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Shadow prices of industrial air pollutant emissions in China

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Abstract

Shadow prices of undesirable outputs assess the opportunity costs of emissions reduction and provide a comprehensive measuring indicator for the overall environmental regulation stringency. Shadow prices of industrial air pollutant emissions in China for 2006–2016 have been estimated by different nonparametric models, and their determinants, as well as the emissions controlling effects of environmental regulations, have been further investigated in this study. Our empirical results reveal that the conventional polluting technology model is consistent with the two sub-technologies model, and that shadow prices estimated by different models differed in absolute values but shared the same growth trends and regional characteristics. Decomposition results according to the logarithmic mean divisia index (LMDI) method indicate that variations in the shadow prices were due to the combined forces of the energy saving and end-of-pipe controlling effects in the analyzed periods. Moreover, we found that China's environmental regulations with regional disparities in recent years (2006–2016) have effectively reduced industrial air pollutant emissions at an increasing rate, and that the environmental taxes imposed in 2018 still followed the existing regional unbalances of environmental regulation stringency.

Keywords: Shadow prices; Industrial air pollutant emissions; Decomposition effects; Environmental tax.

JEL classification: H23; Q52; Q53; Q58

1. Introduction

Since its economic reform and opening up in 1978, China has achieved remarkable successes in its economy and society. However, rapid industrialization and urbanization have led to ecological destruction and environmental degradation. As the world's second-largest economy and largest carbon emitter, China has been faced with major environmental problems including air pollution, water pollution, waste disposal, land desertification, soil erosion, droughts and floods, biological destruction, persistent organic pollution of soil, and destruction of biodiversity. Especially, air pollution and the resulting smog weather have aroused heated discussions in China in recent years.

During the past 11th and 12th five-year Plans (2006–2010 and 2011–2015, respectively) and the ongoing 13th Five-Year Plan (2016–2020), the Chinese central government has set a series of national total pollutant control targets and decomposed the tasks to each local government. Among these targets, air pollutants, including sulfur dioxide (SO_2) and oxynitride (NO_x), have been listed as total control indicators that need to be reduced by 8–10% during each five-year Plan. In addition to these total control targets, more diversified environmental regulations have been implemented. On the one hand, it has continued to strengthen traditional administrative control of environmental pollution through the development of an accountability system and establishment of the Central Environmental Protection Supervision Group. Meanwhile, it has actively introduced market-oriented environmental regulation mechanisms such as constructing a green financial system, launching pilot carbon emissions trading, and changing sewage charges into an environmental tax.

Considering the increasingly stringent environmental regulations in China, a number of researches have employed diversified indicators to measure environmental regulation stringency and investigated its effectiveness from different perspectives (Wang and Shen, 2016; Liu et al., 2017; Liao and Shi, 2018; Wang and Watanabe, 2019). It is noteworthy that some researchers have introduced a shadow price approach, which reflects the multidimensionality of environmental policy (Althammer and Hille, 2016; Hille, 2018). Although less research has studied the effectiveness of China's environmental regulation stringency based on a shadow price approach, numerous studies have calculated the shadow prices of CO_2 emissions in China (Wei et al., 2013; Du and Mao, 2015), which are conducive to the evaluation of carbon emissions regulation stringency in China. Nevertheless, there has been relatively little research considering the shadow prices of China's industrial air pollutant emissions.

This study aimed to estimate the shadow prices of China's industrial air pollutant emissions in recent years (2006–2016) by considering some new discussions and progressions. Our results can be applied in future research to be a more advantageous proxy for China's air pollution regulation stringency. Moreover, we quantify the impacts of different emission reduction channels on the changes in the estimated shadow prices and test the emission reduction effectiveness of the environmental policy in China in the analyzed periods.

The major contributions of this study are as follows: First, the conventional polluting technology is shown to be consistent with a more recent proposed model using two sub-technologies, and shadow prices estimated by different models differed in absolute values but had basically the same growth trends and regional characteristics in China for 2006–2016. Second, shadow prices of undesirable outputs are first decomposed into the energy saving and end-of-pipe controlling effects according to the logarithmic mean divisia index (LMDI) decomposition method. Third, using the estimated shadow prices as the overall environmental regulation stringency in each province, it is confirmed that the mix of environmental policy has been effective at reducing industrial air pollution by an increasing rate.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the methodology. Section 4 presents the data and empirical results, and Section 5 concludes this paper.

2. Literature review

Shadow prices of pollutant emissions may be interpreted as the opportunity costs of reducing an additional unit of pollutant emissions in terms of economic output loss (Zhou, et al., 2014) and are usually referred to as marginal abatement costs (Pittman, 1981; Hailu and Veeman, 2000; Lee, 2005). Numerous researches (e.g., Molinos-Senante and Guzmán, 2018; Lee and Wang, 2019) have applied the theoretical model of Färe et al. (1993) to study the shadow prices of undesirable outputs (e.g., CO_2, SO_2). Färe et al. (1993) stated that the shadow prices of undesirable outputs reflect the impact of regulations faced by a firm and can be used to assess the effectiveness of existing regulations. In addition, shadow prices can provide valuable reference information for policy development and analysis, such as for environmental/carbon tax or pollutants/carbon emissions trading (Zhou et al., 2014; Zhou et al., 2015). Various efficiency models have been used to estimate shadow prices of undesirable outputs at the firm, provincial, regional, sectoral, and worldwide levels (Lee et al., 2014; Du et al., 2015; Boussemart et al., 2017; Zhang and Jiang, 2019).

Based on the duality theory, there are two general approaches to estimating the shadow prices of pollutant emissions: parametric and nonparametric. A parametric method needs a predefined function form to parameterize the Shephard or directional distance function, which is commonly in either the trans-log or quadratic form. For example, Lee and Zhang (2012) selected the trans-log function to compute the shadow prices of CO_2 emissions from China's manufacturing industries, while Molinos-Senante et al. (2015) assumed the quadratic form to estimate the shadow prices of CO_2 emissions from Spanish wastewater treatment. Besides, the generalized Leontief (GL) cost function has been used in some studies for quantifying shadow prices of polluting inputs (van Soest et al., 2006; Althammer and Hille, 2016). In contrast, a nonparametric method does not require a predefined function form, which avoids the risk of a mistaken function form. The data envelopment analysis (DEA) technique proposed by Charnes et al. (1978) has been popularly used for evaluations of productivity performance (Huang et al., 2017; Rath, 2018). Further, the shadow prices of pollutant emissions can be derived from the dual values of the primary linear program used to measure the environmental performance (Zhou et al., 2014). Numerous DEA technologies can be used with the nonparametric method. Zhou et al. (2008) discussed different environmental DEA technologies, and Leleu (2013) proposed a hybrid model to shadow pricing undesirable outputs in nonparametric analysis. In general, DEA technologies can be divided into radial and non-radial efficiency models. The former can only measure the degree of expansion or reduction of desirable or undesirable outputs with equal proportions, while the latter allows different expansive or shrinking proportions. Lee et al. (2002) and Boussemart et al. (2017) applied the radial efficiency model to derive the shadow prices of pollutant emissions. Chen and Xiang (2019) adopted the non-radial efficiency model to analyze the shadow prices of CO_2 emissions from coal-fired power plants in Shanghai, China.

As a kind of non-radial efficiency model, the slacks-based measure (SBM) deals with slacks of input excess and output shortfall simultaneously; this has the advantage of capturing the overall inefficiency (Wei et al., 2012). Since the traditional SBM was developed by Tone (2001), some researchers have extended it to incorporate undesirable outputs in various ways. For example, Zhou et al. (2006) combined the Shephard input distance function and traditional SBM to construct an extended SBM for modeling the environmental performance. An et al. (2019) improved the traditional SBM by considering the pollution from upstream cities as undesirable inputs for downstream cities. Choi et al. (2012) and Wei et al. (2012) added the slack of undesirable output excess to the traditional SBM and derived dual values to estimate the shadow prices of CO_2 emissions in China.

Although many studies have examined the shadow prices of undesirable outputs and shadow pricing technologies, new discussion and progress has continued in recent years. One discussion has been on choosing the distance function for estimating the shadow prices. Many studies have pointed out that different estimation methods lead to different empirical outcomes (Zhang et al., 2014; Zhou et al., 2014, 2015); however, no consistent results have been achieved. Lee et al. (2014) reconciled the engineering and economic perspectives to construct a distance function, while Lee and Zhou (2015) considered a literature-based method and individual-SP method to determine the directional vector. Another discussion has been on improving upon the polluting technology approach proposed by Färe et al. (1993, 2005), which was the core basis for estimating the shadow prices of undesirable outputs. Many researchers have maintained that the construction of the polluting technology should follow the material balance principle (MBP) (Coelli et al., 2007; Rødseth, 2017; Wang et al., 2018). Others have divided the traditional polluting technology into two sub-technologies that follow the MBP (Rødseth, 2013; Shen et al., 2018). These new discussions and progress should be fully considered in studies on the shadow prices of undesirable outputs.

3. Methodology

3.1 By-production models and shadow prices of pollutant emissions

Färe et al. (1993) incorporated a pollutant into the traditional output set and used the duality theory to derive the shadow prices of pollutant emissions. In contrast, a more recent approach has been to model polluting technology with two sub-technologies (Murty et al., 2012; Shen et al., 2018). In this study, however, the approach used by Färe et al. (1993) was found to be supported by the two sub-technologies, and the shadow prices of pollutant emissions can be estimated with either the approach used by Färe et al. (1993) or the approach based on two sub-technologies. Both approaches are called the "by-production model" in this study.

The by-production model with two sub-technologies is given below. The first sub-technology, T_1, is a conventional production process that maximizes the desirable outputs of given inputs, while the second sub-technology, T_2, is an inevitable consequence of pollution resulting from the use of polluting inputs. The two sub-technologies are not independent but rather interact with each other through emissions abatement. The by-production technology, T, is defined as:

$$\begin{aligned}
T &= T_1 \cap T_2 \\
&= \left\{ \left(x^n, x^p, y, y^a, b \right) \in R_+ : \left(x^n, x^p \right) can\ produce\ \left(y, y^a \right); \left(x^p, y^a \right) can\ generate\ b \right\} \\
T_1 &= \left\{ \left(x^n, x^p, y, y^a \right) \in R_+ \middle| F\left(x^n, x^p, y, y^a \right) \le 0 \right\} \\
T_2 &= \left\{ \left(x^p, y^a, b \right) \in R_+ \middle| B\left(x^p, y^a, \mathrm{b} \right) \le 0 \right\}
\end{aligned} \tag{1}$$

where x^n represents clean inputs, x^p represents dirty inputs, y represents desirable outputs, y^a represents abatement outputs, and b represents pollutant emissions. $F(\cdot)$ and $B(\cdot)$ are assumed to be continuous differentiable functions.

The shadow prices of pollutant emissions can be estimated according to the following profit maximization problem:

$$\begin{aligned}
&\pi = \max \pi_y y - \pi_{x^n} x^n - \pi_{x^p} x^p - \omega_b b \\
&s.t.\ F\left(x^n, x^p, y, y^a \right) = 0 \\
&B\left(x^p, y^a, \mathrm{b} \right) = 0
\end{aligned} \tag{2}$$

where π_y, π_{x^n}, π_{x^p}, and ω_b represent the price vectors of the desirable outputs, clean inputs, dirty inputs, and undesirable outputs (i.e., pollutant emissions), respectively.

With the method of Lagrange multipliers, the model in Eq. (2) can be transformed to the following Lagrange function:

$$\begin{aligned}
\max . L &= \pi_y y - \pi_{x^n} x^n - \pi_{x^p} x^p - \omega_b b + \lambda F\left(x^n, x^p, y, y^a \right) + \delta B\left(x^p, y^a, \mathrm{b} \right) \\
&= \pi_y y - \pi_{x^n} x^n - \pi_{x^p} x^p - \omega_b b + \lambda \left[F\left(x^n, x^p, y, y^a \right) + \frac{\delta}{\lambda} B\left(x^p, y^a, \mathrm{b} \right) \right] \\
&= \pi_y y - \pi_{x^n} x^n - \pi_{x^p} x^p - \omega_b b + \lambda D\left(x^n, x^p, y, y^a, \mathrm{b}, \varphi \right)
\end{aligned} \tag{3}$$

where $D\left(x^n, x^p, y, y^a, \mathrm{b}, \varphi \right) = F\left(x^n, x^p, y, y^a \right) + \frac{\delta}{\lambda} B\left(x^p, y^a, \mathrm{b} \right)$ and $\varphi = \frac{\delta}{\lambda}$. φ is the ratio of Lagrange multipliers of the conventional production function and the polluting function. Based on the model in Eq. (3), the two sub-technologies $F\left(x^n, x^p, y, y^a \right) = 0$ and $B\left(x^p, y^a, \mathrm{b} \right) = 0$ can be reduced to the combined technology $D\left(x^n, x^p, y, y^a, \mathrm{b}, \varphi \right) = 0$. Therefore, the approach of Färe et al.

(1993) can be supported by the two sub-technologies because $D\left(x^n, x^p, y, y^a, \mathrm{b}, \varphi\right)=0$ can be converted to $D\left(x^n, x^p, y\left(y^a, \varphi\right), \mathrm{b}\left(y^a, \varphi\right)\right)=0$.

To solve the Lagrange function, the first-order conditions (FOCs) are applied:

$$
\begin{aligned}
&\frac{\partial L}{\partial y}=\pi_y+\lambda\frac{\partial F}{\partial y}=\pi_y+\lambda\frac{\partial D}{\partial y}=0\\
&\frac{\partial L}{\partial x^n}=-\pi_{x^n}+\lambda\frac{\partial F}{\partial x^n}=-\pi_{x^n}+\lambda\frac{\partial D}{\partial x^n}=0\\
&\frac{\partial L}{\partial x^p}=-\pi_{x^p}+\lambda\frac{\partial F}{\partial x^p}+\delta\frac{\partial B}{\partial x^p}=-\pi_{x^p}+\lambda\frac{\partial D}{\partial x^p}=0\\
&\frac{\partial L}{\partial b}=-\omega_b+\delta\frac{\partial B}{\partial b}=-\omega_b+\lambda\frac{\partial D}{\partial b}=0\\
&\frac{\partial L}{\partial y^a}=\lambda\frac{\partial F}{\partial y^a}+\delta\frac{\partial B}{\partial y^a}=\lambda\frac{\partial D}{\partial y^a}=0\\
&F\left(x^n, x^p, y, y^a\right)=0\\
&B\left(x^p, y^a, \mathrm{b}\right)=0
\end{aligned}
\tag{4}
$$

Therefore, the shadow prices of pollutant emissions can be derived from either the combined production function $D\left(x^n, x^p, y, \mathrm{b}\right)=0$ or the two sub-functions $F\left(x^n, x^p, y, y^a\right)=0$ and $B\left(x^p, y^a, \mathrm{b}\right)=0$. This shadow price can also be written as:

$$
\frac{\omega_b}{\pi_y}=\frac{\delta}{\lambda}\left(\frac{\partial B}{\partial b}\bigg/\frac{\partial F}{\partial y}\right)=\frac{\partial D}{\partial b}\bigg/\frac{\partial D}{\partial y}
\tag{5}
$$

3.2 Data envelopment analysis (DEA) models corresponding to the by-production models

Considering the constant returns to scale (CRS), the conventional by-production model is given by: $T_F=\left\{\left(x^n, x^p, y, b\right): \sum_{i=1}^{n}\lambda_i y_i \geq y, \sum_{i=1}^{n}\lambda_i x_i^n \leq x^n, \sum_{i=1}^{n}\lambda_i x_i^p \leq x^p, \sum_{i=1}^{n}\lambda_i b_i \leq b\right\}$, where λ is a non-negative intensity vector.[1]

Accordingly, the by-production model with two sub-technologies under the CRS assumption of Murty et al. (2012) and Shen et al. (2018) is defined as:

[1] The assumption of strong disposability of undesirable outputs ensures the non-negativity of shadow prices of undesirable outputs.

$$T_{MS}=\left\{\left(x^n,x^p,y,b\right):\sum_{i=1}^{n}\lambda_i y_i \ge y,\sum_{i=1}^{n}\lambda_i x_i^n \le x_i^n,\sum_{i=1}^{n}\lambda_i x_i^p \le x_i^p,\sum_{i=1}^{n}\sigma_i b_i \le b,\sum_{i=1}^{n}\sigma_i x_i^p \ge x_i^p\right\},$$

where λ and σ are different non-negative intensity vectors. Because the SBM model has the advantage of capturing the overall inefficiency, the improved SBM model with undesirable outputs was employed to model the by-production technologies T_F and T_{MS} in this study. In addition, the directional distance function introduced by Chambers et al. (1996) was used for comparison.

According to Choi et al. (2012) and Wei et al. (2012), the dual linear program of the improved SBM model with undesirable outputs based on T_F is given by:

$$\begin{aligned}
&\max .\pi_y y_o-\pi_{x^n}x_o^n-\pi_{x^p}x_o^p-\omega_b b_o\\
&s.t.\ \pi_y y_i-\pi_{x^n}x_i^n-\pi_{x^p}x_i^p-\omega_b b_i\le 0, i=1,2,\cdots,\mathrm{n}\\
&\pi_{x^n}\ge\frac{1}{m}\left[1/x_o^n\right]\\
&\pi_{x^p}\ge\frac{1}{m}\left[1/x_o^p\right]\\
&\pi_y\ge\frac{1+\pi_y y_o-\pi_{x^n}x_o^n-\pi_{x^p}x_o^p-\omega_b b_o}{s}\left[1/\mathrm{y}_o\right]\\
&\omega_b\ge\frac{1+\pi_y y_o-\pi_{x^n}x_o^n-\pi_{x^p}x_o^p-\omega_b b_o}{s}\left[1/\mathrm{b}_o\right]
\end{aligned}\tag{6}$$

Based on the work of Shen et al. (2018), a newly improved SBM model based on T_{MS} was constructed in this study. Its corresponding dual linear program is given as:

$$\begin{aligned}
&\max .\pi_y y_o-\pi_{x^n}x_o^n-\pi_{x^p}x_o^p-\omega_b b_o+\omega_{x^p}x_o^p\\
&s.t.\ \pi_y y_i-\pi_{x^n}x_i^n-\pi_{x^p}x_i^p\le 0, i=1,2,\cdots,\mathrm{n}\\
&-\omega_b b_i+\omega_{x^p}x_i^p\le 0, i=1,2,\cdots,\mathrm{n}\\
&\pi_{x^n}\ge\frac{1}{m}\left[1/x_o^n\right]\\
&\pi_{x^p}\ge\frac{1}{m}\left[1/x_o^p\right]\\
&\pi_y\ge\frac{1+\pi_y y_o-\pi_{x^n}x_o^n-\pi_{x^p}x_o^p-\omega_b b_o+\omega_{x^p}x_o^p}{s}\left[1/\mathrm{y}_o\right]\\
&\omega_b\ge\frac{1+\pi_y y_o-\pi_{x^n}x_o^n-\pi_{x^p}x_o^p-\omega_b b_o+\omega_{x^p}x_o^p}{s}\left[1/\mathrm{b}_o\right]
\end{aligned}\tag{7}$$

For comparison, the dual linear programs constructed with the directional distance function introduced by Chambers et al. (1996) and based on T_F and T_{MS} are respectively given below:

$$\begin{aligned}
&\max . \pi_y y_o - \pi_{x^n} x_o^n - \pi_{x^p} x_o^p - \omega_b b_o \\
&s.t.\ \pi_y y_i - \pi_{x^n} x_i^n - \pi_{x^p} x_i^p - \omega_b b_i \le 0, i = 1,2,\cdots,\mathrm{n} \\
&\pi_y \ge \frac{1}{s}\left[1/\mathrm{y}_o\right] \\
&\omega_b \ge \frac{1}{s}\left[1/\mathrm{b}_o\right]
\end{aligned} \tag{8}$$

$$\begin{aligned}
&\max . \pi_y y_o - \pi_{x^n} x_o^n - \pi_{x^p} x_o^p - \omega_b b_o + \omega_{x^p} x_o^p \\
&s.t.\ \pi_y y_i - \pi_{x^n} x_i^n - \pi_{x^p} x_i^p \le 0, i = 1,2,\cdots,\mathrm{n} \\
&-\omega_b b_i + \omega_{x^p} x_i^p \le 0, i = 1,2,\cdots,\mathrm{n} \\
&\pi_y \ge \frac{1}{s}\left[1/\mathrm{y}_o\right] \\
&\omega_b \ge \frac{1}{s}\left[1/\mathrm{b}_o\right]
\end{aligned} \tag{9}$$

In the linear programs of Eqs. (6)–(9), y_o, x_o^n, x_o^p, and b_o represent the estimated decision-making unit (DUM)'s desirable output, clean input, dirty input, and undesirable output, respectively. In addition, m represents the number of clean and dirty inputs, s represents the number of desirable and undesirable outputs, and ω_{x^p} represents the price vector of dirty inputs in T_2. In the following section, the above four linear programs are designated as models 1, 2, 3, and 4, respectively.

3.3 Decomposing the shadow prices of pollutant emissions with LMDI

Some research has employed econometric regressions to analyze shadow prices' determinants such as firm scale, ownership, age, technology, coal consumption, and urbanization (Wei et al., 2013; Du et al., 2015). Unlike the above determinants, the present study investigated some more direct influencing factors with the help of an index decomposition method.

It is concluded from the by-production model with two sub-technologies in Eq. (1) that, there are two channels to reduce industrial air pollutant emissions: consuming less dirty inputs or reducing the end-of-pipe emissions. The former can be measured by the marginal productivity of dirty input ($\frac{\partial y}{\partial x^p}$), and affects shadow prices by the increased marginal productivity of energy[2] (i.e., the shadow price of

[2] In this paper, the dirty input is energy.

energy). The latter can be measured by the marginal emissions of polluting input ($\frac{\partial b}{\partial x^p}$), and affects shadow prices by the terminal emissions reduction capacity. Correspondingly, this study decomposed the changes of shadow prices of industrial air pollutant emissions into energy saving and end-of-pipe controlling effects.

The improvement in productivity technology and reduction in pollution-intensive industries are helpful for a positive change in the energy saving effect. On the other hand, converting more inputs into pollution control, the progress of mitigation technology and the development of clean energy alternatives would lead to an increase in the end-of-pipe controlling effect.

The relationship among the shadow price, energy saving effect, and end-of-pipe controlling effect is expressed in Eq. (10).

$$\frac{\omega_b}{\pi_y} = \frac{\partial D}{\partial b} \Bigg/ \frac{\partial D}{\partial y} = \frac{\partial D / \partial x^p}{\partial D / \partial y} \Bigg/ \frac{\partial D / \partial x^p}{\partial D / \partial b} = \frac{\partial y}{\partial x^p} \Bigg/ \frac{\partial b}{\partial x^p} = \frac{\pi_{x^p}}{\pi_y} \Bigg/ \frac{\pi_{x^p}}{\omega_b} \tag{10}$$

It is concluded from Eq. (10) that the higher marginal productivity and the lower marginal emissions of polluting input, the higher marginal abatement costs for industrial air pollutant emissions. In a broader sense, technology, firm size, and coal consumption affect the shadow prices either by increasing the marginal productivity of energy or by decreasing the marginal emissions of energy consumption.

As the LMDI method has the advantage of producing zero residuals after decomposition (Ang, 2015), it can be used to identify the energy saving and end-of-pipe controlling effects. Specifically, the decomposition equations are given below:

$$\begin{aligned}
&\Delta sp = \Delta e.\mathrm{s} + \Delta e.\mathrm{c} \\
&\Delta e.\mathrm{s} = \frac{sp^t - sp^{t-1}}{\ln\left(sp^t\right) - \ln\left(sp^{t-1}\right)} \ln\left(\frac{e.\mathrm{s}^t}{e.\mathrm{s}^{t-1}}\right) \\
&\Delta e.\mathrm{c} = \frac{sp^t - sp^{t-1}}{\ln\left(sp^t\right) - \ln\left(sp^{t-1}\right)} \ln\left(\frac{e.\mathrm{c}^t}{e.\mathrm{c}^{t-1}}\right)
\end{aligned} \tag{11}$$

where Δsp is the variation of the shadow prices of air pollutant emissions, $\Delta e.\mathrm{s}$ is the energy saving effect on the variation of the shadow prices, and $\Delta e.\mathrm{c}$ is the end-of-pipe controlling effect on the variation of the shadow prices. The sp^t and sp^{t-1} denote the shadow prices of air pollutant emissions in t and $t-1$ years, respectively; $e.s^{t}$ and $e.s^{t-1}$ denote the marginal productivity of energy ($\frac{\partial y}{\partial x^{p}}$) in t and $t-1$ years, respectively; and $e.c^{t}$ and $e.c^{t-1}$ denote the inverse of the marginal emissions of polluting input ($\frac{\partial b}{\partial x^{p}}$)[3] in t and $t-1$ years, respectively.

The values of the energy saving and end-of-pipe controlling effects reflect the trade-off between the two channels to meet emission targets. Under the same stringency of environmental regulations, market participants would choose the channel with lower marginal costs to reduce air pollutant emissions. All the variations (Δsp, $\Delta e.\mathrm{s}$, and $\Delta e.\mathrm{c}$) may be positive and negative. Positive Δsp values show that shadow prices have increased based on the last year, while a negative value represents a decline based on the last year. When $\Delta e.\mathrm{s}$ or $\Delta e.\mathrm{c}$ are positive, it means that the energy saving effect or the end-of-pipe controlling effect have increased based on the last year, and promotes the positive growth of shadow prices. Otherwise, if $\Delta e.\mathrm{s}$ or $\Delta e.\mathrm{c}$ are negative, it means that the energy saving effect or the end-of-pipe controlling effect have decreased based on the last year and pulled down the growth of the shadow prices. In addition, if Δsp takes a positive value, one of the effects has to be positive at least, and the positive one dominates the variation of the shadow prices. For the same reason, if Δsp takes a negative value, at least one of the effects has to be negative, and the negative one dominates the variation of the shadow prices.

It is common to study the relationships among energy consumption, economic development, capital, etc. For example, Narayan et al. (2010) examined the mutual long-run elasticities of energy consumption and gross domestic product (GDP). Smyth et al. (2011) studied the substitution between energy and other inputs in the Chinese steel sector. Liu et al. (2017) analyzed the effect of New-type Urbanization on energy Consumption in China. Nevertheless, this is the first study to research on the impact of energy saving on the increase in the marginal abatement cost.

3.4 Regression model for testing the effectiveness of environmental regulation stringency

As shadow prices of undesirable outputs can be used to measure environmental policy stringency (Färe

[3] When we take the inverse of the marginal emissions of polluting input, the positive value of $\Delta e.\mathrm{c}$ means that the end-of-pipe controlling effect pushes the increase in shadow prices of industrial air pollutant emissions.

et al., 1993; Althammer and Hille, 2016; Hille and Shahbaz, 2019), a regression model has been set to investigate the causal link between shadow prices and emissions reduction, which is specified as follows:

$$\ln emi_{i,t} = \alpha_0 + \alpha_1 \ln sp_{i,t-1} + \alpha_2 \ln^2 sp_{i,t-1} + \alpha_3 \ln \mathrm{ind}_{i,t} + \alpha_4 \ln^2 ind_{i,t} + \varepsilon_{i,t} \tag{12}$$

The term $emi_{i,t}$ denotes industrial air pollutant emissions in province i for year t; $sp_{i,t-1}$ denotes the shadow prices of undesirable outputs estimated by model 1 in province i for year $t-1$, and represents the one-period lagged policy stringency, and its quadratic term is also considered (Hille and Shahbaz, 2019); $ind_{i,t}$ denotes industrial added value in province i for year t, and the Environmental Kuznets Curve (Churchill et al., 2018; Lau et al., 2019) is considered by incorporating the quadratic term of $ind_{i,t}$. The natural logarithm (ln) form is used to conduct elasticity analysis. A balanced panel data of Chinese 30 provinces from 2006–2016 was employed and each type of polluting emissions (i.e., industrial SO_2, NO_x, and smoke dust emissions) and their shadow prices were taken to carry out robust checks.

4. Empirical results

4.1 Dataset

An empirical study was performed to estimate the shadow prices of air pollutant emissions of China's industries at the province level[4] in 2006–2016[5]. The paper considers two clean inputs (i.e., industrial capital and labor), a single dirty input (i.e., industrial energy consumption), a single desirable output (i.e., industrial added value), and a single integrated industrial air pollutant (simply adding the industrial SO_2, NO_x, and smoke dust emissions). Table 1 describes the statistics for all the raw data used in this study. Figure 1 illustrates the trends of the total emissions and emissions intensity of industrial air pollutant in China from 2006 to 2016. In general, the total emissions of industrial air pollutant showed a decreasing trend, especially for 2014–2016, even though there were some temporary increases between 2009 and 2011. Meanwhile, the emission intensity declined from more than 5.54 tons per million yuan (CNY) in 2006 to less than 0.1 ton per million CNY in 2016, just with a slight rise in 2011. Overall, it can be concluded that China has achieved a win-win situation between industrial economic growth and emission reduction in the past decade or so.

[4] China has 31 provinces, municipalities, and autonomous regions; however, Tibet was not included because of the lack of data. The remaining 30 provinces, municipalities, and autonomous regions are referred to as provinces here for simplicity.
[5] Due to the unavailability of data in 2017 and 2018, this study only extended over the sample period to the year 2016.

[Insert Table 1]

[Insert Figure 1]

4.2 Shadow prices of industrial air pollutant emissions in China for 2006–2016

Based on the linear programs of Eqs. (6)–(9) as well as Eq. (5), the average shadow prices of the industrial air pollutant emissions from China's 30 provinces in 2006–2016 are estimated with the four models. Figure 2 presents the average shadow prices estimated by models 1–4. In general, the dual linear programs based on the directional distance function (models 3 and 4) yield shadow prices about three times higher than those estimated by the SBM models (models 1 and 2), while the dual linear programs based on T_{MS} (models 2 and 4) offer slightly higher shadow prices than those based on T_F (models 1 and 3). Although the models estimate different shadow prices in terms of the absolute values, the growth trends over time are basically the same. The shadow prices of industrial air pollutant emissions in China grew from 0.0694–0.2115 million CNY per ton in 2006 to 0.4226–1.6415 million CNY per ton in 2016. It then can be concluded that the marginal abatement costs of industrial air pollutants in China increased largely in the study periods.

[Insert Figure 2]

Robustness checks were carried out for each polluting emissions individually by employing model 1. It is shown in Fig. A.1 (Appendix A) that shadow prices of each polluting emissions increased steeply during 2014–2016, which is in accordance with Fig. 2. Although the shadow prices of industrial NO_x and smoke dust emissions changed intricately around 2010–2014, the average and the integrated shadow prices of industrial SO_2, NO_x, and smoke dust emissions[6] shared nearly the same growth trends according to Fig. A.2 (Appendix A). As this paper aimed to explore the overall shadow prices of industrial air pollutant emissions, and it was difficult to distinguish which one is more important, we focused only on the integrated shadow prices in this study.

4.3 Regional shadow prices of industrial air pollutant emissions for 2006–2016

In 2005, the Development Research Center of China's State Council proposed dividing China into eight comprehensive economic zones: the Northeast, Northern Coast, Eastern Coast, Southern Coast,

[6] The average shadow prices of industrial air pollutant emissions were calculated by first estimating the shadow prices for each industrial pollutant (SO_2, NO_x, and smoke dust) emission individually and then calculating the mean values. The integrated values were calculated by first adding the industrial SO_2, NO_x, and smoke dust emissions to a single integrated indicator and then estimating its shadow prices.

Middle Yellow River, Middle Yangtze River, Great Southwest, and Great Northwest. Table 2 briefly introduces the eight different zones. The division was based on the comprehensive socioeconomic development of each zone, which is more specific than dividing China into eastern, central, and western regions. In general, the three coastal zones are more advanced than the other zones in terms of industrial development, social development, and population size. Besides, the Great Northwest and Great Southwest lag behind the others in terms of economic development, and the remaining zones face greater pressure from industrial transformation.

[Insert Table 2]

The Chinese government issued the Plan for Air Pollution Prevention in Key Regions during the 12th Five-Year Plan. This was China's first comprehensive air pollution prevention and control planning and marked a gradual shift from a focus on total pollutant control to a goal-oriented focus to improve environmental quality. Approximately 19 provinces in China have been covered by this plan, which are listed in Table 2. In addition, additional related policies were issued in the following years. For example, the Air Pollution Prevention and Control Action Plan including phased goals for fine particulate matter ($PM_{2.5}$) was issued in 2013 (Cai et al., 2016). Table 3 presents the shadow prices of industrial air pollutant emissions estimated by models 1–4 for each comprehensive economic zone in 2006, 2011, and 2016. The shadow prices in each zone increased regardless of the model that was adopted, although the absolute values of the shadow prices differed. For the sake of clarity, Fig. 3 shows the shadow prices estimated by model 1 (SBM model based on T_F) in each zone for 2006–2016 as an example. In general, the shadow prices were higher in the three coastal zones (Northern Coast, Eastern Coast, and Southern Coast) and lower in the Great Northwest and Middle Yellow River.

[Insert Table 3]

[Insert Figure 3]

Shadow prices of industrial air pollutant emissions in each zone grew stably and increased rapidly since 2012. For instance, the shadow price in the Northern Coast increased by 73.53% in 2015 and by 58.61% in 2016, while that in the Eastern Coast grew by 48.83% in 2016. Moreover, the disparities in the shadow prices among the eight different zones were relatively small prior to 2012 and subsequently became larger.

Increases in the shadow prices of industrial air pollutant emissions in each zone represent the growth of marginal abatement cost for industrial air pollutant with the increasingly stringent environmental regulations in China. Moreover, the disparities in shadow prices among the different zones indicate that China carried out different regional pollution control strategies. Generally, economically developed regions (mainly concentrated in the Northern Coast, Eastern Coast, and Southern Coast) had relatively heavy emission reduction tasks, while less developed regions (mainly in the Great Northwest) had relatively light tasks.

As models 1–4 produced generally the same growth trends and regional characteristics for shadow prices of industrial air pollutant emissions, the following sections (sections 4.4 and 4.5) simply take the empirical results produced by model 1 to conduct further analysis.

4.4 Decomposing the shadow prices of industrial air pollutant emissions for 2006–2016

Based on model 1 and Eq. (11), Figs. 4 and 5 present the energy saving and end-of-pipe controlling effects on the year-on-year changes of shadow prices in China and in each zone.

[Insert Figures 4 & 5]

According to Fig. 4, except for individual years, both the energy saving and end-of-pipe controlling effects have taken positive values, which drove the growth of shadow prices in China during 2006–2016. Generally, it is difficult to determine the dominating effect in the analyzed periods; nevertheless, we find that the end-of-pipe controlling effect surpassed the energy saving effect during the years of 2015 and 2016.

According to Fig. 5, it was found that both the energy saving and end-of-pipe controlling effects fluctuated more frequently prior to 2013 compared to the more recent three years, which resulted in relatively slow increases in the shadow prices in China during that time. On the other hand, shadow prices of industrial air pollutant emissions in each region experienced large increases in the last year or two under the combined actions of the two effects. Specifically, the Northern Coast and Eastern Coast experienced a rapid increase in the shadow prices for 2015–2016, which was mainly caused by the end-of-pipe controlling effect, while the rapid increase in the Southern Coast during the same period was from the energy saving effect. The Northeast had a superior energy saving effect for the three consecutive years from 2013, but a larger end-of-pipe controlling effect in 2016. The Middle Yellow River, Middle Yangtze River, Great Southwest, and Great Northwest had similar situations where the energy saving effect was dominant in 2015 and the end-of-pipe controlling effect greatly increased in 2016.

4.5 Emissions reduction effectiveness of environmental regulation for 2006–2016

Although the shadow prices of industrial air pollutant emissions have grown largely in recent years, this shows only growing marginal abatement costs and indicates increasing environmental regulation stringency. Have the increasing environmental regulation stringency been effective at controlling pollution?

The results of the panel data regression by controlling provincial and time effects are summarized in Table 4 according to Eq. (12). It is shown that the Environmental Kuznets curve is supported, especially for the industrial NO_x emissions, and that environmental regulation stringency reduced industrial air pollutant emissions significantly and at an increasing rate in China during the study periods. Besides, the time effects of years 2008 and 2009 were negative and significant for the integrated emission and SO_2 emissions, indicating that growth rates of emissions, especially industrial SO_2 emissions, in China contracted under the shock of the 2008 world financial crisis.

[Insert Table 4]

China has not yet established a national pollutant emissions trading market; however, it has imposed an environmental tax on air, water, and solid waste pollution since 2018. Comparing the newly set tax levels on air pollution with the shadow prices in 2016 estimated in this study, it was found that the two indicators are positively correlated (correlation coefficients are 0.6563, 0.7157, 0.6245, and 0.6978 according to model 1, model 2, model 3, and model 4). This indicates that the environmental taxes imposed in 2018 still followed the existing regional unbalances of environmental regulation stringency: economically developed regions tend to have higher shadow prices and have set higher tax standards, while less developed regions have lower shadow prices and have set relatively lower tax standards (more evidence is provided in Table B.2). However, the lowest shadow price estimated among the four models remains higher than the corresponding provincial environmental tax standard in 2018 (See Table B.2). Given that environmental tax is only one policy instrument and shadow prices of undesirable outputs capture the whole policy mix, it is reasonable that the estimated shadow prices are positively correlated with tax standards but are considerably larger. The effectiveness of the overall environmental policy cannot automatically infer the emission reduction effect of environmental taxes. Additional evidence is required to compare the abatement effects between command-and-controlled and market incentive policies in China in future research.

5. Concluding remarks

China has put forward a comprehensive package of regulations for air pollution prevention and control in recent years, and shadow prices of undesirable outputs (such as pollutant emissions) provide a comprehensive measurement indicator for the whole related regulation stringency. Generally, this study provides some robust estimations for the shadow prices of industrial air pollutant emissions in China during 2006–2016 and provides further analysis on the estimated shadow prices from their determinants and the effectiveness of emission reduction.

Specifically, based on the duality theory, this study demonstrates that the by-production model proposed by Färe et al. (1993) for polluting technology is consistent with the two sub-technologies model. Moreover, the use of different models did not change the conclusion that the shadow prices of industrial air pollutant emissions have grown rapidly in each of the eight comprehensive economic zones of China in recent years, and that shadow prices are higher in the Northern Coast, Eastern Coast, and Southern Coast than in other regions. The decomposition results of the LMDI method further demonstrated that neither effect had been dominant in the increases in shadow prices during 2006–2016, and both have given greater positive forces to push the shadow prices higher during the years of 2015 and 2016. The regression analysis confirmed that China's comprehensive environmental regulations with regional disparities in recent years have not only raised the marginal abatement costs but also effectively reduced the growth rates of industrial air pollutant emissions at an increasing rate.

Finally, we need to point out that although the shadow prices estimated in this study could be used as a comprehensive indicator to measure the overall stringency of environmental regulations related to industrial air pollutant emissions, they are not suitable as direct references for the environmental tax levels or prices of tradable emission permits in each province. The DEA method has the advantage of not requiring a predefined function form, however the DEA estimators are sensitive to the outline and the selected directional distance function. As a result, the absolute values of the estimated shadow prices are sensitive to the estimation methods (the four different models in this study), and they are not empirically well-founded references for the environmental tax levels or prices of tradable emission permits. We recommend focusing on the relative values or growth rates of the estimated shadow prices when measuring the overall environmental regulation stringency, as different models provide robust results in terms of relative values among each decision-making unit.

Acknowledgments

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Appendix A.

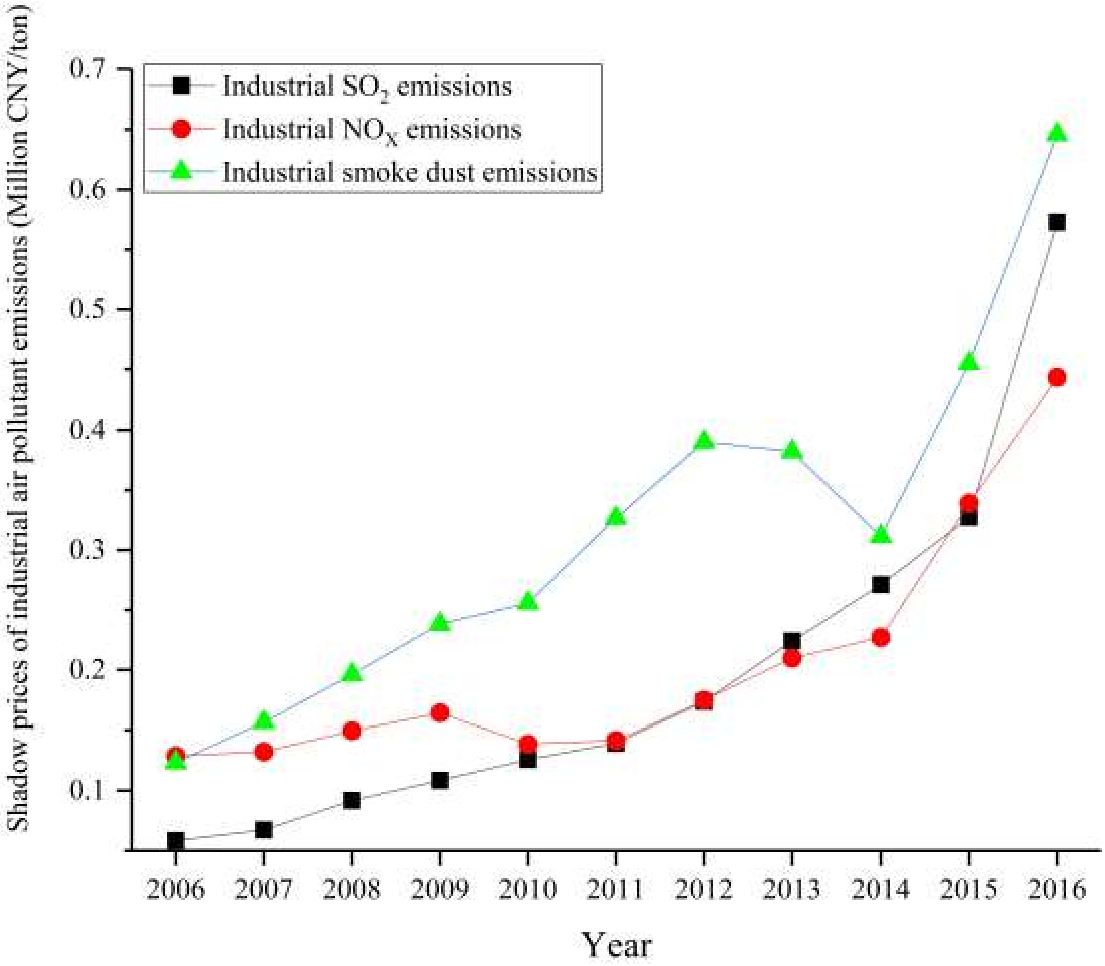

Fig. A.1. Shadow prices of industrial SO_2, NO_x, and smoke dust emissions in China for 2006–2016 estimated by model 1.

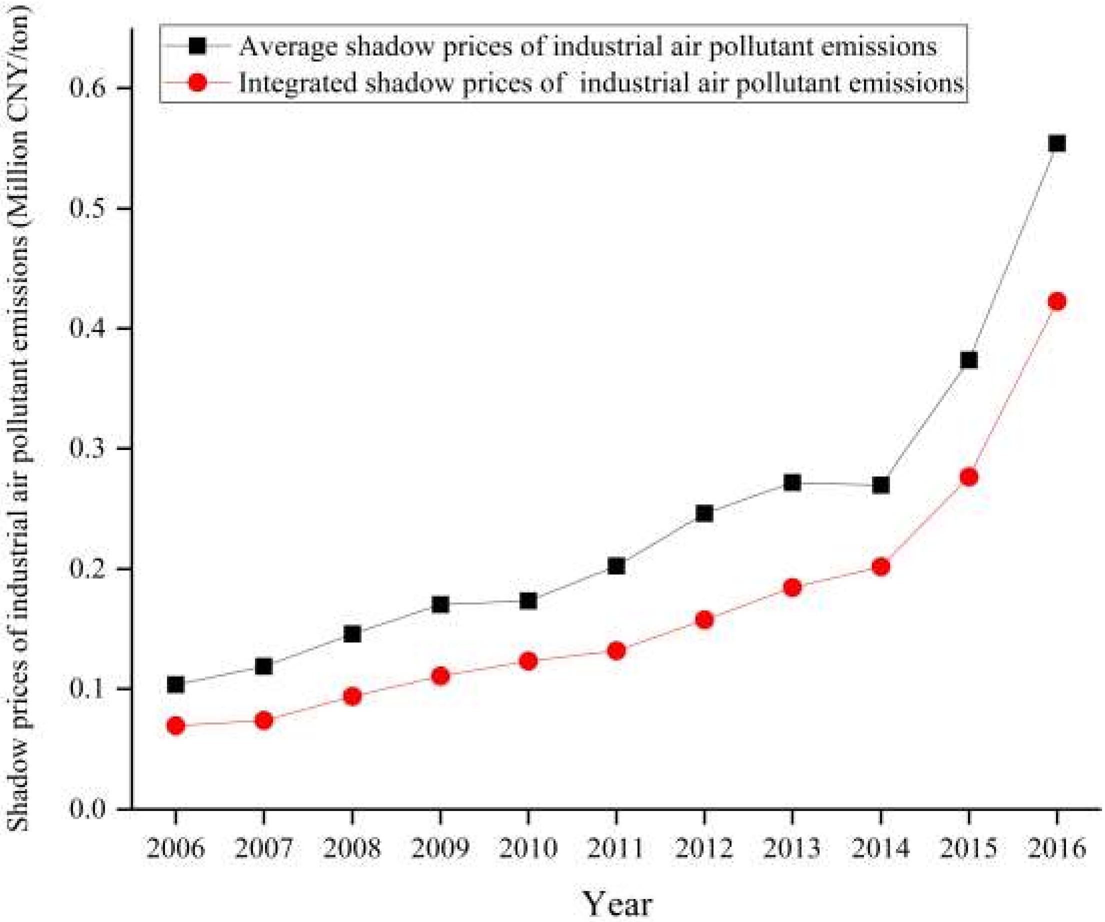

Fig. A.2. Comparison between the average and integrated shadow prices of industrial air pollutant emissions in China for 2006–2016 estimated by model 1.

Note: The average shadow prices of industrial air pollutant emissions were calculated by first estimating the shadow prices for each industrial pollutant (SO_2, NO_x, and smoke dust) emission individually and then calculating the mean values. The integrated values were calculated by first adding the industrial SO_2, NO_x, and smoke dust emissions to a single integrated indicator and then estimating its shadow prices.

Appendix B.

Table B.1

Descriptive statistics for shadow prices of industrial air pollutant emissions in China for 2006–2016 estimated by models 1, 2, 3, and 4.

Model	Unit	Mean	Max	Min	Std dev.
Model 1	Million CNY/ton	0.1678	3.7664	0.0028	0.2790
Model 2	Million CNY/ton	0.2192	5.2501	0.0022	0.3872
Model 3	Million CNY/ton	0.4182	11.2991	0.0028	0.8006
Model 4	Million CNY/ton	0.6205	11.2991	0.0429	0.8783

Table B.2

Shadow prices and environmental tax standards in China's 30 provinces for 2016.

Province	Shadow prices of industrial air pollutant emissions (million CNY/ton) in 2016				Environmental tax standards (million CNY/ton)	Shadow prices/environmental tax standard
	Model 1	Model 2	Model 3	Model 4		
Liaoning	0.17	0.18	0.52	0.52	0.0126	13.65
Jilin	0.19	0.44	0.25	1.25	0.0126	15.24
Heilongjiang	0.17	0.18	0.51	0.51	0.0126	13.55
Beijing	3.77	5.25	11.30	11.30	0.1263	29.82
Tianjin	0.61	1.47	0.90	3.57	0.1053	5.77
Hebei	0.20	0.23	0.67	0.67	0.1011	2.02
Shandong	0.39	0.38	1.20	1.20	0.0126	31.06
Shanghai	0.86	1.65	1.92	4.34	0.0800	10.79
Jiangsu	0.66	0.55	1.92	1.99	0.0505	13.01
Zhejiang	0.51	0.78	1.92	2.77	0.0147	34.83
Fujian	0.23	0.06	0.39	2.10	0.0126	18.34
Guangdong	1.08	1.15	1.92	3.24	0.0189	57.02
Hainan	0.23	0.27	0.69	0.69	0.0253	9.11
Shaanxi	0.28	0.40	0.81	1.10	0.0126	21.89
Shanxi	0.10	0.10	0.29	0.29	0.0189	5.12
Henan	0.51	0.42	1.61	1.61	0.0505	10.07
Inner Mongolia	0.07	0.12	0.13	0.52	0.0253	2.93
Hubei	0.19	0.62	0.19	1.86	0.0295	6.43
Hunan	0.23	0.42	0.19	1.51	0.0253	9.08
Jiangxi	0.27	0.26	0.94	0.94	0.0126	21.49
Anhui	0.30	0.37	1.24	1.24	0.0126	23.48
Yunnan	0.15	0.16	0.45	0.45	0.0295	5.06

Guizhou	0.15	0.16	0.45	0.45	0.0253	5.90
Chongqing	0.37	0.50	1.48	1.48	0.0368	9.92
Sichuan	0.37	0.45	1.24	1.24	0.0411	9.08
Guangxi	0.21	0.41	0.27	1.17	0.0189	10.91
Gansu	0.12	0.13	0.37	0.37	0.0126	9.66
Qinghai	0.12	0.13	0.37	0.37	0.0126	9.82
Ningxia	0.07	0.08	0.22	0.22	0.0126	5.72
Sinkiang	0.09	0.10	0.27	0.27	0.0126	7.02

Note: The ratio of the shadow price to the environmental tax standard is calculated based on model 1.

Captions of figures

Fig. 1. Total emissions and emission intensity of industrial air pollutant in China for 2006–2016.

Fig. 2. Estimated shadow prices of industrial air pollutant emissions in China for 2006–2016 with different models.

Fig. 3. Estimated shadow prices of industrial air pollutant emissions in China's eight comprehensive economic zones for 2006–2016 with model 1.

Fig. 4. Estimated decomposition effects in China for 2006–2016 with model 1.

Fig. 5. Estimated decomposition effects in each comprehensive economic zone of China for 2006–2016 with model 1.

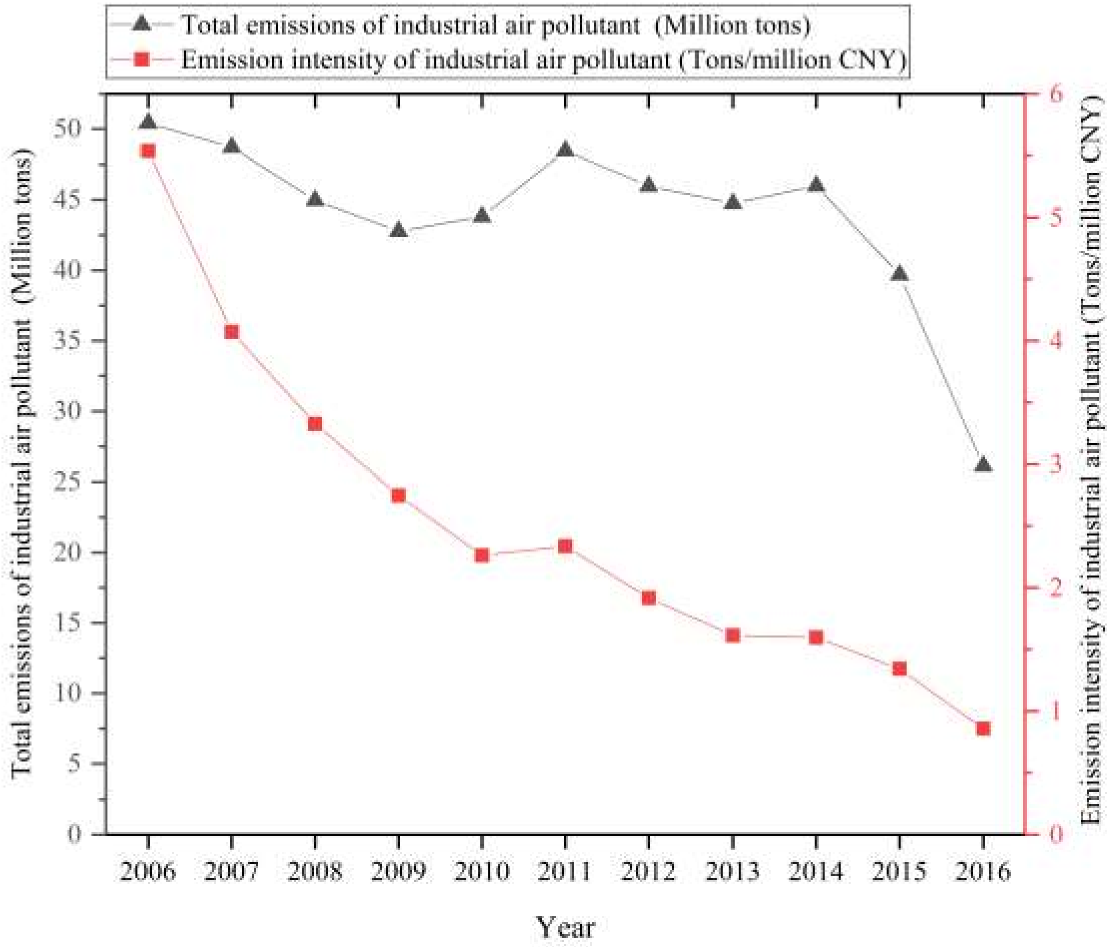

Fig. 1 Total emissions and emission intensity of industrial air pollutant in China for 2006–2016.

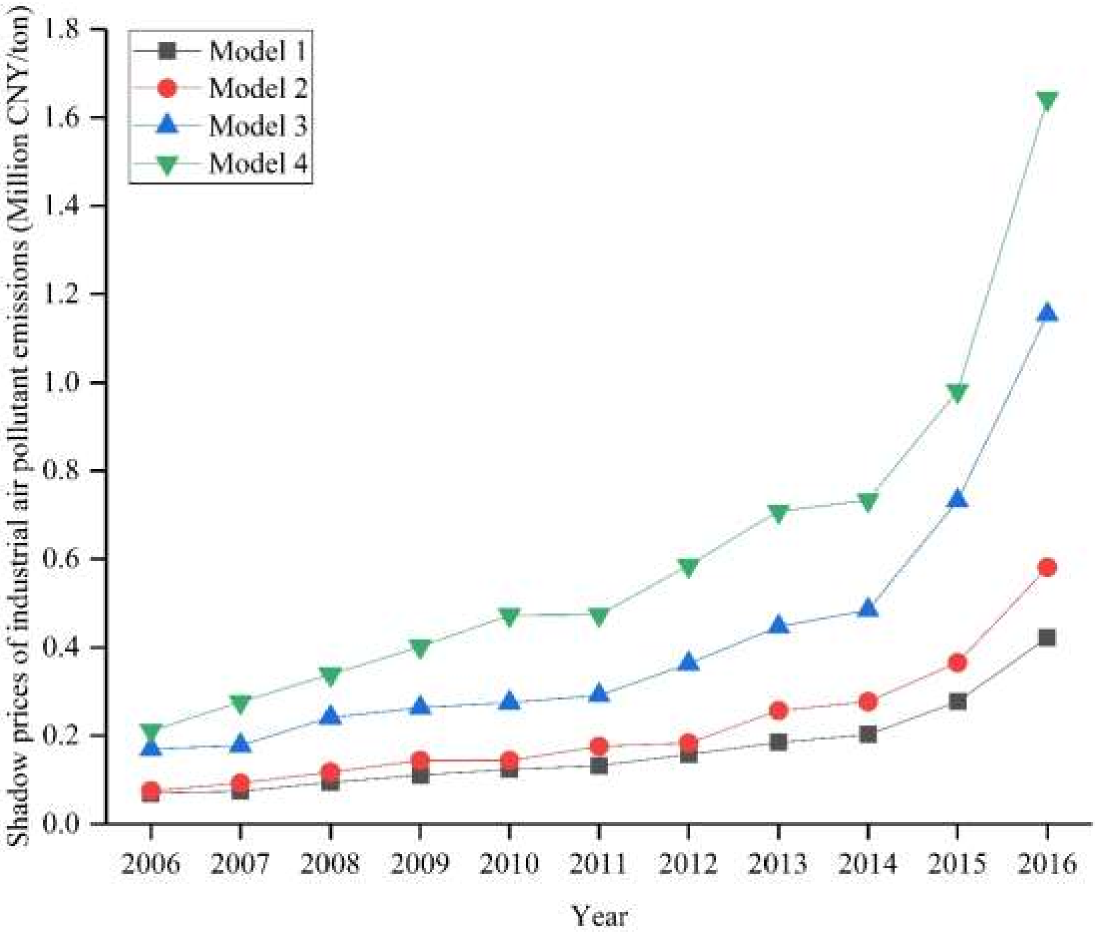

Fig. 2 Estimated shadow prices of industrial air pollutant emissions in China for 2006–2016 with different models.

Notes: Model 1 is the SBM based on T_F, model 2 is the SBM based on T_{MS}, model 3 is based on the directional distance function with T_F, and model 4 is based on the directional distance function with T_{MS}.

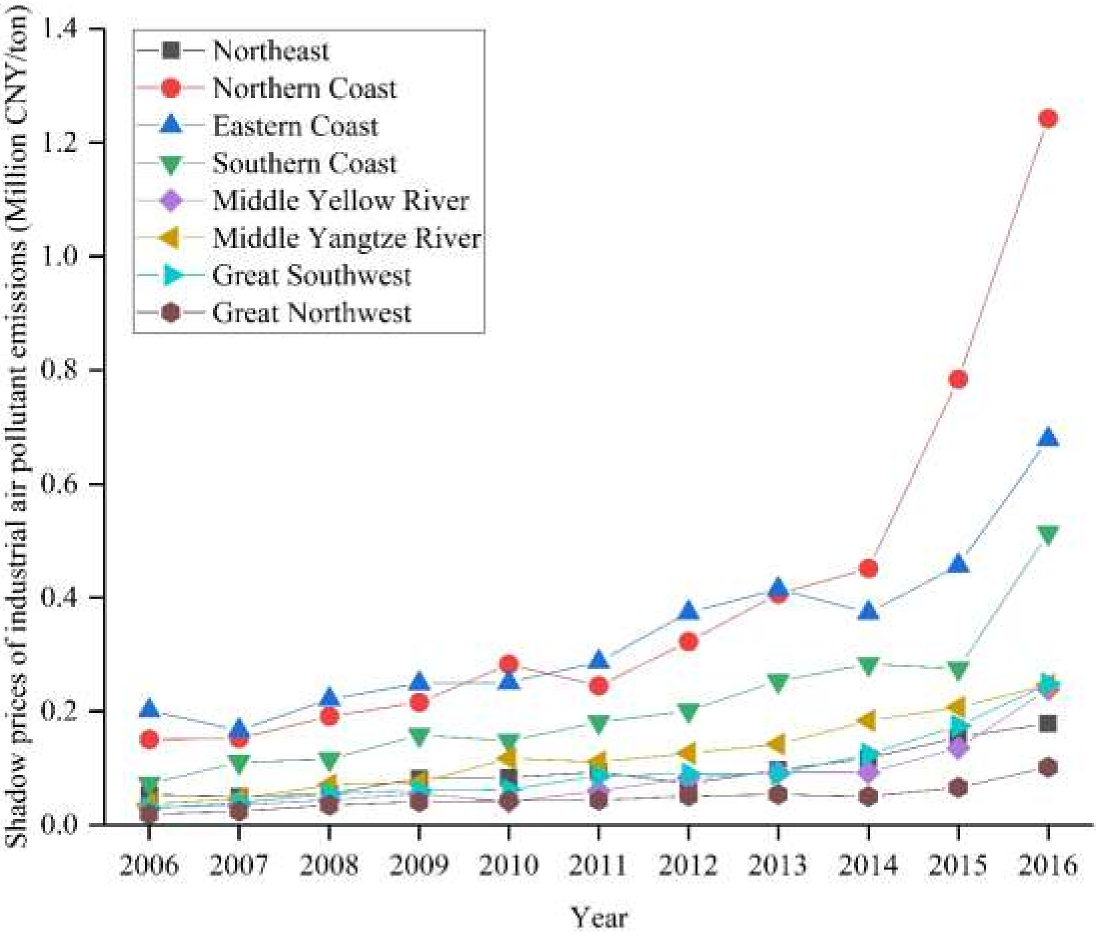

Fig. 3 Estimated shadow prices of industrial air pollutant emissions in China's eight comprehensive economic zones for 2006–2016 with model 1.

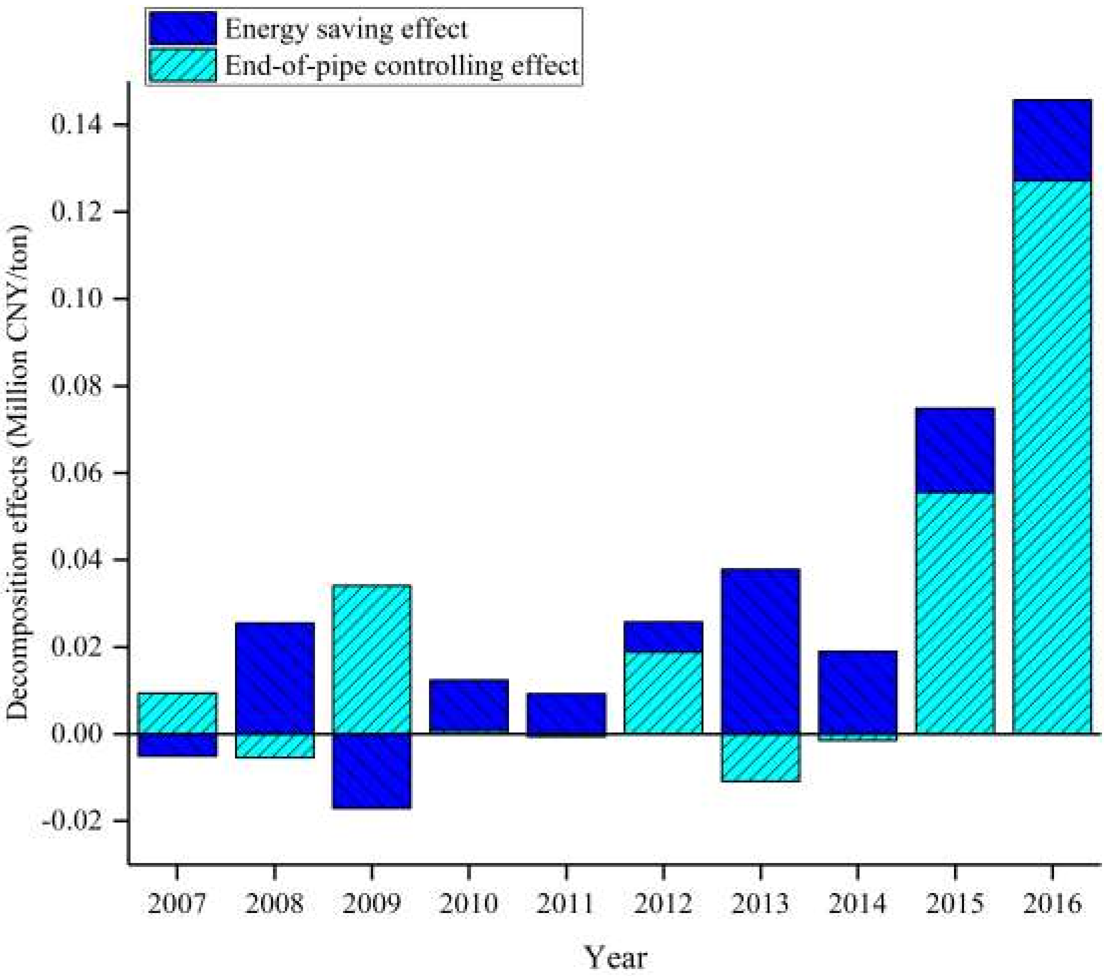

Fig. 4. Estimated decomposition effects in China for 2006–2016 with model 1.

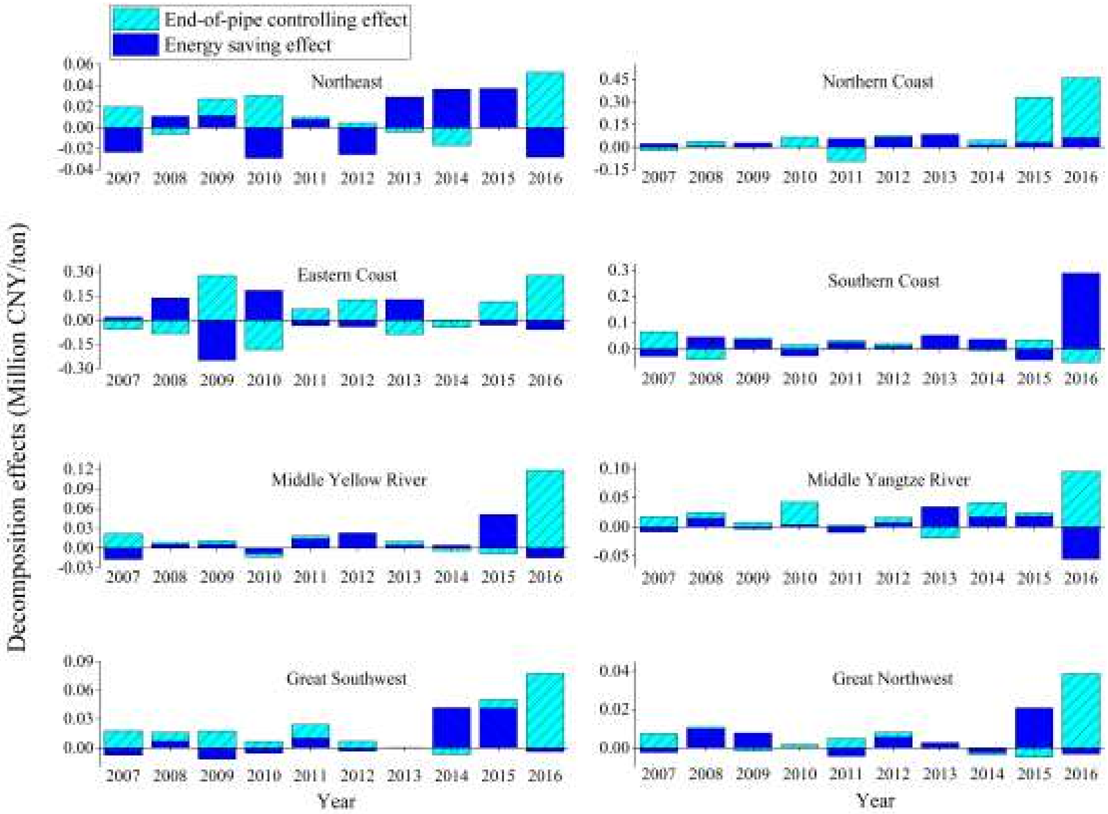

Fig. 5. Estimated decomposition effects in each comprehensive economic zone of China for 2006–2016 with model 1.