate the MACs of China's CO_2 and SO_2 emissions from 2003 to 2012. Zhang and Jiang (2019) applied a parametric meta-frontier input distance function to calculate the shadow price of SO_2 emissions for 93 of China's coal-fired power plants located in China's key 'environmental protection cities'. Adenuga et al. (2020) applied a translog function that is specified in an SFA framework to value the shadow price and cost ratio of pollution of surplus P in dairy farms in Northern Ireland. Wei and Zhang (2020) proposed a partial parametric environmental production frontier to estimate CO_2 and SO_2 emissions shadow prices for 93 coal-fired power plants in China. Qi and Choi (2020) examined DDF calculated by SFA to estimate the CO_2 MAC of 92 coal-fuel generators located in Shanghai, China. Maziotis et al. (2020) used a parametric approach to estimate the shadow price of reducing unplanned water supply interruptions for 21 Chilean water companies. He et al. (2021) used the parameter method to set a quadratic DDF to calculate the shadow price of agricultural greenhouse gases. Ji et al. (2021) parameterised DDF using the quadratic function and applied the parameterisation method to estimate the shadow prices of four pollutants in major cities in China. Rekker et al. (2023) used a parametric quadratic DDF to calculate the MAC of CO_2 in the European chemical industry.

In terms of research regarding the environmental emissions shadow price in China's industrial sector, Chen et al. (2013) used DDF to evaluate the MAC of industrial CO_2 emissions in China and analyse the MAC differences among various industrial sectors. Wu et al. (2020) measured CO_2 shadow prices in China's 36 industrial sectors from 2006 to 2015 using an environmental production frontier DDF based on a non-parametric approach. Cheng et al. (2020) adopted the by-production DEA model's dual formulation to investigate industrial carbon shadow prices based on Chinese provincial panel data. Liu et al. (2020) applied a joint production DEA-based model to analyse the MAC change and its decomposed factors of SO_2 emissions in China's industrial sector. Wang et al. (2020) applied the dual model of the traditional SBM to measure the CO_2 MAC of China's industrial sector from a provincial perspective. Shen et al. (2021) used the revised backpropagation-DEA model to measure the carbon shadow prices generated in China's industrial sector from 1998 to 2017. Zhang et al. (2022) used quadratic DDF and SFA methods to estimate SO_2 and CO_2 emissions shadow prices in China's industrial sector.

The above industrial sector studies produced many meaningful results, providing relevant references for China's future emission reduction in the industrial sector. However, these previous studies have two notable limitations. First, most industrial carbon MAC studies were conducted from the perspective of different sub-industries. Although a few studies examined industrial CO_2 shadow prices at the provincial level, these studies were not conducted according to the characteristic clustering groups of different provinces. Second, as noted above, non-parametric methods carry the defect of the estimation result not being unique when estimating shadow prices. Regrettably, studies that conducted shadow price analysis at the provincial level all adopted the non-parametric approach. As pointed out above, a non-parametric approach may have the defect of the estimation result not being unique when estimating the shadow price. In addition, the boundary of production is represented in the form of a specific production function, and then the shadow price of 'bad' output can be obtained by differentiating through parametric DDF, whereas it is difficult to calculate the shadow price of 'bad' output by differentiating through the non-parametric method.

Considering this, this study conducts extended research in the following two ways. First, we use the data from each province in China's industrial sector from 2000 to 2017 to estimate technical efficiency by adopting a quadratic directional output distance function method (which is a kind of parametric approach) for CO_2 shadow price and potential CO_2 emission reduction (PCR). Second, this study classifies the 30 provinces into different groups based on the characteristics of geographical location, carbon intensity and per capita industrial output value to examine the discrepancies in technical efficiency, shadow price and PCR in different groups.

Models and data

Directional output distance function

In the production process, the desired product and its by-products (such as pollutants) are often produced simultaneously. We assume that n decision-making units use M inputs $x = (x_1, x_2, \cdots x_m) \in R_M^+$ to produce S good output $(y = (y_1, y_2, \cdots y_s) \in R_S^+)$ and J bad output $b = (b_1, b_2, \cdots b_j) \in R_J^+$. Subsequently, the process of production can be formulated as follows:

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

According to Chung et al. (1997), the possibility set of production is bounded and closed, and input and good output can be more easily disposed. Furthermore, according to the co-production relationship of good and bad output, the following two assumptions must also be satisfied: (1) null-jointness, if $(y, b) \in P(x)$ *and* $b = 0$, then $y = 0$; (2) weak disposable of bad output, if $(y, b) \in P(x)$ *and* $0 \le \theta \le 1 = 0$, then $(\theta y, \theta b) \in P(x)$.

Combining the input–output $(x,\ y,\ b)$ and direction vector $g = (g_y, -g_b)$, the following is the definition of the directional output DDF:

$$\vec{D}_o(x, y, b; g_y, -g_b) = \sup\{\beta : (y + \beta g_y, b - \beta g_b) \in P(x)\} \tag{2}$$

This DDF manifests that it is feasible to maximise the good output along the direction vector $g = (g_y, -g_b)$while minimising the bad output under a given production feasibility set $P(x)$.

Fig. 1 illustrates the DDF, revealing that if the producer is at the boundary of the $P(x)$ set, $\vec{D}_o(x, y, b; g_y, -g_b) = 0$ (i.e. $\beta = 0$), this is the most efficient status. If the producer produces within the $P(x)$ set, $\vec{D}_o(x, y, b; g_y, -g_b) > 0$ (i.e. $\beta > 0$), this indicates that the output is inefficient, and there is potential to further expand good output and reduce bad output. Briefly, a higher β value indicates that production efficiency is lower.

Furthermore, the DDF has the following translation properties:

$$\vec{D}_o(x, y + \beta g_y, b - \beta g_b; g_y, -g_b) = \vec{D}_o(x, y, b; g_y, -g_b) - \beta \tag{3}$$

Eq. (3) indicates that if the good output rises by βg_y and the bad output simultaneously decreases by βg_b, then the producer is more efficient and the DDF decreases by β.

Shadow prices of bad outputs

The bad output's shadow price is obtained from the dual relation of DDF and profit function. Suppose that the price vector of good output is $p = (p_1, p_2, \cdots p_s) \in R_S^+$and the price vector of bad output is $= (q_1, q_2, \cdots q_j) \in R_J^+$.

In addition, because $\vec{D}_o(x, y, b; g_y, -g_b) \ge 0$, the profit function is defined as follows:

$$W(x', p, q) = \max_{y,b}\left\{py - qb : \vec{D}_o(x, y, b; g) \ge 0\right\} \tag{4}$$

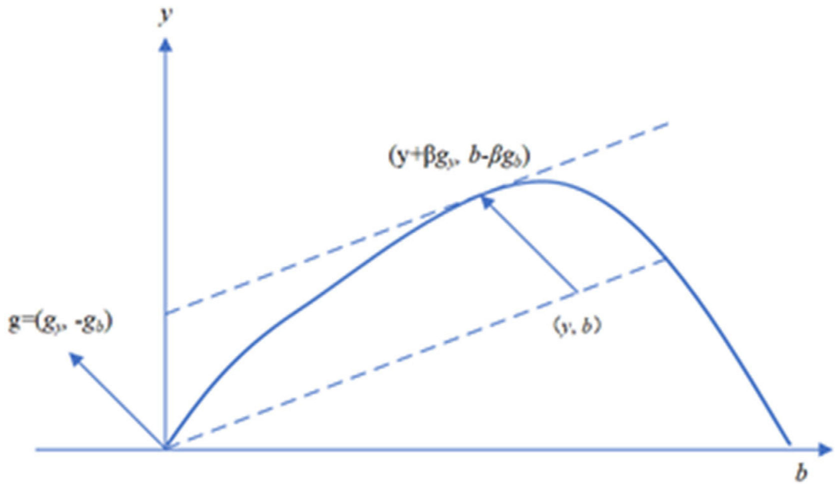

Fig. 1. Directional output distance function.

where x' indicates the prices of inputs. Eq. (4) can be further written as follows:

$$W(x', p, q) \geq (py - qb) + p\vec{D}_o(x, y, b; g)g_y + q\vec{D}_o(x, y, b; g)g_b \tag{5}$$

The left-hand side of Eq. (5) indicates the maximum possible benefit allowed within the production feasibility set. By contrast, the right-hand side is the actual benefit plus the benefit from eliminating inefficiencies by increasing good output while reducing bad output. When the inefficiencies are eliminated along the direction vector and reach the output frontier, we obtain the following:

$$\vec{D}_o(x, y, b; g) = \min_{p,q}\left\{\frac{W(x', p, q) - (py - qb)}{pg_y + qg_b}\right\} \tag{6}$$

Take the following derivative of good and bad output:

$$\begin{cases} \nabla y\vec{D}_o(x, y, b; g) = \dfrac{-p}{pg_y + qg_b} \leq 0, \\ \nabla b\vec{D}_o(x, y, b; g) = \dfrac{q}{pg_y + qg_b} \geq 0. \end{cases} \tag{7}$$

Subsequently, the bad output shadow price can be expressed as follows:

$$\begin{cases} q_j = -p_s\dfrac{\partial\vec{D}_O(x, y, b; g)/\partial b_j}{\partial\vec{D}_O(x, y, b; g)/\partial y_s} \\ j = 1, 2, \cdots, \mathrm{J}; s = 1, 2, \cdots, \mathrm{S}. \end{cases} \tag{8}$$

Parameterised quadratic directivity output distance function

Translog and quadratic forms are often used to parameterise distance functions. Among the forms, the translog form cannot satisfy the transfer property of DDF and is generally used in parameterising the Shepard output distance function (Lee & Zhang, 2012). The quadratic form is a quadratic approximation of the unknown distance function, which satisfies the character of the directional output distance function well. Therefore, this study adopts the quadratic form to parameterise the DDF. We set the directional vector $g = (1, -1)$, which indicates that for a given input, good output expands by a unit and bad output decreases by a unit.

This study sets labour (x_1), capital stock (x_2) and energy (x_3) as inputs, and gross industrial output value (y) and CO_2 emissions (c) as the good and bad outputs, respectively (Yang et al., 2021; Tian & Feng, 2022; Feng et al., 2018, 2024). Notably, the quadratic function includes a region dummy variable (ID_k) and a time dummy variable (T_t) for capturing the effects of individuals and time. Subsequently, the quadratic DDF for the k^{th} province in year t can be expressed as follows:

$$\begin{aligned} \vec{D}_o\left(x_k^t, y_k^t, b_k^t; 1, -1\right) &= \alpha_0 + \sum_{n=1}^{3}\alpha_n x_{nk}^t + \beta_1 y_k^t + \gamma_1 b_k^t \\ &+ \frac{1}{2}\sum_{n=1}^{3}\sum_{n'=1}^{3}\alpha_{nn'}x_{nk}^t x_{n'k}^t + \frac{1}{2}\beta_2\left(y_k^t\right)^2 + \frac{1}{2}\gamma_2\left(b_k^t\right)^2 \\ &+ \sum_{n=1}^{3}\delta_n x_{nk}^t b_k^t + \sum_{n=1}^{3}\varepsilon_n x_{nk}^t y_k^t + \mu y_k^t b_k^t + \sum_{k=1}^{K-1}\lambda_k ID_k \\ &+ \sum_{t=1}^{T-1}\tau_t T_t \end{aligned} \tag{9}$$

This study estimates the parameters of quadratic DDF using the following linear programming algorithm:

$$\begin{cases} Min\displaystyle\sum_{t=1}^{T}\sum_{k=1}^{K}\left[\vec{D}_o\left(x_k^t, y_k^t, b_k^t; 1, -1\right) - 0\right] \\ s.t.(i)\ \vec{D}_o\left(x_k^t, y_k^t, b_k^t; 1, -1\right) \geq 0, k = 1, \cdots, \mathrm{K}; \mathrm{t} = 1, \cdots, \mathrm{T}. \\ (ii)\ \vec{D}_o\left(x_k^t, y_k^t, 0; 1, -1\right) \leq 0, k = 1, \cdots, \mathrm{K}; \mathrm{t} = 1, \cdots, \mathrm{T}. \\ (iii)\ \dfrac{\partial\vec{D}_o\left(x_k^t, y_k^t, b_k^t; 1, -1\right)}{\partial b} \geq 0, k = 1, \cdots, \mathrm{K}; \mathrm{t} = 1, \cdots, \mathrm{T}. \\ (iv)\ \dfrac{\partial\vec{D}_o\left(x_k^t, y_k^t, b_k^t; 1, -1\right)}{\partial y} \leq 0, k = 1, \cdots, \mathrm{K}; \mathrm{t} = 1, \cdots, \mathrm{T}. \\ (v)\ \dfrac{\partial\vec{D}_o\left(x_k^t, y_k^t, b_k^t; 1, -1\right)}{\partial x_n} \geq 0, n = 1, 2, 3; k = 1, \cdots, \mathrm{K}; \mathrm{t} = 1, \cdots, \mathrm{T}. \\ (vi)\ \beta_1 - \gamma_1 = -1; \beta_2 = \gamma_2 = \mu; \delta_n - \varepsilon_n = 0; n = 1, 2, 3. \\ (vii)\ \alpha_{nn'} = \alpha_{n'n}, n, n' = 1, 2, 3. \end{cases} \tag{10}$$

After estimating the parameters of DDF (the parameter values are listed in Appendix Table A.1), the shadow prices of industrial CO_2 emissions in province k no year t can be calculated as follows:

$$q = -p\frac{\gamma_1 + \gamma_2 b + \sum_{n=1}^{3}\delta_n x_n + \mu y}{\beta_1 + \beta_2 y + \sum_{n=1}^{3}\varepsilon_n x_n + \mu b} \tag{11}$$

In the current study, ICE is the unexpected output, and the expected output is gross industrial output; thus, the economic significance of the calculated ICE shadow price is the amount of gross industrial output to be reduced to reduce one ICE unit, representing the MAC of ICE.

Data

This study is conducted using panel data for the 30 Chinese provinces from 2000 to 2017 and calculating technical efficiency, abatement potential and shadow prices based on various input−output datasets. Among the datasets, labour force, energy consumption and capital stock are set as input−output datasets (i.e. x). Conversely, gross industrial output and industrial CO_2 emissions are set as good output (y) and bad output (b), respectively (Liu & Feng, 2023; Wang & Feng, 2020, 2021a,b; Zheng et al., 2023). The data sources and processing are described as follows.

(1) The labour data from 2000 to 2016 are obtained from the Statistical Yearbook of the Chinese Industry (2001−2017), and the labour data in 2017 use the average value between 2016 and 2018. The labour data in 2018 are obtained from the China Economic Census Yearbook—2018. (2) We use the 'perpetual inventory method' to calculate capital stock data, processing the relevant data referencing Chen (2011). (3) Energy consumption data for the industrial sector are obtained from the China Energy Statistics Yearbook of China (2001−2018), and we convert the physical quantity of energy consumption data into standard coal equivalent. (4) Gross industrial output value data from 2000 to 2011 are obtained from CISY (2001−2012), and the data for 2012−2017 are estimated using industrial sales values and the average production−sales ratio. All currency-related data (y and k) are converted to constant prices in 2000. (5) Finally, we calculate CO_2 emissions from fossil energy, referencing Mi et al., (2017), Wang and Feng, (2017) estimating the indirect CO_2 emissions induced from electricity using the CO_2 coefficient of electricity, or the CO_2 emissions per unit of thermal power generation.

Furthermore, to examine the differences between regions with different characteristics, this study groups the 30 provinces into different regions according to geographical location, carbon intensity and per capita gross industrial output value (see Table 1). In terms of carbon intensity and per capita gross industrial output value, the top 10 provinces with high carbon intensity and per capita gross industrial output are set as 'high carbon intensity' and 'high industrial output', the lower 10 provinces are set as 'low carbon intensity' and 'low industrial output' and the middle 10 provinces are set as 'middle carbon intensity' and 'middle industrial output'.

Empirical results and discussion

Technical efficiency

Technical efficiency measures the degree to which the optimal output is achieved with a given input, expressing the level of technology use in a production process. In the present study, technical efficiency is reflected by DDF. If the value of DDF equals 1, production is at its most efficient. Conversely, if the value of DDF is greater than 1, a distance to reach its most efficient point is evident, wherein a greater DDF value indicates lower technical efficiency. As this study includes good output (gross industrial output value) and bad output (ICE), DDF can also reflect production efficiency and potential emission reduction efficiency. Fig. 2 presents the technical efficiency level via DDF.

From a national perspective (see Fig. 2A), the average values of national DDF overall present an ascending tendency from 2000 to 2017, suggesting that technical efficiency in China's industry has gradually decreased since 2000. Fig. 2B shows the average DDF variations of the eastern, central and western regions in the same time period. First, the DDF in the eastern region first exhibited growth, which declined in 2009 as a turning point, presenting an inverted U-shaped change trend suggesting that the technical efficiency in the eastern region decreased from 2000 to 2009 and has increased since 2009. Furthermore, the DDF in the central region rose from 2000 to 2012 and gently dropped from 2012 to 2016, then sharply increased to more than 0.8 in 2017. This result indicates that the central region's technical efficiency decreased from 2000 to 2012, had a slight increase from 2012 to 2016, but significantly decreased in 2017. In contrast to the central and eastern regions, the DDF of the western region exhibited an increasing tendency in the whole sample period, but its growth rate has been extremely minimal since 2014, suggesting that the western region's technical efficiency decreased in all study years. Compared to the DDF values in the other three regions, we find that the eastern region had the highest inefficiency level from 2000 to 2012, followed by the central and western regions. Nevertheless, since the rise of the eastern region's technical efficiency and the decrease of the western region's technical efficiency, the DDF value of the western region has gradually exceeded that of the eastern region since 2013. From 2013 to 2017, the eastern region's technical efficiency was the highest, whereas it was the lowest in the western region except for 2017.

Fig. 2C shows the disparity of DDF change trends in regions with different carbon intensity levels. The results demonstrate that the trajectory of technical efficiency in regions with low carbon intensity first decreased and then increased in 2008 as a turning point, and the technical efficiency in regions with middle carbon intensity also exhibited a similar change trajectory. However, the technical efficiency in regions with high carbon intensity exhibited a decreasing trend from 2000 to 2017. Together with the increase in technical efficiency in low-carbon regions and the decrease in technical efficiency in carbon-intensive regions, low carbon intensity regions have gradually had the highest technical efficiency since 2011, followed by middle and high carbon intensity regions. Fig. 2D compares the disparity of technical efficiency change in regions with different industrial outputs. The results reveal that the technical efficiency of high industrial output regions decreased from 2000 to 2008 and increased from 2008 to 2017. In addition, the technical efficiency in middle industrial output regions decreased from 2000 to 2014, exhibiting a soft increase since 2014; however, the technical efficiency in low industrial output regions showed an overall decreasing trend in the study period. In conclusion, the regions with lower carbon intensity and higher industrial output gradually came closer to the optimal frontier for technology use.

Table 1
Group divisions and associated provinces.

Group division	Associated provinces
Geographical proximity	
East	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central	Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Shanxi
West	Inner Mongolia, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi
Carbon intensity	
Low carbon intensity	Guangdong, Shanghai, Beijing, Tianjin, Jiangsu, Zhejiang, Shandong, Fujian, Jilin, Hainan
Middle carbon intensity	Liaoning, Jiangxi, Henan, Hubei, Sichuan, Chongqing, Hunan, Shaanxi, Anhui, Heilongjiang
High carbon intensity	Guangxi, Hebei, Yunnan, Gansu, Inner Mongolia, Xinjiang, Guizhou, Qinghai, Shanxi, Ningxia
Per capita gross industrial output value	
High industrial output	Tianjin, Shanghai, Jiangsu, Zhejiang, Guangdong, Shandong, Beijing, Fujian, Liaoning, Jilin
Middle industrial output	Inner Mongolia, Chongqing, Hubei, Hebei, Henan, Anhui, Ningxia, Jiangxi, Sichuan, Hunan
Low industrial output	Shaanxi, Qinghai, Shanxi, Guangxi, Heilongjiang, Hainan, Xinjiang, Gansu, Yunnan, Guizhou

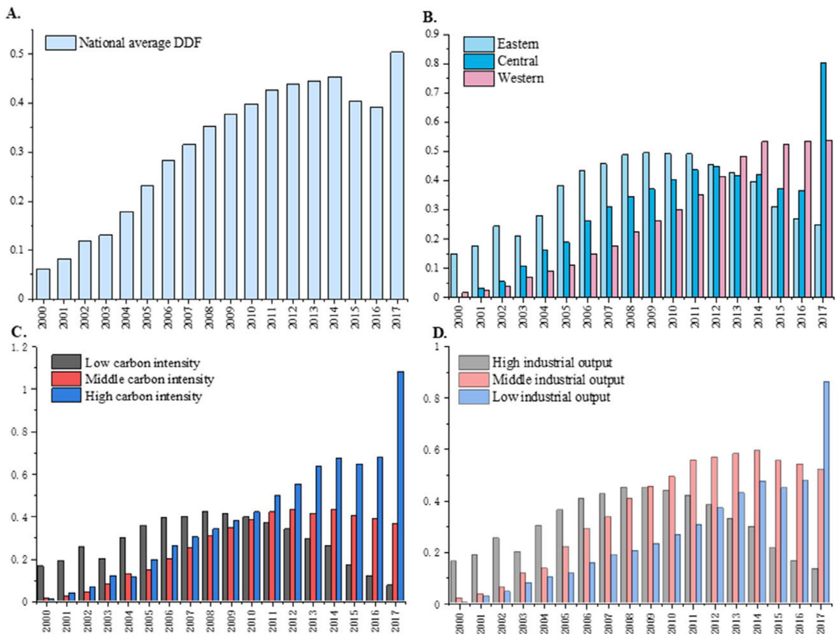

Fig. 2. Average DDF in all of China and different regional groups.

Abatement potential of industrial CO_2 emissions

Section "Technical efficiency" reflects the production efficiency and potential efficiency of reducing emissions by DDF; thus, DDF is employed to determine the upper limit of good output expansion and the potential reduction in bad output. For example, the national average DDF from 2000 to 2017 was 0.3112, and the national average ICE in the same time period was 5284.97 Mt, suggesting that the national average ICE could be reduced to 5284.97 Mt $\times$ 0.3112 = 1644.46 Mt. Fig. 3 illustrates the average PCR in the whole nation and different regional groups in the study period.

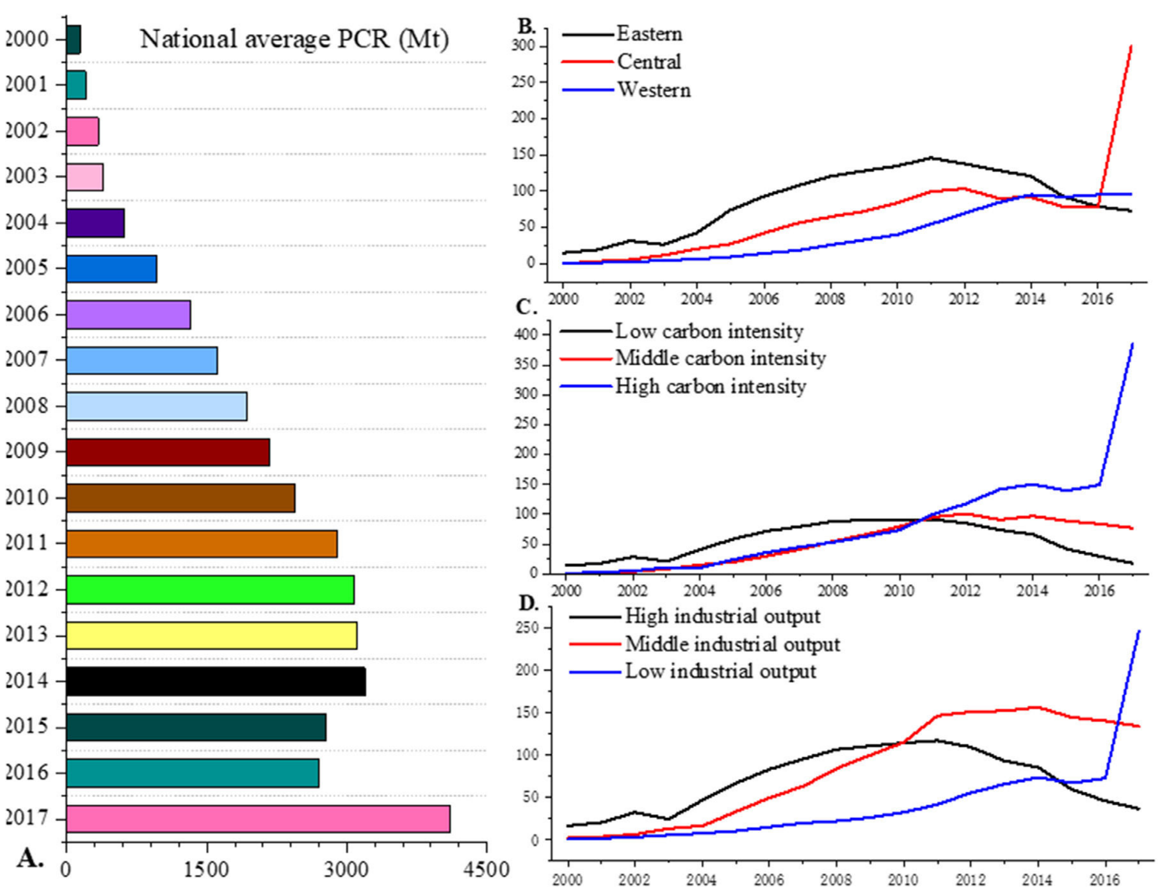

Fig. 3. Average potential carbon reduction in the whole nation and different regional groups.

As demonstrated in Fig. 3A, the industrial average PCR increased from less than 300 Mt in 2000 to approximately 4400 Mt in 2017. This result is partially attributable to rising technical inefficiency and partially attributable to increasing ICE. Fig. 3B indicates that the PCR in the eastern region maintained an increasing trend from 2000 to 2011 and then decreased after 2011. The eastern region's PCR was the highest in most years until 2015. The central region with the second-largest PCR exhibited an upwards trend in almost all study years. In 2017, the central region's PCR exceeded the eastern and western regions and had the largest PCR. Additionally, the western region had the lowest (but rising) PCR in most years. Since 2015, the PCR in the western region has exceeded that of the eastern area.

Fig. 3C shows the PCR change disparity between regions with different carbon intensities, revealing that the PCR change of low carbon intensity regions exhibited an inverted U-shaped curve during the study period and had the lowest PCR since 2011. Combined with the results in Fig. 2C, we can assert that the decrease in the low carbon intensity region's PCR was attributable to an improvement in technical efficiency. From 2000 to 2011, the PCR in middle and high carbon intensity regions were almost similar; however, since 2011, the PCR in middle carbon intensity regions has gradually decreased, becoming the region with the lowest PCR. By contrast, the PCR in high carbon intensity regions significantly increased, becoming the region with the largest PCR. Fig. 3D shows the disparities in PCR change between regions with different industrial outputs. From 2000 to 2010, the PCR of the high industrial output regions exhibited an increasing trend and had the largest PCR, decreasing since 2010 and becoming the region with the lowest PCR since 2015. The PCR in middle and low industrial output regions all exhibited an overall increasing trend throughout the study period. Some notable differences are evident. The growth ratio of PCR in the middle industrial output regions was relatively larger prior to 2011 and then became smooth from 2011 to 2017; however, the growth ratio of PCR in the low industrial output regions was relatively soft before 2016 and became sharp from 2016 to 2017.

Table 2 presents the average PCR of the 30 Chinese provinces from 2000 to 2017. Hebei Province had the largest emission reduction potential, with an average annual PCR of 388.23 Mt, suggesting that the province has the potential to further reduce CO_2 emissions by approximately 388.23 Mt if it reaches the frontier of technology use. Table 2 indicates that the reasons that led to Hebei having the largest PCR are attributable to its high level of technical inefficiency and the high CO_2 emissions, particularly the former. The average DDF in Hebei was as high as 0.9096, suggesting that inefficient production accounted for 90.96 % of total production in Hebei, and the emission reduction potential ratio also reached 90.96 %; therefore, Hebei Province may be related to a serious problem of inefficient production. Additionally, Hebei Province was a considerable carbon emitter (i.e. average CO_2 emissions were 426.81 Mt). These two circumstances led to high PCR in Hebei Province. Shandong Province followed Hebei with an average of 259.04 Mt. As shown in Table 2, the main reason for Shandong's high PCR was its considerable CO_2 emissions. In addition, Shanxi, Guangdong, Jiangsu, Henan and Inner Mongolia exhibited a relatively high average PCR, with average DDF values that were all greater than 0.5, suggesting that these provinces may all benefit from technical inefficiency to different degrees.

In contrast, Hainan exhibited the smallest reduction potential, and its average annual PCR was only 0.47 Mt, which indicates that Hainan may be able to further reduce its CO_2 emissions by approximately 0.47 Mt if the province produces at the frontier of technology use. The emission reduction space of Hainan is extremely small and has primarily benefitted from its high technical efficiency and low CO_2 emissions. As reported in Table 2, the DDF in Hainan was 0.0301, suggesting that there was only 3.01 % inefficient industrial production in Hainan. The average annual CO_2 emissions in Hainan were only 15.61 Mt. Beijing, Qinghai, Chongqing and Jilin also exhibited low average PCR, which was primarily attributable to relatively high technical efficiency and low CO_2 emissions.

Shadow prices of industrial CO_2 emissions

Shadow price in the whole nation and different groups

As noted in Section "Introduction", the MAC is represented by the shadow price of ICE in this study. Fig. 4A illustrates the average shadow price of ICE between 2000 and 2017. Compared to previous research, the results of this study appear to be reasonable. The shadow price presents three distinct stages. First, from 2000 to 2011, a significant downwards trend in the shadow price is shown, decreasing from 2.45 (10^4 yuan per ton) in 2000 to 2.1 (10^4 yuan per ton) in 2011, suggesting that the reduced cost decreased during this period, with some apparent fluctuations. The second stage occurred from 2011 to 2016, when the shadow price of ICE exhibited an upwards trend with a relatively large growth rate, suggesting that controlling ICE became expensive in this period. Finally, in the third stage (2016–2017), the shadow price decreased from more than 2.3 (10^4 yuan per ton) to approximately 2.2 (10^4 yuan per ton).

Fig. 4B–D shows the shadow prices of ICE in each region. Comparing the three figures reveals that the shadow price change trajectories in the eastern region, low carbon intensity regions and high industrial output regions were similar, achieving a sharp, fluctuating

Table 2
Average annual potential CO_2 emission reduction across provinces (Mt).

Provinces	Average DDF	Average emissions	Average PCR	Provinces	Average DDF	Average emissions	Average PCR
Hebei	0.9096	426.81	388.23	Fujian	0.1662	146.61	24.37
Shandong	0.5550	466.71	259.04	Anhui	0.1485	162.59	24.15
Shanxi	0.7803	317.57	247.79	Guangxi	0.2046	115.86	23.71
Guangdong	0.6969	333.27	232.26	Guizhou	0.2001	105.88	21.18
Jiangsu	0.5615	391.92	220.06	Shanghai	0.1598	116.09	18.55
Henan	0.5879	304.38	178.94	Gansu	0.1826	88.00	16.07
Inner Mongolia	0.6004	213.64	128.26	Jiangxi	0.1633	96.43	15.74
Sichuan	0.3931	207.96	81.75	Heilongjiang	0.1250	108.44	13.55
Liaoning	0.2999	255.13	76.52	Ningxia	0.1628	78.85	12.84
Zhejiang	0.2798	238.67	66.78	Tianjin	0.1595	79.19	12.63
Hubei	0.2502	202.94	50.77	Jilin	0.1131	100.10	11.32
Xinjiang	0.4085	123.99	50.64	Chongqing	0.0942	92.40	8.70
Hunan	0.2804	159.79	44.81	Qinghai	0.1156	45.81	5.30
Yunnan	0.3100	127.15	39.42	Beijing	0.1025	47.30	4.85
Shaanxi	0.2933	115.90	33.99	Hainan	0.0301	15.61	0.47

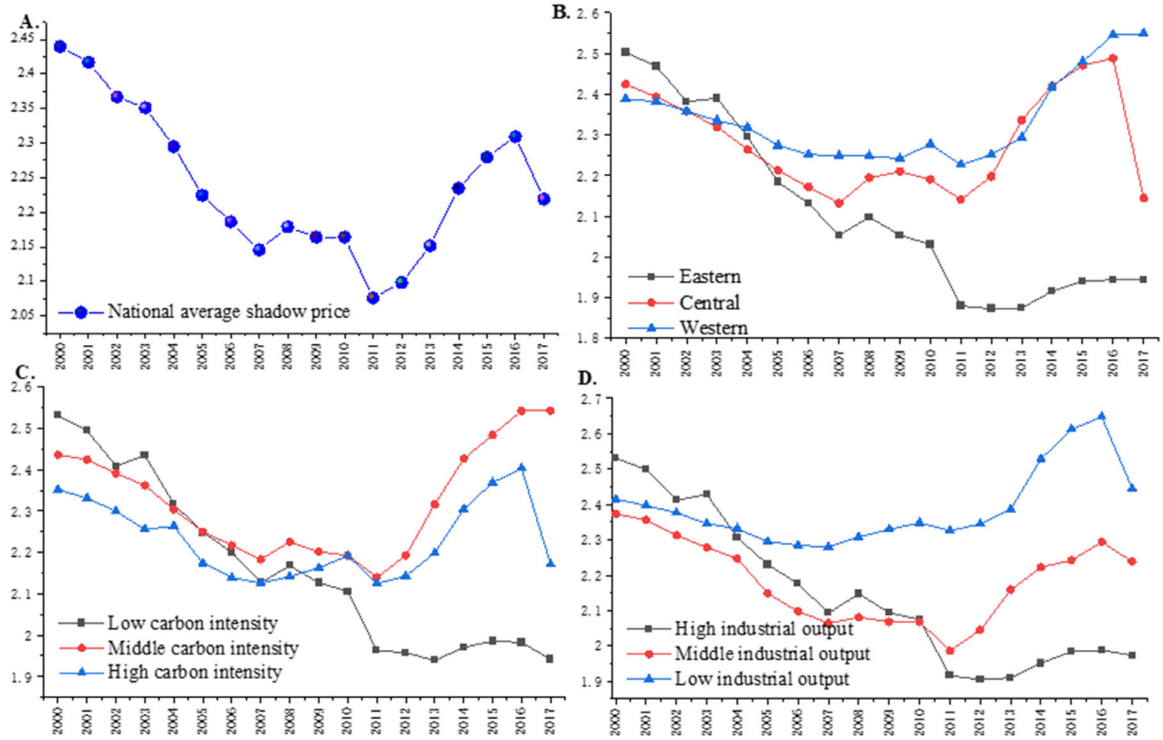

Fig. 4. Average industrial carbon shadow price in the whole nation and different regional groups. (Unit: 10^4 yuan RMB per ton).

decrease from 2000 to 2011 as the regions with the lowest shadow price. Since 2011, the change rate of the shadow price has become milder, presenting a rising trend. The results indicate that the cost of reducing ICE gradually became more costly as the study period progressed. Additionally, the shadow price change trajectory in the central region, middle carbon intensity regions and middle industrial output regions presented an inverted U shape. Furthermore, as shown in Fig. 4B, the shadow price in the western region first exhibited a steady and mild decrease from 2000 to 2011, maintaining a significant rise after 2011. In recent years, the western region has become the region with the highest ICE shadow price. The shadow price in the high carbon intensity regions also presented a U-shaped variation, with 2011 as the turning point. Since 2010, the middle carbon intensity region has had the largest shadow price, followed by the high and low carbon intensity regions. For regions with different industrial output, since 2004, low industrial output regions have had the costliest MAC, whereas high industrial output regions have had the smallest MAC (see Fig. 4D).

Shadow price discrepancies across provinces

Fig. 5 illustrates the industrial carbon shadow prices across the 30 Chinese provinces. From Fig. 5A, the four provinces with the lowest average shadow price were Hebei, Shandong, Jiangsu and Guangdong, with prices of 1.7120, 1.7598, 1.8848 and 1.9775, respectively (10^4 yuan per ton). This result suggests that these four provinces have a relatively low marginal cost for further reducing ICE and should be China's preferred choice for industrial carbon reduction. In contrast, Shaanxi, Heilongjiang and Beijing exhibited the highest average shadow price, at 2.6855, 2.6000 and 2.4953, respectively (10^4 yuan per ton). This result indicates that these three provinces have a relatively high marginal cost for further reducing their ICE.

Fig. 5B presents the changing trend of industrial carbon shadow prices from 2000 to 2017. The 30 provinces can be classified into four groups according to their features. The first group represents provinces with ICE shadow prices that showed an overall increasing trend during the study period, which includes Beijing, Heilongjiang, Yunnan, Shaanxi and Xinjiang. For these five provinces, the cost of further reducing ICE became increasingly expensive. The second group represents provinces with ICE shadow prices that exhibited a U-shaped change trend, which includes Liaoning, Jilin, Shanghai, Henan, Hubei, Hunan, Sichuan, Guizhou and Gansu. The third group represents provinces with ICE shadow prices that showed an overall downwards trend, which includes Tianjin, Hebei, Shanxi, Inner Mongolia, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong and Guangdong. For these 11 provinces, the cost of further reducing ICE gradually decreased. The fourth group represents provinces with ICE shadow prices that were steady and did not change considerably during this study.

Actually, there are large differences in the estimations of the MACs of ICE in China in the previous literature. For example, Chen et al. (2013) and Wu et al. (2020) all applied non-parametric DDF to estimate the MAC of China's industrial sectors. The former study forecasted the MACs of ICE at 2731 and 4012 yuan per ton of carbon emissions during the 12th and 13th Five-Year Plans, respectively. By contrast, the latter study found that the average MAC of the top five industrial sectors with the highest carbon intensity is 373.92 yuan/ton, and the top five sectors with the lowest carbon intensity are 50,254.54 yuan/ton. We find that both studies are based on China's industrial sector data and used a similar estimation approach; however, the calculated MAC results are quite different. This may be attributed to the fact that non-parametric methods have a defect in estimating ICE results that are not unique. Considering this, this study adopted a parametric DDF model to estimate the MAC of ICE and then discussed the MACs according to the characteristic clustering groups of different provinces, which may provide more detailed references for local government to formulate emission reduction measures targeted to each province's actual situation.

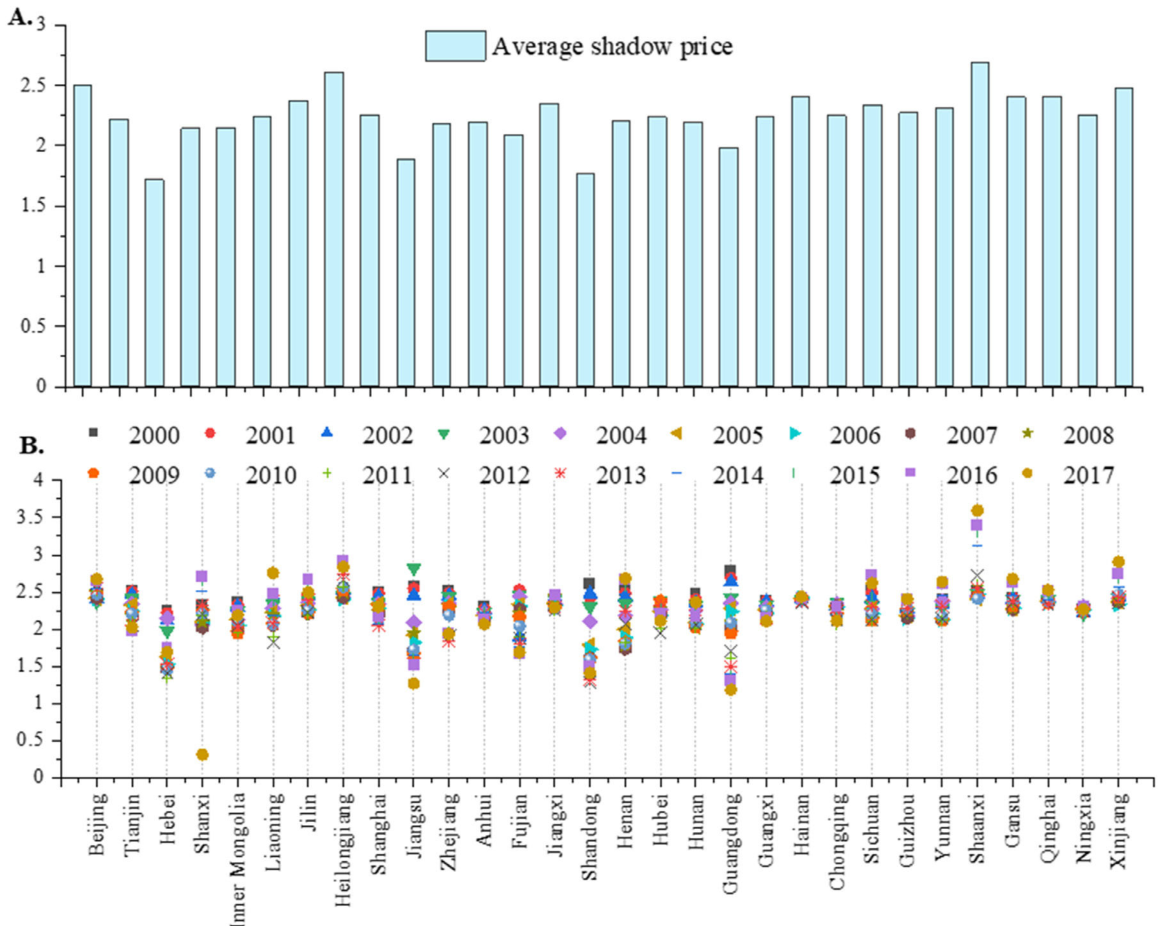

Fig. 5. Industrial carbon shadow prices across 30 Chinese provinces. (Unit: 10^4 yuan RMB per ton).

Conclusions and policy implications

This study used a quadratic directional output distance function to analyse the efficiency of technology, potential emission reduction and shadow prices of China's industrial carbon emissions. We draw three notable conclusions from the empirical results.

(1). From 2000 to 2017, the technical efficiency of China's industry exhibited a gradual decline, with some fluctuations in 2015 and 2016. The technical inefficiencies of the eastern and central regions formed an inverted U-shaped trend, with 2009 and 2012 as the respective turning points. By contrast, the western region's technical inefficiency exhibited an overall upwards trend. Comparatively, since 2013, the eastern region has had the highest technical efficiency, whereas the western region has had the lowest technical efficiency.

(2). Due to rising technical inefficiency and ICE, industrial average PCR also exhibited an upwards trend. The eastern region's PCR was the highest in most years until 2015. The central region, with the second highest PCR, exhibited an upwards trend in almost all study years. The western region had the lowest (but rising) PCR in most years. Hebei presented the largest reduction potential and can further reduce its ICE by approximately 388.23 Mt if it produces at the frontier of technology use. In contrast, Hainan exhibited the smallest reduction potential.

(3). The MAC of ICE presented a U-shaped change trend, with 2011 as the turning point. Generally, as time progressed in the study period, regions with lower carbon intensity and higher industrial output regions had relatively expensive MACs of ICE. Hebei, Shandong, Jiangsu and Guangdong exhibited the lowest average MAC. In contrast, Shaanxi, Heilongjiang and Beijing showed the highest average MAC.

The empirical findings of this study further supplement existing studies and are significant for implementing ICE reduction policies. First, this study reveals an increasing trend in the overall MAC of China's ICE, which implies that the unit output loss due to ICE reduction efforts has increased. Consequently, it is essential to further augment support for clean technologies, carbon capture and storage while fostering interregional exchanges and diffusion of low-carbon technologies to enhance carbon reduction efficiency. Second, the empirical results reveal the technical efficiency, PCR and MAC of ICE in different regions, revealing that the principle of 'easy before difficult' can be followed to promote ICE reduction. Emission reduction should start in regions with lower MAC or high PCR. Under the premise that the shadow price is lower than MAC, regions with high MAC can employ the carbon trading mechanism to purchase emissions permits from regions with low MAC to achieve emission reduction targets. Third, for provinces with low technical efficiency, local governments should prioritise improving technical efficiency through establishing technology exchanges with developed regions (Zhou et al., 2020). In fact, the MAC of ICE is not only affected by carbon intensity and industrial output per capita but is also affected by the influence of industrial development stage, energy structure, population density, technology research and development support and other factors. Previous research has also indicated that the clean development mechanism (CDM) can promote emission reduction that is lower than the original cost, and developed countries can cooperate with less developed countries to advance the CDM. Limited by space restrictions, we do not discuss the influence factors and changing reasons (such as emergencies and government policies) for technical efficiency, abatement potential and carbon shadow prices (Ray et al., 2022), which is an investigation that we will pursue in the future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

CRediT authorship contribution statement

Xiaoyu Li: Data curation, Funding acquisition, Methodology, Writing – original draft, Writing – review & editing, Validation, Visualization. **Miao Wang:** Formal analysis, Funding acquisition, Methodology, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Wenxuan Wan:** Formal analysis, Validation, Visualization, Writing – review & editing.

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Appendix

Table A.1
Estimated parameter values.

Parameters	Values	Parameters	Values	Parameters	Values
$\alpha0$	−0.1546	$\gamma1$	0.7200	$\delta1$	0.0326
$\alpha1$	0.0015	$\gamma2$	−0.0665	$\delta2$	0.0815
$\alpha2$	0.2108	$\beta1$	−0.2800	$\delta3$	0.0000
$\alpha3$	0.0000	$\beta2$	−0.0665	$\varepsilon1$	0.0326
$\alpha11$	−0.0158	$\alpha12$	−0.0245	$\varepsilon2$	0.0815
$\alpha22$	−0.1595	$\alpha13$	0.0000	$\varepsilon3$	0.0000
$\alpha33$	0.0000	$\alpha23$	0.0000	μ	−0.0665
Time dummy variable (take 2017 as the benchmark)					
$\tau1$	0.0072	$\tau7$	−0.0356	$\tau13$	−0.0728
$\tau2$	0.0099	$\tau8$	−0.0417	$\tau14$	−0.0319
$\tau3$	0.0036	$\tau9$	−0.0456	$\tau15$	−0.0091
$\tau4$	0.0059	$\tau10$	−0.0464	$\tau16$	−0.0092
$\tau5$	0.0002	$\tau11$	−0.0503	$\tau17$	0.0039
$\tau6$	−0.0332	$\tau12$	−0.0729		
Region dummy variable (take Xinjiang as the benchmark)					
$\lambda1$	0.1468	$\lambda11$	−0.2120	$\lambda21$	0.1430
$\lambda2$	0.1461	$\lambda12$	−0.2607	$\lambda22$	−0.0519
$\lambda3$	−0.5330	$\lambda13$	−0.0505	$\lambda23$	−0.2226
$\lambda4$	−0.3238	$\lambda14$	−0.0126	$\lambda24$	−0.0723
$\lambda5$	−0.1201	$\lambda15$	−0.5047	$\lambda25$	−0.0594
$\lambda6$	−0.5103	$\lambda16$	−0.3454	$\lambda26$	−0.0401
$\lambda7$	−0.0853	$\lambda17$	−0.3286	$\lambda27$	−0.0354
$\lambda8$	−0.1937	$\lambda18$	−0.1248	$\lambda28$	0.0789
$\lambda9$	0.0447	$\lambda19$	0.2357	$\lambda29$	−0.0015
$\lambda10$	−0.0940	$\lambda20$	−0.0751		

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